International Journal of Application or Innovation in Engineering & Management (IJAIEM)
Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 6, Issue 12, December 2017 **ISSN 2319 - 4847**

The Evaluation of Data sets with Computed Tomography Images using Image Processing Algorithms

J. Uma Maheswari[1] , M.U. Sai Ranga[2]

[1.]GRD College of Science, Coimbatore

[2.] Medico Student, Vinayaka Mission Medical College, Karaikal

ABSTRACT

According to the World Health Organization, cancer is leading cause of deaths globally. Among all types cancer, liver cancer has the lowest survivability, with approximately one million deaths each year. Its rising incidence in the past decade is projected to continue which is associated with varying demographic factors. It is essential for medical practitioners to decide a suitable treatment for cancer patients. For this reason cancer cells should be identified correctly. Computed Tomography (CT) Imaging has developed into a significant tool for physicians to identify liver cancer for decays. A computer-aided analysis of liver cancer in CT images is enormously hard due to some imaging parameters. The techniques considered in this paper are Region growing, Otsu's Threshold, watershed and K-means clustering segmentation algorithms. These techniques are evaluated and examined for finest results and highest accuracy.

Keywords: Image segmentation, Computed Tomography, Liver Cancer, Region growing, Otsu's Threshold, watershed, K-means clustering.

1.Introduction

Liver cancer is one of the most familiar cancers in worldwide and its early detection gives a better possibility for proper treatment. This is calculated as the fifth most common cancer disease imperils human life among men and ninth among women. More than 80% of these cases are affected by Hepato Cellular Carcinoma (HCC) that originates from Hepatocytes which are the major cells in the liver [1] [2].

Image processing techniques are used to improve the performance of detecting liver cancer in CT images. Image segmentation is a complex information extraction technique. The objective of image segmentation is to partition a digital image into multiple segments that segments are more meaningful and easier to analyze [3]. This paper is an attempt to compare some image segmentation techniques. The techniques considered in this paper are Region growing, Otsu's Threshold, watershed and K-means clustering segmentation algorithms. All the techniques are compared and analysed for best results and maximum accuracy. The following figure illustrates the overview of this paper

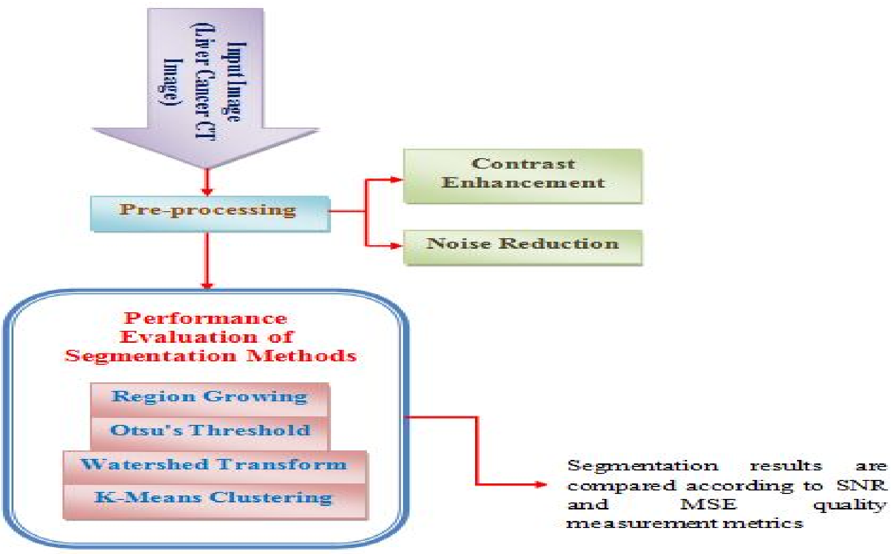


Fig.1 Overview of the paper

2. Liver Cancer

The human liver is generally complex and main organ in the human body. Liver cancer is dangerous dieses that begin in the cells of liver. Human liver is a football sized organ that sits in the upper right portion of abdomen [Fig.2].

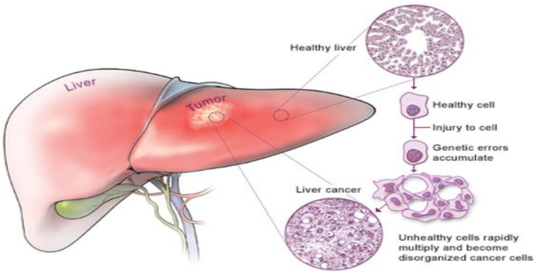


Fig.2 Liver cancer

Liver tumors are either cancerous (malignant) or noncancerous (benign). Some benign liver tumors need treatment. Malignant tumors begin in the liver are called primary liver cancer. Liver cancer has spread (metastasized) to the liver from other organs (secondary liver cancer) [4].

Risk factors associated with liver cancer

The common reasons of liver cancer still unknown. Various risk factors for liver cancer are in the following table [1],

Table1. Risk factors of liver cancer

S.NO	Reasons	Description
1	Cirrhosis	Cirrhosis is a rife and progressive chronic liver infection. This infection is depressed due to excessive amounts of fibrous scar tissue inhibiting blood flow.
2	Hepatocellular Adenoma	It is a solid tumour. Consuming large amounts of alcohol and chronic hepatitis have a greater risk for this kind of liver cancer.
3	Aflatoxin	Aflatoxin is made by a fungus frequently originate in warm steamy areas. Ongoing revelation to this fungus by eating contaminated food increases risk of liver
4	Angiomyolipoma	It is an infrequent liver tumour. It is detected most commonly in women. It is not indicative and is generally diagnosed incidentally at autopsy, tissue. This is originated outer surface of the liver tissue but inside the Glisson's capsule.
5	Thorotrast	Thorotrast is an agent that produces high levels of radiation. It was used as a dye in X-ray studies at 1930s and this agent has been linked to liver cancer. It is no longer used.
6	Vinyl chloride	Vinyl chloride is a chemical used for the producing of some kind of plastics.

3.Computed Tomography

Over the past years, Computed Tomography (CT) has gained acceptance as a minimally invasive method for evaluating patients with suspicion of liver cancer. Typically, the diagnosis of liver cancer from CT images is manually performed by radiologists using the expertise gained from their training, experience and individual judgment. It is a time-consuming and error-prone process, especially because of the huge amount of data. Indeed, a typical CT dataset that is used for liver diagnosis may have more than 600 slices. Although the quality of CT images has been significantly improved during the last years, it is difficult in some cases, even for experienced radiologists, to make an accurate diagnosis [6].

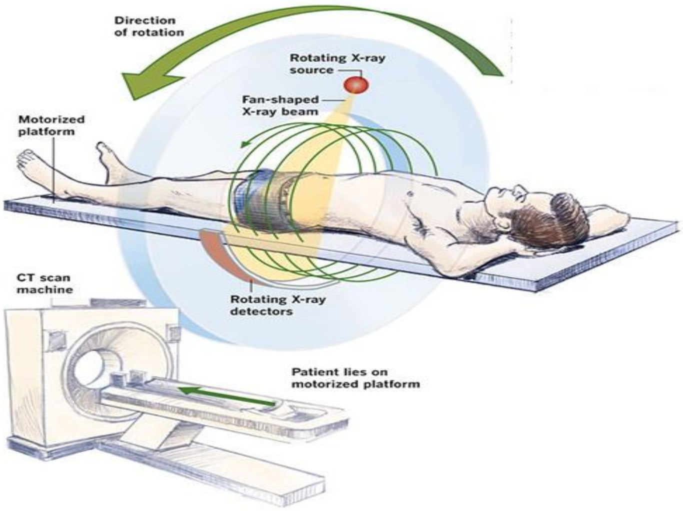


Fig 3. The principle of computed tomography system

Computed Tomography scans are made by rotating an X-ray beam around the patient. Imaging the body in a series of slices then the computer slices together and gives the resultant image [7]. The above figure shows the principle of computed tomography system.

4.Segmentation

Segmentation is a process of extracting information from an image and to group pixels together into regions of similarity. This is typically used to locate objects and boundaries in images. The main objective , is partitioning of an image into a set of disjoint regions that are visually different, homogeneous and meaningful with respect to several computed properties otherwise characteristics, like grey level, texture or color to allow easy image analysis (object identification, classification and processing) [8]. Image segmentation can be categorized as three types such as Threshold Segmentation, Region Based Segmentation, and Edge Based Segmentation.

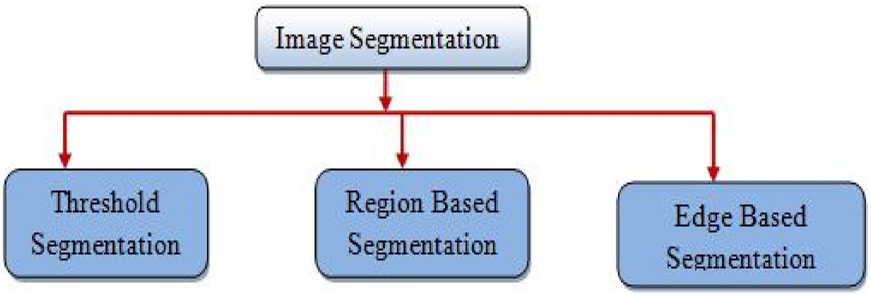


Fig 4. Image Segmentation Techniques

The primary objective of the paper is to compare segmentation algorithms among the CT liver cancer images. Four methods were selected, Region growing, Otsu's Threshold, watershed and K-means clustering segmentation algorithms. All the techniques are compared and analysed for best results and maximum accuracy with the standard data set explained in this paper.

1. Otsu’s thresholding algorithm

The algorithm presumes that the image includes two classes of pixels following bi-modal histogram (foreground pixels and background pixels). It finds the optimum threshold and separating the two classes. So, that their combined spread (intra-class variance) is minimal or equivalent and their inter-class variance is maximal [9]. Otsu's method is approximately a one-dimensional, discrete analog of Fisher's Discriminant Analysis. Otsu's thresholding algorithm involves iterating during each possible threshold values determine a compute of spread for the pixel levels every side of th9e threshold, i.e. the pixels that either falls in foreground or background [Table.2]. The goal is to determine the threshold value where the sum of foreground and background spreads is at its least [10].

Table 2. Steps in Otsu's thresholding algorithm

Step1:	To read a gray scale image:	The input gray image can be represented in L gray levels [1, 2, 3… L].
Step 2:	To calculate the number of pixels:	Calculate the number of pixels N at level I denoted by ni as follows N= n1+n2+n3+……+nL
Step 3:	Select a threshold and referred as t, i. Calculate foreground variance i. Calculate background variance. To divide the pixels into two classes Cb (background) and Cf (foreground) by a threshold at level t. then Cb pixels with indicates levels [1, 2, 3,……, t] and Cf indicates pixels with levels [t+1,t+2,….., L].	To calculate background pixel class Cb: $Weight\ W_b = \sum_{i=1}^{t} \frac{n_i}{N}$ $Mean\ \mu_b = \frac{\sum_{i=1}^{t} i * n_i}{\sum_{i=1}^{t} n_i}$ $Variance \sigma_b^2 = \frac{\sum_{i=1}^{t} (i-\mu_b)^2 * n_i}{\sum_{i=1}^{t} n_i}$ To calculate foreground pixel class Cf: $Weight\ W_f = \sum_{i=t+1}^{L} \frac{n_i}{N}$ $Mean\ \mu_f = \frac{\sum_{i=t+1}^{L} i * n_i}{\sum_{i=1}^{t} n_i}$ $Variance \sigma_b^2 = \frac{\sum_{i-t+1}^{L} (i-\mu_b)^2 * n_i}{\sum_{i=1}^{t} n_i}$
Step 4:	To calculate Within-Class variance by simply sum the two variances multiplied by their associated weights:	$Within\ Class\ Variance \sigma_w^2 = W_b \sigma_b^2 + W_f \sigma_f^2$
Step 5:	To Repeat steps 3 and 4 for all possible threshold value.	
Step 6:	Final global threshold value T = threshold in MIN(Within-class variance)	
Step 7:	Binarize Image = gray scale image > T Finally select a threshold value T. It has the lowest 'sum of weighted variances' which is the final globally selected threshold. All pixels with a level less than T are background, all those with a level greater than or equal to T are foreground.	

2. Region Growing

These methods group pixels in an entire image into sub regions or large regions based on predefined criterion. In other words, the basic idea is to group a collection of pixels with similar properties to form a region [11]. Region growing the basic algorithm,

- I f (x, y) the image to be segmented
- S(x, y) binary image with the seeds (it is 1 simply wherever the seeds are positioned)
- Q, establish to be tested for each location (x, y).

An easy region growing algorithm (based on 8-connectivity) is the following: [Table. 3]

Table 3. Steps in Region Growing algorithm

Step1:	Erode all the connected components of S until they are only one pixel wide.
Step 2:	Generate the binary image fQ such that fQ(x, y) = 1 if Q(x, y) is true.
Step 3:	Create the binary image g where g(x, y) = 1 if fQ(x, y) = 1 and (x, y) is 8-connected to a seed in S.

In the resulting connected components in 'g' are the segmented regions [11].

3.K-means clustering Algorithm:

K-means clustering algorithms have been developed as a digital image segmentation technique in various fields and applications. Novel K-means algorithm select k points as initial clustering centers, various points may obtain different solutions. The K-means algorithm develops a divisive clustering and utilizes a correspondence metric to assign every document to one of k clusters. The clusters are considered as a standard of all pixels contained within the cluster. This standard value is the centroid of the cluster [12]. The following figure demonstrates the methodology of K-means clustering algorithm,

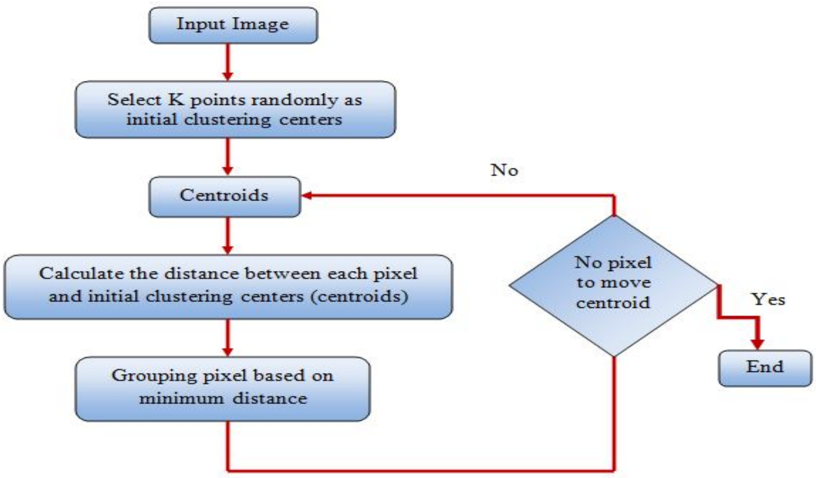


Fig 5. Methodology of K-means clustering Algorithm

While k-means has the benefit of being easy to implement, it has some limitations. The quality of the final clustering results is based on the random selection of first centroid. Consequently if the first centroid is randomly chosen, it will obtain different result for different initial centers. So the initial center will be carefully selected so it obtains our desire segmentation. The computational complexity is another term which we need to consider while designing the K-means clustering. It depends on the number of data elements, clusters and iteration [13].

3. Watershed Transform Segmentation

The watershed transform is a popular segmentation method in image processing. The intuitive description of this transform is quite simple. If we consider the image as a topographic relief, where the height of each point is directly related to its gray level, and consider rain gradually falling on the terrain, then the watersheds are the lines that separate the "lakes" really called catchment basins. Normally, the watershed transform is calculated on the gradient of the original image, consequently that the catchment basin boundaries are positioned at elevated gradient points. Particularly, show how the watershed transformation contributes to improve the numerical results for objet segmentation problems [14]. Let $f(x, y)$ with $(x, y) \in$ R2, be a scalar function describing an image I. The morphological gradient of I is defined by

$$g = (f \oplus b) - (f \ominus b)$$

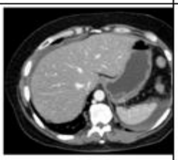
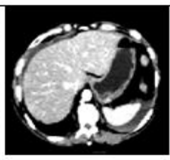
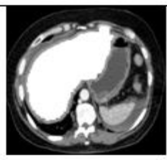
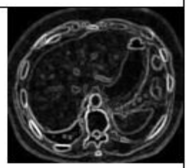
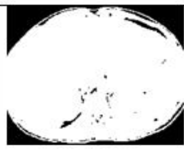
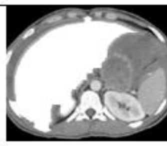
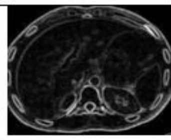
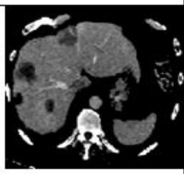
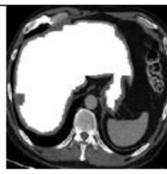
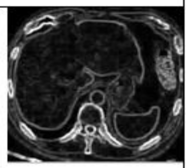
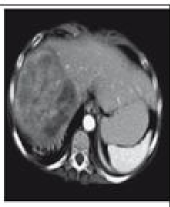
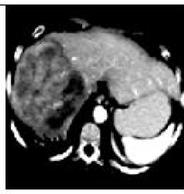
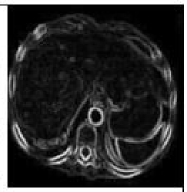
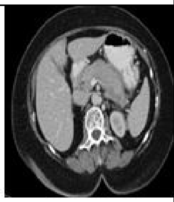
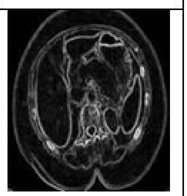
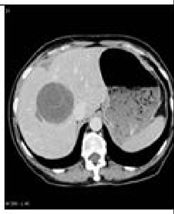
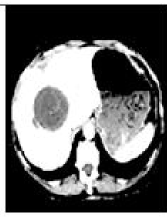
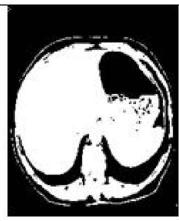
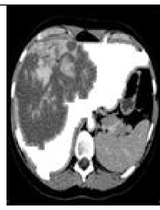
Where $(f \oplus b)$ and $(f \ominus b)$are respectively the elementary dilation and erosion of f by the structuring element b. The morphological Laplacian is given by

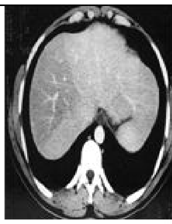
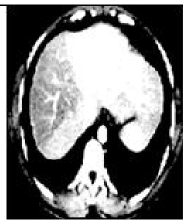
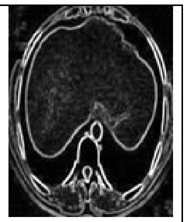
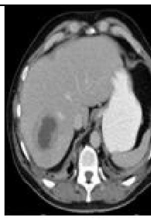
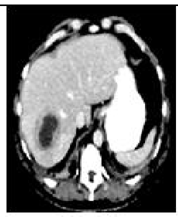
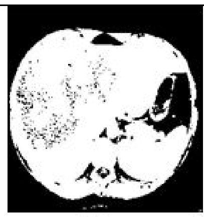
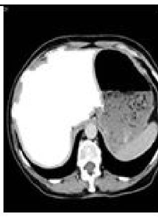
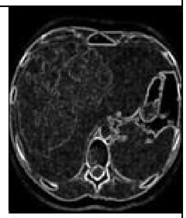
$$G_L = (f \oplus b) - 2f + (f \ominus b)$$

We note here that this morphological Laplacian allows us to distinguish influence zones of minima and suprema: regions with *GL* < 0 are considered as influence zones of suprema, while regions with *GL* > 0 are influence zones of minima. Then *GL* = 0 allows us to interpret edge locations, and will represent an essential property for the construction of morphological filters. The basic idea is to apply either dilation or erosion to the image *I*, depending on whether the pixel is located within the influence zone of a minimum or a maximum.

The digital image contains many objects of different sizes that are touching each other. Object detection in an image is an example of image segmentation. To segment touching objects, the watershed transform is frequently used. If we analysis an image as a surface, with mountains (high intensity) also valleys (low intensity), the watershed transform determines intensity valleys in an image. The main drawback of the Watershed Transform is that for most natural images it creates extreme over segmentation [15].

Table 4. Comparisons of different segmentation techniques for liver cancer CT images

S.No	Segmented Liver Cancer CT Images				
	Normalized Images	Region growing	Otsu's Threshold method	Watershed transform	K-means clustering
1					
2					
3					
4					
5					
6					

7					
8					

5. Results and Discussion

This paper proposes some segmentation techniques which use these filtered images for the segmentation task. The performances of all these segmentation methods were tested vigorously and the results obtained areshown in this section. The below table shows the comparisons of different segmentation techniques for CT liver cancer images, The segmentation results of CT liver cancer images are compared and analyzed according to SNR and MSE quality measurement metrics. From the performance analyses, the Region growing method gives better results. The image quality measurement metrics are applied and results are presented for a CT liver cancer images.

Table.5 SNR and MSE Comparisons for different segmentation methods

IMAGE	Watershed Transform		K-means clustering		Otsu's Threshold		Region Growing	
	SNR	MSE	SNR	MSE	SNR	MSE	SNR	MSE
IM1	13.0298	7.7461	10.0766	4.8469	11.0766	5.7469	15.3583	4.8469
IM2	13.0020	6.5321	10.4472	4.5092	10.4472	5.5791	14.8614	4.5092
IM3	13.3902	6.3412	11.3871	4.0695	11.3871	4.1165	15.6706	4.0695
IM4	8.4766	18.2858	6.9675	13.7343	6.9675	5.7343	9.9051	3.7343
IM5	9.4231	10.2674	9.7290	5.8094	12.1487	5.8422	12.1487	5.8094
IM6	11.1791	10.5824	10.2628	6.3885	12.6332	6.3885	12.6332	6.3885
IM7	11.6746	10.2867	11.1284	5.8422	13.7627	6.8094	13.7627	5.8422
IM8	11.1907	14.9492	12.5049	7.1039	14.0285	7.1039	14.0285	7.1039

Metrics for Performance Evaluation of Segmentation Algorithms

To evaluate the performance of segmentation algorithms, four performance metrics, namely SNR (Signal to Noise Ratio), MSE (Mean Squared Error) are proposed in this paper. The proposed metrics evaluate the performance of given segmentation algorithm by comparing the qualities of input and output images.

i. Signal-to-noise ratio (SNR):

The signal-to-noise ratio (SNR) for a point source depends on both the noise of the object and on noises associated with the background. Signal-to-noise ratio is a measure used in science and engineering that compares the level of a desired image to the level of background noise. It is defined as the ratio of image power to the noise power. A ratio higher than **1:1 indicates more image than noise.**

SNR can be applied to any form of image.

The signal to noise ratio (SNR) is a representative of the average signal power to the estimated noise component present for a pair of original and filtered image [16]. The (SNR) is defined by the equation,

$$SNR = 10\log_{10}\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(g_{i,j}^2 + f_{i,j}^2)}{\sum_{i=1}^{M}\sum_{j=1}^{N}(g_{i,j} - f_{i,j})^2}\right)$$

Let $g_{i,j}$ is the original image plus $f_{i,j}$ is the evaluated image. $i = 1, 2.., M$ (range index) and $j = 1, 2.., N$ (cross-range index). The given below [Fig.6] shows the performance comparison using SNR.

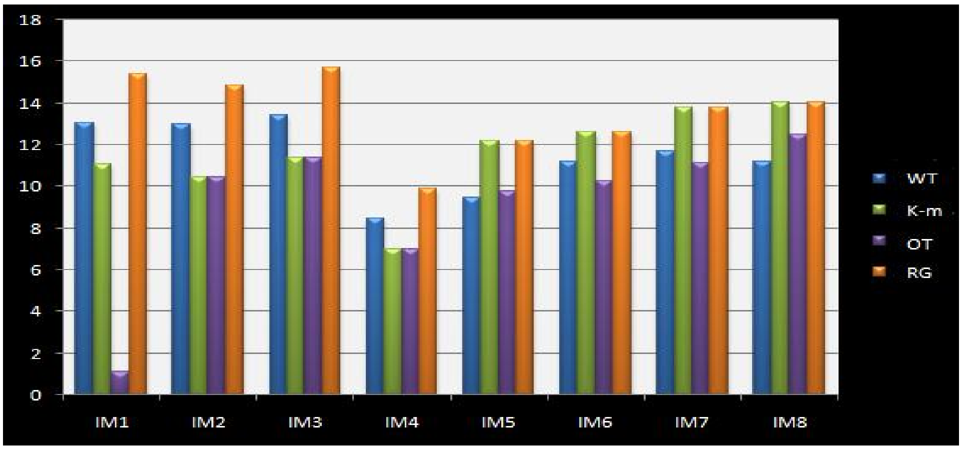


Fig 6. Performance Comparison using SNR

ii. Mean Squared Error (MSE):

Mean Squared Error (MSE) metric is calculated to calculate the change in quality among the original image and filtered image.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(g_{i,j} - f_{i,j})^2$$

The mean square error is the square of the Euclidean distance among the original image plus its estimate. In equation (8), $g_{i,j}$ is the original image and $f_{i,j}$ is the estimated image. $i = 1, 2.., M$ (range index) and $j = 1, 2.., N$ (cross-range index) [16]. The given below [Fig.7] shows the performance comparison using MSE.

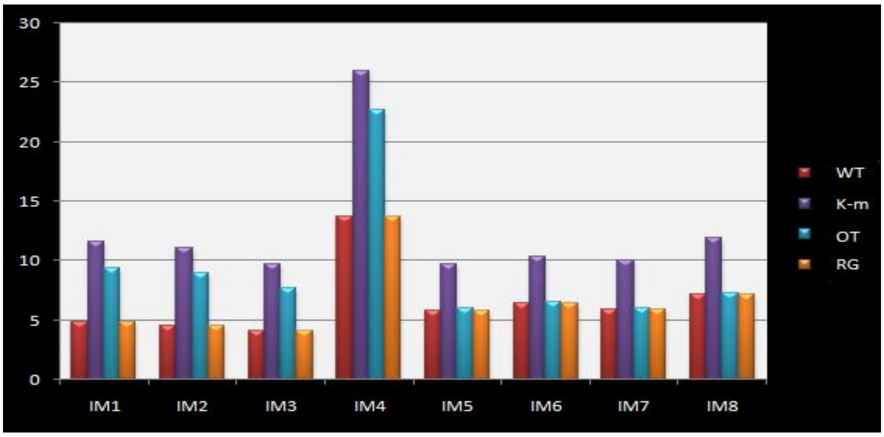


Fig7. Performance Comparison using MSE

6. Conclusion

This Paper is an attempt to compare some image segmentation techniques. The techniques considered in this paper are Region growing, Otsu's Threshold, watershed and K-means clustering segmentation algorithms. All the techniques are compared and analysed for best results and maximum accuracy. In segmentation process, the liver cancer CT images were clearly segmented using region growing, otsu's Threshold, watershed and K-means clustering segmentation algorithms. From the experimental results of segmentation, it is shown that Region growing gives the better performance in terms of accuracy over the Otsu's Threshold, watershed and K-means clustering segmentation algorithms.

REFERENCES

[1]. El-Serag, H.B., and Rudolph, K.L., (2007) Hepatocellular carcinoma: epidemiology and molecular carcinogenesis. Gastroenterology. 132:2557-76.
[2]. Jemal, A., Siegel, R., Ward, E., Hao, Y., Xu, J., and Thun, M.J., (2009) Cancer statistics. CA Cancer J Clin 59: 225-249.
[3]. Upadhyay, Y. and Wasson, V. 2014. "Analysis of Liver MR Images for Cancer Detection using Genetic Algorithm". Interna-tional Journal of Engineering Research and General Science. Vol.2, No.4, PP: 730-737.
[4]. Manfredi S, Lepage C, Hatem C, et al. Epidemiology and management of liver metastases from colorectal cancer. Annals of Surgery, 2006 Aug;244(2):254-9.
[5]. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1435346/
[6]. Satheesh Nair, M.D.a, K.S. Shivakumar, M.D.b, and Paul J. Thuluvath, M.D. Mortality from hepatocellular and biliary cancers: changing epidemiological trends. American Journal of Gastroenterology. Volume 97 Page 167 - January 2002.
[7]. Novelline, R M.D. Squire's Fundamentals of Radiology- 6th Edition. Harvard University Press, Cambridge, Massachusetts, 2004. p. 304-306.
[8]. Yen-Wei Chen, Katsumi Tsubokawa, Amir H. Foruzan, Shigehiro Morikaw, and Yoshimasa Kurumi, Image segmentation and registration techniques for mr-guided liver cancer surgery, 978-1-4673-2349-9/12/$31.00 ©2012 IEEE.
[9]. Rafael C. Gonzalez, "Digital Image Processing" in , Beijing:Publishing House of Electronics Industry, 2007
[10]. Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histogram".
[11]. Y. M. Zhou, S. Y. Jiang, and M. L. Yin, "A region-based image segmentation method with mean-shift clustering algorithm," in Proc. Fifth International Conference on Fuzzy Systems and Knowledge Discovery, 2008, pp. 366-370.
[12]. Fang R., Zabih R., Raj A. and Chen T. 2012. Segmentation of Liver Tumor Using Efficient Global Optimal Tree Metrics Graph Cuts, H. Yoshida et al. (Eds.): Abdominal Imaging 11, LNCS 7029, pp. 51– 59.
[13]. S.S.Kumar, R.S.Moni, I.Rajeesh, "Automatic liver and lesion segmentation: a primary step in diagnosis of liver diseases", Signal, Image and Video Processing DOl: I 0.1007/s11760-011-0223-y, March 31, 2011
[14]. Boren Li and Mao Pan, "An Improved Segmentation of High Spatial Resolution Remote Sensing Image using Marker-based Watershed Algorithm,"" pp. 98-104, IEEE,2012.
[15]. Yuqian Zhao, Jianxin Liu , Huifen Li and Guiyuan Li, "Watershed Algorithm for Dowels Image Segmentation," World Congress on Intelligent Control and Automation, pp7644-7648, IEEE, 2008.
[16]. PavlosStathis, ErginaKavallierataou and Nikos Papamarkos, "An Evaluation Technique for BinarizationAlgorithms",Journal of Universal Computer Science, vol. 14, no. 18 (2008), 3011-3030submitted: 1/3/08, accepted: 29/9/08, appeared: 1/10/08 © J.UCS