

## Analysis of Fast Adaptive Bilateral Filter and Morphological Segmentation on MRI Images



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### ABSTRACT

Image segmentation methodology is a part of nearly all computer schemes as a pre-processing phase to extract more meaningful and useful information for analysing the objects within an image. Segmentation of an image is one of the most conjoint scientific matter, essential technology and critical constraint for image investigation and dispensation. There has been a lot of research work conceded in several emerging algorithms and approaches for segmentation. Segmentation is one of the popular and efficient technique in context to medical image analysis. The purpose of the segmentation is to clearly extract the Region of Interest from the medical images. The main focus of this paper is to review and analyze the effect of segmentation over different tumor images for different parts of the body. In this paper fast adaptive bilateral filter is used with morphological segmentation of image and their application to medical imaging.

**Key words:** Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Positron Emission Tomography (PET), Image Segmentation, Filter.

### 1. INTRODUCTION

In computer vision, the image segmentation is the procedure to partition the digital images into several segments. The segmentation process is to label each pixel in the images and locate the boundaries and the objects. The pixel with the identical labels will share the characteristics. Each pixel in the same region have some similarity like intensity, texture or color. The set of segments of the entire image is the final result after segmentation. The purpose of doing the segmentation is to increase the quality of the medical image. In the recent years, there are increasing use of the Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Positron Emission Tomography (PET) images for clinical study and diagnosis. The methods which are available for the segmentation technique on medical images varies for each application. For example, the segmentation of the brain differs from the segmentation of the heart. Since there are huge

variation and complexity, it is tough to drive the analytical explanations or the simple calculations to represent the anatomy of the medical images. There is no common algorithm for the segmentation of all the medical images. Reliable segmentation is required for the anatomical structure and the Region of Interest (ROI). Every imaging system has its own specific limitation [1].

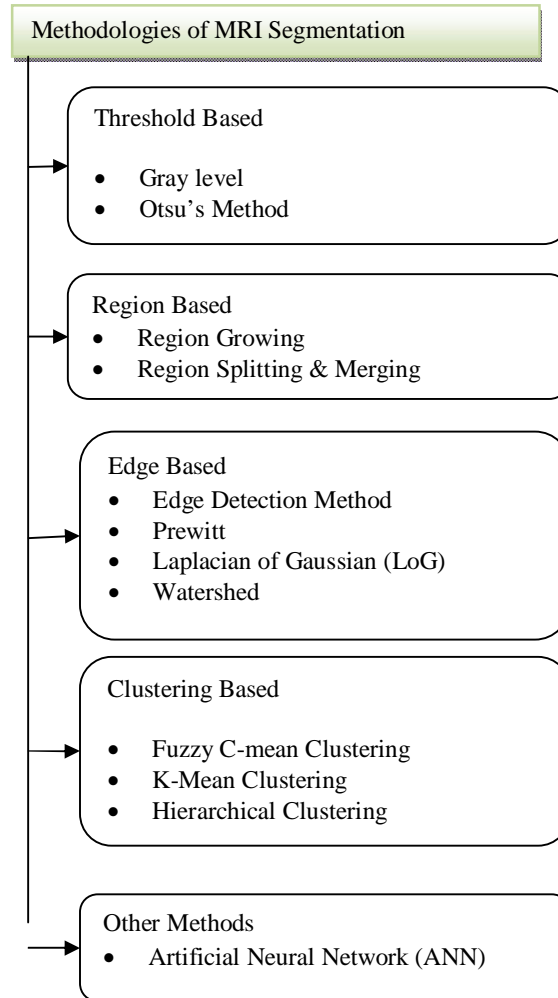
Image segmentation can be defined as the grouping of similar pixels in a parametric space, where they are associated with each other in the same or different images. Classical image segmentation methodologies include thresholding, edge detection, and region detection [2]. Thresholding methods are relatively simple but lack sensitivity and specificity for accurate segmentation in the presence of different objects with similar intensities or colours. Edge-based methods, quite similar to the contour detection, are fast but sensitive to noise in the background and fail to link together broken contours. While region detection is superior to thresholding and edge-based methods in terms of stability and consistency, nevertheless, these approaches need further modifications in order to effectively handle e.g. image occlusions which commonly exist in real scenarios. Better segmentation is achieved by connectivity-preserving relaxation methods, also referred to as the active contour models [3], which start from an initial contour shape, followed by applying shrink or expansion operations according to a defined object function. However, here the convergence of the computation is affected by local minima of the function which hence might lead to incorrect segmentation.

In medical fields nowadays, medical imaging is a crucial component in a many applications. Such applications take place throughout the clinical track of events; not only within diagnostic settings, but prominently in the area of preparation, carrying out and evaluation before surgical operations. Generally, image segmentation is the procedure of separating an image into several parts. Instead of considering the whole data presented in an image all at once, it is better to focus on a certain region-based semantic

object in image segmentation. Image segmentation has been widely implemented in medical imaging to separate homogeneous area.

Studied reflects that region of interest (ROI) segmentation (shown in Figure 1) plays a crucial role in multilevel authentication [1]. Thus the goal of image segmentation is to find the regions that represent meaningful parts of objects for easier analysis purpose. This survey aims to gather and

analyze methods used in image segmentation. So, in general this paper will summarize suitable image segmentation methods to be used for each types of medical images scan. Segmentations are divided mainly in four different techniques, which are thresholding-based, region-based, edge-based, and clustering-based. Additionally there are also other methods for image segmentations, as shown in Figure 2.



**Figure 1:** Methodologies of MRI segmentation

## 2. RELATED WORKS

Phooi Yee Lau et al. [3] describes about the various attributes of input MRI images and categorized them into three groups: edge, gray, contrast. The edge parameter is used to determine the edges or boundaries of tumor. The contrast parameter is used to characterize extend of variation in pixel intensity. The 3 parameters are grouped together to get a multiparameter value that is used to represent the whole brain. Then developing an estimation model using healthy brain dataset. Then hierarchical

representation of the brain is studied and obtaining the exact location of brain tumor. The input MRI images are preprocessed and are done in two functions: image previewing function and image adaptation function. The images are post processed using image classification and they are implemented as multiparameter features, hierarchical representation, and estimation model.

Kalyani A. Bhawar et al. [4] implements a method for brain tumor classification is the neural network based

method. There are mainly 4 stages and in first stage the input MRI images are represented by a feature vector and extracted. Feature vector extraction is done by DWT (Discrete Vector Transform) and reduced by PCA (Principal Component Analysis). Then images are classified and that phenomenon is known as model learning. For model learning two neural networks are used. They are feed forward artificial neural network based classifier and back propagation artificial neural network based classifier.

Riries Rulaningtyas *et al.* [5] studied three edge detection algorithms i.e. Prewitt, Sobel and Robert. Among the above three methods, they found that Sobel method is preferable to use for detecting edges of brain tumor because it has a little mean and standard deviation value. A pair of 3x3 convolution masks are used for evaluating the gradient in x-direction and gradient in y-axis.

Jun Kong *et al.* [6] proposed the method to locate the tumor composing of four stages. In the initial stage, the noise available in the image is removed using wavelet filter. In second stage watershed algorithm is applied to MRI image pixels as an initial method for segmentation. Next, merging operation is implemented on the segmented area by using fuzzy clustering algorithm. At last, the re-segmentation process is applied to those regions which are not partitioned completely by using k-NN classifier.

Ed-Edily Mohd. Azhari *et al.* [7] proposed an effective approach that can localize and detect brain tumor in MRI images. This technique comprises of five steps i.e. acquisition of image, pre-processing, edge detection, histogram clustering, and morphological operations. The affected portions get detected by post morphological operations where tumor appeared as pure white color in the pure black background. The proposed system resulted 92% accuracy.

Jaskirat Kaur *et al.* [8] described a new clustering algorithm for image segmentation and did a study on diverse varieties of image segmentation methods. They also suggested a technique to quantify and classify various clustering process based on their consistency in different operations.

Priya *et al* [9] discussed that image segmentation is an essential but critical component in low level vision image analysis, pattern recognition, and in robotic systems. It is one of the most difficult and challenging tasks in image processing which determines the quality of the final result of the image analysis. Image segmentation is the process of dividing an image into different regions such that each region is homogeneous. A precise segmentation of medical

image is an important stage in contouring throughout radiotherapy preparation. Medical images are mostly used as radiographic techniques in diagnosis, clinical studies and treatment planning. This review paper defines the limitation and strength of each methods currently existing for the segmentation of medical images.

### 3. METHODOLOGY

In this paper, the first problem is finding an region of interest and the second one of detecting a tumor region. For the former, the proposed algorithm is developed to detect tumor in MRI images of brain, lungs and bone.

Figure 2 shows the proposed flow of algorithm. The proposed algorithm is described in steps as follows:

*Procedure: Tumor detection from MRI images*

Input: MRI images

Output: Tumor region detection

Step 1: Take input image.

Step 2: Afterward the image is converted into grayscale which reduces the computational complexity.

Step 3: After noise removal is performed using fast adaptive bilateral filter.

Step 4: Further applying morphological segmentation.

Step 5: Then further edges are detected using canny edge detection.

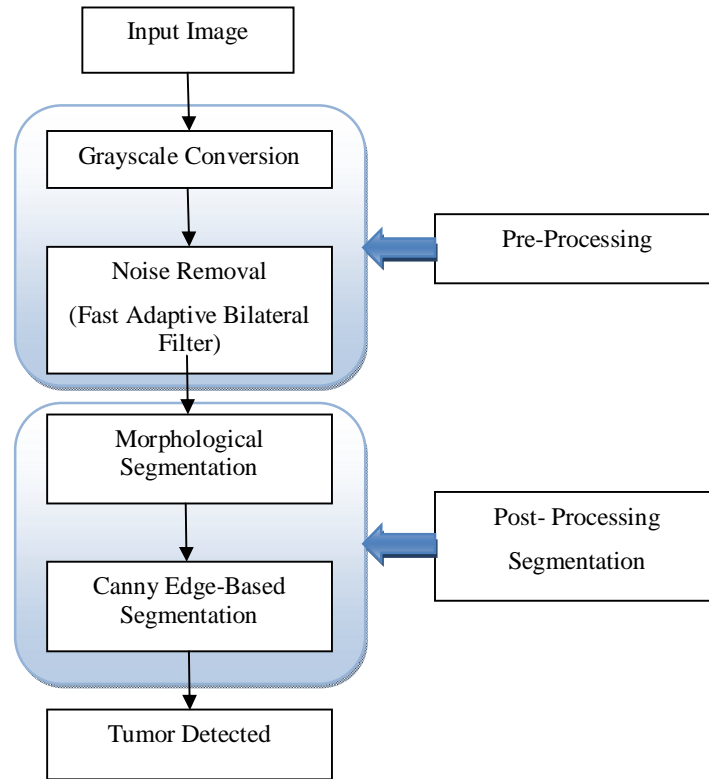
Step 6: Tumor region is segmented out.

#### *Fast Bilateral filter*

The bilateral filter is widely used in computer vision and image processing for edge-preserving smoothing. Unlike linear convolutional filters, the bilateral filter uses a range kernel along with a spatial kernel, where both kernels are usually Gaussian. The input to the range kernel is the intensity difference between the pixel of interest and its neighbor. If the difference is large (e.g., the pixels are from different sides of an edge), then the weight assigned to the neighboring pixel is small, and it is essentially excluded from the aggregation. This mechanism, which avoids the mixing of pixels with large intensity differences, ensures the preservation of sharp edges. However, this also makes the filter non-linear and computation intensive. An adaptive variant of the bilateral filter was introduced in [10], where the center and width of the Gaussian range kernel is allowed to change from

pixel to pixel. It was used for image sharpness enhancement along with noise removal. Adaptation of the range kernel was necessary since the standard bilateral filter cannot perform sharpening. The amount of sharpening and noise removal at a particular pixel is controlled by adapting the center

and width of the kernel. A variable-width range kernel was also used in [11] for removing compression and registration artifacts.



**Figure 2:** Image Segmentations

#### 4. RESULT ANALYSIS

In this research work a database is created using collection of different images from MRI images of brain, bone and lungs to show the performance of proposed algorithm. To evaluate the performance of the proposed system following parameters are used: Sensitivity measures the proportion of correct ROI region segmentation.

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

Specificity measures the proportion of correct segmentation of non-ROI region.

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

It measures the degree of closeness between the segmented and ground truth images

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

Where, True Positive (TP) = Correctly detected object in image.

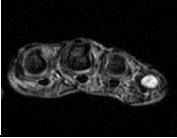
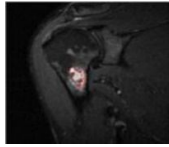
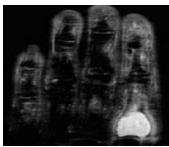
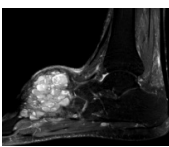
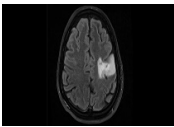
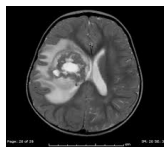
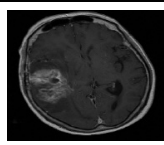
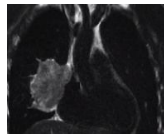
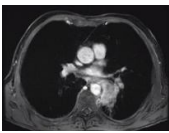
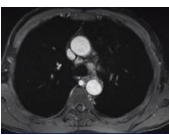
True Positive (TN) = No object region correctly detected in image.

False Positive (FP) = Object incorrectly identified in images.

False Negatives (FN) = Object that are failed to be detected in image.

The results of proposed methodology are evaluated on 10 different input images the result analysis of these images is illustrated in Table 1.

**Table 1:** Result Analysis of Methodology on Different MRI Images

Image No.	Category	Sensitivity	Specificity	Accuracy
	Bone	0.9891	0.9941	0.9925
		0.9408	0.9937	0.9677
		0.8897	0.9657	0.9374
		0.9133	0.9909	0.9637
	Brain	0.8846	0.9939	0.9643
		0.9971	0.9776	0.9863
		0.9726	0.9783	0.9749
	Lung	0.9997	0.9994	0.9995
		0.9391	0.9851	0.9675
		0.9997	0.9994	0.9995
	<b>Average</b>	<b>0.95257</b>	<b>0.98781</b>	<b>0.97533</b>

## 5. CONCLUSION

MRI images are quite preferred for detecting the brain tumor. Here, we mainly analysed various image processing techniques and have discussed its requirements and properties in the context of brain tumor detection on MRI scanned images. The application of segmentation and edge detection is directly beneficial for medical diagnosis. To distinguish the tumor affected regions from various brain tissues we have employed the thresholding segmentation technique. Using the proposed algorithm, identification of the brain tumor regions is done efficiently. After analyzing the experimental results, fast adaptive bilateral filter with morphological segmentation gives accurate segmentation. We tested on 10 images of Enchondroma MRI of bone, brain and lungs. Finally, we have achieved 95% Sensitivity, 98% Specificity and 97% accuracy. In future, the sensitivity measure can be improved and more features can be achieved.

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