Effect of Various Gradients on Watershed

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***Abstract*—The watershed transform is known to be a powerful tool for morphological image segmentation. Usually, the watershed starts with the gradient of the image to be segmented. The watershed lines partition the gradient image into different catchment basins, which correspond to homogeneous regions. Consequently, the watershed result is significantly influenced by the morphological gradient chosen for the computation. In this paper, we propose a watershed algorithm based on local minima and follow gradient downhill for each pixels. The experiments have shown that the effect of various gradients on watershed technique with the help of four different image i.e. two of them are the standard images and two are remote sensing images. In this paper the results of watershed based on different types of gradient are shown. The results are measured on the basis of peak signal to noise ratio.**

Keywords- Gradient through convolution; watershed; segmentation;psnr

I. INTRODUCTION

One of the goals of computer vision is to construct meaningful descriptions of physical objects from images. Before the objects in the image can be recognized and manipulated, images must be segmented. Many segmentation procedures have been proposed in the literature to partition an image into homogeneous regions. Yet, no sufficiently rigorous and general solution of the segmentation problem is available [1].

The watershed transform is a well established tool for the segmentation of images. Instead of using the image directly, the transform uses a gradient image extracted from the original image. The initial stage of any watershed segmentation method is therefore to produce a gradient image from the actual image. Some element of smoothing is always necessary within gradient extraction schemes (e.g., [2]) in order to emphasize the significant gradient within the image and reduce the gradient caused by noise or other minor structures [3].

Although the over-segmentation property of the watershed method somewhere seems to be desirable for finely structured images but many of the times over-segmentation creates problems while identifying the region of interest. So in our work we suppress this over-segmentation problem up to the great extent.

The purpose of this work is to introduce the effect of various gradients on watershed and on the basis of peak signal to noise ratio their performance is measured. The paper is organized as follows. Section 2 refers to proposed work. The experimental results are shown in section 3. Finally, conclusions are drawn in section 4.

II. PROPOSED WORK

A. Gradient through Convolution

Convolution is a simple mathematical operation which is fundamental to many common image processing operators. Convolution provides a way of multiplying together two arrays of numbers, generally of different sizes, but of the same dimensionality, to produce a third array of numbers of the same dimensionality. This can be used in image processing to implement operators whose output pixel values are simple linear combinations of certain input pixel values. In an image processing context, one of the input arrays is normally just a grey level image. The second array is usually much smaller, and is also two dimensional (although it may be just a single pixel thick), and is known as the kernel. Convolution is a mask with an image. Similarly, filter masks are also sometimes called Convolution Masks.

$$\begin{matrix} I_{11} & I_{12} & I_{13} & I_{14} & I_{15} & I_{16} & I_{17} & I_{18} & I_{19} \\ I_{21} & I_{22} & I_{23} & I_{24} & I_{25} & I_{26} & I_{27} & I_{28} & I_{29} \\ I_{31} & I_{32} & I_{33} & I_{34} & I_{35} & I_{36} & I_{37} & I_{38} & I_{39} \\ I_{41} & I_{42} & I_{43} & I_{44} & I_{45} & I_{46} & I_{47} & I_{48} & I_{49} \\ I_{51} & I_{52} & I_{53} & I_{54} & I_{55} & I_{56} & I_{57} & I_{58} & I_{59} \\ I_{61} & I_{62} & I_{63} & I_{64} & I_{65} & I_{66} & I_{67} & I_{68} & I_{69} \end{matrix}$$

$$\begin{matrix} K_{11} & K_{12} & K_{13} \\ K_{21} & K_{22} & K_{23} \end{matrix}$$

The convolution is performed by sliding the kernel over the image, generally starting at the top left corner, so as to move the kernel through all the positions where the kernel fits entirely within the boundaries of the image. Each kernel position corresponds to a single output pixel, the value of which is calculated by multiplying together the kernel value and the underlying image pixel value for each of the cells in the kernel, and then adding all these numbers together. So in our example, the value of the bottom right pixel in the output image will be given by:

$$O_{57} = I_{57}K_{11} + I_{58}K_{12} + I_{59}K_{13} + I_{67}K_{21} + I_{68}K_{22} + I_{69}K_{23}$$

Convolution, the mathematical, local operation which is central to modern image processing. The basic idea is that a window of some finite size and shape, the support is scanned across the image. The output pixel value is the weighted sum of the input pixels within the window where the weights are the values of the filter assigned to every pixel of the window itself. The window with its weights is called the convolution kernel.

B. Peak Signal to Noise Ratio

Peak signal to noise ratio is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is the logarithmic function of the peak value of the image and the mean square error.

PSNR=10 LOG(2552/MSE) (1)

where MSE is the mean square error . Its value must be high.

C. Proposed Algorithm

The proposed work is shown in Fig.1

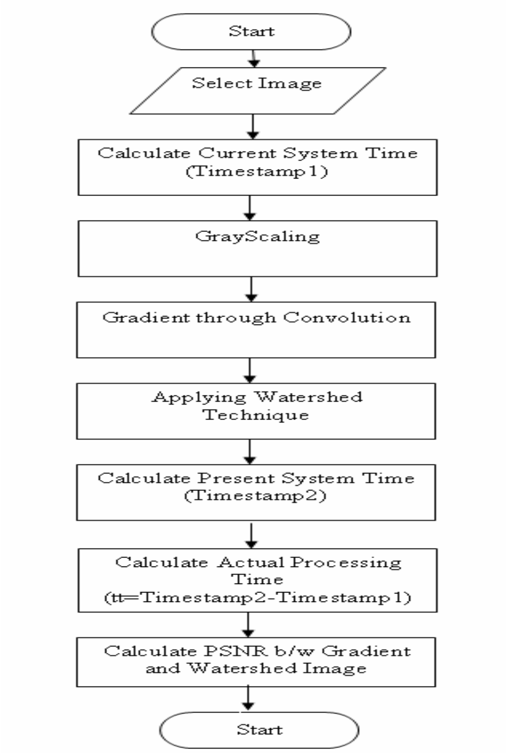
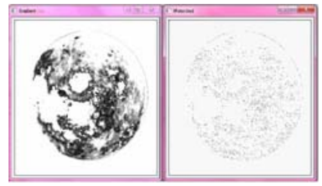


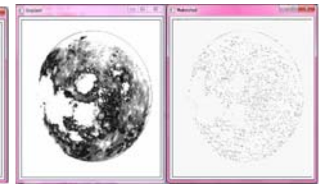
Fig.1: Flowchart of Proposed Algorithm

III. RESULTS

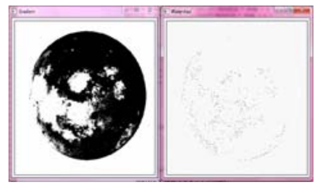
The results of the proposed work are shown in Fig.2, Fig.3, Fig.4, and Fig.5.



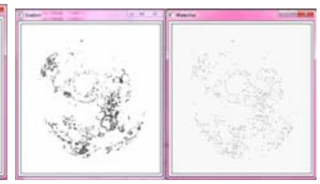
1st Method (Sobel)



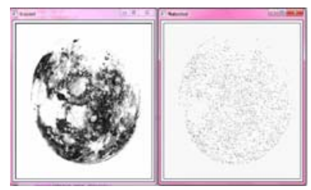
2nd Method (prewitt)



3rd Method (Laplacian)

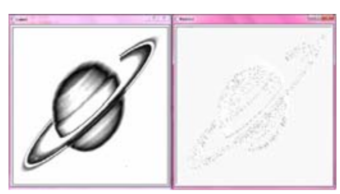


4th Method (Kirsch)

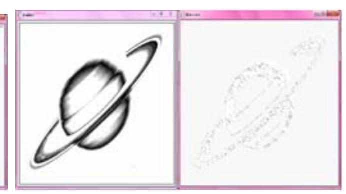


5th Method (Robinson)

Fig. 2: Result of various Gradients on moon image



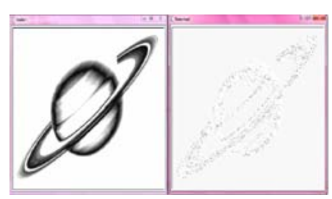
1st Method (Sobel)



2nd Method (Prewitt)

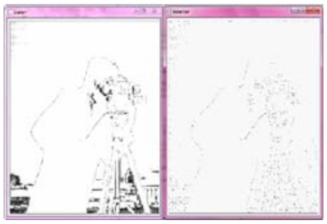
3rd Method (Laplacian)

4th Method (Kirsch)

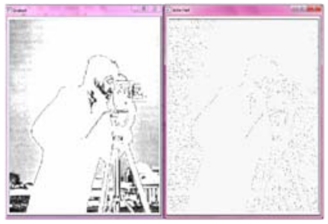


5th Method (Robinson)

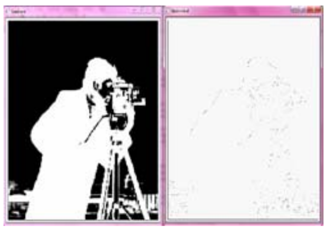
Fig. 3: Result of various Gradients on Saturn image



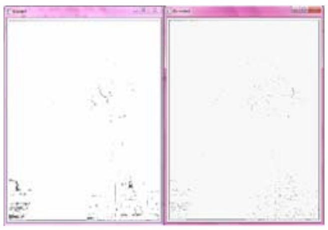
1st Method (Sobel)



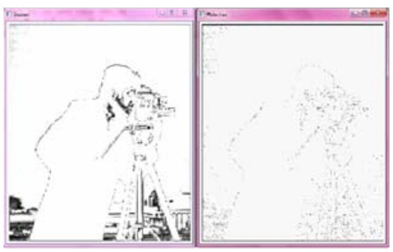
2nd Method (Prewitt)



3rd Method (Laplacian)

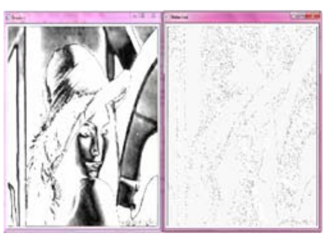


4th Method (Kirsch)

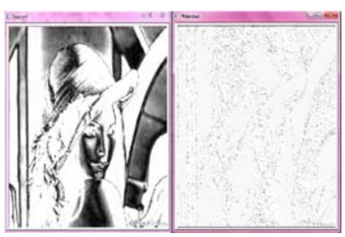


5th Method (Robinson)

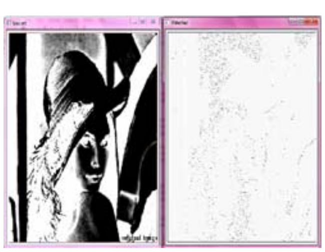
Fig. 4 Result of various Gradients on Cameraman image



1st Method (Sobel)



2nd Method (Prewitt)



3rd Method (Laplacian)

4th Method (Kirsch)

5th Method (Robinson)

Fig. 5: Result of various Gradients on Leena image

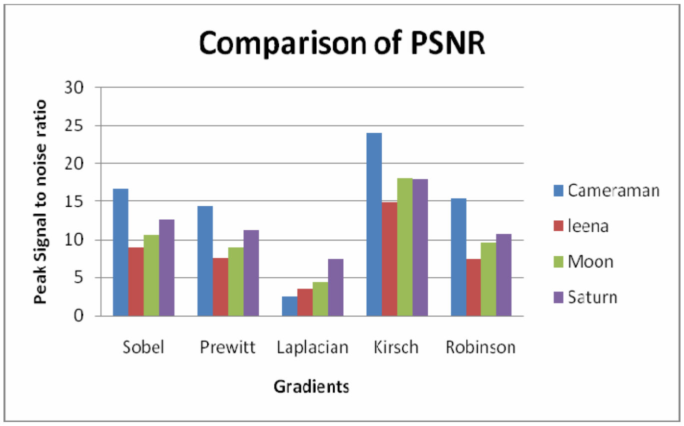
IV. CONCLUSION

From the results and comparison of the effect of different methods of gradient through convolution on watershed, it is concluded that the gradient through convolution using Kirsch operator on watershed gives maximum result in case of peak signal to noise ratio. In this work ,the watershed lines of the image using proposed algorithm has been produced.The results of various gradients like sobel, canny, Prewitt and Laplician of Gaussian method has been studied and compared on subjective basis as well as objective manner. In this paper, experiment is performed on remote sensing images and two of the standard images. And different methods using different structuring element in multidirections has been studied and compared. The comparison shows that the Peak Signal to Noise Ration is high in case of effect of gradient through Kirsch operator on watershed. The results are shown with the help of Table I and Graph I.

TABLE I: PSNR of different images

Gradient Through Convolution	PSNR(on Cameraman)	PSNR(on Leena)	PSNR(on Moon)	PSNR(on Saturn)
1st Method(Sobel)	8.981826	16.7244	10.599354	12.569682
2nd Method(Prewitt)	7.633667	14.390090	9.043650	11.301448
3rd Method(Laplacian)	3.559685	2.503851	4.417709	7.541099
4th Method(Kirsch)	14.902586	24.009273	18.141390	17.937831
5th Method(Robinson)	7.543739	15.349880	9.567714	10.80576

Graph I: Comparison of PSNR between Images



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