Effect of Morphological Filters on Medical Image Segmentation using Improved Watershed Segmentation

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Abstract- In this paper, denoising and segmentation of medical image is performed using morphological filters and watershed algorithm. Watershed Algorithm provides the complete division of image. It has low computational complexity but it suffers from over-segmentation. Segmentation is a process which divides the image into number of segments but it is very sensible to noise. Although technology has been evolved but still, noise may come into image during the acquisition of image either due to instrumental error or environmental factors. So, for obtaining acceptable results of segmentation, it is necessary to eliminate or reduce the amount of noise. For denoising, in this paper various morphological filters are used with the improved watershed segmentation. The proposed algorithm is applied on different medical images like X-Ray, Ultrasound, and MRI and results are evaluated on the basis of MAE, MSE, PSNR and number of segments.

Keywords— Denoising, Morphology, Segmentation, Watershed

I. INTRODUCTION

Segmentation subdivides an image into its constituent regions or objects [1]. The main aim of segmentation is to find certain objects of interest which may be depicted in the image. But it is sensible to noise [7] [13]. That means if image contains noisy signals, results of segmentation are unpredictable. Noise is the random variation of brightness or color information which is either due to technology limitation or environmental factor [11]. It is undesirable product. Therefore, before performing segmentation on images, it is necessary to remove noise from it. Although various spatial and frequency domain filtering techniques exist, in this paper morphological filters are used. Morphological filtering is combined with the watershed segmentation to yield good results.

II. DENOISING OF IMAGES

Noise is an unwanted signal present in the image which reduces the quality of image [2]. Noise effects the visualization of actual data in image. It also affects the output of other processes performed on images [7]. So, removing noise becomes a pre-processing step in image processing. For enhancement various filtering techniques exist. In our proposed technique, morphological filtering is used. Mathematical morphology is a new concept which is based on set theory. These filters come under the category of non-linear filters. For the denoising, various filters such as average, disk, Gaussian, Laplacian, LOG, motion, Sobel and Prewitt are used with proposed algorithm.

III. SEGMENTATION

With the segmentation, objects of interest from image are extracted. Various techniques discovered till now for segmentation, here watershed algorithm is used. Watershed is also based on morphology. It is a region based algorithm having low computational complexity and high efficiency. It provides complete division of the image. Besides, all these advantages, it has a major drawback; it suffers from over-segmentation. Due to this, image content is distorted completely. So, some modifications are required to remove the problem of over-segmentation. In this paper, a post-processing step is proposed which actually reduces the number of segments produced by watershed algorithm.

A. Watershed Algorithm

Watershed algorithm is a powerful mathematical morphological tool for the image segmentation [3][10]. It is more popular in the fields like biomedical, medical image segmentation and computer vision. It is based on the geography. Image is taken as geological landscape; the watershed lines determine boundaries which separate image regions. The watershed transform computes catchment basins and ridgelines, where catchment basins are correspond to image regions and ridgelines relating region boundaries [10][15].

There are mainly three stages for watershed based image segmentation approach.

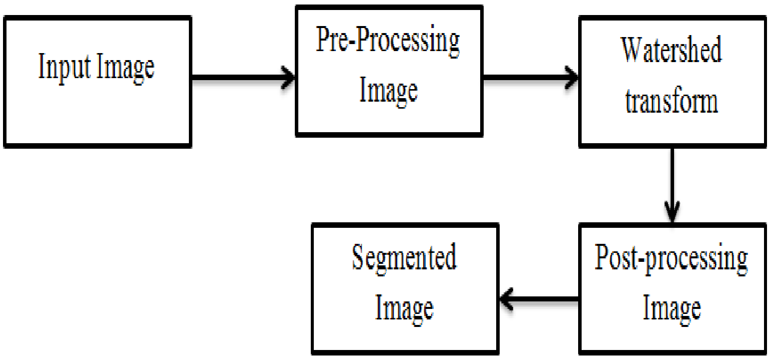


Figure 1: Block Diagram of Watershed Segmentation

Firstly, pre-processing step is done on the original image, second step to apply the watershed algorithm and last step post-processing to eliminate over-segmentation. Pre-processing and post-processing is a mandatory and important step to overcome the over-segmentation problem in watershed based image segmentation [10]. There are two variations of watershed algorithm exist.

a. Flooding Based Watershed Algorithms

In flooding based approach, image is considered as a topographic surface which contains three different types of points:

1. Points which indicate regional minimum.
2. Points where the water falling has the highest probability to fall into a single minimum region.
3. Points where the water falling has probability to fall into more than one such a minimum region [11].

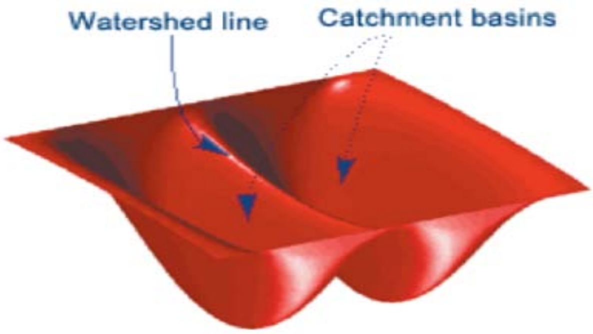


Figure 2: Catchment Basins

For regional minimum, the groups of points satisfy second condition called watershed or catchment basins of that minimum and the groups of point satisfy third condition makes a crest line on topographic surface termed as watershed line [11].

The principle idea lies behind this is to find the watershed lines. Suppose, holes are at each regional minimum and water is flooded from bottom into these holes with constant rate. Water level will rise in the topographic surface uniformly. When the rising water in different catchment basins is going to merge with nearby catchment basins then a dam is built to prevent all merging of the water. Flooding of water will reach at the point when only top of the dams are visible above water line. These continuous dam boundaries are the watershed lines [11].

b. Rain falling watershed algorithm

The rain-falling algorithm exploits slightly different concept to extract mountain boundaries than traditional flooding based algorithm. Rainy water drops fall on the mountain and move to descending direction because of the gravity until they reach to the local minimum surface. The algorithm tracks the path of water drop for each point on the surface towards the local minimum, if rain drops pass through that point or fall on that point. All points make a segment when water drops related to them flow downwards to the same deepest location. When a point has more than one path towards the different steepest surfaces then it can be allocated to any one of the local minimum [11].

The drowning threshold is used to suppress the lowest mountain. Mountains are not considered if their heights come under the drowning threshold value [11].

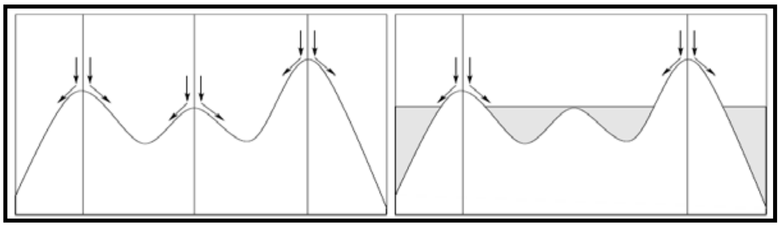


Figure 3: Rain Failing Watershed

IV. Proposed Algorithm

The proposed algorithm has one major objective to be met is the de-noised image having less number of segments. Here, three types of images are considered such as X-rays, ultrasound, and MRI. Basically, proposed algorithm is divided into three parts:

1. Implement Standard watershed approach on the given image and analyze the results. This image has large number of segments and can't be considered for diagnosis purpose. For removing the problem of over-segmentation, as per previous approaches, opening/closing operation will be used and some smoothing results will be obtained.
2. In the second step, standard algorithm implemented in the first objective is taken and then improvement is done in this algorithm to overcome over-segmentation. Foreground and background markers are used to control the over-segmentation.
3. After the improvement is achieved, effect of various denoising filters on the segmentation of the image has been analyzed.

A. Improved Watershed Algorithm

1. Input a gray level/ color medical image.
2. Remove noise from the image using two-dimensional filter. (Sobel, Gaussian, Prewitt, Motion, Unsharp, Disc, Log, Laplacian)
3. Find the gradient magnitude of the image.
4. Perform watershed algorithm for finding initial segmentation map and analyze the result (over-segmentation).
5. Find the locations of regional minima of gradient image and perform opening/closing operations to reduce the number of segments.
6. Compute the external markers using watershed distance transform and for smooth edges compute extended regional minima.
7. Compute the watershed gradient and superimpose it on original image.
8. Compute internal markers.
9. Reconstruct the gradient image by modifying the intensity image.
10. Apply watershed transform and visualize the results.

Results will be taken in terms of MAE, MSE, PSNR, and number of segments. On an image, various filters are applied and results are compared.

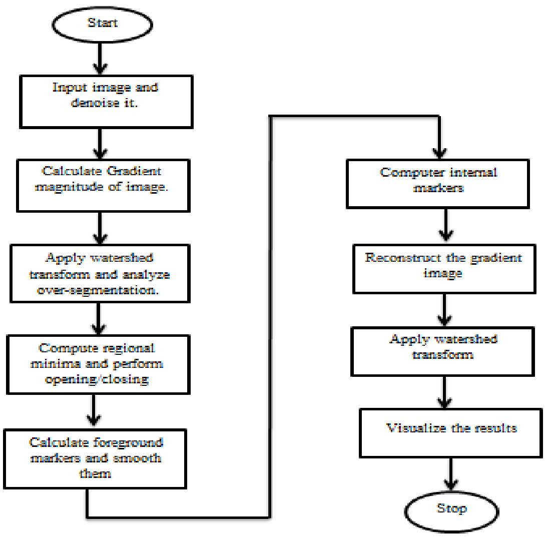


Figure 4: Flow Chart of Improved Watershed Algorithm

V. RESULTS & DISCUSSION

The proposed algorithm is implemented in MATLAB 7.10.0. From the series of experiments that have performed, it has been concluded that proposed technique is producing better results as compared to previous approaches.

The proposed algorithm is applied on six different images by taking different filters (Average, Disk, Gaussian, Laplacian, LOG, Motion, Prewitt, and Sobel). For each filter: four different parameters are calculated i.e. MAE, MSE, PSNR, and Number of Segments. On the basis of these values, final result and conclusions has been drawn.

A. Mean Absolute Error (MAE)

It considers the quality of the resulting de-noised image based on its visual impression. The mean absolute error (MAE) is defined as:

$$\boldsymbol{MAE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}|(f(m,n) - f'(m,n)|} \qquad (1)$$

The value of the MAE should be low for an efficient filter.

B. Mean Square Error (MSE)

It considers the quantity of the removed noise. The mean square error (MSE) is defined as:

$$\boldsymbol{MSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(f(m,n) - f'(m,n))^2} \qquad (2)$$

Value of MSE should be low for an efficient filter [2][11].

C. Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is an approximation to human perception of reconstruction quality. A higher PSNR generally indicates that the reconstruction is of higher quality. PSNR is most easily defined by the Mean Squared Error (MSE). PSNR can be defined as:

$$\boldsymbol{PSNR = 10 * log_{10}\left(\frac{255^2 * M * N}{\sum\sum(x(i,j) - y(i,j))^2}\right)} \qquad (3)$$

Value of PSNR should be high for an efficient filter [2][11].

D. Number of Segments

It gives the number of divisions of an image [9]. As the number of divisions is more, then many of the features of image may distort and if number of divisions are very less then it may passible that segmented image is not showing the actual and complete details of the image. So, number of segments obtained depends upon the image type.

TABLE I. PROPOSED ALGORITHM WITH VARIOUS FILTERS ON X-RAY IMAGE

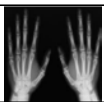
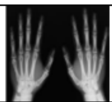
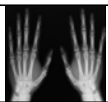
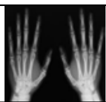
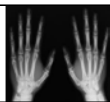
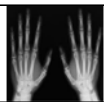
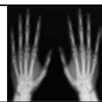
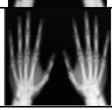
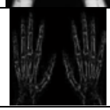
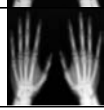
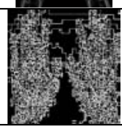
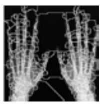
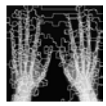
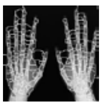
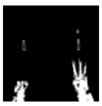
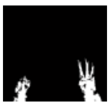
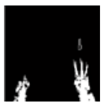
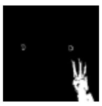
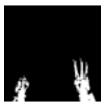
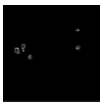
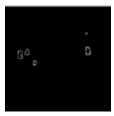
Filter	Average	Disk	Gaussian	Laplacian	LOG	Motion	Prewitt	Sobel
Original Image								
Gradient Magnitude								
Standard Watershed								
Opening/ closing								
Segmented image								

TABLE II. COMPARISON OF VARIOUS FILTERS ON X-RAY IMAGE

Filter	MAE	MSE	PSNR	No. of Segments
Average	23.2787	1.2459	-6.8893	5
Disk	23.3043	1.2131	-6.7735	2
Gaussian	23.2787	1.2472	-6.894	3
Laplacian	46.7364	5.8397	-13.5985	3
LOG	37.6128	4.9634	-12.8924	2
Motion	23.689	1.1971	-6.716	2
Prewitt	19.8496	5.1855	-13.08	6
Sobel	6.9898	6.4935	-14.05	5

TABLE III. PROPOSED ALGORITHM WITH VARIOUS FILTERS ON ULTRASOUND IMAGE

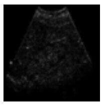
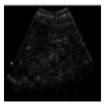
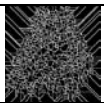
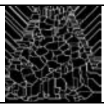
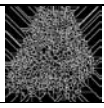
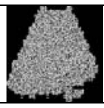
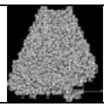
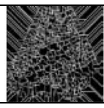
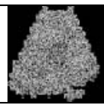
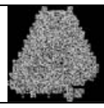
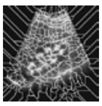
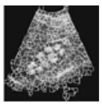
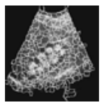
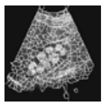
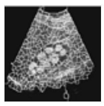
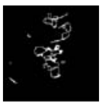
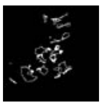
Filter	Average	Disk	Gaussian	Laplacian	LOG	Motion	Prewitt	Sobel
Original Image								
Gradient Magnitude of Original Image								
Standard Watershed Algorithm								
After Opening/ closing operation								
Segmented image on gradient image								

TABLE IV. COMPARISON OF VARIOUS FILTERS ON ULTRASOUND IMAGE

Filter	MAE	MSE	PSNR	No. of Segments
Average	23.3373	1.0354	-6.0856	16
Disk	22.8346	1.1828	-6.6636	9
Gaussian	22.7065	1.0734	-6.2421	14
Laplacian	45.4696	3.7484	-11.673	4
LOG	34.2797	2.918	-10.5854	6
Motion	22.3663	1.1371	-6.4925	10
Prewitt	20.3151	2.4736	-9.8679	11
Sobel	5.9701	3.6197	-11.5214	13

TABLE V. PROPOSED ALGORITHM WITH VARIOUS FILTERS ON MRI IMAGE

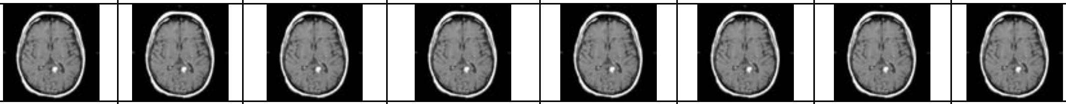
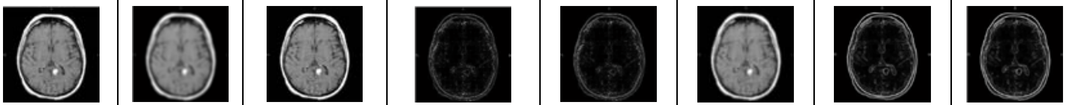
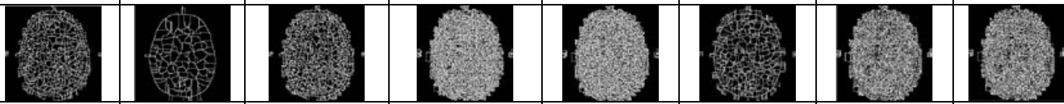
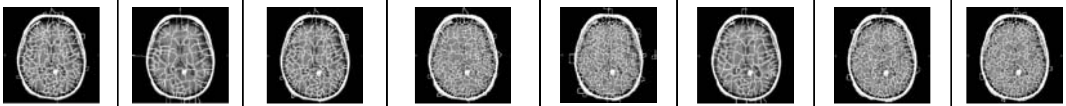
Filter	Average	Disk	Gaussian	Laplacian	LOG	Motion	Prewitt	Sobel
Original Image								
Gradient Magnitude of Original Image								
Standard Watershed Algorithm								
After Opening/ closing operation								
Segmented image on gradient image								

TABLE VI. COMPARISON OF VARIOUS FILTERS ON MRI IMAGE

Filter	MAE	MSE	PSNR	No. of Segments
Average	23.1694	1.7409	-8.3422	37
Disk	21.2566	1.9919	-8.9273	32
Gaussian	23.7193	1.7399	-8.3398	36
Laplacian	51.0797	7.4801	-14.6737	6
LOG	36.8385	7.0727	-14.4305	10
Motion	22.5331	1.816	-8.5256	33
Prewitt	12.4199	1.1238	-16.4415	7
Sobel	6.9734	1.8426	-18.5889	6

Comparison of all the images on various filters on the basis of MEAN ABSOLUTE ERROR

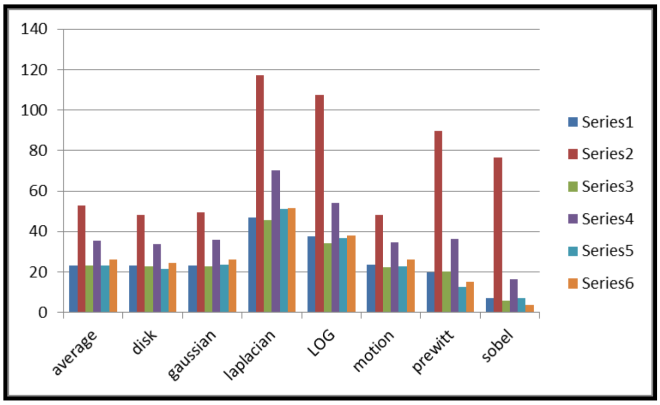


Figure 5: Comparison of all filters on the basis of MAE

Comparison of all the images on various filters on the basis of MEAN SQUARE ERROR

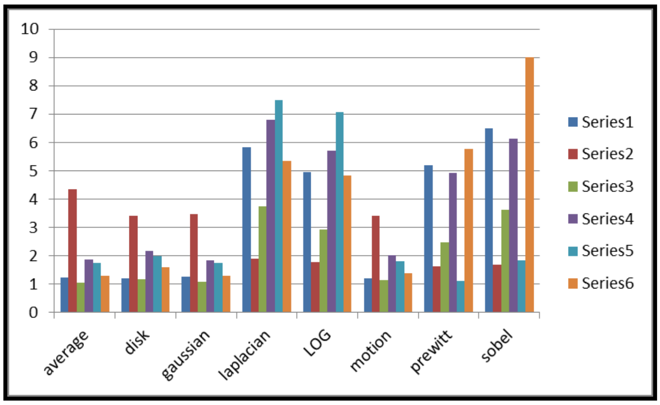


Figure 6: Comparison of all filters on the basis of MSE

Comparison on all images on the basis of PEAK SIGNAL TO NOISE RATIO

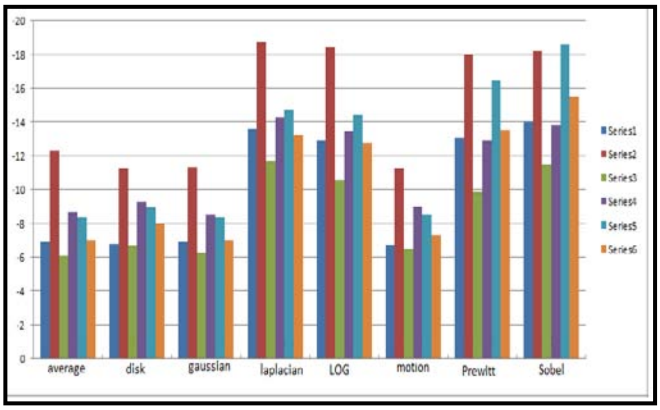


Figure 7: Comparison of all filters on the basis of PSNR

Comparison of all images on the basis on Number of Segments generated

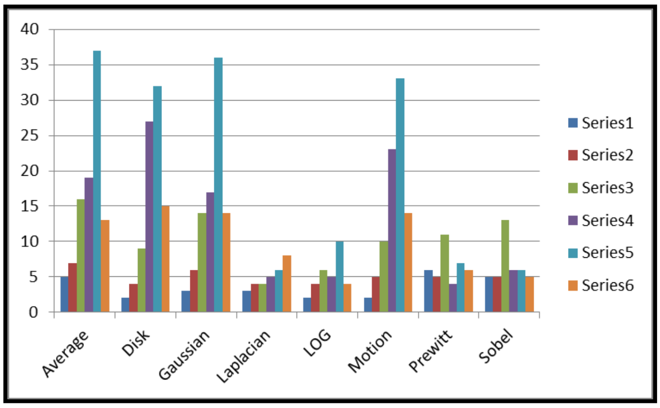


Figure 8: Comparison of all filters on the basis of No. of Segments

On the basis of these tables, it is observed that as per MAE, Sobel filter is giving better performance. But if all the performance matrices have been evaluated i.e. MAE, MSE, and PSNR: Motion filter, Disk filter and Gaussian filler give the best result for de-noising. Average, Sobel and Prewitt filter has low performance. And Laplacian and LOG filters are least preferable.

In case of number of segments generated Sobel and Prewitt produces sufficient number of segments, while segments generated by Laplacian and LOG filter are very less. And Motion, Disk, Gaussian and Average filter produces large number of segments.

Therefore, choice of a particular filter depends upon the image type need to be de-noised and segmented. Overall, Sobel and Prewitt filter are efficient filters in terms of de-noising and segmentation.

VI. CONCLUSION & FUTURE SCOPE

Different images are tested for de-noising and segmentation quality, produced results are visually acceptable and are verified quantitatively by using different performance matrices. From the results, this can be concluded that one type of filter is better for one type of image.

1. Performance of LOG and Laplacian filters is not very good as numbers of segments produced by them are very less. Although for denoising these provide acceptable results.
2. Disk, motion, Gaussian and Average filters produce best results for denoising but numbers of segments obtained are very large which actually distort the image.
3. Sobel and Prewitt filter although gives moderate performance for denoising but number of segments generated are sufficient. These filters give acceptable results as compared to other filters.

Although number of segments obtained depends upon the threshold value. If the threshold value is less, numbers of segments produced are large and if value is large, number of segments will reduce accordingly.

There is always trade-off between denoising and segmentation. As segmentation is totally depend upon quality of image. So, there is a need to balance both the parameters. Therefore considering both the parameters, Sobel and Prewitt gives better result. And work fine with each image.

A lot of work is in progress for processing of medical images. Till now, techniques are built for performing de-noising and segmentation task simultaneously but only salt-and-pepper noise is considered. In this, three types of images are considered using morphological opening closing, but in future the proposed technique can be implemented by using other filtering techniques.

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