Watershed: A Comparative Study

Shikha Manrai [#1], Rajiv Bansal [#2]

[#1,2] *Computer Science & Engineering, Seth Jai Parkash Mukand Lal Institute of Engineering & Technology, Radaur, Yamunanagar, Haryana, India*

[1] shikhamanrai@gmail.com

***Abstract*—Morphological gradient is often used to find the gradient of an image which is further used for the transformation. However, noise in the gradient image results in to over-segmentation which have an undesirable bad effect on resulting segmented image. For the fine segmentation results the quality of the gradient estimate has a major influence on the segmentation performance. In this paper it is shown that different types of gradient are computed with the help of different operators and further these various gradients are used to segment the image with the help of watershed transformation. The resulting image constitute of watershed divide lines and the catchment basins. The purpose of this work is to show that the gradient obtained through different operators like Sobel, Prewitt, kirsch etc. have varying effect on watershed in terms of peak signal to noise ratio.**

Keyword- Watershed, gradient, image segmentation.

I. INTRODUCTION

In gray scale mathematical morphology the watershed transform, originally proposed by Digabel and Lantu´ejoul [1], and later improved by Beucher and Lantu´ejoul [2], is the method of choice for image segmentation [3], [4]. Image segmentation is the process of isolating objects in the image from the background, i.e. partitioning the image into disjoint regions, such that each region is uniform with respect to some property, such as gray value or texture [5].

The watershed transform is a broadly used technique for image segmentation. The watershed transform can be classified as a region-based segmentation approach. The intuitive idea underlying this method comes from geography: it is that of a landscape or topographic relief which is flooded by water, watersheds being the divide lines of the domains of attraction of rain falling over the region [4]. An alternative approach is to imagine the landscape being immersed in a lake, with holes pierced in local minima. Basins (also called 'catchment basins') will fill up with water starting at these local minima, and, at points where water coming from different basins would meet, dams are built. When the water level has reached the highest peak in the landscape, the process is stopped. As a result, the landscape is partitioned into regions or basins separated by dams, called watershed lines or simply watersheds.

In practice, the watershed is applied to the image gradient and the watershed lines separate homogeneous regions, giving the desired segmentation result. The gradient image for the transform is often found using the morphological gradient. However, noise in the gradient image results in over-segmentation which can have a significant adverse affect on the quality of the segmentation results. The quality of the gradient estimate has a major influence on the segmentation performance. So the result of different gradients on watershed has been found with the help of peak signal to noise ratio.

II. DIFFERENT GRADIENT TECHNIQUES

Gradient Edge Detectors measure the gradient of the image along two orthogonal axes. It is the best for abrupt discontinuities [6]. The edge detectors contain classical operators and uses first directional derivative operation. It includes algorithms such as Sobel (1970), Prewitt (1970), and Kirsch operators.

A. Gradient Using Sobel mask

The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical and is therefore relatively inexpensive in terms of computations.

The standard Sobel operators, for a 3×3 neighborhood, each simple central gradient estimates the vector sum of a pair of orthogonal vectors [7]. Each orthogonal vector is a directional derivative estimate multiplied by a unit vector specifying the derivative's direction. Thus for a point on Cartesian grid and its eight neighbors having density values as shown in Fig. 1:

$$S1=\begin{bmatrix}-1 & -2 & -1\\ 0 & 0 & 0\\ 1 & 2 & 1\end{bmatrix}\quad S2=\begin{bmatrix}0 & -1 & -2\\ 1 & 0 & -1\\ 2 & 1 & 0\end{bmatrix}\quad S3=\begin{bmatrix}1 & 0 & -1\\ 2 & 0 & -2\\ 1 & 0 & -1\end{bmatrix}\quad S4=\begin{bmatrix}2 & 1 & 0\\ 1 & 0 & -1\\ 0 & -1 & -2\end{bmatrix}$$

$$S5=\begin{bmatrix}1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{bmatrix}\quad S6=\begin{bmatrix}0 & 1 & 2\\ -1 & 0 & 1\\ -2 & -1 & 0\end{bmatrix}\quad S7=\begin{bmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{bmatrix}\quad S8=\begin{bmatrix}-2 & -1 & 0\\ -1 & 0 & 1\\ 0 & 1 & 2\end{bmatrix}$$

Fig. 1. Sobel edge operator convolution mask

Algorithm of Gradient Using Sobel Mask is as follows:

Step 1: Input to this algorithm is the 1 D image matrix of Original Image for R, G, B planes..
Step 2: Conversion of Original Image into Grayscale Image.
Step 3: Convolution with Sobel Mask is done using Grayscale Image.
Step 4: The resultant image which is Gradient of the original image is stored in 1 D image matrix for R, G, B planes as an input to Watershed.

B. Gradient Using Prewitt Mask

The prewitt operator is limited to 8 possible orientations, however experience shows that most direct orientation estimates are not much more accurate. This gradient-based edge detector is estimated in the 3x3 neighborhood for eight directions [8].

All the eight convolution masks are calculated. For each pixel the local edge gradient magnitude is estimated with the maximum response of all 8 kernels at this pixel location:

$|G| = \max(|G_i|: i=1 \text{ to } n)$

Where Gi is the response of the kernel i at the particular pixel position and n is the number of convolution kernels. The local edge orientation is estimated with the orientation of the kernel that yields the maximum response. Various kernels can be used for this operation [9] are given in Fig. 2.

$$y1=\begin{bmatrix}-1 & -1 & -1\\ 0 & 0 & 0\\ 1 & 1 & 1\end{bmatrix}\quad y2=\begin{bmatrix}0 & -1 & -1\\ 1 & 0 & -1\\ 1 & 1 & 0\end{bmatrix}\quad y3=\begin{bmatrix}1 & 0 & -1\\ 1 & 0 & -1\\ 1 & 0 & -1\end{bmatrix}\quad y4=\begin{bmatrix}1 & 1 & 0\\ 1 & 0 & -1\\ 0 & -1 & -1\end{bmatrix}$$

$$y5=\begin{bmatrix}1 & 1 & 1\\ 0 & 0 & 0\\ -1 & -1 & -1\end{bmatrix}\quad y6=\begin{bmatrix}0 & 1 & 1\\ -1 & 0 & 1\\ -1 & -1 & 0\end{bmatrix}\quad y7=\begin{bmatrix}-1 & 0 & 1\\ -1 & 0 & 1\\ -1 & 0 & 1\end{bmatrix}\quad y8=\begin{bmatrix}-1 & -1 & 0\\ -1 & 0 & 1\\ 0 & 1 & 1\end{bmatrix}$$

Fig. 2. Prewitt edge operator convolution mask

Algorithm of Gradient Using Prewitt Mask is as follows:

Step 1: Input to this algorithm is the 1 D image matrix of Original Image for R, G, and B planes.
Step 2: Conversion of Original Image into Grayscale Image.
Step 3: Convolution with Prewitt Mask is done using Grayscale Image.
Step 4: The resultant image which is Gradient of the original image is stored in 1 D image matrix for R, G, and B planes as an input to Watershed.

C. Gradient Using Kirsch Mask

The Kirsch-operator is a non-linear edge detector that finds the maximum edge strength in a few predetermined directions.

The kirsch edge detector detects edges using eight filters are applied to the image with the maximum being retained for the final image. The eight filters are a rotation of a basic compass convolution filter. For comparison with Sobel and Prewitt operator here only two directions horizontal and vertical convolution kernels (3x3) are considered as shown in Fig. 3.

$$K1=\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}\quad K2=\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}\quad K3=\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}\quad K4=\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}$$

$$K5=\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}\quad K6=\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}\quad K7=\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}\quad K8=\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}$$

Fig. 3. Kirsch edge operator convolution mask

Algorithm of Gradient Using Prewitt Mask is as follows:

Step 1: Input to this algorithm is the 1 D image matrix of Original Image for R, G, and B planes.
Step 2: Conversion of Original Image into Grayscale Image.
Step 3: Convolution with Kirsch Mask is done using Grayscale Image.
Step 4: The resultant image which is Gradient of the original image is stored in 1 D image matrix for R, G and B planes as an input to Watershed.

III. Proposed Work

The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels belonging to a common minimum form a catch basin, which represents a segment.

Step 1: Select the Original image
Step 2: Apply Grayscale Technique.
Step 3: Gradient through convolution is applied on Grayscale image
Step4: Watershed Technique is applied.
Step 5: Calculate PSNR (peak Signal to noise Ratio)

IV. Results

Results of different gradient on watershed are shown below. Fig. 4 , Fig. 5. shows the original image and gray scale image.

(a) (b)

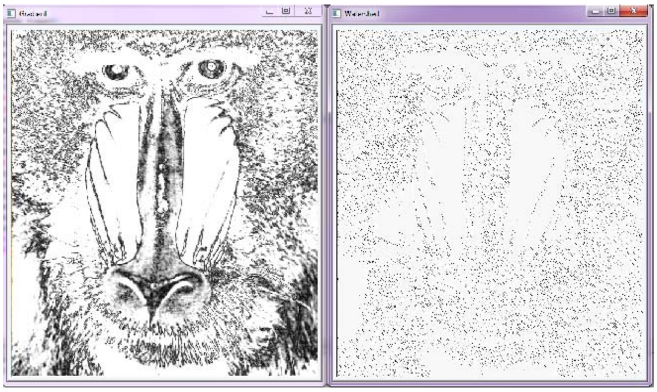
Fig. 4. (a)Original Image (b) Grayscale Image of Baboon

(a) (b)

Fig. 5. (a)Original Image (b) Grayscale Image of Saturn

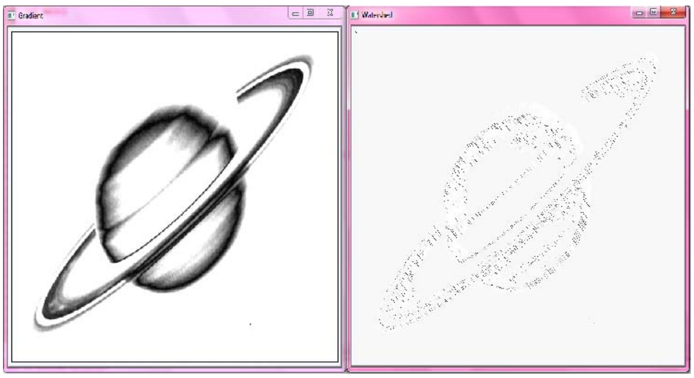
A. Using Sobel operator

The results after applying gradient through sobel operator on watershed are shown in Fig. 6, Fig. 7.



(a) (b)

Fig. 6. (a)Gradient Image (b) Watershed Image of Baboon

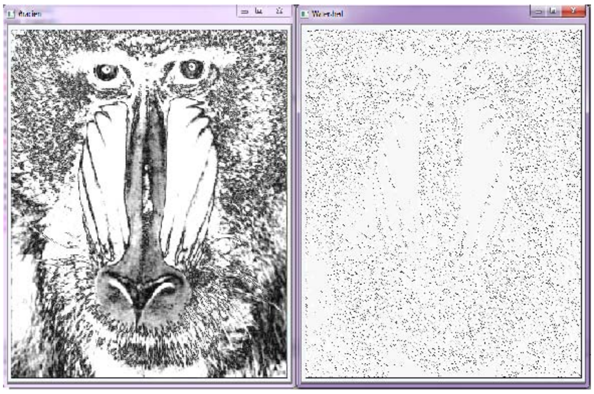


(a) (b)

Fig. 7. (a)Gradient Image (b) Watershed Image of Saturn

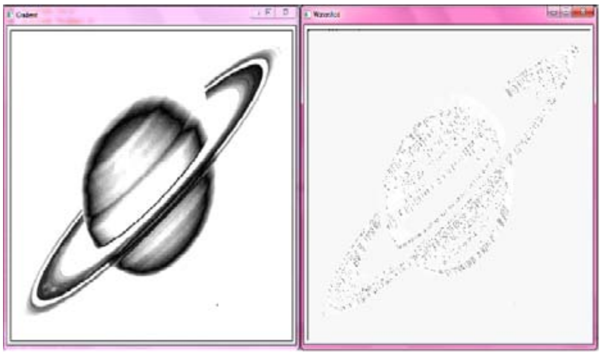
B. Using Prewitt operator

The results after applying gradient through Prewitt operator on watershed are shown in Fig. 8, Fig. 9.



(a) (b)

Fig. 8 (a) Gradient Image (b) Watershed Image of Baboon

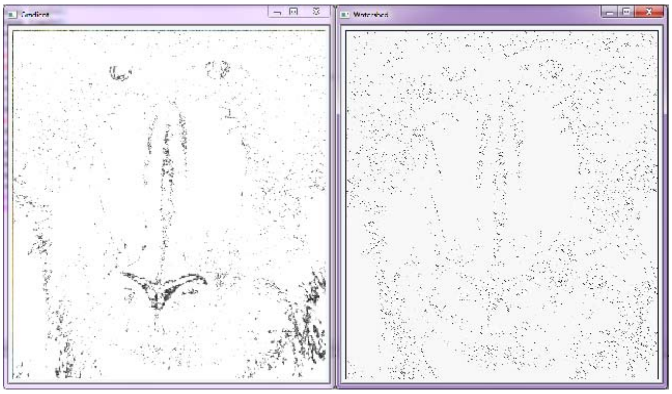


(a) (b)

Fig. 9. (a)Gradient Image (b) Watershed Image of Saturn

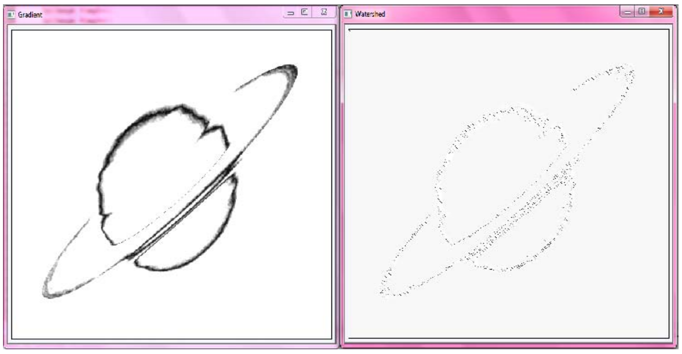
C. Using Kirsch Operator

The results after applying gradient through Sobel operator on watershed are shown in Fig. 10, Fig. 11.



(a) (b)

Fig. 10. (a) Gradient Image (b) Watershed Image of Baboon



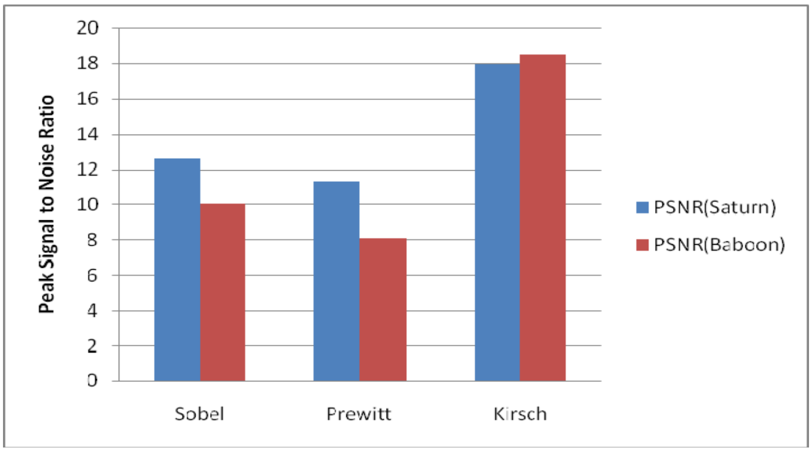
(a) (b)

Fig. 11. (a) Gradient Image (b) Watershed Image of Saturn

V. CONCLUSION

In this paper, two images are taken to compare the effect of gradient through which operator on watershed comes out to be more advantageous in case of PSNR i.e. peak signal to noise ratio. Firstly Gradient through convolution using operators namely Sobel , Prewitt , Kirsch is found out and is given as an input to watershed algorithm and resulting watershed image is obtained.

From Graph 1, it was found that the effect of gradient through Kirsch operator on watershed is having the maximum peak signal to noise ratio between gradient and watershed image. Hence it can be concluded that gradient through kirsch operator on segmented image comes out to be more preferable in terms of PSNR ratio. The watershed image using kirsch operator comes out to be more precise one.



Graph 1: Comparison of various effects of gradients on watershed

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