Comparative Study and Analysis of Edge Detection Operators in Marker Controlled Watershed Transformation Algorithm on Various Medical Images

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ABSTRACT
Edge is a basic and important piece of information that can be examined and manipulated by various edge detection methods. Edge detection is the process used in digital image processing to determine image boundaries and remove unwanted areas from digitised images. Edge detection generally filters out the important and useful information from the whole structural image. In this chapter, edge detection methods and their mathematical implementations have been compared through first-order edge detection operators like Sobel, Canny, Robert, Prewitt, etc. using marker-controlled watershed transformation. In morphological image processing, the edge detection algorithm includes functions such as edge and marker-controlled watershed segmentation. The edge detection techniques are applied to different medical images. Simulation of edge detection techniques has been carried out using MATLAB, and the comparison is made on the basis of statistical measurements.

General Terms
Image processing, Medical imaging, image segmentation.

Keywords
Medical imaging, image segmentation, edge detection, watershed algorithm, markers.

1. INTRODUCTION
The majority of digital image processing experiments have primarily focused on improving the recognition of objects of interest, such as local features distinguishable from other objects present as well as background objects. Then we generally check each individual pixel in the digitally processed image to see whether the pixel belongs to an object of interest or not. This operation produces a binary image, and the process of doing this is known as segmentation of images. If a pixel belongs to an object, it has a value of one; otherwise, it has a value of zero. After the segmentation process, it is clearer to understand which pixel belongs to which object. The image is divided into different regions because of the discontinuities created by the present boundaries between the regions. Applications of image segmentation include automatic traffic control systems, video surveillance, object detection and recognition tasks, content-based image retrieval, and mainly medical imaging. Image segmentation is basically divided into two main types: local segmentation, which is concerned with specific areas or specific regions of any image, and global segmentation, which is concerned with segmenting the full image because it contains a large number of pixels [1].

Edge detection and segmentation of images are the fundamental problems of image processing and the most concerning issues. The edges of an image are the areas that contain strong intensity contrasts, where a jump in intensity from one pixel of an image to another pixel can create major changes or effects in the quality of the picture and the segmentation of the image as well. To interpret or do a deep analysis of an image to get proper information, they first must be able to detect the edges of each object in the image to be analysed. In this paper, a research has been done with edge detection operators like average, Disk, Gaussian, Laplacian, log, motion, Prewitt, Sobel, and Unsharp with condensational watershed transform and marker controlled watershed transform [2-5]. The different types of edges are like [6]:

Step Edge, which work out the power of picture unexpectedly fluctuates from one worth aside of the breakage to an alternate worth on opposite side.

Roof Edge, is when power change isn't unconstrained and shows up over a limited distance for the most part produced by availability of surfaces then, at that point, line edges become rooftop edges.

Ramp Edge, is the point at which the force change isn't unconstrained and seems a restricted distance then step edges are changed to slope edges.

Line Edge, is the point at which the power of picture unexpectedly changes values and afterward gets back to the beginning stage inside brief distance.

Various edge detection algorithms yield the best subjective segmented view of the tested images, and in this paper a analysis has been done with most of the edge detection operators in different medical images like CT, MRI, and USG to test the performances and the segmentation procedure with an improved marker-controlled method compared with a conventional marker-controlled algorithm to get a proper analysis of how various edge detection operators work and which one can be best applied for noise removal. The statistical measurements of PSNR, SNR, MSE, and execution time are also studied in this study, and the main objective of this paper is to analyse and compare all the operators and analyse their performance to improve the image segmentation process in the field of medicine by using the MATLAB 2021 software.

2. TRADITIONAL EDGE DETECTORS
Edges define the boundaries of an object. So, edge detection is a vital pre-processing step for any object identification or recognition process. At the point when the image edge

detection algorithm is used, it is important to play out the edge estimation and edge testing of the picture, with the goal that the picture can be perceived and the picture can be examined simultaneously [7–9]. Edge detection kernels are based on an estimation of the gradient of an image. To make image processing steps easier, the detection of edges is most important, as edges are often connected with various boundaries. The detection of edges is mainly focused on image data extraction and segmentation. The basics of different traditional edge detectors used in this study are introduced in the following [10-12].

Average: It is a noise removal edge detection algorithm consisting within a smoothing filter that is only incorporate with the pixels that satisfying some validity criterion. If some noise elements feature is known then it is only possible to use this to define a criterion and detect the invalid pixels and then selectively smooth the invalid pixels data that are coming from the valid pixels, thus to avoid the other features of the image.

Disk: This edge detection operator estimates tracks down alternative ways of handling pictures to such an extent that the outcome looks like the result from a traditional image processing activity or pipeline. The objective of operator estimate is frequently to reduce the time expected to deal with an image.

Gaussian: This edge detection generally blurs images and then removes the noises present in image. It has some properties of having no overshoot to a stage capability input while limiting the rise and fall time. The best blend of concealment of high frequencies while also limiting spatial spread, being the basic place of the vulnerability guideline.

Laplacian: It is a second order derivative operator which used to find out the edges of an image and can be divided into two types of Laplacian mask like positive and negative. Mask helps to find the edges it may one or many directions or horizontally and vertically also. One the edges get extracted from an image the operator also helps to sharpen the image. Since the Laplacian edge detector is a vector without typical vector, the Laplace edge administrator must be processed on a format. Dissimilar to the pixel slope administrator, the Laplacian edge administrator doesn't have to ascertain the two subordinates. The Laplacian edge administrator can be directed by a specific picture.

Log: This classical edge detector used to often calculate edges and tested in a 5x5 template. This operator first smooths the image and then calculates the Laplacian. This process produces the double edge image. It locates edges then searches the zero crossing between the double edges.

Motion: The initial step is to recognize moving edges based on the fact that they will be set at various positions when continuous frames are thought of. The marked differences between edges extracted from central frame and edges comparing to two closest neighbours are figured. From the distinctions, just certain pixels are considered pixels with a negative value are set to zero.

Prewitt: This edge detection operator masks are the best understood and eldest edge detection method of images. The operator can perfectly measure the orientation and magnitude of image edges. By using maximum responses from mask this method evaluates the edge directions directly. It has total 8 directions.

Sobel: This edge detection method is used by calculating the gradient of image intensity of each pixel of an image which helps to find the direction of most increase from light to dark portion and the rate of changes in the directions. From this we can get the changes of image smoothing and abrupt ability at each pixel and from there we can represent an edge pixel in proper informative way.

Unsharp: This is an old technique of edge detection which mostly used by photographers to change the relative high pass content present in an image by eliminating the low pass filtered or blurred portion of an image. This should be possible optically by first fostering an unsharp image on a negative film and afterward involving this film as a mask in a subsequent improvement step. A method for edge honing Consolidate image with smoothed (blurred) variant of image.

3. IMAGE GRADIENT

The gradient of the image can very well describe the local grey level variation in the image. The first-order derivative of an image is basically a gradient process. A gradient mainly helps in detecting the edges by avoiding the merging and thickening of image edges through image enhancement procedures. Gradient images are even used to develop saliency maps that help enhance or highlight the focus area of an image. In a gradient image, the magnitude helps to change the image very quickly and is used for pre-processing images before applying any morphological approaches. The gradient gives a global analysis of the picture, so the undesirable shapes that are added because of the presence of noise are remarkably decreased. The occurrence of the over segmentation problem can be reduced by using the gradient, and the gradient also aids in detecting the main edges present in the image and computing the watershed and marker of the detected gradient image. The first-order derivative of a decision in image processing is the gradient. Mathematically, the gradient of a two-variable capability at each picture point is a 2D vector, with the parts given by the derivatives in the vertical and horizontal directions. At each image point, the gradient vector focuses on the biggest possible increase in intensity; the intensity of the gradient vector relates to the rate of change in that direction [13–15].

Gradient magnitude mainly represents the strength of the adjustment of the intensity level of the image. It is determined by the given formula:

Gradient magnitude: $\sqrt{((\text{change in x})^2 + (\text{change in Y})^2)}$

The higher the Gradient magnitude, the more grounded the adjustment of the picture intensity.

4. CONVENTIONAL WATERSHED SEGMENTATION

The watershed algorithm has the advantages of a light burden and high computational accuracy. It is an image segmentation algorithm that combines geomorphology and regional growth ideas. It generally takes the gradient of an image as an input and continuous edge lines with a single-pixel width as an output. The gradient operator output for conventional watersheds should be equal to the edge height, which is the image pixel grey difference between both sides of the edges, not the difference between edge slopes. Using image intensity and altitude, the technique of processing the digital image is called "watershed transformation." This transformation entails constructing a barrier where different sources meet and placing a water source in each catchment basic (regional minimum) to flood the discharge from sources. We then receive sharp watershed edges because the grey level changes with the number of pixels in an image. Pixels with the highest gradient magnitude powers relate to watershed lines, which address area limits. Water put on any pixel encased by a normal watershed line streams downhill to a normal nearby force minimum where pixels depleting to a typical least-structure catchment basin, which addresses the regions [16–18].

5. MARKER-CONTROLLED WATERSHED SEGMENTATION

The direct application of the watershed segmentation algorithm generally leads to over-segmentation due to different irregularities and the presence of noise in the gradient of the image. For this reason, sometimes the segmented result can lead to useless image information being output for further pre-processing. To avoid or reduce this type of case, we can incorporate a pre-processing stage to bring additional knowledge and proper information into the segmentation procedure.

The most widely used and improved approach to segmentation control is based on markers. A marker is a connected component that belongs to an image. The internal markers are associated with objects of interest, and the external markers are associated with the background. A marker process is primarily comprised of two major concepts: the pre-processing stage and a set of criteria that must be met by the marker. To minimise the effect of small spatial details, the pre-processing step basically consists of filtering the image with a specific smoothing filter. After the image smoothing, the internal marker work is also done to allow the regional minima. Then watershed was applied, and as a result, we got watershed ridge lines. The ridge lines are defined by external markers. The external markers divide the image into regions, and each of the regions contains an internal marker and part of the background as well. We can also simply take the gradient of the smoothed image and restrict the process to execute on a single watershed method that contains the marker in the particular region [19–22].

For a simple process, marker selection results primarily from a procedure based on intensity values and connectivity; for a more complex process, the procedure includes size, shape, relative distance, texture content, location, and so on. Markers provide the necessary knowledge and information about the segmentation issue.

6. PROPOSED METHODOLOGY

In the proposed methodology, nine combinations of edge-detecting filters and shapes of the structuring elements have been chosen to carry out the image segmentation of medical images with the watershed method. There are several types of medical images, including CT, MRI, and USG. First, all nine (Gaussian, Sobel, Prewitt, Laplacian, LoG, Average, Unsharp, Disk, Motion) edge detection operators were applied to every CT, MRI, and USG image for the conventional watershed transformation, and then to every CT, MRI, and USG image for the marker-based watershed transformation. Figure 1 shows the conventional watershed transformation, and Figure 2 shows the marker-based watershed transformation. The comparative analysis for both algorithms and statistical analysis has been done to obtain proper segmented knowledge and information which can improve the morphological approaches and help the medical analysis area be improved. The basic theory of edge-detecting filters and morphologically structured elements is to construct different structural elements in the same square window.

In Figure 1, the conventional watershed approach is proposed. In this process, the first step is to read the original images and convert the original RGB images into greyscale images. On that greyscale image, we apply a filtering process to the images and then calculate the gradient of the images from the filtered image. The image is then segmented using the traditional watershed segmentation process. Then, as an output image, we get the watershed image. By using this process while doing the watershed segmentation step, all nine edge detection techniques have been applied one by one for each image and for each technique.

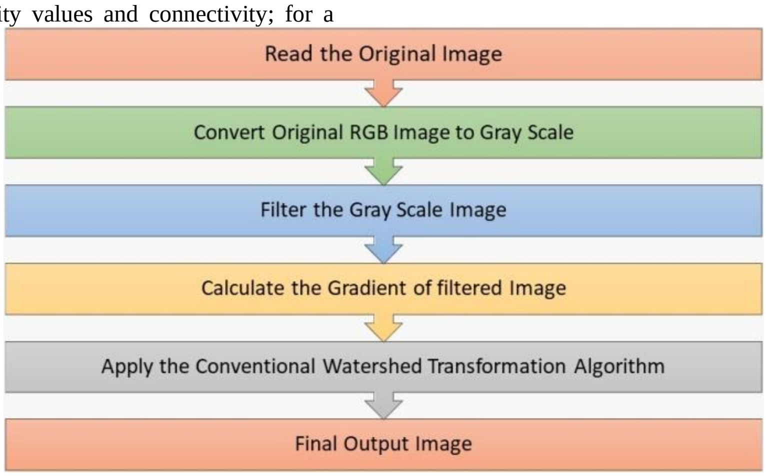

Fig 1: Flowchart of the Conventional Watershed Algorithm approach

In Figure 2, the marker-controlled watershed approach is proposed. The first step in this process is to read the original images and convert them to greyscale images, after which we calculate the gradient magnitude of the images. After that, the watershed segmentation process is applied. Then the edge detection technique is applied. After obtaining the image's edges, the opening and closing by reconstruction process is used to determine the background and foreground of the objects. From there, we calculate the ridge lines of the image. After all the processing, we finally applied the marker-base algorithm to get the final segmented image. All nine edge detection techniques (Gaussian, Sobel, Prewitt, Laplacian, LoG, Average, Unsharp, Disk, Motion) were applied one by one for each image and technique by using this process while performing the marker-controlled segmentation step.

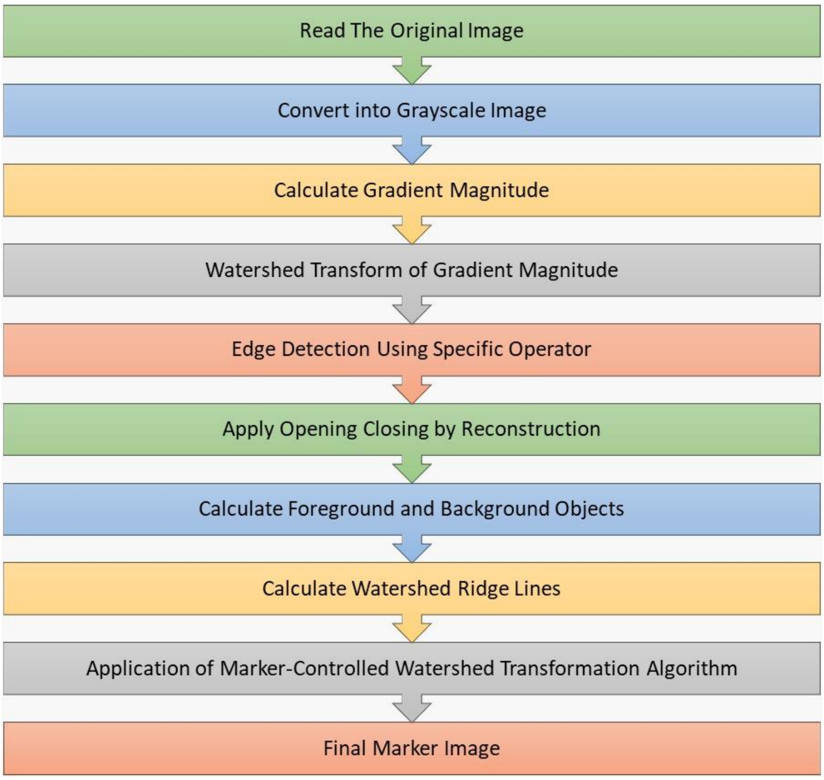

Fig 2: Flowchart of the Marker-Controlled Watershed approach

7. EXPERIMENTAL RESULTS AND DISCUSSION

Three CT (dimensions of 1296*728), MRI (dimensions of 1000*750), and USG (dimensions of 2560*1744) images have been taken for experimental purposes and accordingly shown in figure 3(a) to 3(c) respectively. To represent the experimental results for both the methodology of conventional and marker-based approaches, the quantitative statistical measurement analysis of different resultant images have been used. The resultant output images with conventional watershed approach with different structural elements or edge detectors are shown in figures 4(a) to 4(i) and the resultant output images with marker-based watershed approach with different structural elements are shown in figures 5(a) to 5(i).

(a) CT image (b) MRI image (c) USG image

Fig 3: Orignal input images

In figures 4(a) to 4(i) the ridge lines on the CT images are not very clear, and the MRI ridge lines are not clear on the majority of images, whereas the ridge lines on the USG images are quite clear but not very well segmented. The watershed lines have been imposed on the edge-detected images. The dark or more colourful spots present in images are prominent for USG and MRI images with Laplacian, Sobel, and some other processes, but for CT images, the spots are not so prominent and are not segmented.

Fig 4(a): Conventional Watershed Images with Average Edge Detector

Fig 4(b): Conventional Watershed Images with Disk Edge Detector

Fig 4(c): Conventional Watershed Images with Gaussian Edge Detector

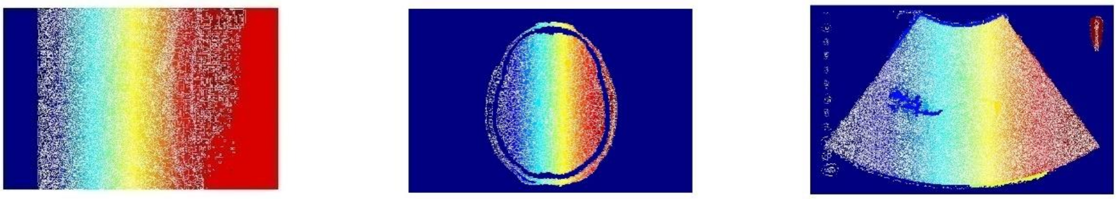

Fig 4(d): Conventional Watershed Images with Laplacian Edge Detector

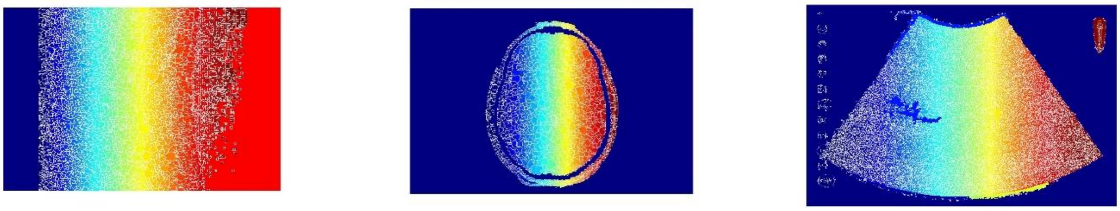

Fig 4(e): Conventional Watershed Images with LoG Edge Detector

Fig 4(f): Conventional Watershed Images with Motion Edge Detector

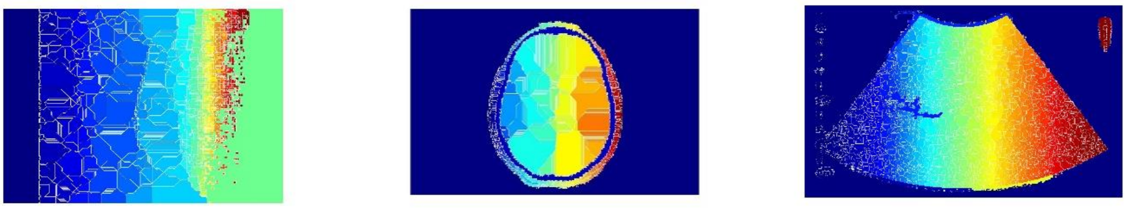

Fig 4(g): Conventional Watershed Images with Prewitt Edge Detector

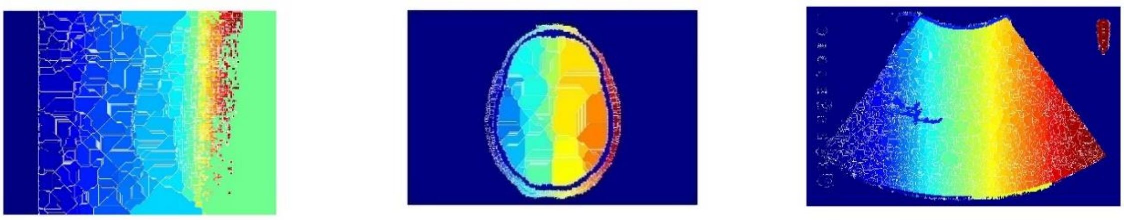

Fig 4(h): Conventional Watershed with Sobel Edge Detector

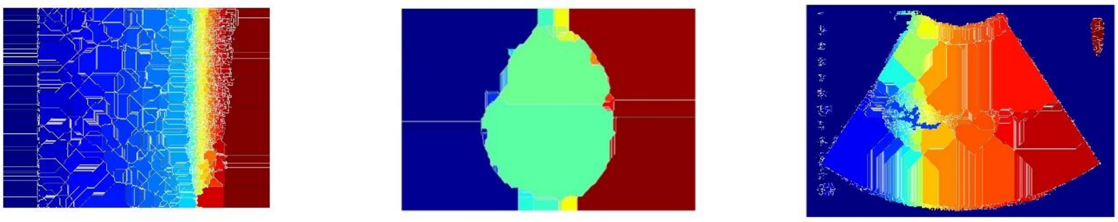

Fig 4(i): Conventional Watershed Images with Unsharp Edge Detector

In figures 5(a) to 5(i) the ridge lines are clearer and more prominent in every CT, MRI, and USG image and also segmented properly. The marked lines have been superimposed on the edge-detected images. The dark or more colourful spots present in images are prominent for USG, MRI, and CT images in most of the edge detection processes. Dark patches on images have become more prominent, and they have become larger in area compared to the conventional approaches. Laplacian, Log, Sobel, and Prewitt are the most affected resultant images after applying the marker-based approach. The watershed ridge lines are straight and sharp, as it is explained that the opening and closing reconstruction worked well and can be applied in medical image analysis processes.

Fig 5(a): Marker-Controlled Images with Average Edge Detector

Fig 5(b): Marker-Controlled Images with Disk Edge Detector

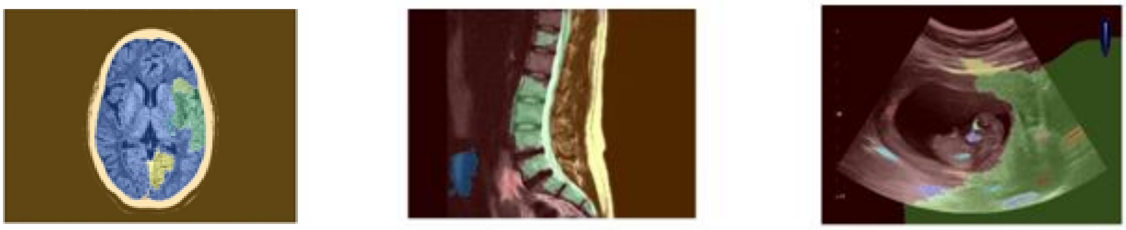

Fig 5(c): Marker-Controlled Images withG aussian Edge Detector

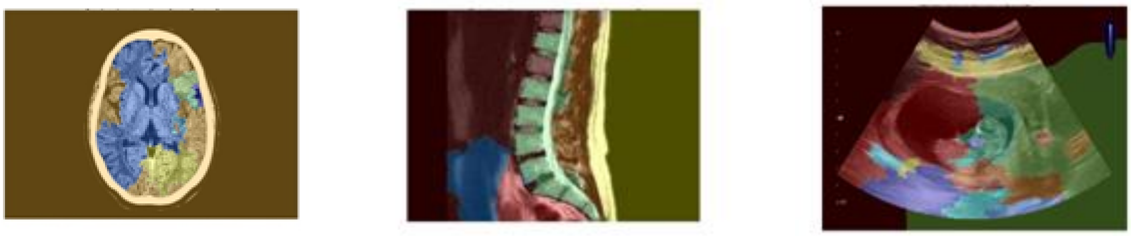

Fig 5(d): Marker-Controlled Images with Laplacian Edge Detector

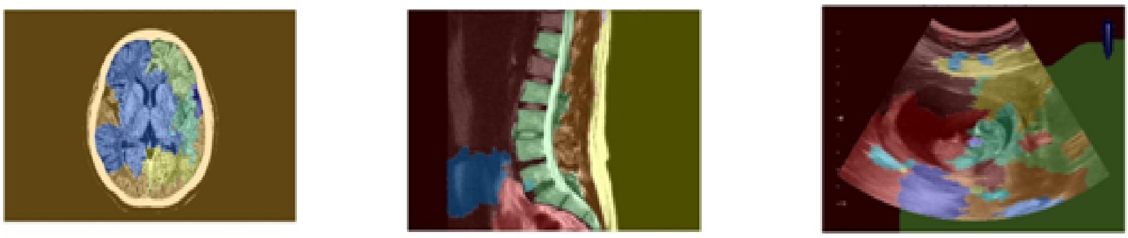

Fig 5(e): Marker-Controlled Images with Log Edge Detector

Fig 5(f): Marker-Controlled Images with Motion Edge Detector

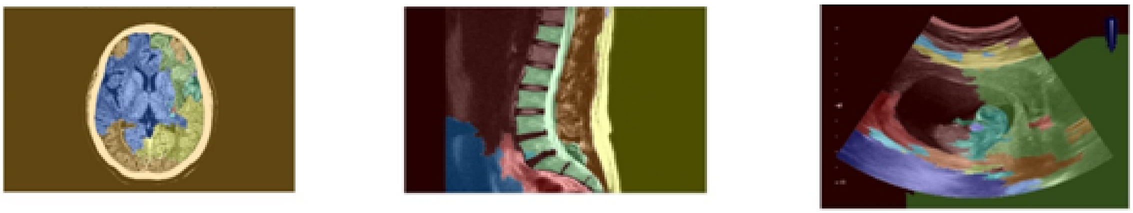

Fig 5(g): Marker-Controlled Images with Prewitt Edge Detector

Fig 5(h): Marker-Controlled Images with Sobel Edge Detector

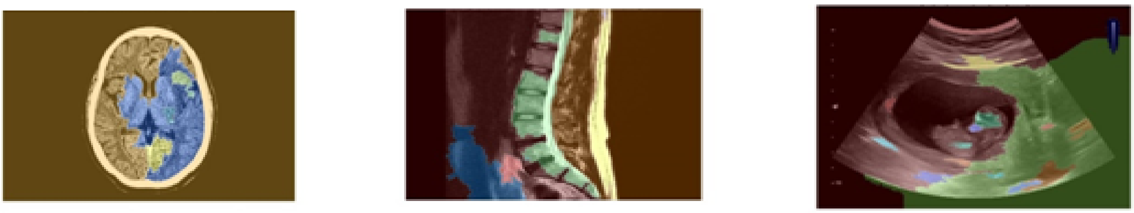

Fig 5(i): Marker-Controlled Images with Unsharp Edge Detector

In Table I and II below, the conventional controlled watershed approaches statistical measurements along with the marker controlled watershed approaches statistical measurements have been taken where it is visible that every edge detection process has gradient image statistical values and then the final values after applying the segmentation algorithms as well. To evaluate the performance of the proposed segmentation, process the PSNR (It is the ratio between the permitted power of a signal and the power of corrupting noise that changes the accuracy of its depiction.), SNR(Signal to Noise Ratio is defined as ratio of average signal power to average noise power for an image.), MSE(It indicates the dissimilarity of the pixels all over the real image with edges found in the image and it measures the average squared difference between the parameter and the estimator) and Execution time were calculated over each of the images for every edge detection technique [23-25]. The graphical representation of conventional watershed statistical measurements charts for PSNR, SNR, MSE and Elapsed Time are shown in figure 6 to 9 respectively. The graphical representation of conventional watershed statistical measurement charts for PSNR, SNR, MSE and Elapsed Time are shown in figure 10 to 13 respectively.

Table I. Statistical measurements of conventional watershed approach

Images	PSNR			SNR			MSE			Elapsed Time		
	CT	MRI	USG	CT	MRI	USG	CT	MRI	USG	CT	MRI	USG
Conventional watershed with Unsharp	19.5269	20.2235	19.3562	16.2801	17.6008	15.6722	106.8554	110.8654	110.2480	4.120690	0.999676	2.348346
Conventional watershed with Sobel	19.6226	20.5086	19.4580	16.2849	18.3392	16.0669	111.5346	99.9930	107.5264	0.665379	0.556280	2.487624
Conventional watershed with Prewitt	19.6367	20.4839	19.4550	16.3129	18.2905	16.0597	111.5509	100.4222	107.6406	0.589388	0.558091	2.433080
Conventional watershed with Motion	23.2669	20.3084	19.4130	22.1248	17.7311	15.9300	107.2060	109.7816	108.0573	0.617644	0.760230	5.819922
Conventional watershed with LoG	19.5289	20.7052	19.5416	16.0746	18.5950	16.4264	110.8098	104.5522	104.3510	0.768620	0.676177	2.569940
Conventional watershed with Laplacian	19.5394	19.5442	19.6344	16.1129	16.1580	16.6747	110.6085	112.9651	103.4437	0.587331	1.019047	2.603558
Conventional watershed with Gaussian	23.2780	20.3647	19.3847	22.1360	17.6292	15.8219	107.2060	117.6667	109.3664	0.986543	0.571059	2.044602
Conventional watershed with Disk	23.2788	21.1772	19.4613	22.1368	18.9206	16.0403	107.2060	122.7270	109.0056	0.908311	0.961343	2.683186
Conventional watershed with Average	23.2771	20.3145	19.3994	22.1351	17.5746	15.8073	107.2060	115.9413	109.6757	0.527151	7.443173	2.307331

Table II. Statistical measurements of marker Controlled watershed approach

Images	PSNR			SNR			MSE			Elapsed Time		
	CT	MRI	USG	CT	MRI	USG	CT	MRI	USG	CT	MRI	USG
Marker with Unsharp	19.0861	19.2674	18.5650	15.3382	15.4057	13.3119	90.4871	102.7241	92.8376	10.571576	6.614966	12.193580
Marker with Sobel	19.0922	19.2712	18.5662	15.3613	15.4807	13.4136	90.4137	100.8276	93.0003	7.460574	24.199397	17.378515
Marker with Prewitt	19.0860	19.2754	18.5615	15.3502	15.4849	13.4073	90.4471	100.8275	92.9967	8.034131	6.923468	14.142299
Marker with Motion	19.0888	19.2704	18.5655	15.3116	15.3739	13.3060	90.5886	103.2410	92.8322	8.152924	8.376484	12.455813
Marker with LoG	19.0966	19.2706	18.5664	15.3579	15.4817	13.4145	90.4253	100.7315	92.9805	7.596698	7.969570	14.845719
Marker with Laplacian	19.0893	19.2696	18.5646	15.3436	15.4834	13.4635	90.4984	100.6430	92.8658	7.455009	6.084218	17.626242
Marker with Gaussian	19.0885	19.2680	18.5648	15.3232	15.3856	13.3066	90.5304	103.0859	92.8960	9.946352	6.928921	14.222054
Marker with Disk	19.0921	19.2689	18.5604	15.3228	15.3720	13.3000	90.5564	103.2361	92.8273	7.501971	6.379830	12.956691
Marker with Average	19.0957	19.2715	18.5541	15.3297	15.3827	13.2951	90.5295	103.1604	92.8899	11.590916	7.443173	14.975594

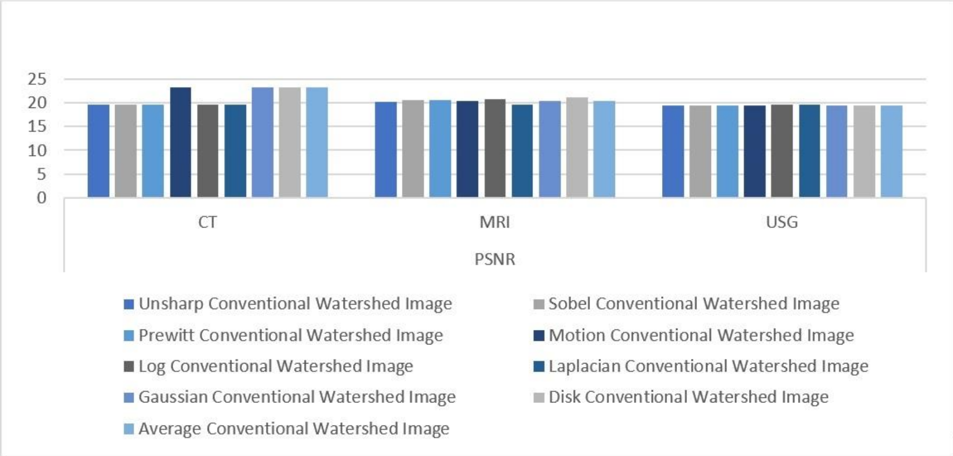

Fig: 6: Graphical representation of PSNR for Table I

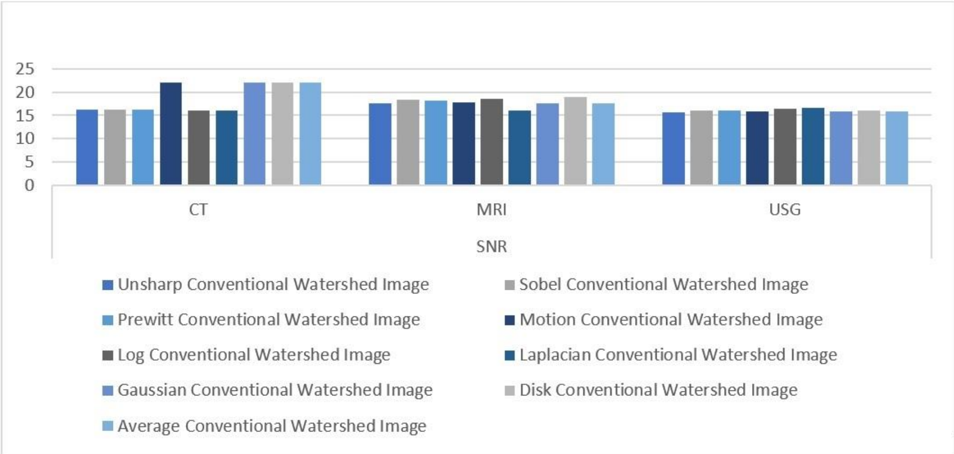

Fig: 7: Graphical representation of SNR for Table I

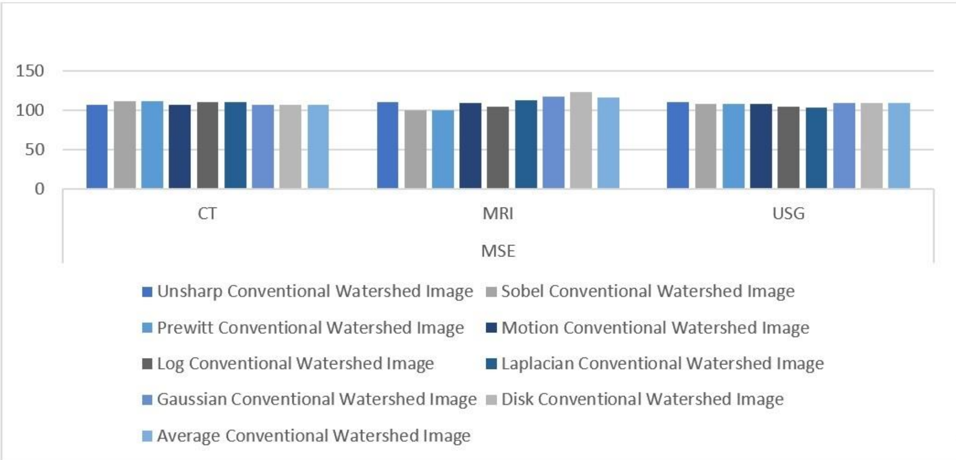

Fig 8: Graphical representation of MSE for Table I

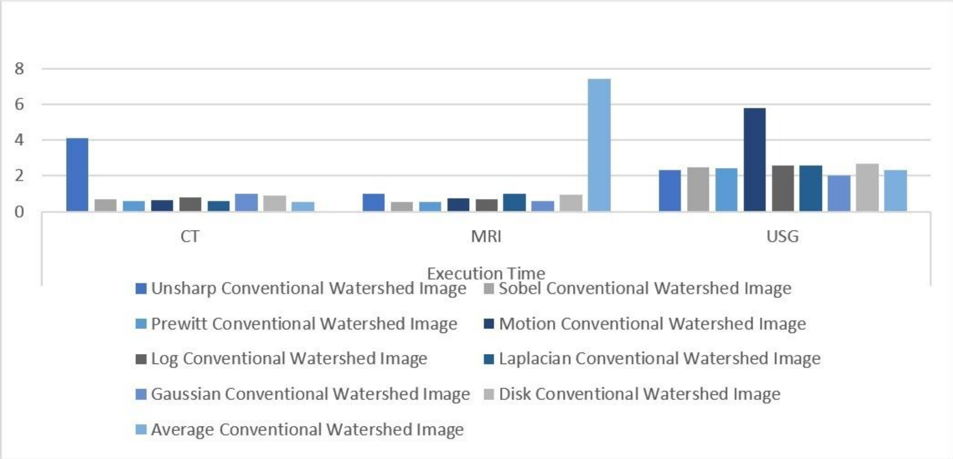

Fig 9: Graphical representation of Execution Time for Table I

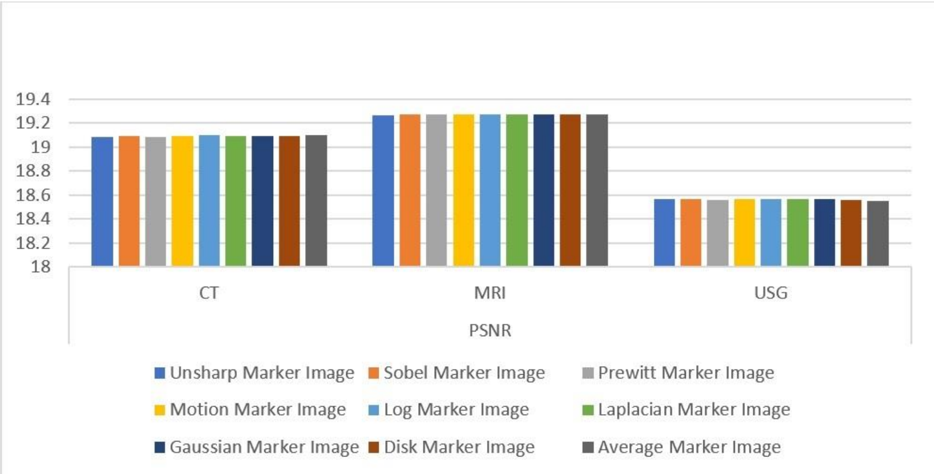

Fig 10: Graphical representation of PSNR for Table II

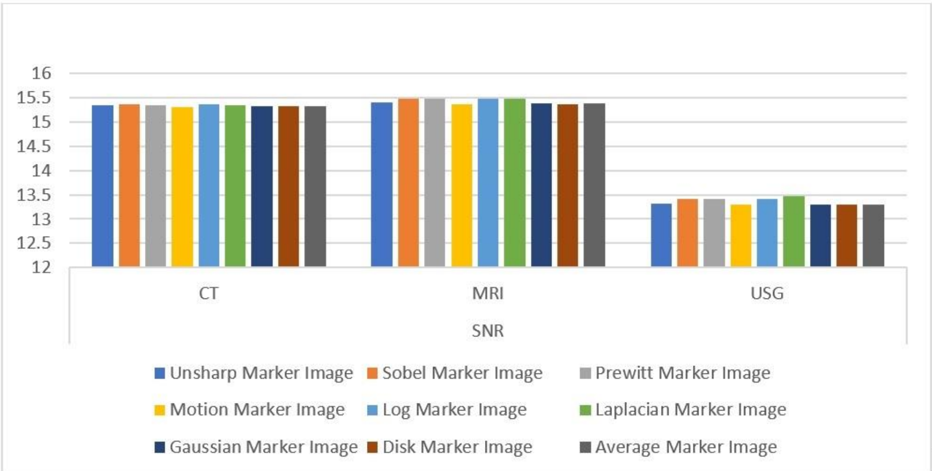

Fig 11: Graphical representation of SNR for Table II

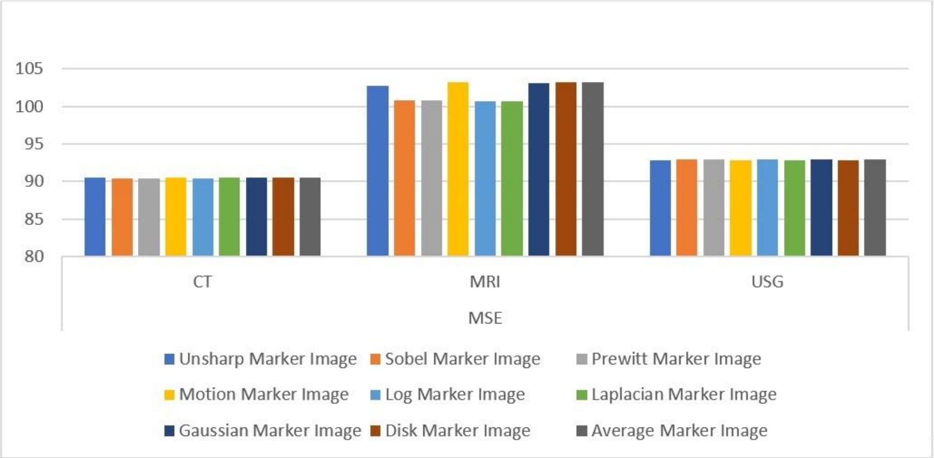

Fig 12: Graphical representation of MSE for Table II

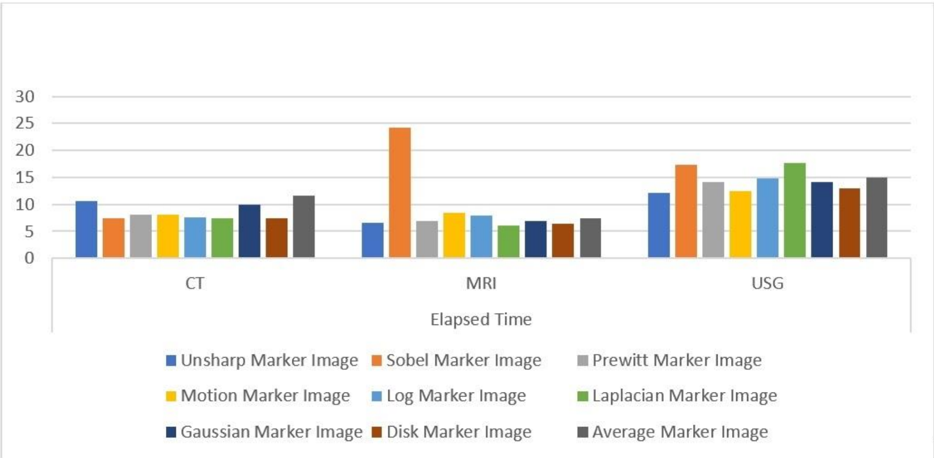

Fig 13: Graphical representation of Execution Time for Table II

The histogram of resultant images are shown from figure 14(a) to 14(i) for conventional approaches and 15(a) to 15(i) for the marker-base watershed segmentation approaches. An image histogram is a value distribution in gray scale that shows the frequency of occurrence of each gray level value to the processing level. From where we can see the output image clarity differences between conventional and marker base approach with the pixel intensity value of every approach separately.

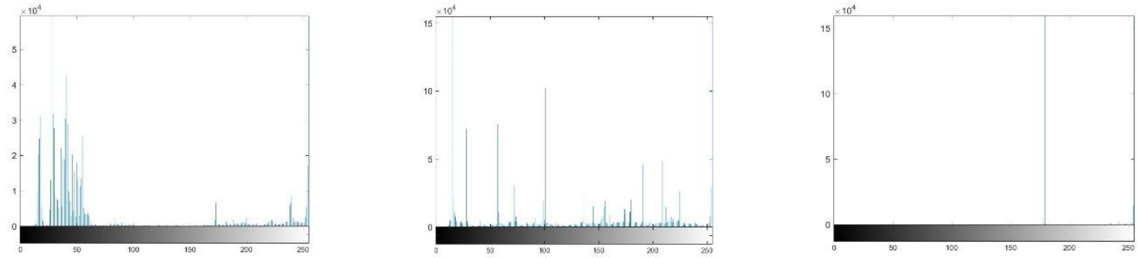

Fig 14(a): Histograms of Conventional Watershed Images with Average Edge Detector

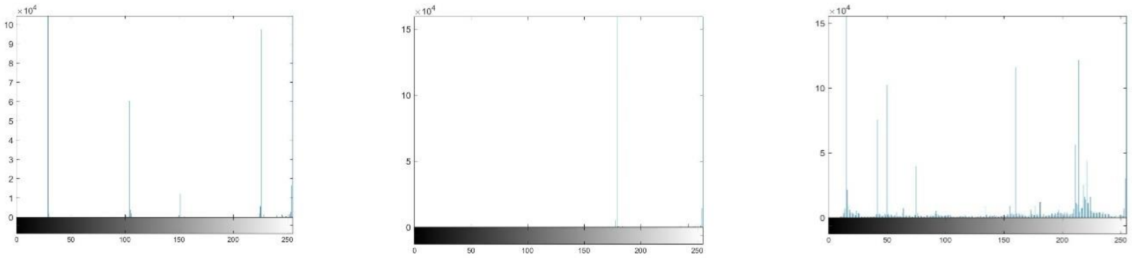

Fig 14(b): Histograms of Conventional Watershed Images with Disk Edge Detector

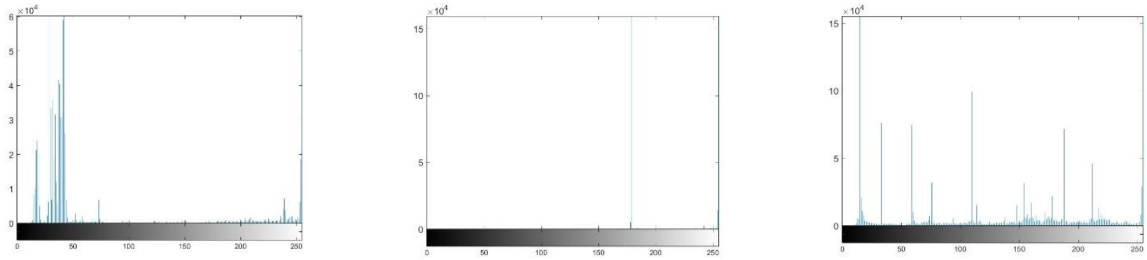

Figure 14(c). Histograms of Conventional Watershed Images with Gaussian Edge Detector

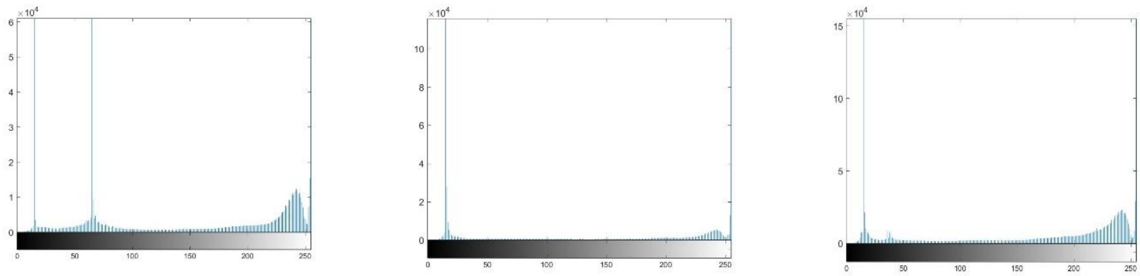

Fig 14(d): Histograms of Conventional Watershed Images with Laplacian Edge Detector

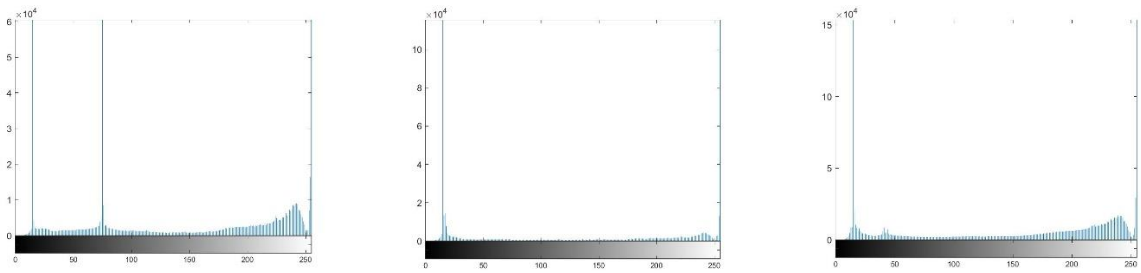

Fig 14(e): Histograms of Conventional Watershed Images with LoG Edge Detector

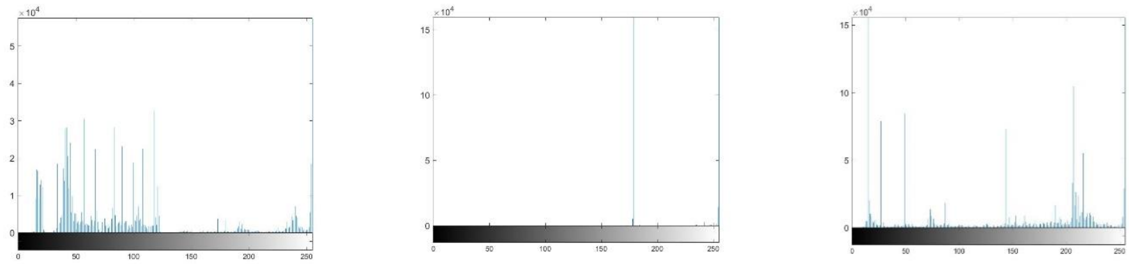

Fig 14(f): Histograms of Conventional Watershed Images with Motion Edge Detector

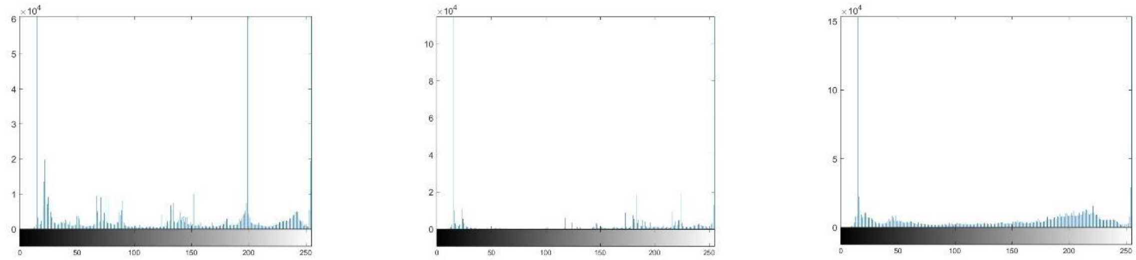

Fig 14(g): Histograms of Conventional Watershed Images with Prewitt Edge Detector

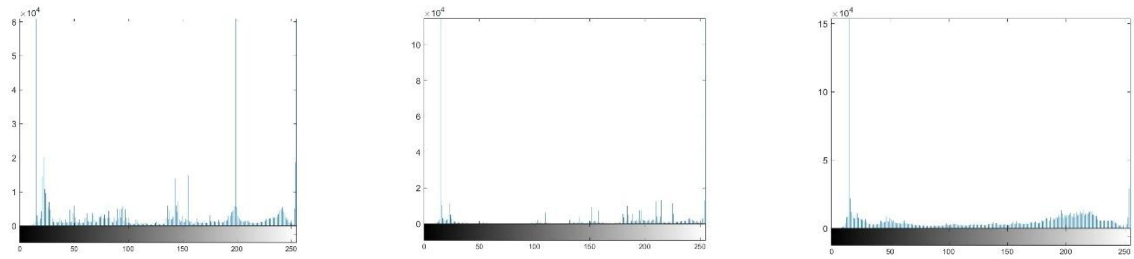

Fig 14(h): Histograms of Conventional Watershed with Sobel Edge Detector.

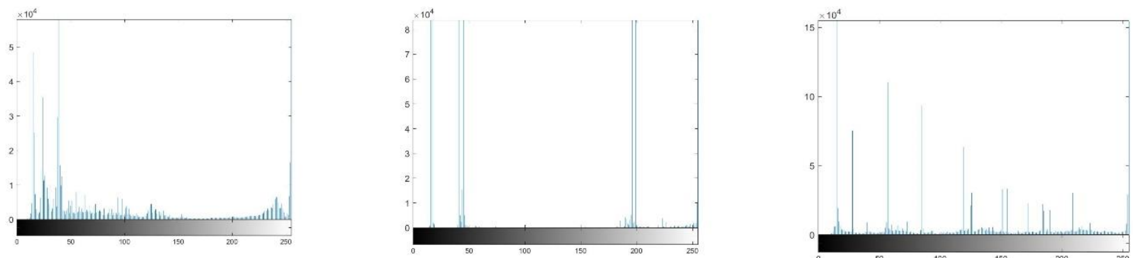

Fig 14(i): Histograms Conventional Watershed Images with Unsharp Edge Detector

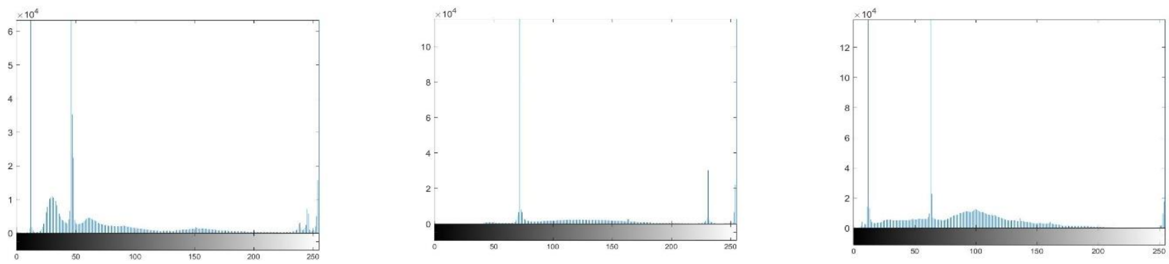

Fig 15(a): Histograms of Marker-Controlled Images with Average Edge Detector

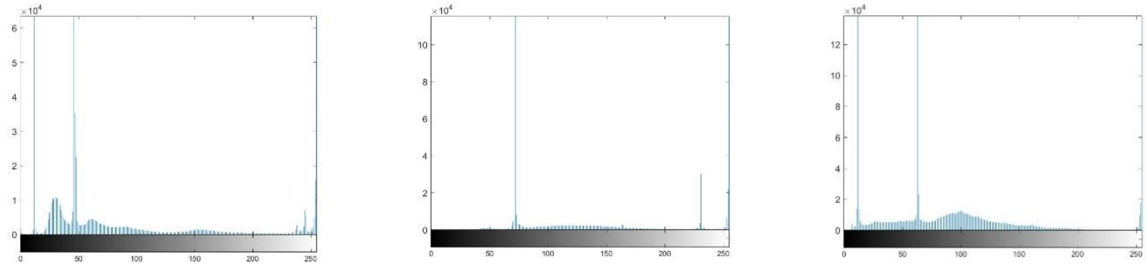

Fig 15(b): Histograms of Marker-Controlled Images with Disk Edge Detector

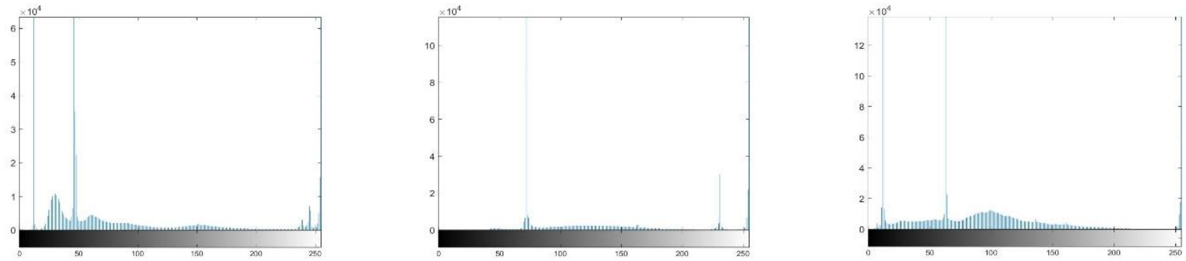

Fig 15(c): Histograms of Marker-Controlled Images withG aussian Edge Detector

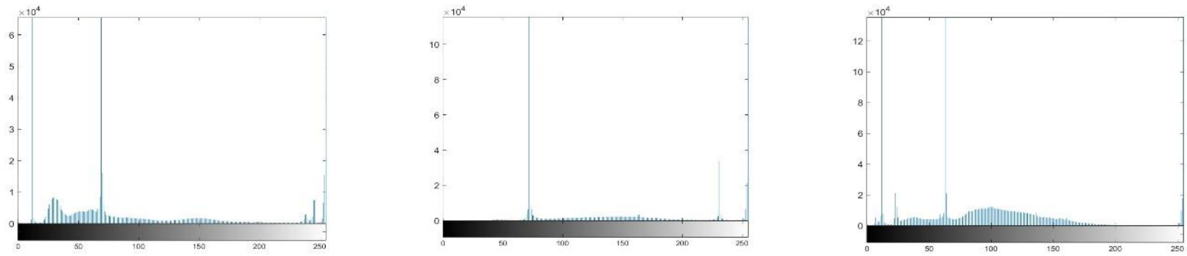

Fig 15(d): Histograms of Marker-Controlled Images with Laplacian Edge Detector

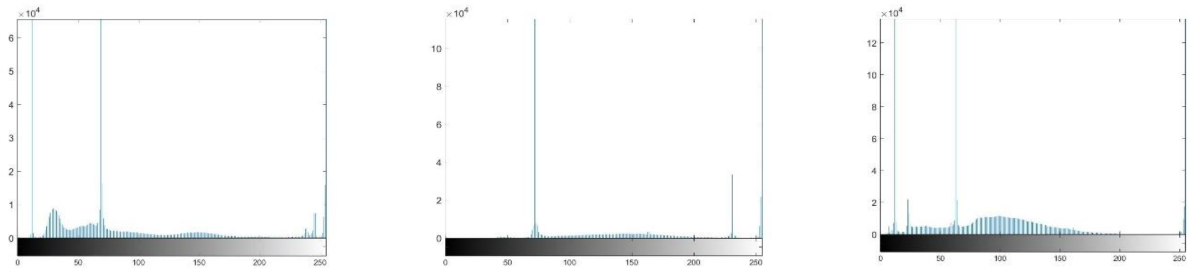

Fig 15(e): Histograms of Marker-Controlled Images with Log Edge Detector

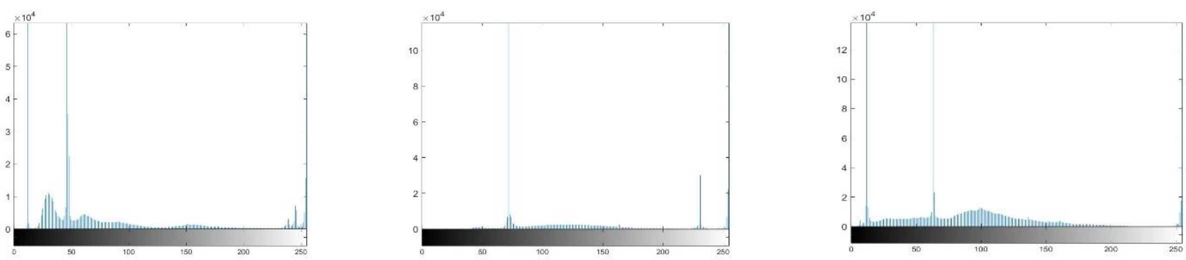

Fig 15(f): Histograms of Marker-Controlled Images with Motion Edge Detector

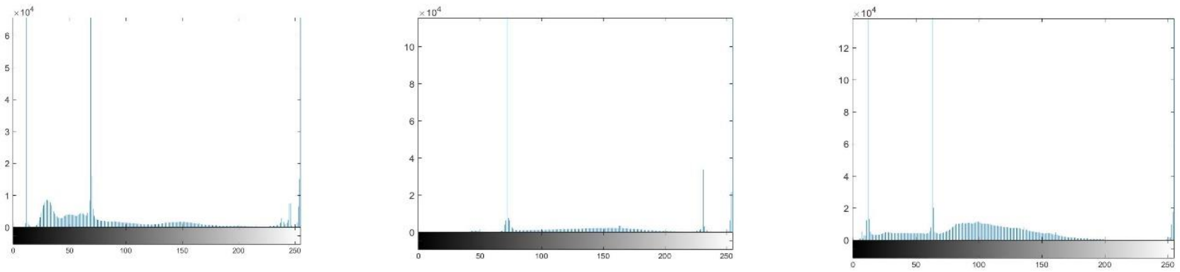

Fig 15(g): Histograms of Marker-Controlled Images with Prewitt Edge Detector

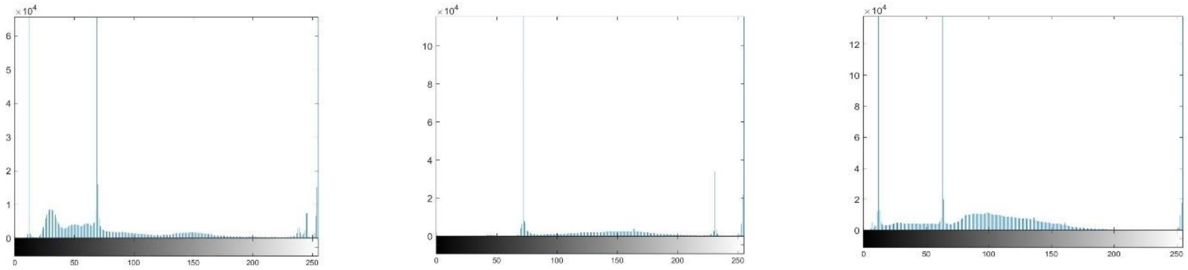

Fig 15(h): Histograms of Marker-Controlled Images with Sobel Edge Detector

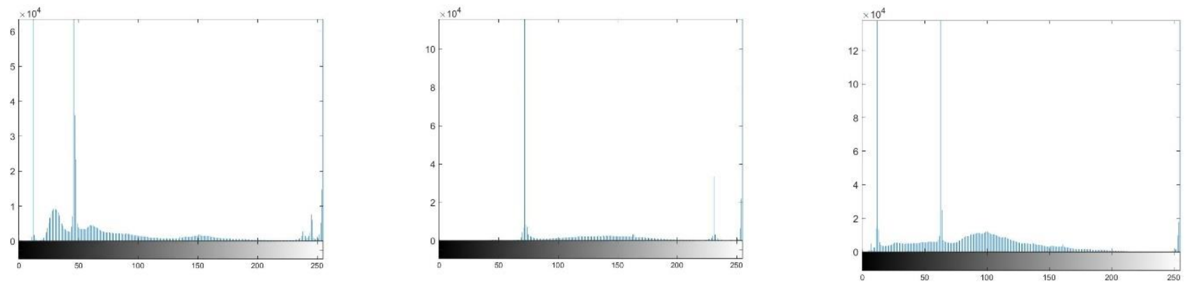

Fig 15(i): Histograms of Marker-Controlled Images with Unsharp Edge Detector

8. CONCLUSION

According to the results obtained in this study, most marker-controlled watershed edge detection algorithms prove to be a more promising technique for the segmentation of medical images, detecting the edges and, upon that edge, performing a segmentation approach to improve the image quality in terms of noise. The full process of segmenting the edges is done by comparing each of the objects taken into the examination process with the marker-controlled watershed segmentation. We came to the conclusion that the marker-based edge detection methods perform well for the maximum edge detection algorithm and can effectively differentiate the improvement of image segmentation by their nature. All the statistical resultant values are increased; it seems the applied marker-controlled watershed algorithm is segmented in a way that we can improve the segmentation.

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