

## **MODULE – 4 LECTURE NOTES – 3**

### **FILTERING AND EDGE ENHANCEMENT**

#### **1. Introduction**

Spatial feature manipulations are the processes which help to emphasize or deemphasize data of various spatial frequencies. The term spatial frequency represents the tonal variations in the images such that higher values indicate rough tonal variations whereas lower values indicate smoother variations in the tone.

Spatial feature manipulations are generally local operations where the pixel values in the original image are changed with respect to the gray levels of the neighboring pixels. It may be applied to either spatial domain or frequency domain. Filtering techniques and the edge enhancement techniques are some of the commonly used local operations for image enhancement.

This lecture explains the mechanics of filtering and edge enhancement as applied to the remote sensing satellite images.

#### **2. Filtering Techniques**

If a vertical or horizontal section is taken across a digital image and the image values are plotted against distance, a complex curve is produced. An examination of this curve would show sections where the gradients are low (corresponding to smooth tonal variations on the image) and sections where the gradients are high (locations where the digital numbers change by large amounts over short distances). Filtering is the process by which the tonal variations in an image, in selected ranges or frequencies of the pixel values, are enhanced or suppressed. Or in other words, filtering is the process that selectively enhances or suppresses particular wavelengths or pixel DN values within an image.

Two widely used approaches to digitally filter images are convolution filtering in the spatial domain and Fourier analysis in the frequency domain. This lecture explains the filtering techniques with special reference only to the spatial domain.

A filter is a regular array or matrix of numbers which, using simple arithmetic operations, allows the formation of a new image by assigning new pixel values depending on the results of the arithmetic operations.

Schematic of filtering technique is shown in Fig.1.

Consider the pixel having value  $e$ . A  $3 \times 3$  window is considered in this case. The 8 neighbors of the  $3 \times 3$  window are marked in the figure. The figure also shows the corresponding  $3 \times 3$  filter and the filter coefficients marked in it. The filter is applied to the neighborhood window or the filter mask, and the modified pixel value  $e_p$  is estimated. When the filter is applied to the original image, this  $e_p$  replaces the original value  $e$ .

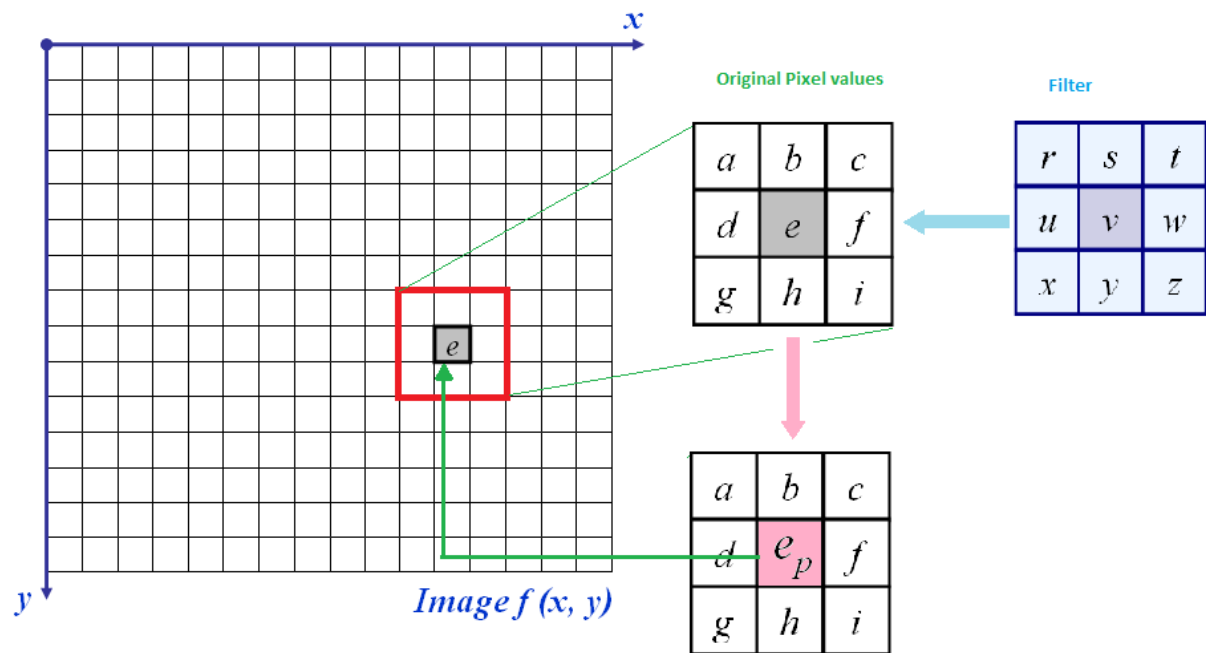


Fig.1 Schematic of the working principle of a spatial filter

The mechanics of the spatial filtering involves the movement of the filter mask over the image and calculation of the modified pixel value at the center of the filter mask at every location of the filter. Thus values of all the pixels are modified. When the spatial filter is applied to the image, the  $e_p$  values are estimated by using some pre-defined relationship using the filter coefficients and the pixel values in the neighborhood or filter mask selected. Convolution filter is a good example.

Filtering in the spatial domain manipulates the original pixel DN values. On the other hand, frequency domain filtering techniques used the Fourier analysis to first transform the image into the frequency domain and the filtering is performed on the transformed image, which is the plot of frequencies at every pixel. The filter application in the frequency domain thus gives frequency enhanced image.

## 2.1 Convolution filter

Convolution filter is one of the most commonly used filters in image enhancement in the spatial domain. In convolution filter, the filter mask is called convolution mask or convolution kernel. The convolution kernels are square in shape and are generally of odd number of pixels in size viz., 3x3, 5x5, 7x7 etc.

The kernel is moved over the input image for each pixel. A linear transformation function involving the kernel coefficients and the pixel values in the neighborhood selected is used to derive the modified DN of the pixel at the centre of the kernel, in the output image. Each coefficient in the kernel is multiplied by the corresponding DN in the input image, and averaged to derive the modified DN value of the centre pixel.

For example, the filter shown in Fig. 1 is a convolution filter of kernel size 3x3. DN value of the centre pixel in the input image is  $e$ . The modified DN value is obtained as given below.

$$e_p = (e.v + a.r + b.s + c.t + d.u + f.w + g.x + h.y + i.z)/9$$

Based on the elements used in the matrix and the procedure used for calculating the new digital number, different digital filters are developed for different purposes. Using different kernels, different type of enhancement can be achieved. For example, high pass and low pass filters are special types of convolution filters, which emphasize the high frequency and low frequency features, respectively.

Fig 2 shows different types of kernels used in spatial filtering.

1	1	1
1	1	1
1	1	1

Low pass

-1	-1	-1
-1	8	-1
-1	-1	-1

High pass

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

Directional gradient  
filter - N/S features  
highlighted

0	0	1
0	0	0
-1	0	0

Emboss NW

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

x

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

Prewitt

y

$$\text{Prewitt gradient} = \sqrt{x^2 + y^2}$$

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

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

Sobel

$$\text{Sobel} = \sqrt{x^2 + y^2}$$

0	-1	0
-1	5	-1
0	-1	0

Laplacian edge enhanced

Fig.2 Different types of kernels generally used for spatial filtering

Low pass filters are also called averaging filters as the filter output is the average pixel value of all the pixels in the neighborhood. When such filter is applied on an image, it will replace every pixel with the average of the surrounding pixel values. Thus, the low frequency values in the image are highlighted after filtering. Low pass filter reduces the effects of noise component of an image.

High pass filter, on the other hand, enhances the high frequency values in an image. Accordingly, in the resulting image, low frequency values are de-emphasized.

Directional gradient filters help to highlight the features oriented in any specific direction. For example:  $30^{\circ}$ NW and  $45^{\circ}$  NE. They are particularly useful in detecting and enhancing linear features with a specific orientation.

Emboss filter when applied to an image, highlights the features that are having gradient in the specified direction.

Prewitt gradient and Sobel gradients are used to estimate the digital gradient in an image, and are useful for edge detection. The kernels of these filters when moved over an image highlight the higher gradients corresponding to edges and make the lower values smooth.

Laplace filter is also useful in edge enhancement. It helps to detect sharp changes in the pixel values and hence enhances fine edges.

In Fig. 3 image enhancement obtained using high pass and low pass filter kernels are compared. ASTER Global DEM of 30m resolution is used as the input image.

In Fig.4 the input image is compared with that obtained after the application of NW embossed filter.

Fig 5(a) shows the original input image. The NW emboss filtered output is combined with the input data. This operation helps to retain much of the information from the input image, however with enhanced edges as shown in Fig. 5(b).

Fig. 6 shows the images enhanced using Sobel gradient and Laplace filter. Sobel filter enhanced the higher values, whereas the lower values are compressed. Laplace filter on the other hand, enhances not only the high values, but edges in all orientations are also enhanced.



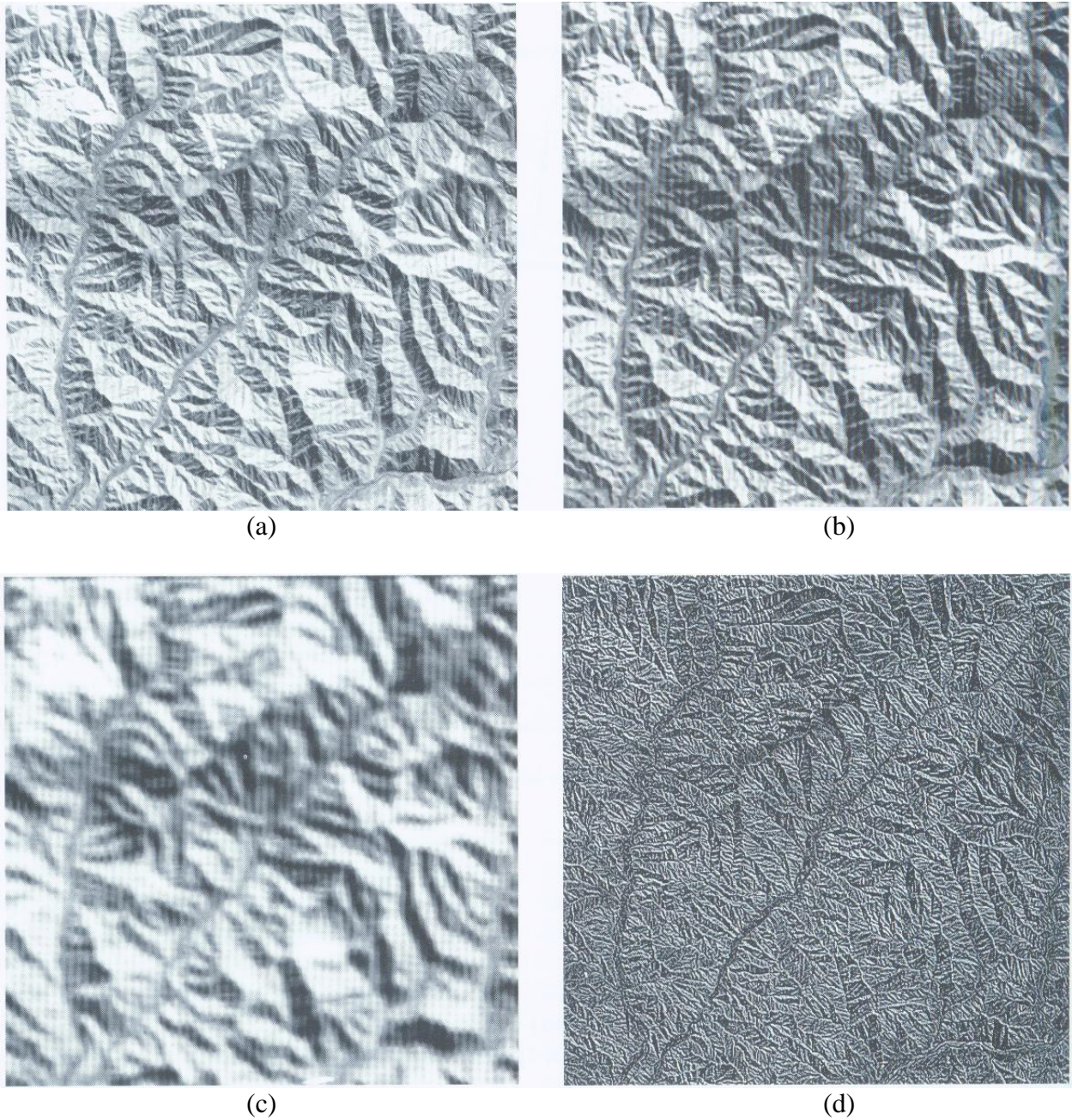


Fig. 3 (a) Input image : ASTER GDEM (b) 3x3 low pass filtered image (c ) 11x11 low pass filtered image and (d) 3x3 high pass filtered image



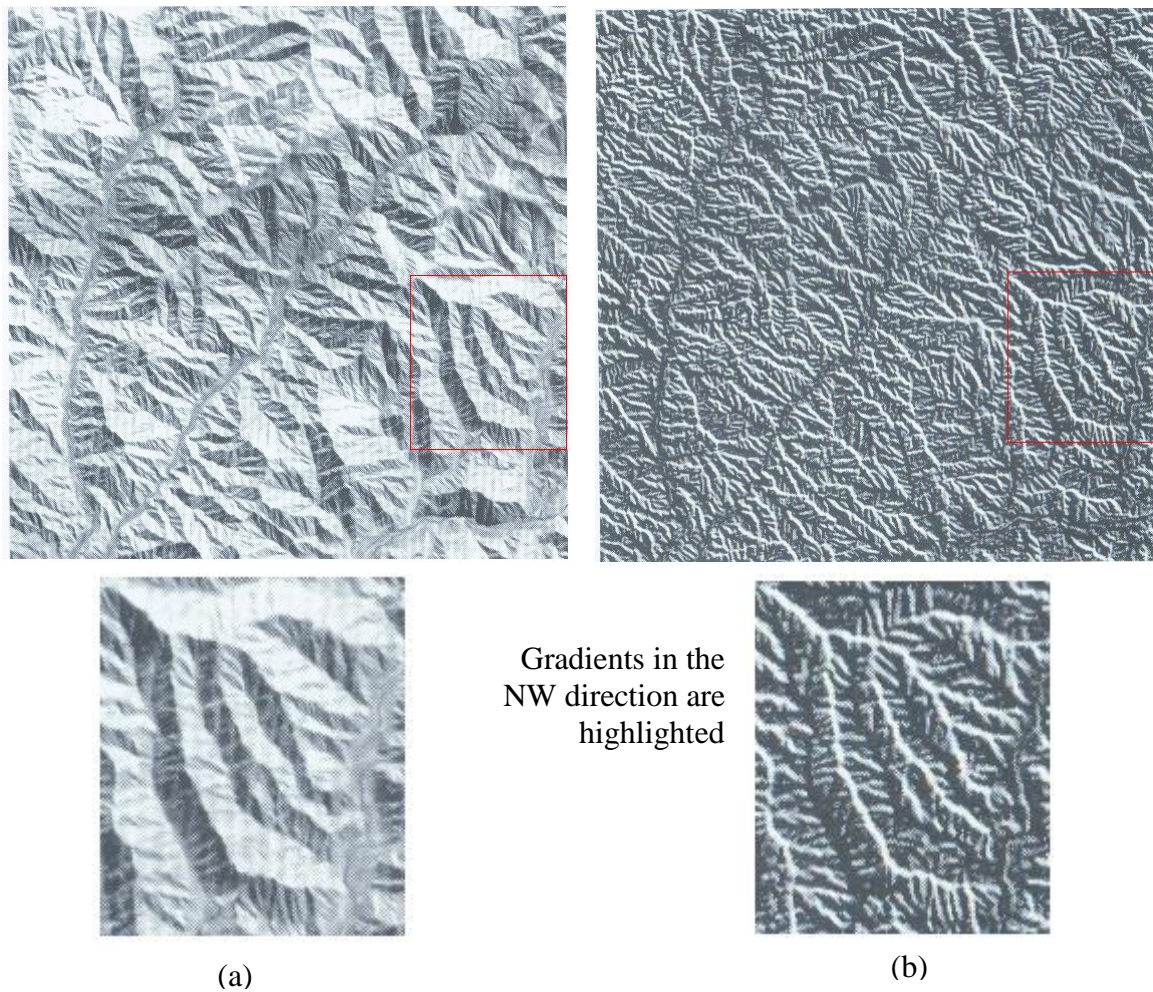
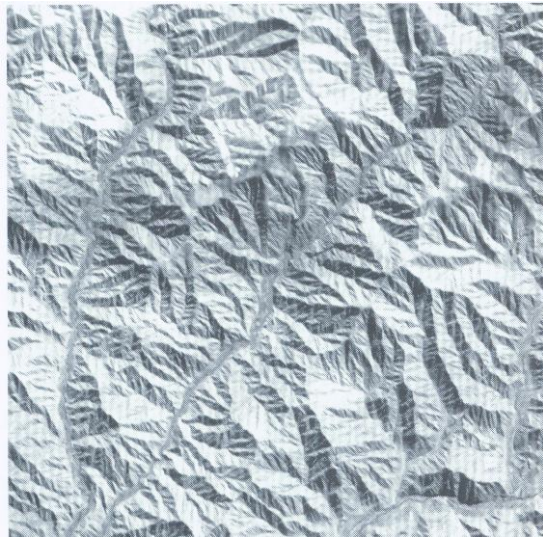
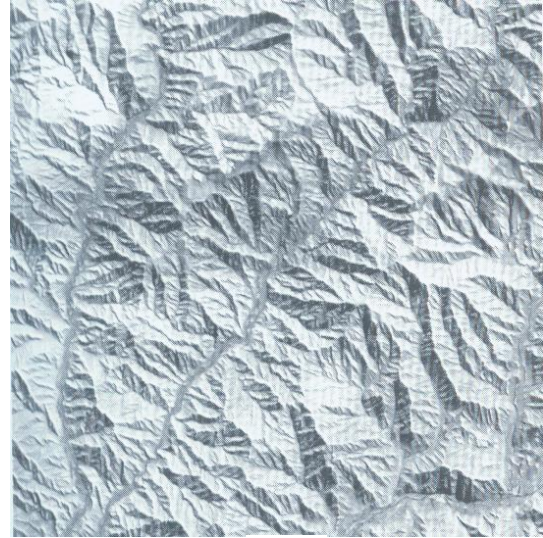


Fig. 4 (a) Original image: ASTER GDEM (b) Image filtered using NW emboss filter



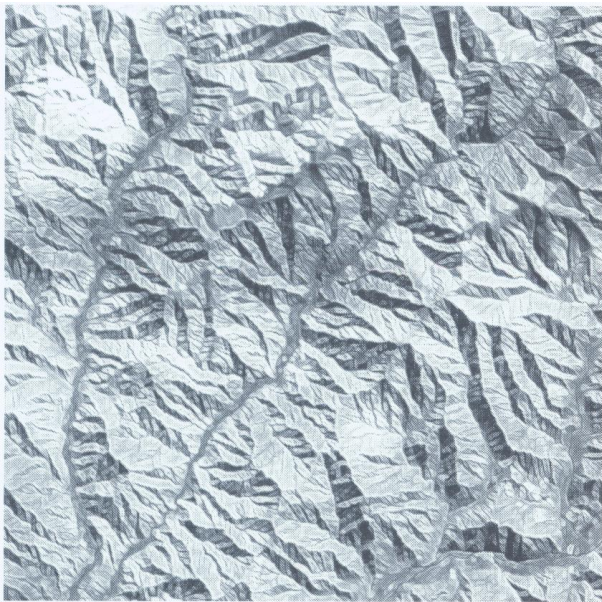


(a)



(b)

Fig.5 (a) original image (b) Combination of original image and NW emboss filtered image



(a)



(b)

Fig. 6 (a) Sobel filtered image (b) Laplacian filtered image



It may be noted that filtering decreases the size of the original image depending on the kernel size. In the case of  $3 \times 3$  digital filter, there won't be any filtered values for the pixels in first row, last row, first column and last column, as these pixels cannot become central pixels for any placement of  $3 \times 3$  digital filter. Thus the filtered image from a  $3 \times 3$  kernel will not contain first row, last row, first column and last column of the original image.

### 3. Edge enhancement

Edges in the images are generally formed by long linear features such as ridges, rivers, roads, railways, canals, folds and faults. Such linear features (edges) are important to geologists and Civil Engineers. Some linear features occur as narrow lines, whereas some edges are marked by pronounced differences that may be difficult to be recognized. Such narrow linear features in the image can be enhanced using appropriate filtering techniques.

Fig. 7 (a) shows a part of IRS LISS III Band 4 (Near Infrared) data showing a portion of Uttara Kannada district in Karnataka state, India. The image shows a river and the Arabian Sea on the left. Fig.7 (b) shows the edges extracted from the image. Linear features such as shore line and the river banks are extracted using the edge enhancement and edge detection algorithms.

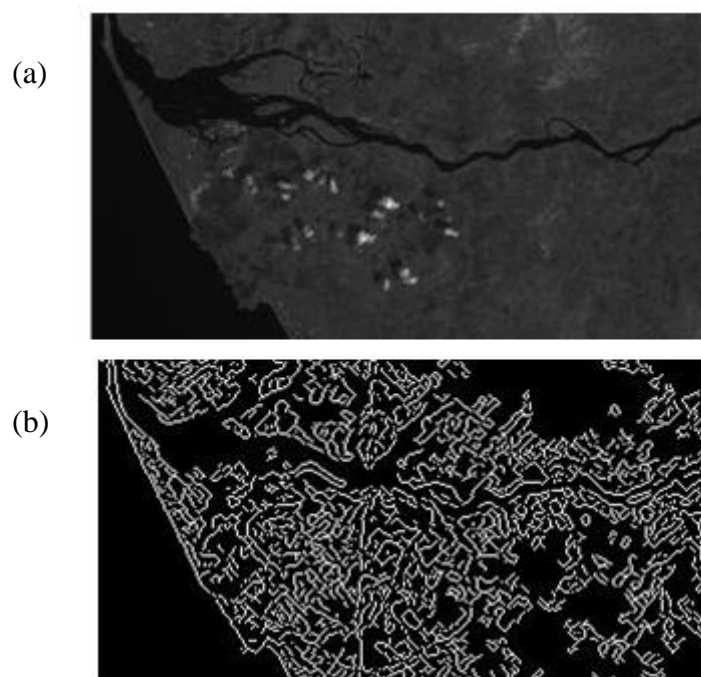


Fig. 7 (a) IRS LISS-III Band 4 image (b) Edges detected from the image using the digital edge detection algorithm

Digital filters used for edge enhancement in images are of two broad categories:

- Directional filters
- Non-directional filters

Directional filters will enhance linear features which are having specified orientation (say those oriented to  $30^\circ$  North) whereas non-directional filters will enhance linear features in almost all orientations.

Pewitt gradient, Sobel, Canny and Lapalaican filters are some of the examples of non-directional filters.

This section explains directional filter and the Laplacian non-directional filter in detail

### 3.1 Directional Filter

Directional filter will enhance linear features with a specific orientation (direction). Direction in which the edges are to be enhanced is specified in degrees with respect to North. Angles within the North-East quadrant are considered with negative sign and those falling in the North-West quadrant are considered with positive sign (Fig. 8).

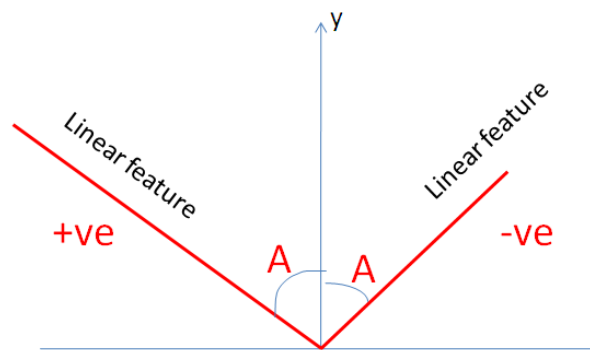


Fig.8 Concept of orientation angle of the linear features as used in directional filter

Directional filters consist of two kernels of size  $3 \times 3$  pixels, which are referred as left and right kernels. Both left and right kernels are moved over the original image and the pixel values are multiplied using the kernel coefficients. The values obtained for the nine pixels within the filter mask are added up for each kernel separately. The value added up for the right kernel is multiplied by  $\sin(A)$ , where  $A$  is the angle specified. Similarly, the value

added up for the left kernel is multiplied by  $\cos(A)$ . The resulting two kernel values are summed up to obtain the directional filter value.

In the original image, if there is any sharp gradient between the pixels in the specified direction, the resultant directional filter would show the maximum absolute pixel value for the corresponding pixels, and thereby highlight the edges. The directional filter gives negative values if the feature is aligned in the NE direction and positive values if the feature is aligned in the NW direction.

For example, Fig.9 shows the application of a directional filter (Fig. 9.a) to a hypothetical sample data (Fig. 9.b). The data shows a sharp gradient from pixel value 50 to 45 aligned approximately at 45 degrees in the NE direction (angle  $A = -45^\circ$ ).

The right kernel is first applied to the data and the resulting 9 values are summed up. For the 3x3 window marked in the figure, the resulting value is 10. The left kernel is then applied to the image. For the same 3x3 window, the resultant value is obtained as -10.

The value obtained from the right kernel is multiplied with the sine of the angle [ $\sin(-45^\circ) = -0.71$ ] and that obtained from the left kernel is multiplied with the cosine of the angle [ $\cos(-45^\circ) = 0.71$ ] and both are added up. Thus for the pixel at the center of the selected window, the kernel value is obtained as -14. This procedure is repeated for all the pixels in the input data. The resulting kernel values are shown in Fig. 9(c). Absolute values of the kernel values are the maximum (14) along the line where there is a sharp change in the pixel values. Thus the edge of the linear feature can be easily identified.

The kernel values are then added to the original data to generate the filtered output, which is also shown in the Fig. 9(d).

Contrast ratio of the lineament in the original data set is  $50/45 = 1.11$ . Application of the directional filter increases the contrast ratio along the linear features in the specified direction. Thus in the filtered output the contrast ratio is increased  $50/31 = 1.61$ . Thus, in this example, the contrast along the lineament has been enhanced 45 percent [ $100 \times (1.61 - 1.11)/1.11 = 45$ ].



$$\text{Cos A} * \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} + \text{Sin A} * \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

a. Directional Filter

50	50	50	50	50	50
50	50	50	50	50	45
50	50	50	50	45	45
50	50	50	45	45	45
50	50	45	45	45	45
50	45	45	45	45	45

b. Original Data

0	0	0	0	-7	-14
0	0	0	-7	-14	-14
0	0	-7	-14	-14	-7
0	-7	-14	-14	-7	0
-7	-14	-14	-7	0	0
-14	-14	-7	0	0	0

c. Kernel Values

50	50	50	50	43	36
50	50	50	43	36	31
50	50	43	<b>36</b>	31	38
50	43	36	31	38	45
43	36	31	38	45	45
36	31	38	45	45	45

d. Filtered Data

Fig.9. Edge Enhancement using Directional Filter

The directional filter also enhances the linear features in directions other than the specified direction. In this example the filter passing through the  $N45^{\circ}W$  direction also enhances linear features that tend obliquely to the direction of filter movement. As a result, many additional edges of diverse orientations get enhanced.

Fig. 10 (a) shows a small area from Landsat ETM<sup>+</sup> band-5 image. A linear feature with NW orientation, a river, can be observed in the image. Fig.10 (b) shows the filtered image obtained after applying the right diagonal edge enhancement filter to the original image. The edges formed by the main river are highlighted in the right diagonal edge enhancement. Fig 10 (c) shows the left diagonal edge enhanced output of the same image. The main river channel which is oriented in the NW direction is not emphasized in the filtered image. On the other hand, other linear features that have orientation mainly in the NE direction are highlighted in this image.

Horizontal edge enhanced output is also shown in Fig 10 (d)

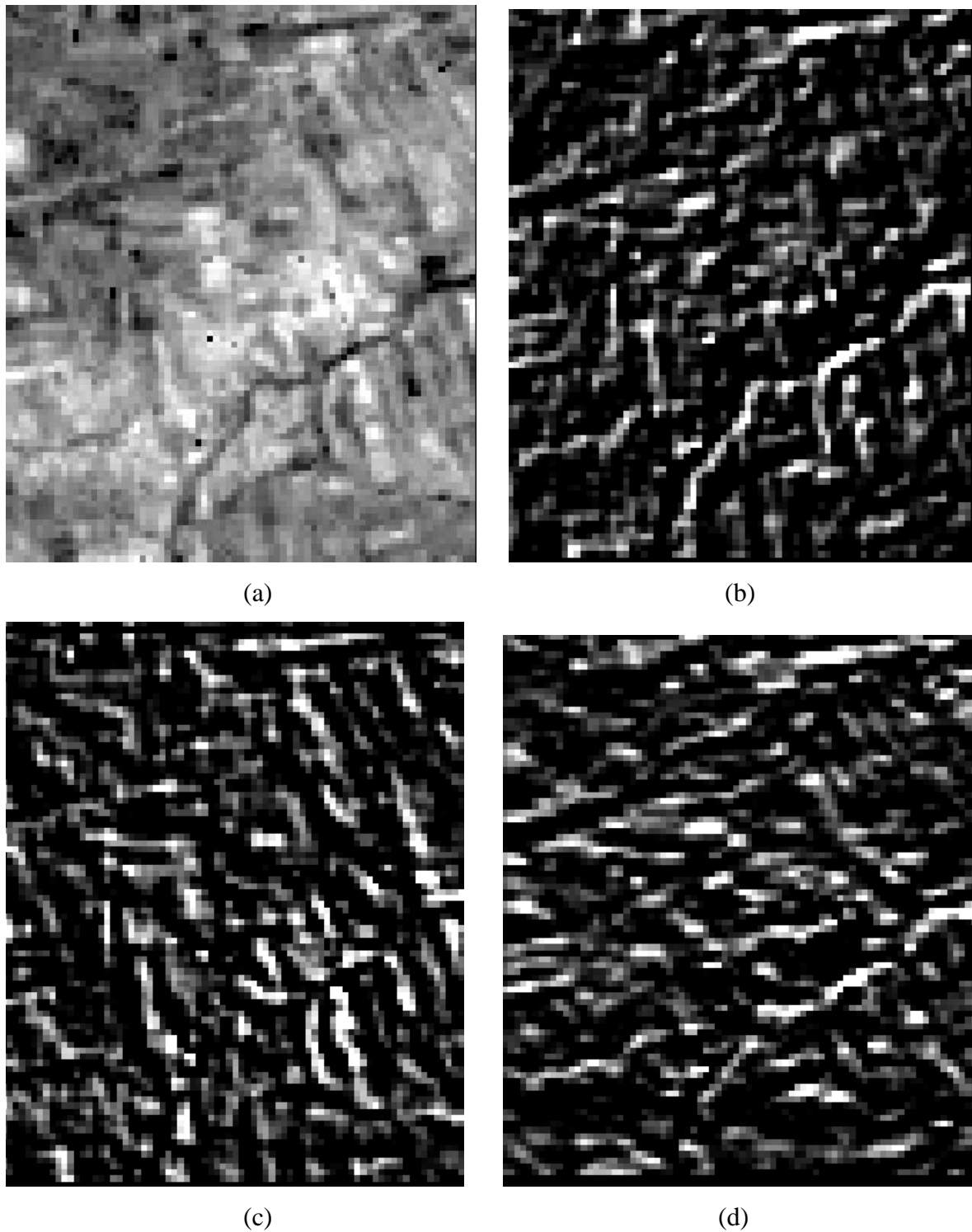


Fig. 10 (a) Landsat ETM<sup>+</sup> Band-5 image and the output of (b) right diagonal edge enhancement (c ) left diagonal edge enhancement (d) horizontal edge enhancement



### 3.2 Non-directional filter: Laplacian Filter

Linear features in an image are identified using the contrast between the pixels on either side of it. Contrast between the pixels varies with the difference in the pixel values between them. For example, in Table 1 the contrast between the pixels  $(x+1)$  and  $x$  depends on the difference in the pixel values  $a_{x+1}$  and  $a_x$ , which is the first derivative of the pixel values. For the sample data, pixels values ( $a$ ) and the 1<sup>st</sup> and 2<sup>nd</sup> derivatives of the pixel values are shown in Table 1.

A first order derivative simply shows the difference in the pixel value for adjacent pixels. In Table 1, the first order derivative is found less capable of highlighting the edges and the noise in the pixel 9. On the other hand, second order derivative shows the difference in the first derivative and is better capable of identifying the thin linear features and noises in the image.

As seen from Table 1, the second derivative gives sharper contrast along the edges as shown by the higher magnitudes along pixels 2 and 6. It also gives very high values for the pixels corresponding to the noises in the data (Pixel 9).

Table 1. Sample data showing the application of first and second order derivatives in edge enhancement

Pixel (x)		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Value (a)		50	50	40	30	20	10	10	10	60	10	10	10	50	50	60
1st derivative	$a_{x+1} - a_x$		-10	-10	-10	-10	0	0	50	-50	0	0	40	0	10	
2nd derivative	$a_{x-1} + a_{x+1} - 2a_x$		-10	0	0	0	10	0	50	-100	50	0	40	-40	10	

**Laplacian filter** is a non-directional filter based on the second spatial derivative of the pixel values.

The second order derivative in the x and y direction may be represented as given in Fig. 11 and Eq. 1-3.

	$a_{x,y+1}$	
$a_{x-1,y}$	$a_{x,y}$	$a_{x+1,y}$
	$a_{x,y-1}$	

Fig. 11 Schematic of the Laplacian filter kernel

$$\frac{\partial^2 a}{\partial^2 x^2} = a_{x-1} + a_{x+1} - 2a_x \quad (1)$$

$$\frac{\partial^2 a}{\partial^2 y^2} = a_{y-1} + a_{y+1} - 2a_y \quad (2)$$

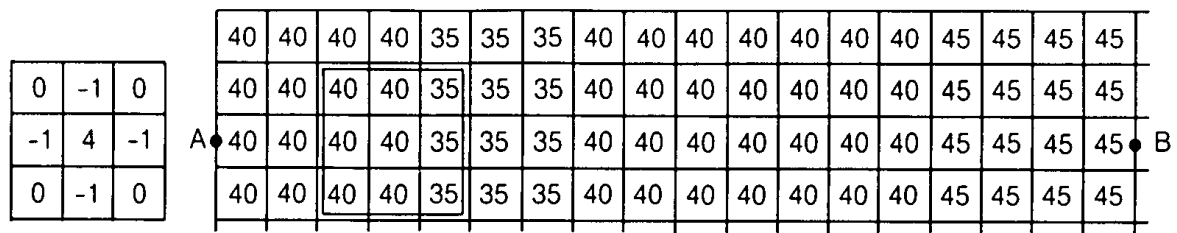
$$\nabla^2 a = \frac{\partial^2 a}{\partial^2 x^2} + \frac{\partial^2 a}{\partial^2 y^2} = a_{x-1,y} + a_{x+1,y} + a_{x,y-1} + a_{x,y+1} - 4a_{x,y} \quad (3)$$

This equation is implemented using a kernel with -4 at the center, and 1 at the 4 adjacent directions as shown in Fig 12.

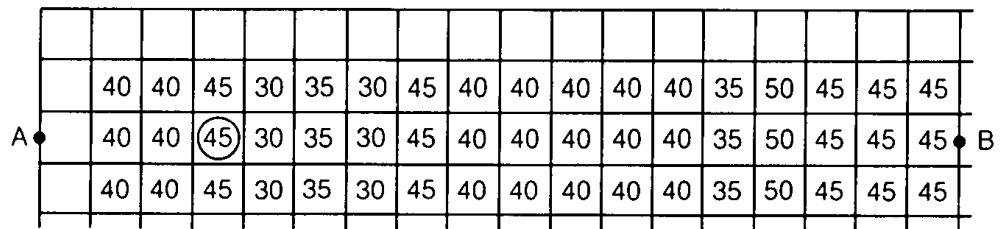
0	1	0
1	-4	1
0	1	0

Fig.12. Laplace filter kernel

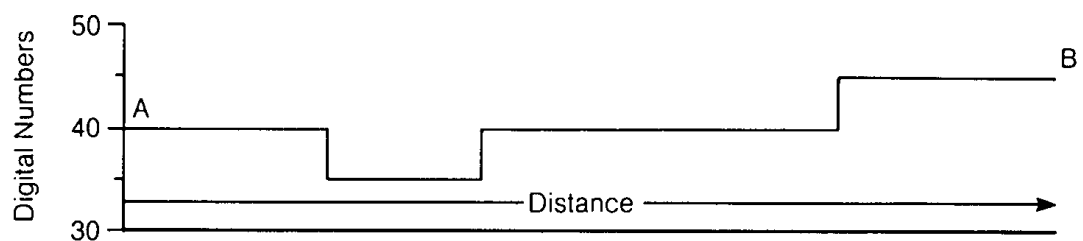
For example, consider the application of the above mentioned Laplace filter to a sample data given in Fig.13 (Source: <http://www.ciesin.org/docs/005-477/005-477.html>). Fig.13 (a) shows the Laplace filter kernel and the sample data. Profile of the pixel values along the section AB is shown in Fig. 13 (c). Contrast ratio along the edges is only 1.14 (40/35). Fig.13(b) shows the filtered data set obtained using Laplace filter. The contrast ratio has been increased to  $45/30 = 1.5$  (31% increase).



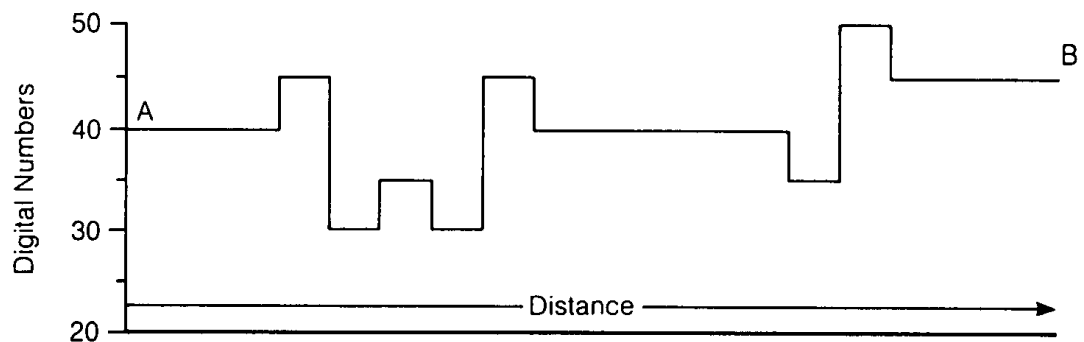
#### A. ORIGINAL DATA SET AND LAPLACIAN FILTER KERNEL.



### B. FILTERED DATA SET.



### C. PROFILE OF THE ORIGINAL DATA.



#### D. PROFILE OF THE FILTERED DATA.

Fig. 13. Application of Laplace filter to a sample data

(Source : <http://www.ciesin.org/docs/005-477/005-477.html>)



Fig. 14 compares the Landsat ETM<sup>+</sup> Band-5 image with the edge enhanced image obtained after applying the Laplace filter of kernel shown in Fig.12. As compared to the images in Fig. 10, edges in all important directions are enhanced by applying the Laplace filter.

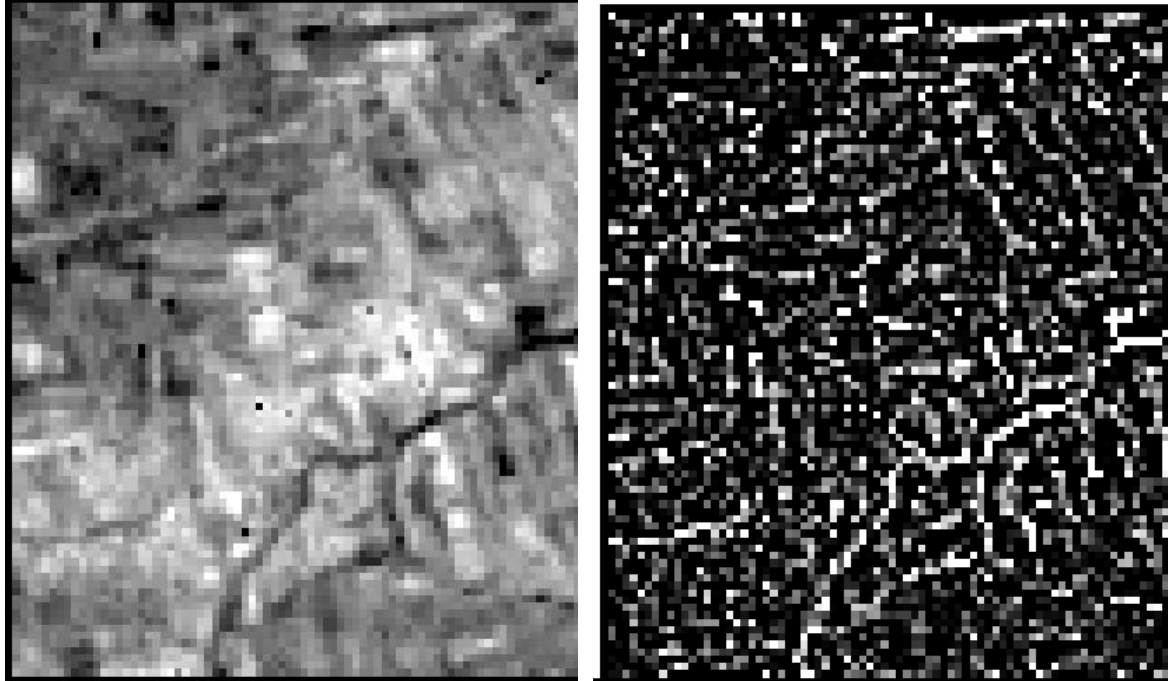


Fig. 14 (a) Landsat ETM<sup>+</sup> Band-5 image and (b) Edge enhanced image using Laplace filter

Having considered the variation in the 4 adjacent directions, the kernel shown in Fig.12 gives isotropic results for rotation in 90° increments.

The 4 diagonals can also be incorporated in the second derivative by adding two more terms to Eq.3, for the diagonal corrections. The resultant kernel can be represented as shown in the Fig. 15

1	1	1
1	-8	1
1	1	1

Fig. 15 Laplace filter kernel for isotropic results for rotation in multiples of 45°

Having incorporated the corrections in the 8 neighboring directions, the kernel gives isotropic results for all rotations in  $45^\circ$  increments. Due to this property, the Laplacian filters are considered to be highly effective in detecting the edges irrespective of the orientation of the lineament.

During edge enhancement using Laplacian filter, the kernel is placed over  $3 \times 3$  array of original pixels and each pixel is multiplied by the corresponding value in the kernel. The nine resulting values are summed and resultant kernel value is combined with the central pixel of  $3 \times 3$  array. This number replaces the original DN of central pixel and the process is repeated for all the pixels in the input image.

Laplacian filter will enhance edges in all the directions excepting those in the direction of the movement of the filter (i.e., linear features with east-west orientation will not get enhanced).