Effect of Various Spatial Sharpening Filters on the Performance of the Segmented Images using Watershed Approach based on Image Gradient Magnitude and Direction

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ABSTRACT
In various spectrum of image processing, images are acquired with low variations in the intensity level and thus they possess small gradient values. In these cases, it is convenient to apply watershed segmentation on the gradient image, rather than the original image. The most common output of these segmented images is over segmentation and it implies the presence of numerous watershed ridges that do not correspond to the object boundaries of interest. Under this intermingled problematic scenario, the role of the spatial edge sharpening filters should not be ignored. This research paper deals with the role of various edge sharpening filters and to find the ultimate effect of them on the output image using watershed algorithm is presented.

Keywords
Iimage segmentation, spatial sharpening filters, watershed algorithm.

1. INTRODUCTION
The basic philosophy of watershed based image segmentation is laid on the fact that viewing the pixel intensity as a third dimension added to the two dimensional image plane and subsequently to treat the entire three dimensional spaces from topological point of view. Thus mathematical morphology based image segmentation can be considered as an attempt to apply the topological knowledge on the image morphology. The strength and efficiency of watershed segmentation approaches that includes distance transform based application [1-6] as well as marker controlled approach [7-8] can be judged from the inherent ability to produce stable segmentation with continuous watershed boundaries thus precluding post processing like edge linking etc. The second point with warrants attention is the speed of processing and invoking the simplicity in the algorithm. Although a large number of mathematical morphology based image segmentation approaches [9-18.] are found in the available in the available literature, out of which the algorithm put forward by F. Meyer [13] and L. Vincent and P. Soille [7] are found to be the most widely acceptable and used in different areas of application of image processing.

One of the main applications of watershed segmentation is in the extraction of almost uniform objects from the background [7-13]. In various spectrum of image processing, images are acquired with low variations in the intensity level and thus they possess small gradient values. In these cases, it is convenient to apply watershed segmentation on the gradient image, rather than the original image. In this framework of approach, the regional minima of catchment basin correlate beautifully with the tiny value of the gradient related to the image under test.

Gradient magnitude [19-21] is often used to preprocess a gray level image prior to put the image under watershed operation and this has been mentioned above. The gradient magnitude image has comparatively high value along the edges of the object and watershed lines which are ultimately obtained are nothing but the object various segments. The most common output of these segmented images is over segmentation and it implies the presence of numerous watershed ridges that do not correspond to the object boundaries of interest. To alleviate the problem, Meyer has utilized a morphological smoothing operation between the gradient formulation and watershed algorithm application [13].

Under this intermingled problematic scenario, the role of the spatial edge sharpening filters should not be ignored. Thus the present study has deal with the role of various edge sharpening filters and to find the ultimate effect of them on the output image. In this context, in addition to the widely found gradient operators [20-21] like Roberts, Prewitt, Sobel, Canny, Isotropic, the effect of compass operators, Laplacian operators and Laplacian of Gaussian (Log) on the ultimate segmented image have also been studied. The merit of the compass operators are that they are capable of finding object edges from various direction in segmentation process of digital images acquired from various directions as in the case of radar imaging and satellite imagery. Study as the present one is not so far available in published or online literature, and it is worthwhile to investigate the effects of gradient operator based spatial filters along with those capable of finding edges from various directions on the output segmented images. It has been found that the watershed segmented images are best obtained in case of canny and double derivative based gradient operators and the watershed segmented Images have been found to be clumsy in case of direction based spatial high pass filter. It has also been found that canny and LoG filter can yield better result in noisy environment [20-21].

This paper is divided into a choice of sections. In section 2 spatial sharpening filters or gradient operators are publicized. Section 3 introduces a brief description on watershed algorithm. Section 4 presents the proposed approach. The experimental results are discussed in section 5 and we finish this paper with some concluding remarks with section 6.

2. SPATIAL SHARPENING FILTERS OR GRADIENT OPERATORS

The gradient operators are customarily represented by a pair of masks H1, H2 which measure the gradient of the image f (m,n) in two orthogonal direction. Defining the bidirectional gradients $g_1(\mathrm{m,n}) = (\mathrm{U}, H_1)_{\mathrm{m,n}}$, $g_2(\mathrm{m,n}) = (\mathrm{U}, H_2)_{\mathrm{m,n}}$, The gradient vector magnitude and direction are given by:

$$\mathrm{g(m,n)} = \sqrt{{g_1}^2(\mathrm{m,n}) + g_2(\mathrm{m,n})} \qquad (1)$$

$\Theta_{\mathrm{g}}(\mathrm{m,n}) = \arctan \frac{g_2(m,n)}{g_1(m,n)}$ often the magnitude gradient is evaluated as:

$$g(m,n) = |g_1(m,n)| + |g_2(m,n)| \qquad (2)$$

The equation (2) is preferred to equation (1) because of simplicity in calculation and ease of application in digital hardware.

Some common gradient operators like Roberts, prewitt, Sobel and isotropic are shown below. They can compute horizontal and vertical differences of local sums and thus reduces the effects of noise in the data.

H_1:

0	1
-1	0

H_2:

1	0
0	-1

Fig 1: Sobel.

H_1:

-1	0	1
-1	0	1
-1	0	1

H_2:

-1	-1	-1
0	0	0
1	1	1

Fig 2: Prewitt.

H_1:

-1	0	1
-2	0	2
-1	0	1

H_2:

-1	-2	-1
0	0	0
1	2	1

Fig 3: Sobel.

H_1:

-1	0	1
$-\sqrt{2}$	0	$\sqrt{2}$
-1	0	1

H_2:

-1	$-\sqrt{2}$	-1
0	0	0
1	$-\sqrt{2}$	1

Fig 4: Isotropic.

The pixel location (m,n) is described as an edge location when g(m,n) exceeds some threshold t. The locations of edge points constitute an edge map:

$$\epsilon\ (\mathrm{m,n}) = \begin{cases} 1, g(m,n) > t \\ 0, otherwise \end{cases} \qquad (3)$$

The edge map renders the requisite data for tracing the object boundary in an image.

2.1. Compass Operators

They can measure gradient in a selected number of directions as shown in the figure below.

(N):

1	1	1
0	0	0
-1	-1	-1

(S):

-1	-1	-1
0	0	0
1	1	1

(SW):

0	-1	-1
1	0	-1
1	1	0

(NW):

1	1	0
1	0	-1
0	-1	-1

(SE):

-1	-1	0
-1	0	1
0	1	1

(NE):

0	1	1
-1	0	1
-1	-1	0

(W):

1	0	-1
1	0	-1
1	0	-1

(E):

-1	0	1
-1	0	1
-1	0	1

Fig 5: Krisch Compass Operators

The following figure shows four different compass gradients for north going edges. An anti clockwise circular shift of the eight boundary elements of these fillers gives a 45 degree rotation of the gradient direction.

(a):

1	1	1
1	-2	1
-1	-1	-1

(b):

5	5	5
-3	0	-3
-3	-3	-3

(c):

1	1	1
0	0	0
-1	-1	-1

(d):

1	2	1
0	0	0
-1	-2	-1

Fig 6: Compass gradients (North). Each clockwise rotation of elements about the center rotates the gradient direction.

Let $g_k(m,n)$ denote the compass gradient in the direction:

$$\Theta_{\mathrm{g}} = \frac{\mathrm{r}}{2} + \mathrm{k}\frac{\mathrm{r}}{4}. \text{ Where k=0,1,2,…..,7.} \qquad (4)$$

The gradient location (m,n) is defined as:

$$g(m,n) = {}^{max}_{k}\{|g_k(m,n)|\} \quad (5)$$

This can be threshold to yield an edge map out of the eight original compass operators, only four are linearly independent [21]. Thus, it is possible to define four 3x3 arrays which are mutually orthogonal and span the space of these compass gradients. These arrays are termed as orthogonal gradients and can be utilized in place of the compass gradient [21]. Compass gradient with higher angular resolution can be designed by increasing the dimension of the sharpening filters. Robinson operators are similar to kirsch masks, with masks coefficient of 0,1 and 2.

(N)

-1	0	1
-2	0	2
-1	0	1

(S)

1	2	1
0	0	0
-1	2	-1

(SW)

0	-1	-2
1	0	-1
2	1	0

(NW)

1	0	-1
2	0	-2
1	0	1

(SE)

-1	-2	-1
0	0	0
1	2	1

(NE)

-2	-1	0
-1	0	1
0	1	2

(W)

0	1	2
-1	0	1
-2	-1	0

(E)

2	1	0
1	0	-1
0	-1	-2

Fig 7: Robinson Compass Operators.

3. WATERSHED TRANSFORM

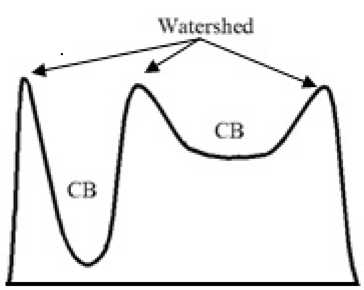

Fig 8: Watershed segmentation-local minima yield catchment basins, local maxima define the watershed lines.

Watershed transform is the technique which is commonly used in image segmentation. It is now being recognized as a powerful method used in image segmentation due to its many advantages such as simplicity, speed and complete division of the image. Watershed transform or Watershed Algorithm is based on grey-scale morphology. It is classified as a region-based segmentation approach. Even when the target regions having low contrast and week boundaries, watershed transformation can provide closed contours. When a landscape or topographic relief is flooded with water, the divide lines of the domains of rain falling over the regions forms the watersheds. Intuitively, a drop of water falling on a topographic relief flows towards the "nearest" minimum. The "nearest" minimum is that minimum which lies at the end of the path of steepest descent. In terms of topography, this occurs if the point lies in the catchment basin of that minimum. An alternative approach is to imagine the landscape being immersed in a lake in which holes are pierced in the local minima is called the catchment basin. Water will be filled up at these starting local minima and at points where water coming from different basins would meet and dams will be built. When the water level reaches 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. The mathematical formulations are shown in below.

Assume, Mi where i= 1 to n be the set of coordinates points in the regional minima (catchment basins), of the image P(x,y) and C(Mi) be the coordinates points of catchment basins associated with the regional minima Mi

$$Tn = \{(s,t) \mid P(s,t) < n\} \quad (6)$$

Where,

T[n] = set of points in P(x,y) which are lying below the plane p(x,y) = n

min, max = minimum or maximum gray level value.

n = stage of flooding varies from min + 1 to max + 1

Let Cn(M1) be the set of points in the catchment basin associated with M1 that are flooded at stage n.

$$Cn(M1) = \cap \{C(M1), T[n] \quad (7)$$

Where,

$$Cn(M_i) = \begin{cases} 1, & if\ (x,y) \in C(M_i) and (x,y) \in T[n] \\ 0, & otherwise \end{cases} \quad (8)$$

C[n] is the union of flooded catchment basin portions at the stage *n*.

Where,

$$C[n] = Cn(m1) \cup Cn(m2) \ldots\ldots Cn(mR) \quad (9)$$

$$C[max + 1] = C(m1) \cup C(m2) \ldots\ldots C(mR) \quad (10)$$

If the algorithm keeps on increasing flooding level then Cn(Mi) and T[n] will either remain constant or increase. Algorithm initializes$C[min + 1] = T[min + 1]$, and then precedes recursively by assuming that at step n C [n - 1] has been constructed.

Let, G is a set of connected components in T[n] and for each connected component g ∈ G[n], there possibilities will arise.

1. g ∩ C[n - 1] is empty.

2. g ∩ C[n - 1] contains one connected component of C[n - 1].

3. g ∩ C[n - 1] contains more than one connected component of C[n - 1].

4. PROPOSED APPROACH

Spatial sharpening filters on the performance of the segmented images in digital image processing and in mathematical morphology plays a very significant role. The term Morphology refers to a special type of filtering and structuring elements. Besides extracting boundaries, morphology can shape smoothing and removal of small holes. Watershed algorithm is a morphological tool for segmentation of images. The basic philosophy of watershed based image segmentation is laid on the fact that viewing the pixel intensity as a third dimension added to the two dimensional image plane and subsequently to treat the entire three dimensional spaces from topological point of view. In this research article morphological image segmentation based on generating gradient images using spatial sharpening filters, followed by morphological smoothing and watershed transform has been proposed. Morphological smoothing is applied in intermediate state because of reducing over segmentation. One way to achieve smoothing is to perform a morphological opening followed by a closing. Opening smoothes the contour by removing thin bridges and eliminating thin protrusions.

$$A \circ B = (A \ominus B) \oplus B \qquad (11)$$

Closing also smoothes the contour, but by enforcing bridges and closing small holes.

$$A \bullet B = (A \oplus B) \ominus B \qquad (12)$$

The boundary of opening with a circular structuring element corresponds to rolling a ball on the inside of the set. The boundary of closing corresponds to rolling a ball on the outside of the set. The flowchart of the proposed approach is stated below. In first step of proposed approach one real life color image of very famous "Laure" is chosen and accordingly converted into a gray scale image in second step. The gray scale image also called as black and white image only contains the intensity information of an image varying from black at the weakest intensity to white at the strongest. In third step the gradient image is computed using different compass operators. The gradient magnitude image has high pixel values along object edges and low pixel values everywhere else. In next step morphological smoothing operation in done on gradient images and accordingly watershed transform is computed in the final step. The final segmented images are shown in Figure 11 to 26.

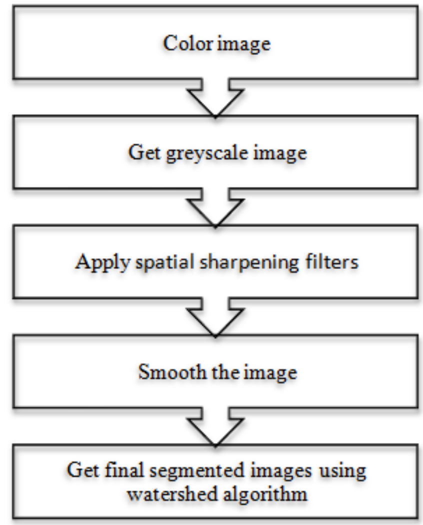

Fig 9: Flow chart of proposed approach.

5. EXPERIMENTAL RESULTS AND DISCUSSION

Various spatial sharpening filters or compass operators namely Krisch and Robinson operators for generating gradient images have been discussed in this research article to carry out image segmentation process. Two real life images of "Laure" of 256 x 256 dimensions and "Fruits" of 356x282 (Figure 10) has been chosen to do the experimental work. It has been observed and studied that using watershed algorithm directly on the gradient images produce over segmented. To reduce the over segmentation, in this research article a new approach of segmentation using different compass operators and watershed algorithm has been applied.

In first step of the segmentation process two color images are chosen (Figure 10) and accordingly converted in to gray scale images. The grayscale images are converted into gradient images using spatial sharpening filters or compass operators namely Krisch and Robinson operators of different gradient magnitudes and different directions. Eight different directions and gradient magnitudes for Krisch operator and eight different directions and gradient magnitudes (Section 2.1) for Robinson operator are applied for generating gradient images. To reduce the over segmentation morphological smoothing operation are done on the gradient images in fourth step of the proposed approach. In final step watershed algorithm is applied on the morphologically smoothed images to get the final segmented results and accordingly shown from figure 11 to figure 26 and better result is achieved with lesser over segmentation. The statistical measurements with entropy, PSNR and MSE are also shown in table 1 for Laure image and in table II for Fruits image.

Fig 10: Original Images. (a) Laure, (b) Fruits.

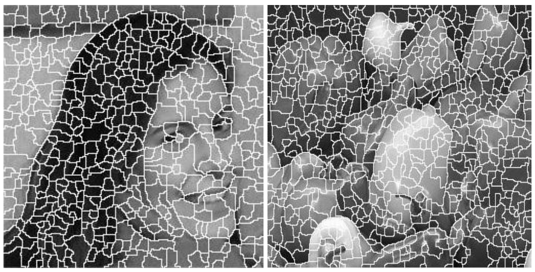

Fig 11: Final segmented image with Krisch operator of north direction. (a) Laure, (b) Fruits.

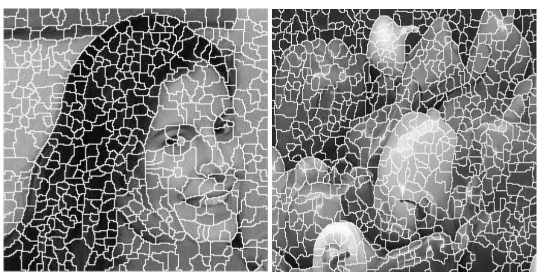

Fig 12: Final segmented image with Krisch operator of south direction. (a) Laure, (b) Fruits.

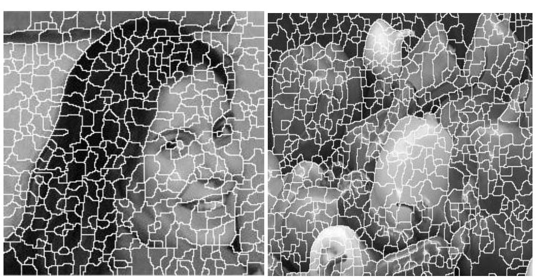

Fig 13: Final segmented image with Krisch operator of north west direction. (a) Laure, (b) Fruits.

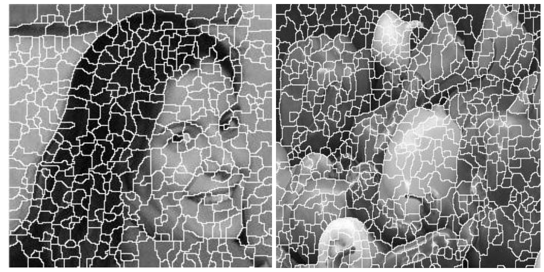

Fig 14: Final segmented image with Krisch operator of south east direction. (a) Laure, (b) Fruits.

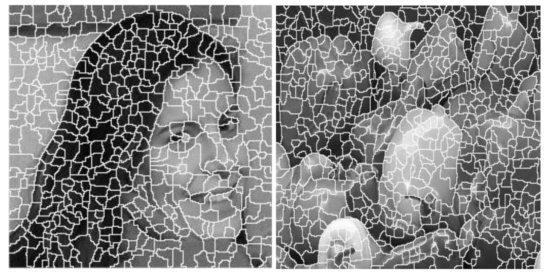

Fig 15: Final segmented image with Krisch operator of west direction. (a) Laure, (b) Fruits.

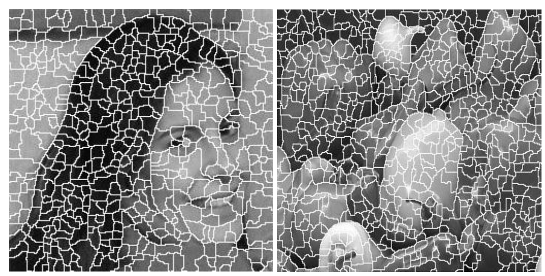

Fig 16: Final segmented image with Krisch operator of east direction. (a) Laure, (b) Fruits.

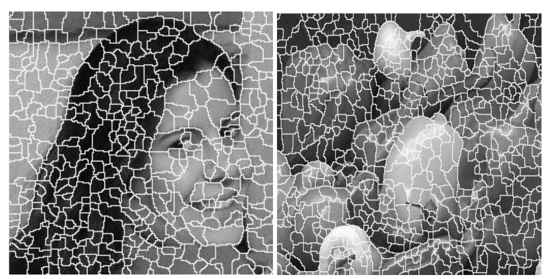

Fig 17: Final segmented image with Krisch operator of south west direction. (a) Laure, (b) Fruits.

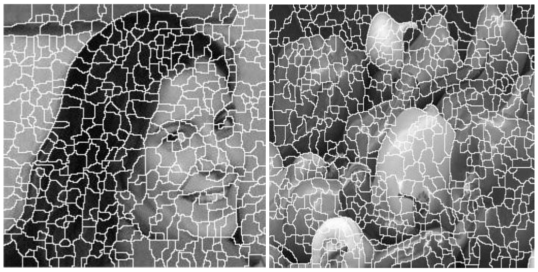

Fig 18: Final segmented image with Krisch operator of north east direction. (a) Laure, (b) Fruits.

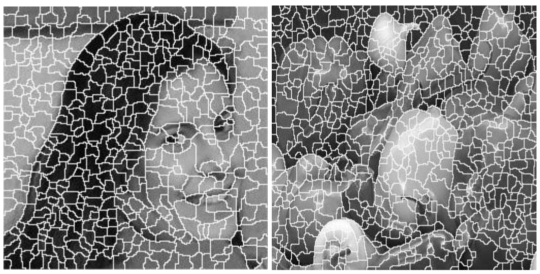

Fig 19: Final segmented image with Robinson operator of north direction. (a) Laure, (b) Fruits.

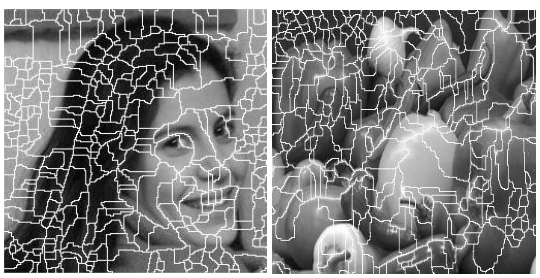

Fig 20: Final segmented image with Robinson operator of south direction. (a) Laure, (b) Fruits.

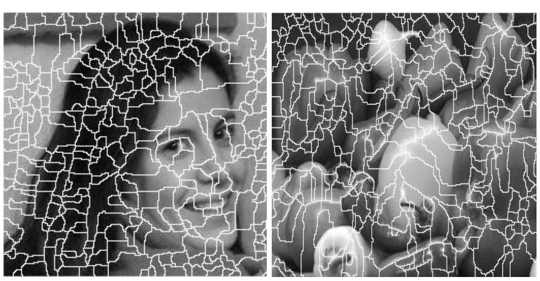

Fig 21: Final segmented image with Robinson operator of north west direction. (a) Laure, (b) Fruits.

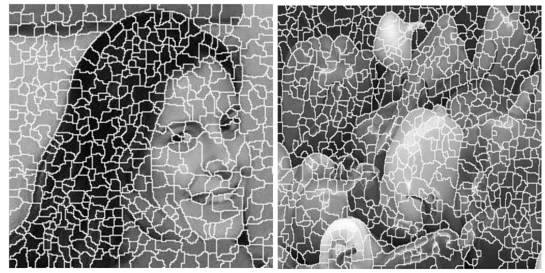

Fig 22: Final segmented image with Robinson operator of south east direction. (a) Laure, (b) Fruits.

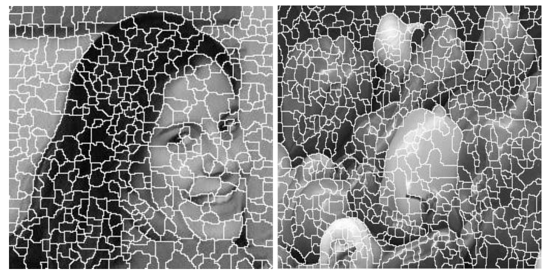

Fig 23: Final segmented image with Robinson operator of west direction. (a) Laure, (b) Fruits.

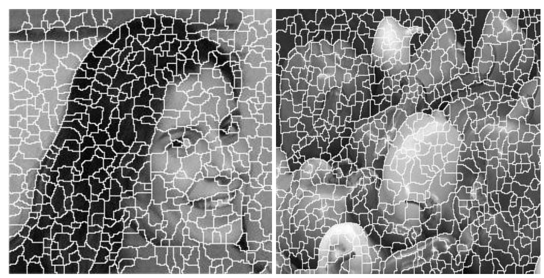

Fig 24: Final segmented image with Robinson operator of east direction. (a) Laure, (b) Fruits.

Fig 25: Final segmented image with Robionson operator of south west direction. (a) Laure, (b) Fruits.

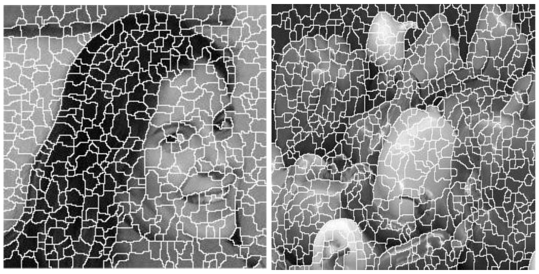

Fig 26: Final segmented image with Robinson operator of north east direction. (a) Laure, (b) Fruits.

Table I. Statistical measurement of segmented images using various spatial sharpening filters with watershed transform for Laure image.

Image	Operator Used	Direction	Entropy	PSNR	MSE
Figure 11(a)	Krisch	North	4.2032	5.0215	2.0461e+004
Figure 12(a)	Krisch	South	4.2032	5.0215	2.0461e+004
Figure 13(a)	Krisch	North West	4.2242	5.0613	2.0274e+004
Figure 14(a)	Krisch	South East	4.2242	5.0613	2.0274e+004
Figure 15(a)	Krisch	West	4.2032	5.0215	2.0461e+004
Figure 16(a)	Krisch	East	4.2032	5.0215	2.0461e+004
Figure 17(a)	Krisch	South West	4.2248	5.0564	2.0298e+004
Figure 18(a)	Krisch	North East	4.2248	5.0564	2.0298e+004
Figure 19(a)	Robinson	North	4.1979	5.0140	2.0497e+004
Figure 20(a)	Robinson	South	4.2843	5.1386	1.9917e+004
Figure 21(a)	Robinson	North West	4.2915	5.1412	1.9905e+004
Figure 22(a)	Robinson	South East	4.1979	5.0140	2.0497e+004
Figure 23(a)	Robinson	West	4.2221	5.0494	2.0330e+004
Figure 24(a)	Robinson	East	4.2135	5.0552	2.0303e+004
Figure 25(a)	Robinson	South West	4.2811	5.1380	1.9920e+004
Figure 26(a)	Robinson	North East	4.2135	5.0552	2.0303e+004

Table II. Statistical measurement of segmented images using various spatial sharpening filters with watershed transform for Fruits image.

Image	Operator Used	Direction	Entropy	PSNR	MSE
Figure 11(b)	Krisch	North	4.6725	6.4453	1.4742e+004
Figure 12(b)	Krisch	South	4.6725	6.4453	1.4742e+004
Figure 13(b)	Krisch	North West	4.6958	6.4970	1.4567e+004
Figure 14(b)	Krisch	South East	4.6958	6.4970	1.4567e+004
Figure 15(b)	Krisch	West	4.6725	6.4453	1.4742e+004
Figure 16(b)	Krisch	East	4.6725	6.4453	1.4742e+004
Figure 17(b)	Krisch	South West	4.7009	6.5008	1.4555e+004
Figure 18(b)	Krisch	North East	4.7009	6.5008	1.4555e+004
Figure 19(b)	Robinson	North	4.6740	6.4499	1.4726e+004
Figure 20(b)	Robinson	South	4.7994	6.6933	1.3924e+004
Figure 21(b)	Robinson	North West	4.7873	6.6784	1.3971e+004
Figure 22(b)	Robinson	South East	4.6740	6.4499	1.4726e+004
Figure 23(b)	Robinson	West	4.6873	6.4695	1.4660e+004
Figure 24(b)	Robinson	East	4.6879	6.4919	1.4585e+004
Figure 25(b)	Robinson	South West	4.7950	6.6889	1.3938e+004
Figure 26(b)	Robinson	North East	4.6879	6.4919	1.4585e+004

6. CONCLUSION

This research paper the role of various edge sharpening filters and to find the ultimate effect of them on the output image using watershed algorithm is presented. In various spectrum of image processing, images are acquired with low variations in the intensity level and thus they possess small gradient values. In these cases, it is convenient to apply watershed segmentation on the gradient image, rather than the original image. The most common output of these segmented images is over segmentation and it implies the presence of numerous watershed ridges that do not correspond to the object boundaries of interest. Under this intermingled problematic scenario, the role of the spatial edge sharpening filters should not be ignored. In this paper gradient images are acquired by various edge sharpening filters (Krisch and Robinson) and watershed algorithm is applied after morphological smoothing operation is applied on the gradient images which results lesser over segmentation.

7. DEDICATION

One of the others (Dibyendu Ghoshal) dedicates the entire study to the loveliest and loving memory of his only one and younger sister Kumari Sumita Ghoshal who herself was a gem of the scholars, a symbol of wisdom and art, peerless beauty and simplicity, unfathomable knowledge and generosity.

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