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Oral Cancer Detection Using Improved Segmentation Algorithm

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Abstract— Cancer is one of the leading causes of death in developing countries. Among various cancers, Oral cancer is a common cancer which affects both men and women. This work presents the detection of oral cancers using Image Processing. Dental X – Rays are used as the Input Image for detection. At first, Linear Contrast Stretching is used to remove noise from the Dental X – Ray Image. Initially Watershed Segmentation and Marker Controlled Watershed Segmentation are used to segment tumors from the enhanced Image. Problem of oversegmentation arises in both the segmentation algorithms. So, Marker Controlled Watershed Segmentation is improved. The Segmentation Algorithms are compared for speed and accuracy. The speed is calculated before and after Linear Contrast stretching. The proposed algorithm provides better segmentation.

Keywords— Image Processing, Watershed Segmentation, Marker Controlled Watershed Segmentation, Improved Marker Watershed Segmentation, Linear Contrast Stretching

I. INTRODUCTION

Systemic problems those that affect the entire body many times appear in the mouth first. In general, mouth is a good indicator of what's going on in the body, which is why the physicians for generations have asked patients to open their mouth. The discovery of a wound in the mouth indicates so many problems in the Human Body Despite advances in surgery, radiation and chemotherapy, the mortality rate associated with oral cancer has no improvement in the last 40 years. Eventually, 50 percent of people who have oral cancer die as a result of the malignancy. Early evaluation of oral precancerous lesions can have a dramatic impact on oral cancer mortality rates [1]. Tumors can be benign, premalignant or malignant. Benign tumors are harmless and do not spread. Premalignant tumors can transform into Malignant. Malignant tumors are cancerous. Oral cancer can affect any area of the oral cavity including the lips, gum tissues, tongue, cheek lining and the hard and soft palate. "Maharashtra has the highest incidence of mouth cancer in the world". The common oral precancerous lesions are leukoplakia, erythroplakia, and oral sub – mucous fibrosis (OSF). The diagnosis of Oral precancer and cancer remains a challenge to the dental profession, particularly in the detection, evaluation and management of early phase alterations or frank disease [2]. Prediction of Oral Leukoplakia (premalignant) and Oral Squamous Cell Carcinoma becomes a challenging task. Due to the lack of timely diagnosis, in all conventional methods or differential diagnosis, Biopsy is required [3]. This paper focuses on detecting and classifying oral cancers at an earlier stage. X – Rays are an essential part of dental care. Although X – rays are effective diagnostic tools, some dental practices particularly those that handle a large number of dental implant cases, are using more advanced imaging techniques to ensure an even higher degree of accuracy. Dental radiographs are used for screening oral pathologies continuously and it is often a difficult task to detect early stage cancer tissues in a dental radiograph. Unlike other types of cancers, oral cancers are visibly seen with the naked eye, some cancers are located internally in the mouth, making their detection difficult. And also some non cancerous tissues are not harmful. The input dental X – ray image is preprocessed using Linear Contrast Stretching. Initially, for Segmentation Watershed Segmentation and Marker Controlled Watershed Segmentation is used. Due to the drawbacks of oversegmentation, the existing Marker Controlled Watershed Segmentation is improved. Later, the image is segmented and the tumor is detected. The proposed technique will quantify each result with the diagnostic accuracy and helps the radiologist as a second guidance.

The paper is organized as follows: Section 2 gives the related study of the survey. Section 3 gives a description about the methodology of the proposed work. Section 4 presents the discussions. Conclusion is given in Sections 5.

II. RELATED WORK

An expert who suspects the presence of tumor has the following options: 1) Recommend Biopsy immediately. 2) X – rays studies to find the cancer's exact location. 3) Provide Medications. 4) Remove the cancer. 5) Other Scan procedures and 6) Suspend it as it is and wait for some more time. Many researchers have worked on Oral Cancer Detection and Classification. They used various techniques in Data Mining, Image Processing, Neural Networks, Genetic Programming, Wavelets etc. The following table (Table 1) presents a comparative study of the different methods used for cancer detection and classification.

TABLE 1 COMPARATIVE ANALYSIS OF ORAL CANCER DETECTION AND CLASSIFICATION ALGORITHMS

Reference	Cancer Type	Input Image	Techniques	Algorithms used	Description	Result
4	Oral cysts	Dental X - Rays	Neural Networks, Image Processing	Contrast stretching, Radial Basis Function	The severity of the cysts is calculated using circularity values	Severity of cysts is measured. For each dental image, accuracy is calculated for classification of cysts
5	Oral Cancer / cysts	Histopathological OSF images	Image Processing	Region Growing, Hybrid Segmentation Algorithm	Misclassification rate were calculated for both the algorithms.	Finally, Hybrid Segmentation method found to be suitable for segmentation of cancers in OSF images.
6	Oral Cancer / Breast cancer	Plethysmography images / Mammogram	Artificial Neural Networks, Statistical Methods		The work compared the classification accuracy of the TNM staging along with that of the Chi – square Test and Neural Networks.	ANN was significantly more accurate than the TNM staging system.
7	Oral cancer	True Color Images	Image Processing	Active Contour Model (Snakes)	Segmentation of oral lesion is obtained in single band images from true color images	To further automatize and improve segmentation, additional or enhanced energy terms and more human knowledge should be incorporated
8	Oral Cancer	Histopathological Images, TEM images	Wavelets, Neural Networks	Multi Layered Perceptron, Feed Forward Neural Network	The feature vectors were extracted from each contiguous 64 x 64 blocks by wavelet decomposition	In case of less advanced stage of disease, some of the blocks are showing the signature of normal collagen image, whereas some are having the signature of advanced stage of OSF. As a result, the false detection rate is high in this less advanced stage but the PCBI is always greater than 50%. As the final decision is taken based on the magnitude of PCBI, it always leads to correct diagnosis.
9	Oral Cancer	Histopathological Image	Wavelets, Data mining, Neural Networks	Bayesian Classifier, SVM classifier	The proposed method, involves feature extraction using wavelet transform, feature selection using Kullback – Leibler (KL) divergence and diagnostic classification using Bayesian Approach and Support Vector Machines	
10	Oral cancer	Data set	Genetic Programming, Neural Networks		The comparison between a Genetic Programming system and Neural Network model was provided.	The Genetic Programming system played a major advantage in diagnosing the tumor. The results obtained were good and accurate

11	Oral cancer	Biopsy Images	Image Processing, Neural Network	Histogram Based Feature Extraction, SVM	Classification is performed to differentiate normal and OSF images	Experiments showed significantly satisfactory results with an accuracy of 94%.

From Table 1, it is identified that many researchers used Histopathological Images (Biopsy Images) for detection / classification. Only few used Dental X – Ray images as the input images. Dental X – Rays are chosen due to following:

1) MR Images may become blurry because of the artifacts of the moving tongue.
2) CT scans are able to detect the actual presence of masses, but only a biopsy can verify that the mass is malignant.
3) Ultrasonography can find masses within an area.
4) Risks are caused by PET scans due to Radio active compounds (twice more than X – rays).
5) Biopsy is painful task and patients may feel uncomfortable when unnecessary biopsies are recommended at initial stage.
6) With these methods, tumor inside bone / jaw is not visible, only X – rays can show.

With these drawbacks Dental X – Rays are chosen as the input image.

III. METHODOLOGY

The methodology comprises of various steps: 1) Image Preprocessing 2) Image Segmentation 3) Comparison of Image Segmentation Algorithms 4) Feature Extraction 5) Classification 6) Comparison of Feature Extraction methods.

A. Image Preprocessing

Dental X-Ray images always suffer from problems like noise, low contrast, and uneven exposure. The images have poor visibility and formation is not much clear. A technique is required which enhances the image by increasing the contrast for a selected region. So, Linear Contrast Stretching is used. While contrast is increased for a selected region, the teeth and bone regions become brighter and other regions including the tumor regions are clearly visible. The input dental X – ray image is shown in Fig 1.

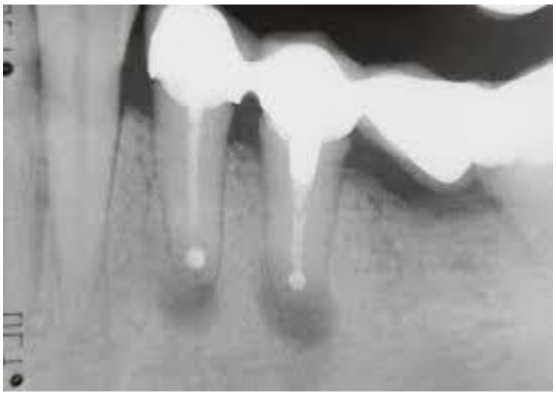

Fig 1 Input Image

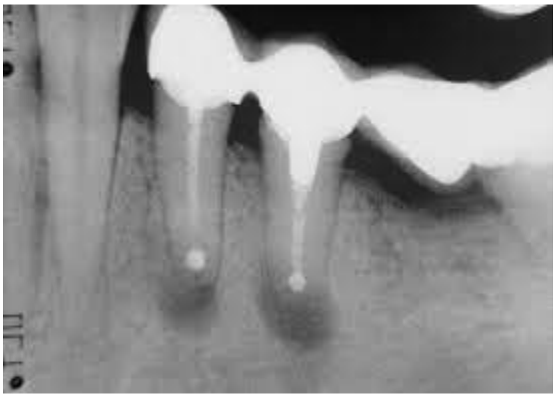

Fig 2 Enhanced Image

The contrast is increased when the slope is more than 1. Fig 2 is the enhanced image using Linear Contrast Stretching.

B. Image Segmentation

Image segmentation is an essential process for most image analysis techniques. Segmentation 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. All subsequent interpretation tasks, such as object recognition and classification, rely heavily on the quality of the segmentation process [3]. In [13] combination of watershed and thresholding technique is used. Main problem with thresholding is to deciding threshold value. The proposed technique in [14] focuses on the solution of under segmentation problem of low contrast images by applying pre-processing on the input image. The technique for pre-processing on the images is Curvelet transform. It is an approach used to enhance the image contrast when image is degraded. Marker based watershed is used but still there is problem of over-segmentation. Hence in this paper a method is proposed which uses watershed with region merging process. With the drawbacks of Watershed and Marker – Controlled Watershed Segmentation, a new method is proposed which improves the Marker Controlled Watershed Segmentation.

1) Watershed Algorithm

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.

Fig 3 Image after watershed

Furthermore, several researchers have proposed techniques to embed the watershed transformation in a multiscale 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. The enhanced image (Fig 2) is segmented by using the watershed segmentation first. The image shown in Fig 3 is the output after watershed segmentation. 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.
The steps for Watershed algorithm are:
1. Read the Input the image.
2. Compute the gradient magnitude.
3. Compute watershed of the gradient magnitude.
4. Superimpose the gradient on the original image.

Drawbacks of Watershed Algorithms:
From Fig 3, the tumor part is not clearly segmented. Over – segmentation also occurs. It is not an efficient idea to conclude Watershed Algorithm as the final segmentation algorithm. So Marker Controlled Watershed Algorithm is used.

2) Marker Controlled Watershed Segmentation Algorithm

As Watershed Segmentation leads to oversegmentation and other drawbacks, Markers are introduced into the algorithm. The Marker – Controlled watershed segmentation solves all the problems faced by the previous segmentation algorithm. The Marker based watershed segmentation can segment unique boundaries from an image or stack of images, however it has no smoothing or generalization properties. Markers are used in this algorithm. A marker is a connected region belonging to the image. There are two markers. Internal Markers (Foreground Markers) associated with the object of interest and External Markers (Background Markers) associated with the background of an image.
The steps for Marker Controlled Watershed Segmentation:
1. Compute a segmentation function. This is an image whose dark regions are the objects to be segmented.
2. Compute foreground Markers. These are connected blobs of pixels within each of the objects.
3. Compute background Markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background Marker locations.
5. Compute the watershed transform of the modified segmentation function.

The segmented image using Marker Controlled Watershed Segmentation is shown in Fig 4.

Fig 4 Image after Marker Controlled Watershed Segmentation Algorithm

From Fig 4, it is also seen that the image is not properly segmented. Hence to overcome this problem, the marker controlled watershed segmentation is modified.

3) Improved Marker Controlled Watershed Segmentation Algorithm

In the proposed method, the Marker Controlled Watershed Algorithm is modified by comparing the neighbourhood (8 connected) pixels and plotting the pixels which are more or less same and segmenting it. The steps for Marker controlled watershed is used by modifying it slightly.

The steps for Improved Marker Controlled Watershed Segmentation are:

1. Compute a segmentation function. This is an image whose dark regions are the objects to be segmented.
2. Compute foreground Markers. These are connected blobs of pixels within each of the objects.
3. Compute background Markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background Marker locations.
5. Connect the points (pixels) of the same or relative intensity level (which reduces sudden change).
6. Compute the watershed transform of the modified segmentation function.

The Advantages with this method is that it reduces the sudden change in the intensity level.

Fig 5 Output after Improved Marker Controlled Watershed Segmentation Algorithm

4) *Comparison of Algorithms*

The algorithms are compared by comparing their processing speed. The speed is calculated using:
Average Speed (S): S = 100 – (Processing Time – Input Time) /60 in seconds
Ten images are taken as samples and the speed is calculated for all the algorithms.

TABLE 2 COMPARISON OF ALGORITHMS

Segmentation Algorithm	**Speed (Without Stretching)**	**Speed (With Stretching)**
Watershed Segmentation	87%	91%
Marker Controlled Watershed Segmentation	90%	92.55%
Improved Marker Controlled Watershed Segmentation	90.5%	92.6%

The Processing Speed is calculated before stretching and after stretching. Due to presence of noise, the algorithm speed is lower before stretching.

IV. DISCUSSIONS

The algorithms are compared and are shown in Table 2. The speeds of the algorithms are calculated before and after contrast stretching. For Watershed Segmentation the speed is 87% (before stretching) and 91% (after Linear Contrast Stretching). For Marker Controlled Watershed Segmentation, it is 90% (before stretching) and 92.55% (after Linear Contrast Stretching). Similarly, for Improved Marker Controlled Watershed Segmentation, the speed calculated is 90.5% (before stretching) and 92.6% (after Linear Contrast Stretching). From this, it is known that the speed for all the algorithms before stretching is lower than the speed after stretching. As the input images contain more noise, it takes more time for processing (Fig 6).

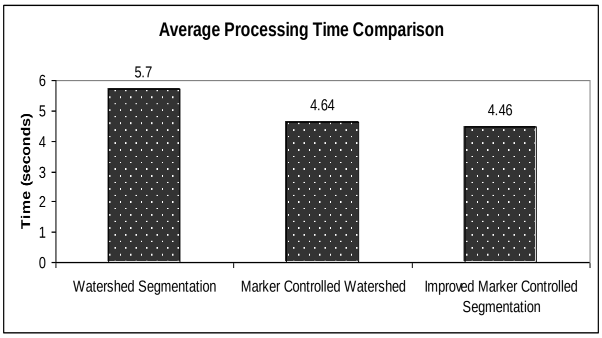

Fig 6 Processing Time Comparison

From Fig 6, the processing time is more for Watershed segmentation.

V. Conclusion

In this proposed work, the dental X – ray is preprocessed using Linear Contrast Stretching to remove noise. After that Watershed Segmentation is used to segment regions from the image. Due to the problem of Watershed segmentation, Marker Controlled Watershed segmentation is used. Marker Controlled watershed segmentation reduces the over segmentation problem. But the image is not properly segmented, so the existing Marker Controlled Watershed Segmentation is improved. The proposed algorithm is compared with the input image to check the image quality and tumor area. The processing time is compared for all the algorithms, and the proposed algorithm is found to be better than other techniques.

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