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Computer-aided Bone Tumor Segmentation Using X-ray Images

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Abstract— ***CAD is useful to doctors for diagnosis. It reduces inter and intra-observer variations, are more reliable and accurate. There are various medical imaging modalities but X-rays found to be the first and foremost technique used for imaging bones because they are inexpensive and due to their inherent nature that different tissues absorb X-rays differently. There are various cues for segmentation i.e. intensity, density and texture. Hybrid techniques are always beneficial as compared to individual cue based techniques. In the paper, intensity and density cues are opted for bone tumor segmentation because texture is more prevalent in microscopic images. Thus, bone tumor is segmented using adaptive thresholding and local density-based clustering. The results are qualitatively and quantitatively evaluated against various parameters. The proposed segmentation shows 89% accurate results as compared to other techniques.***

Keywords— ***Bone tumor segmentation, local density-based clustering, adaptive thresholding, hybrid medical segmentation, Quantitative analysis***

I. INTRODUCTION

Segmentation of bones in X-ray images is challenging due to noise, film sensitivity, screen conversion efficiency, screen absorption efficiency, intensity in-homogeneity and diffused boundaries [1]. The problems have been addressed by performing segmentation on the basis of different cues such as intensity, density, and texture. Performing segmentation on the basis of each of these cues has certain limitations. The intensity-based segmentation techniques are sensitive to intensity homogeneity, depend on the radiation exposure and consume time. The density-based segmentation techniques depend on the minimum number of neighbor points and the radius to form a cluster. The texture-based segmentation techniques are dependent on the prominence and homogeneity of the texture. Although texture is highly prominent in microscopic X-ray images, it is not in X-ray images. Moreover, the tumor region does not have homogenous texture. Thus, a hybrid segmentation approach is always beneficial which takes two or more cues into account. The architecture of the proposed algorithm is shown in Figure 1. As an initial step, X-ray images of bones are pre-processed. Initially, histogram adjustment is done to enhance the contrast of image. Then, denoising is performed. X-ray images have Poisson noise [2].

The noise is removed using Weiner filter [3]. Weiner filter preserves edges as well as high frequency areas. Weiner filter takes 3 inputs: image to be filtered, Point Spread Function (PSF) with which noise is distributed and Noise-to-Signal Ratio (NSR). After pre-processing, tumor area is segmented using intensity and density based segmentation methods. The proposed method uses Bernsen’s technique based on the local gray scale range for the segmentation. It uses local statistics i.e. intensity of neighbors around a pixel. Simultaneously, density–based clustering technique based on local statistics is employed. The tumor regions are less dense and have inflammatory area so it is possible to segment the area with the help of these techniques.

The local density-based segmentation algorithm used in the proposed method is based on Lee’s sigma filter [4] [5]. It keeps count of the number of pixels having same or similar intensities within a window. If the calculated count is more than the desired count, which is static, then the pixel is classified as dense else non-dense. The technique is based on the point density estimate as each pixel individually is classified as dense or non-dense. The method also keeps track of all the pixels which help in making the centre pixel of window dense. Then, recursive call is made to the unvisited pixels. The results of intensity and density-based segmentation techniques are merged together to segment the bone tumor. The regions are very much clear and prominent. The qualitative and quantitative analysis is performed. It is compared with different techniques on different parameters. Quantitative analysis [6 7 8] is performed with the help of accuracy, compactness, dice-similarity co-efficient, ROC analysis, Symmetric surface measure, Relative area difference and area overlap error. Rest of the paper is organized as follows. Various modules of the hybrid medical segmentation i.e. medical image pre-processing, intensity-based segmentation, density-based segmentation and hybrid segmentation are discussed in Sections 2. Then qualitative and quantitative analysis is performed in Sections 3 and 4. Finally, Section 5 presents the concluding remark.

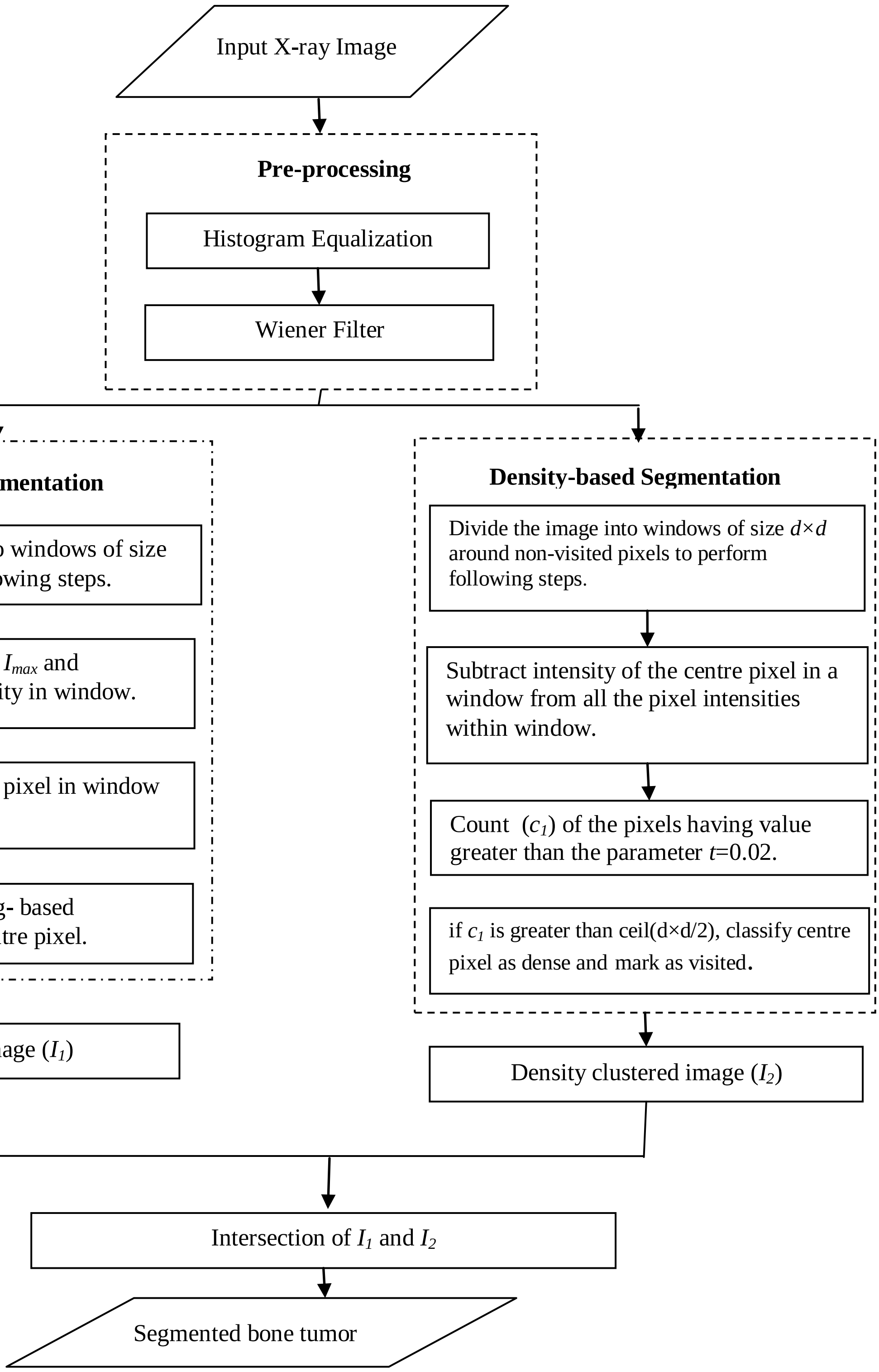


Figure 1: Architecture of the proposed method.

II. METHODS

A. Pre-processing

Histogram equalization is performed to widen the dynamic intensity range of the image. The enhancement also amplifies noise. Since, X-ray images have Poisson noise so, it is removed using Weiner filter. For the final segmentation, the enhanced image is used.

SNR [9] is defined as ratio of the average signal value to the standard deviation of noise. It is calculated by subtracting the intensities of input image from output image. Then, the mean of pixel intensities gives value of SNR. Large SNR will denote better quality of image.

$$SNR = 10\, log_{10}^{\frac{\sigma_{signal}^2}{\sigma_{noise}^2}} \quad (1)$$

B. Intensity-based segmentation

Thresholding is one of the widely used methods for intensity-based segmentation. Many authors have used thresholding in addition to other approaches to segment tumor. Intensity-based segmentation in the proposed method is done via adaptive thresholding technique.

In particular, Bernsen's technique [10] based on local gray scale range is used for segmentation. By selecting an adequate threshold value *T*, the gray level image can be converted to binary image. The binary image contains all the required information about the region-of-interest. Binary image reduces complexity of data and simplifies the process of segmentation.

$$T(x,y) = 0.5\left(I_{\max(i,j)} + I_{\min(i,j)}\right) \quad (2)$$

First of all, window of size $n \times n$ is considered. Then, Bernsen's technique is applied on each centre pixel of the image. Once, the threshold is calculated, the image is converted to binary form. It can be thought as global thresholding applied to each pixel of the image.

C. Density-based clustering

Many image features are used to characterize spatial density of objects. An effective feature should not only represent object density variations but also allows segmentation of ROI. For biomedical applications, the region-of-interest, such as tumor should be a region with irregular but usually smooth boundaries.

With the aim of separating ROI from background, pixels of the tumor are grouped by using local density-based clustering. It is based on Lee's sigma filter. It takes X-ray image as input and delineates only significantly important regions. This algorithm is appropriate for density-based segmentation where the tumor region shows density variations as compared to the surrounding tissues. The pixels are classified as core pixels and border pixels. The core point is the centre point in the window of $w \times w$ size which contains at least *ceil* $(w \times w/2)$ pixels. In short, to classify a pixel as dense, the density in the neighborhood should exceed pre-defined threshold. The threshold can be dynamic according to mean or standard deviation of pixel intensities within the window or it can be static. The definition of neighborhood is determined by the choice of pixels within the sub-image. As expected, a neighborhood query for a border pixel returns noticeably less points than a neighborhood query for a core pixel. Thus, in order to include all pixels belonging to the same cluster, the minimum number of points is set to a standard value. Local scaling in density-based clustering is a technique of clustering the data by considering local statistics around the pixel. For an image of size $M \times M$, a window of size $m \times m$, is selected around a pixel. Scaling factor is m/M. In this, local statistics of neighborhood pixels are considered. In conventional DBSCAN [11], for all unvisited points, neighborhood is obtained using Euclidean distance. It takes as input radius *r* and minimum number of points *minpts* which are required to classify the cluster as dense. For any pixel, it first returns all points within the radius of the pixel. If the number of points are greater than *minpts*, then it is classified as core point, else noise.

The working of local density-based clustering is explained with the help of an example. Let *X* denotes the image. In the technique, a 3×3 window *w* around each pixel $X(i,j)$ is considered.

$$w = X(i-1:i+1\,, j-1:j+1) \; (3)$$

Then, to classify the pixel as dense or non-dense, intensity of the centre pixel is subtracted from the intensities of all the neighboring pixels. It denotes deviation of neighborhood pixels from the centre pixel. For each pixel (i,j) in the window, deviation is calculated as:

$$v(i,j) = |w(i,j) - w(2,2)| \; (4)$$

The matrix *v* obtained has centre value=0. It is ignored while classifying the density. Lesser is the difference, closer the pixel in intensity to the centre pixel. Then, the method counts the number of pixels closer to 0 and closer to 1. Thus, two counts c_1 and c_2 are maintained.

$$c_1 = c_1 + 1, \qquad w(i,j) \le t \; (5)$$
$$c_2 = c_2 + 1, \qquad w(i,j) > t (6)$$

where, *t* is a parameter which decides the threshold value. *t* can be static or dynamic. Dynamically, it is calculated as mean of neighboring pixels or any other mathematical operation. It is taken a static value of 0.02 in the proposed method because mean of neighboring pixels' intensities is used in adaptive thresholding method. c_1 counts all the pixels having intensities closer to the centre pixel whereas c_2 counts the pixels having large intensity variations w.r.t. the centre pixel.

The neighborhood of $X(i,j)$ has 8 points in a 3×3 window. If c_1 is greater than c_2, the point is classified as a dense point, otherwise, non dense.

$$X(i,j) = \begin{cases} 1 & c_1 \ge c_2 \\ 0 & c_1 \le c_2 \end{cases} \; (7)$$

The local density-based clustering technique gives notion of point density functions. It doesn't require any input as *minpts* or *radius* which is needed in conventional DBSCAN. Moreover, this approach is based on intensity values, rather than calculating Euclidean distance between pixels as well as it works for high dimensionality of data.

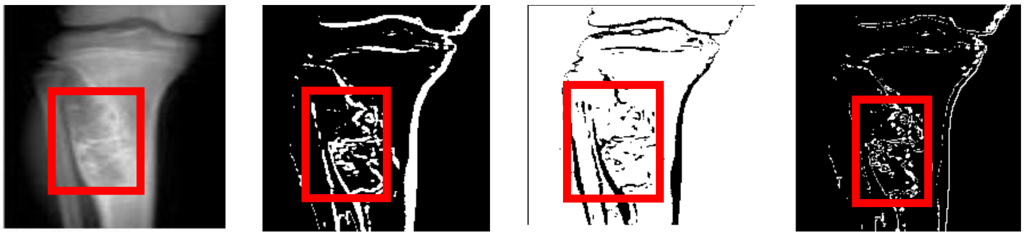
The proposed method uses matrix *visited* of same size as an image. It keeps a check whether the pixel are processed or not. After that pixel is classified as dense or non-dense, then all the unvisited or unprocessed pixels are visited one by one and the algorithm is called recursively.

D. Hybrid segmentation

The results from both segmentation techniques i.e. adaptive thresholding and local density-based clustering are merged together to segment tumor. ROI is marked with red borders in the Figure 2.

Figure 2 shows intermediate results of the proposed algorithm. Figure 2(a) is the input X-ray image then, the pre-processing is done. SNR is calculated. Bernsen's technique when applied on the input image gives the result as shown in

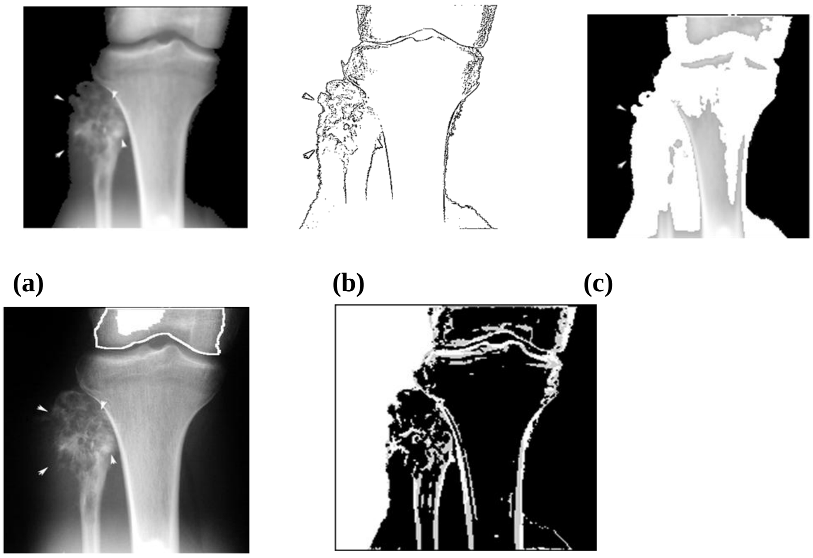
Figure 2(b). Similarly, when Figure 2(a) is given as input to the local density-based segmentation technique, the output is as shown in Figure 2(c). Finally the results of Figure 2(b) and 2(c) are merged together to give Figure 2(d) as output i.e. the region-of-interest. The white irregular shaped clutter is the more severe tumor whereas the black portion adjoining white pixels show less severity. The results are pronounced in case of severe tumor, whereas for radiology images having inflammation or swelling, the proposed method just outlines the area.



(a) **(b)** **(c)** **(d)**

Figure 2: Experimental results of the proposed algorithm (a) Input image (b) Result after adaptive thresholding (c) Result after local density-based clustering (d) Result after hybrid approach.

III. QUALITATIVE EVALUATION



(a) **(b)** **(c)**

(d) **(e)**

Figure 3: Qualitative analysis of different tumor segmentation techniques (a) Original image (b) Adaptive thresholding (c) Region-growing segmentation (d) Watershed-based segmentation (e) Proposed method.

In Figure 3, bone tumor is to be detected. It is compared with adaptive thresholding, region-growing and watershed-based segmentation. Adaptive thresholding technique i.e. Bernsen's technique gives good results and the tumor region is highlighted by small black pixels in the white region. Similarly, in region-growing segmentation, when the seed is selected in the tumor area, the region grows and it doesn't give an indication about the tumor area whereas in the proposed method, the highlighted constituent of gray pixels in the black region shows tumor.

IV. QUANTITATIVE ANALYSIS

A. Accuracy

Accuracy is the number of images in which bone tumor is correctly detected out of the total images in a dataset. It is the most important parameter for judging the performance of different techniques. The proposed method shows 89% accurate results whereas region-growing shows 58% and fcm shows 50% accurate results.

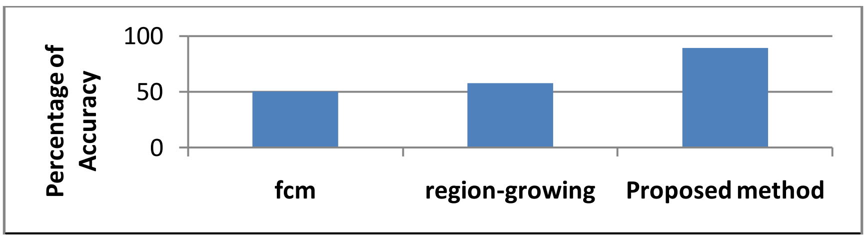


Figure 4: Accuracy

B. Compactness

Tumor nodules are generally circular (in 2D) or spherical (in 3D) and the rest is due to inflammation. Compactness is a parameter which shows the closeness of a detected lesion to the circular shape. It is calculated as follows:

$$c = \frac{p^2}{A} \quad (8)$$

where, c is compactness, p is perimeter and A is area of tumor nodules. Compactness is inversely proportional to the resemblance of lesion to a circle. Lesser is the value of compactness, more closely the segmented region to the circle. Circular characteristics also help in classifying the detected tumor as benign or malignant tumor.

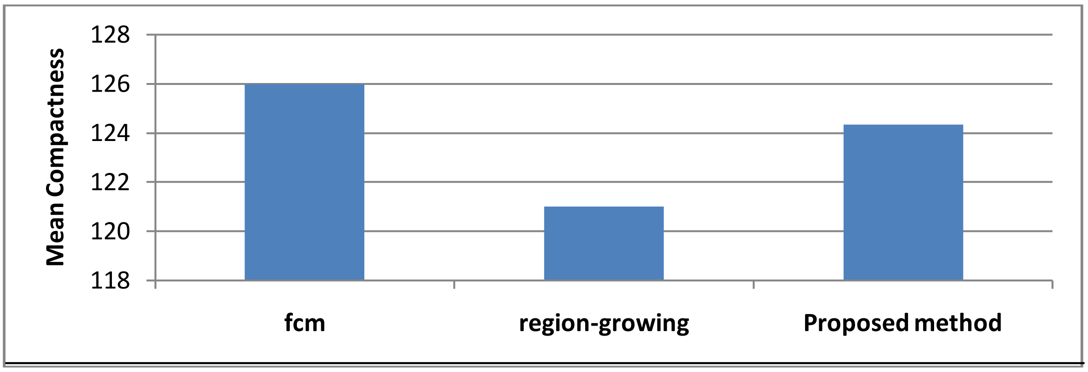


Figure 5:Comapctness

Lesser the value of compactness more accurate is the tumor segmentation. More value of compactness indicates the inclusion of inflammation area in actual tumor area. Figure 5 reveals the difference between fcm, region-growing and the proposed method on compactness metric.

C. Dice Similarity Co-efficient

This refers to the similarity between actual and segmented, tumor and non-tumor pixels. It is calculated according to equation (9).

$$DSC = \frac{I_{GT} \cap I_{IM}}{I_{GT} \cup I_{IM}} \quad (9)$$

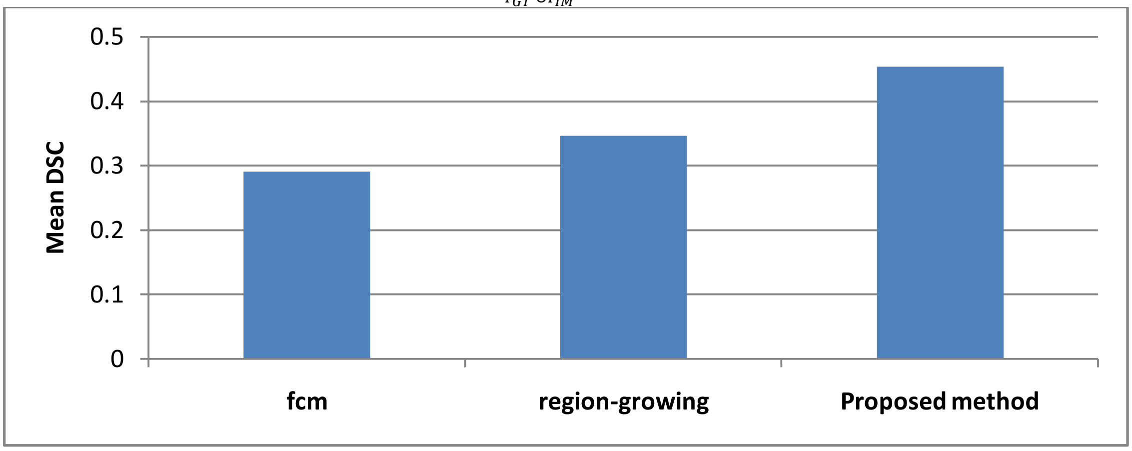


Figure 6: DSC

DSC is 1 for perfect segmentation and 0 for no segmentation. Proposed method shows DSC=1 for larger number of images in dataset as compared to fcm and region-growing.

D. Receiver-Operating Characteristics (ROC)

ROC Curve is a graph between True Positive Rate TP_{rate} and False Positive Rate FP_{rate}. Sensitivity SE is defined as TP_{rate}. True Positive TP are the findings which are actually tumor regions. TP_{rate} is the ratio of actual tumor regions to the total tumor area segmented through an algorithm.

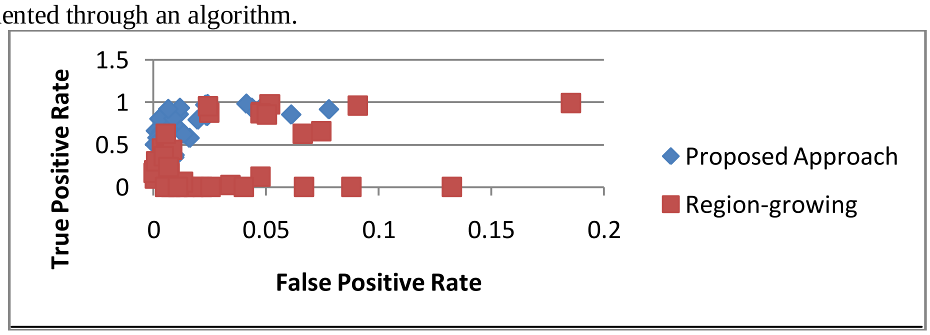


Figure 7:ROC Curve

Figure 7 shows that region-growing has values closer to 0 means low FP_{rate} and low TP_{rate} whereas the proposed method has low FP_{rate} and high TP_{rate}. Low FP_{rate} and high TP_{rate} is desirable for the better performance.

E. Symmetric Surface Measure (SSM)

Minimal distance is defined as the minimum distance between tumor area in manual segmentation I_{GT} to the proposed segmentation I_{IM}. Then, SSM is computed by calculating average value of all the distances of pixels from a pre-defined pixel. It determines the closeness of the boundary of the actual tumor region to the automatic segmented tumor region.

$$SSM = \frac{1}{I_{GT} + I_{IM}} \left(\sum_{X \in I_{GT}} d(X, I_{IM}) + \sum_{Y \in I_{IM}} d(Y, I_{GT}) \right) \quad (10)$$

Here, *d(x,y)* denotes Euclidean distance between two pixels.

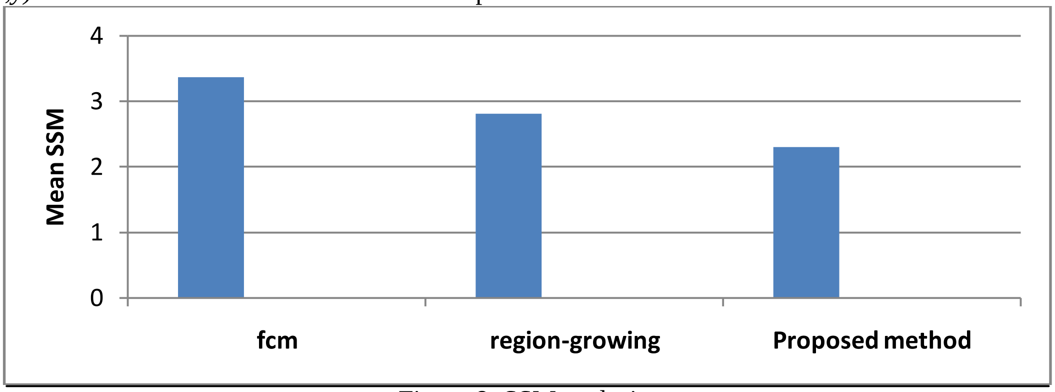


Figure 8: SSM analysis.

Lesser the value of SSM, closer is segmentation to ground truth. Figure 8 show that hybrid approach has an edge over other segmentation techniques.

F. Area Overlap Error

This metric denotes the actual overlap area between manual segmentation and the proposed segmentation method.

$$Area\ Overlap\ Error = 100(1 - DSC) \quad (11)$$

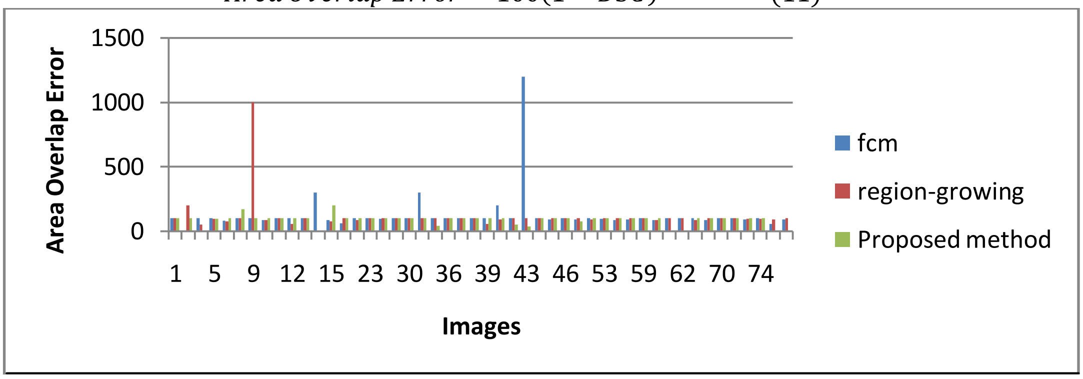


Figure 9: Area overlap error analysis.

It is 0 for perfect segmentation and 100 if there is no overlap area i.e. the segmented area is altogether different from the actual area.

G. Relative Area Difference

Relative Area Difference (RAD) is the difference in area of actual segmentation and automatic segmentation method. It is calculated as follows.

$$RAD = 100((|I\_IM| - |I\_GT|)/|I\_GT|) \quad (12)$$

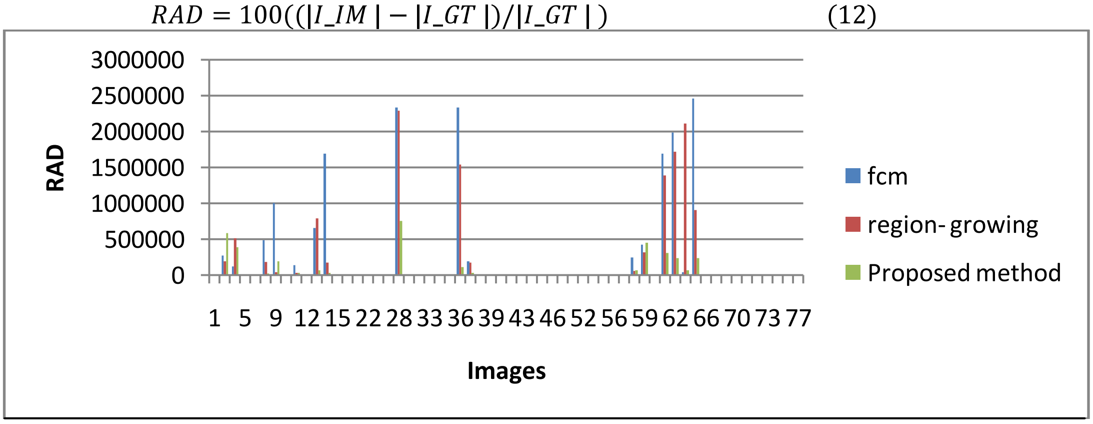


Figure 10: RAD analysis.

It should not be used as a single metric as it doesn't reveal the actual intersection between the tumor areas. There could be different regions having same areas. Thus, it is used as a secondary metric to reveal over-segmentation or under-segmentation of the result.

V. Conclusion

The implementation of the proposed algorithm along with the experimental results is discussed. The experimental results are shown. The results are qualitatively evaluated against individual cue based segmentation techniques i.e. watershed, region-growing and model-based segmentation. It shows that the proposed method has better results as compared to other techniques. From mean, confidence interval measures and the results of images on various parameters, different parameters are analyzed. The proposed method shows 89% accurate results as compared to 58% of region-growing and 50% of fcm. In terms of compactness, region-growing outperforms the proposed method because it does not segment the bone tumor showing swelling or inflammation characteristics which are, otherwise segmented by the proposed method. The proposed method has larger number of images corresponding to DSC=1 as compared to other methods. It shows high sensitivity and low specificity which is desired for the better performance of an algorithm whereas region-growing shows low sensitivity and low specificity. The average values of the proposed method in case of SSM and RMS is less, thus indicating bone tumor segmentation closer to the ground truth as obtained by domain experts. In terms of overlap area between actual and the proposed segmented region, it is quiet less for the proposed method. Similarly, RAD which is the secondary metric also has the lowest peak among all the techniques compared.

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