Lab Exercise: 01

The collected grayscale images are shown in Figure 1 and in Figure 2. Of all those images three are borrowed from websites and only one image is synthesized. All the color images are converted to grayscale using MATLAB.

In Figure 1(a) the structure has many sharp edges on an uniform background. Figure 1(b) is an example of fine texture. In Figure 1(c) the divergent objects are showing the example of oriented or directional features. Figure 1(d) is presenting some geometric shapes and structures. The squares, circles, triangles etc. are clearly visible.

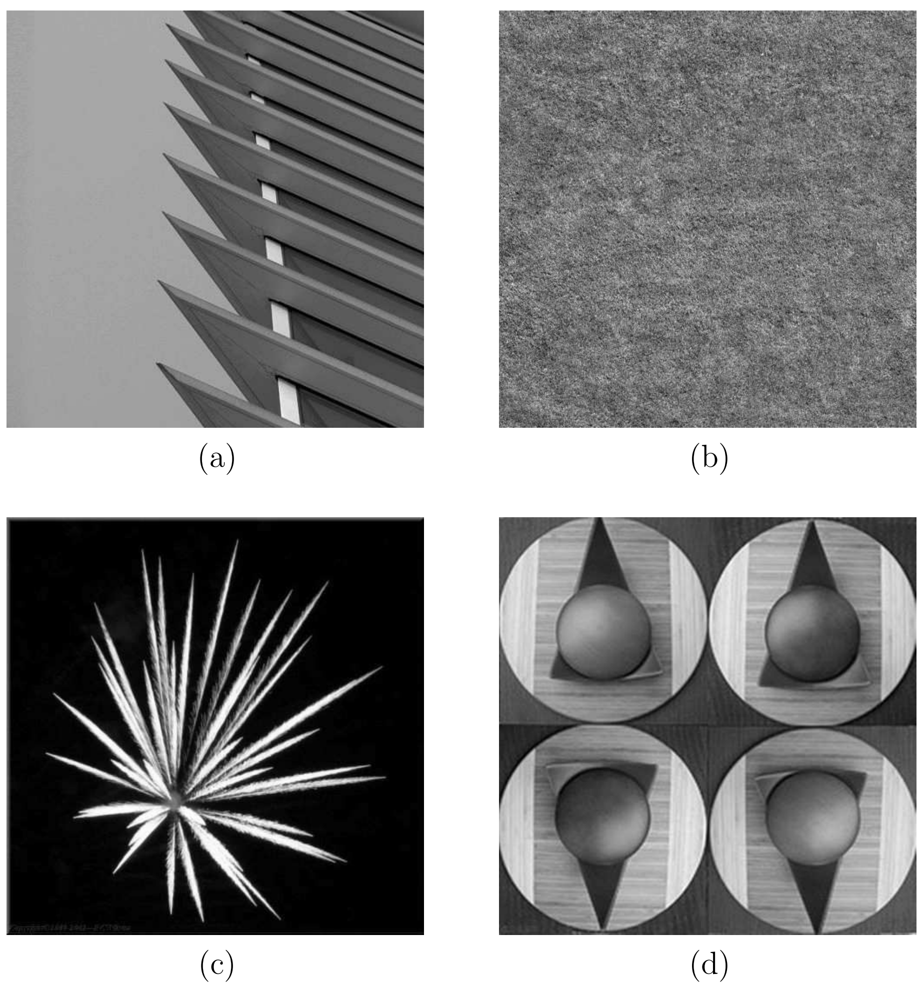
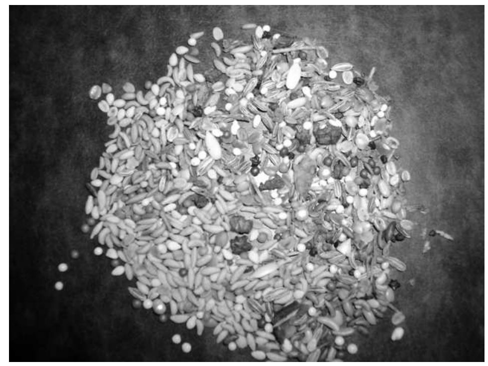


Figure 1: Collection of Images (a) Sharp Edges; (b) Fine Texture ; (c) Directional/Oriented Features; (d) Geometric Shapes.

In Figure 2(a) all those high buildings are examples of a collection of large objects while Figure 2(b) is displaying a collection of small objects. Figure 2(c) is a representative case of coarse texture. The coarse nature of the image can be understood easily when compared to Figure 1(b). Figure 2(d) is showing some waves where edges are not distinguishable as in Figure 1(a). So, this can be considered as an example of smooth features. In figure 2(e) all the circular coins together are giving an impression of almost circular feature which is an example of periodic pattern. A human face is displayed in Figure 2(f).

(a)

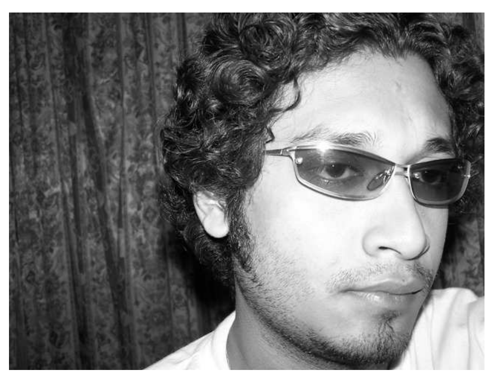


(b)

(c)

(d)

(e)



(f)

Figure 2: Collection of Images((a) A collection of Large Objects; (b) A collection of Small Objects; (c) Coarse Texture; (d) Smooth Features; (e) Periodic Patterns; (f) Human Face.

Lab Exercise: 02

In Figure 1(b) and 1(c), the log magnitude spectra (Fourier Transform) and the histogram of 1(a) has been displayed respectively. The peak around 60 in the histogram corresponds to the graylevels of most of the portions of the image and the higher values of graylevels in the range of 175 to 210 correspond to the white snow present in the image. As the image is an example of coarse nature , the gray levels are distributed over the range from 20 to 210. Though a major portion of energies are present near the dc in the fourier spectra but still energies are distributed over a large band of frequencies. An almost vertical bright segment across the center of fourier spectra (barely noticeable) corresponds to the directional nature of the white snow in the middle of the image.

The image in 1(d) is an example of smooth texture. The histogram in 1(f) has two distinct peaks (bimodal distribution). As there is not much sharp features present in the image (other than sharp waves and white portion in front of the far end trees) the first wide peak corresponds to the uniformity of the gray levels of the sea shore and the second peak is representing little brighter background sky. The effective dynamic range for this image can be considered from 70 to 170 as there is very small number of pixels outside that range. The fourier spectra in 1(e) shows that most of the power in concentrated in the lower frequency region. There are some veritical and horizontal high frequency components resulted from some oriented sharp features mentioned earlier. Due to some oriented and repetative nature of waves and the mark of water on the sand, many irregular strips are visible in the fourier spectra in parallel to the vertical axis (not clearly visible here).

In Figure 1(g) many circular coins are assorted in periodic manner. The periodicity of those circular shapes are clearly visible in the fourier spectra (Figure 1(h)). The fourier spectra of a circle is bessel function. So, the fourier response for each circular shapes are superimposed in the spectra and giving rise to periodic, co-centric and omnidirectional pattern with gradual decrease of energies from the low to high frequency regions. Some energies in the low frequency areas may be responsible for bigger circlular pattern created by the coins. The sharp vertical lin in the spectra represents the stripes on the wood. In the histogram, there is not significant amount of pixels with gray level values below 50. The region between 150 to 240 gray level values corresponds to the background wood and the sharp peak near 250 is due to the bright reflection of light from the coins. The comaparatively darker coins and the stripes are responsible for the region below gray level values of 150.

In Figure 2(b), the fourier spectra of the directional or oriented features of Figure 2(a) is shown. In the spectra, the radiating lines from the centers correspond to the oriented diverging pattern in different directions. Though a large portion of energies are around low frequency regions but a significant portion of energies are along the radiating directions. Due to sharp transitions between the background and the fireworks, high frequency components are noticeably present in the fourier spectra. Due to complete dark background, a large number of pixels correspond to lower gray level values giving rise to the peak at around 5 in the histogram (Figure 1(c)). A small number of pixels with different gray level values of between 50 to 200 are also

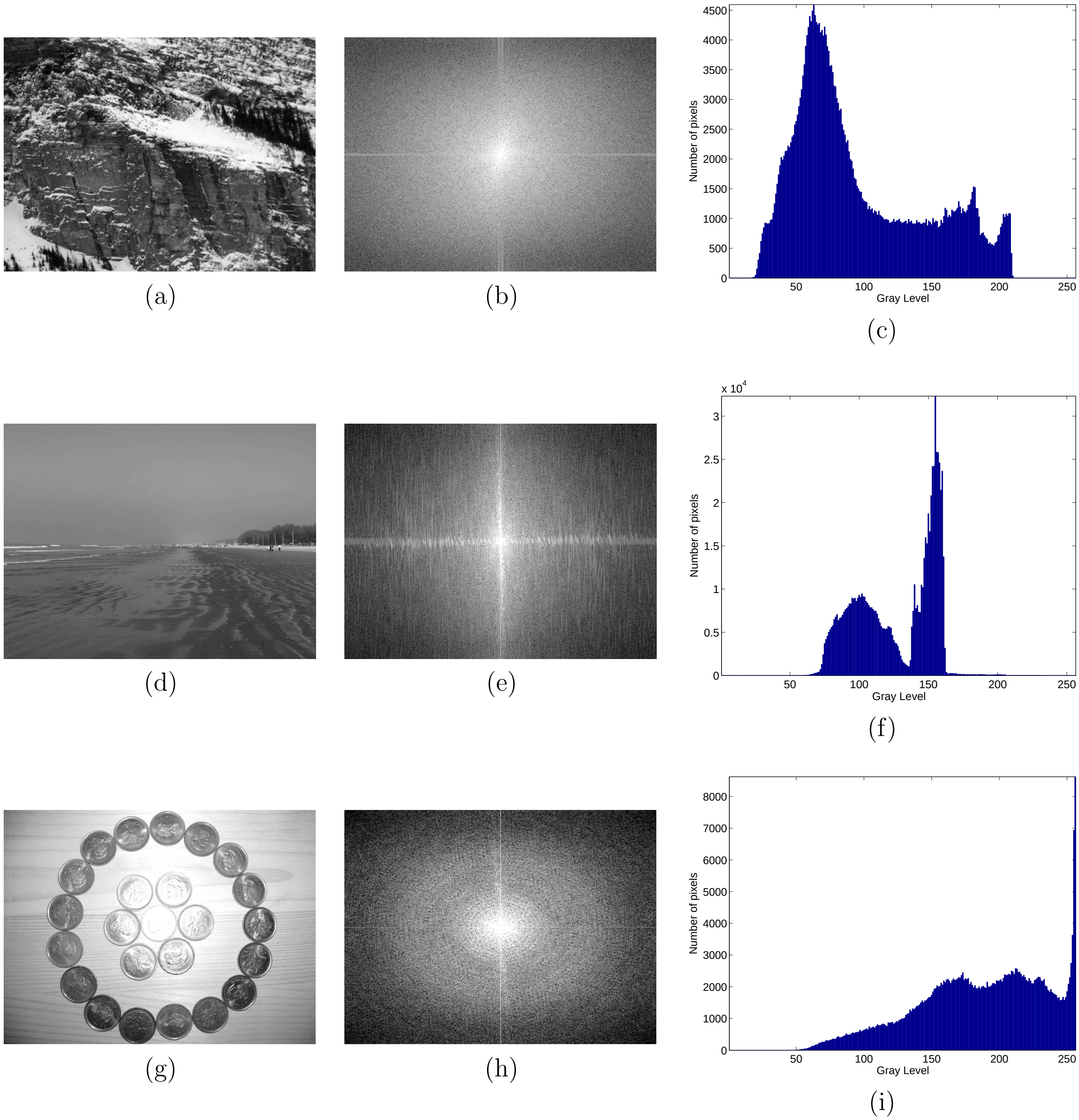


Figure 1: (a) Coarse Texture; (b) Log Magnitude Spectra of (a),display range [1.5 5.2]; (c) Histogram of gray levels in (a);(d) Smooth Features; (e) Log Magnitude Spectra of (d), display range [1.9 4.8];(f) Histogram of gray levels in (d);(g) Periodic Pattern; (h) Log Magnitude Spectra of (g), display range [2.8 4.7];(i) Histogram of gray levels in (g)

present in the image. The histogram also shows the presence of bright pixels in the 200 to 256 region that corresponds to white fireworks.

Figure 2(d) is displaying some periodic pattern and sharp edges. In presense of sharp edges there are a significant amount of energy present in the high frequency regions of the fourier spectra. Due to directional nature of the edges of the building there are many small and large

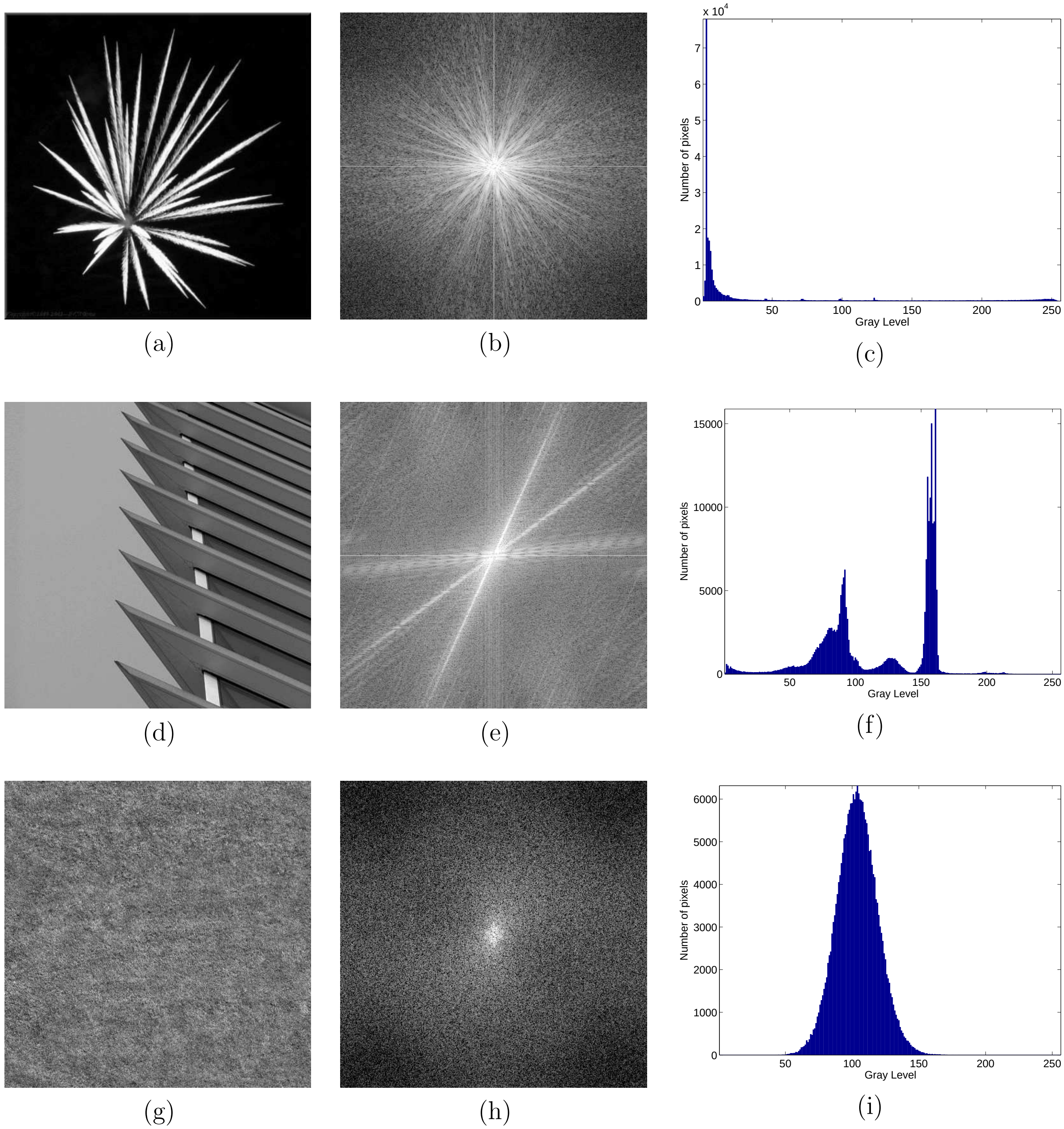


Figure 2: (a) Oriented Features; (b) Log Magnitude Spectra of (a), display range [2 5.5]; (c) Histogram of gray levels in (a);(d) Sharp Features; (e) Log Magnitude Spectra of (d), display range [0.8 5.2];(f) Histogram of gray levels in (d);(g) Fine Texture; (h) Log Magnitude Spectra of (g), display range [3.3 4.7];(i) Histogram of gray levels in (g)

bright stripes visible in the spctrum. The slightly inclined vertical white beam is responsible for the scattered strip of lines along the horizontal axis directions. Two crossing bright lines across the lower left quadrant to the upper right quadrant are resulted from the parallel sharp edge pattern of the building. The region from 0 to 50 gray level values in the histogram (Figure 2(f)) is resulted from the relatively darker glasses of the building. The peak around the gray level value of 80 correspond to the visible lower side of the building extentions and the small peak near 125 is for the sides of the building edges. The large peak in the histogram is definitely represents the brighter background sky. A number of pixels are also present around gray level value of 200 resulting from the white vertical pillar or beam.

The histogram (Figure 2(i)) of Figure 2(g) is consistent with the uniformity of gray levels in a fine texture image. Almost all the pixels have gray level values within the range 50-150 with a smooth peak near 100 and the histogram looks like a perfect gaussian distribution. The energy is distributed over the frequency range and the image has a portion of concentrated energy near dc for some uniformity of gray levels in the image as shown in the log magnitude fourier spectra (Figure 2(h)).

Lab Exercise:03

In Figure 1(a) the original test image is displayed and the filtered version of that image after applying the 3x3 mean filter (b) once, (c) three times and (d) five times are shown.The original image is sythesized and for lacking of high resolution of the image the circle at the center is not perfect. If there were a large number of pixels involved, we might have got smoother edges of the circle. But still, due to the fact that pixels are of square shape in an image, it is impossible to get a perfect circle in an image without very high resolution.

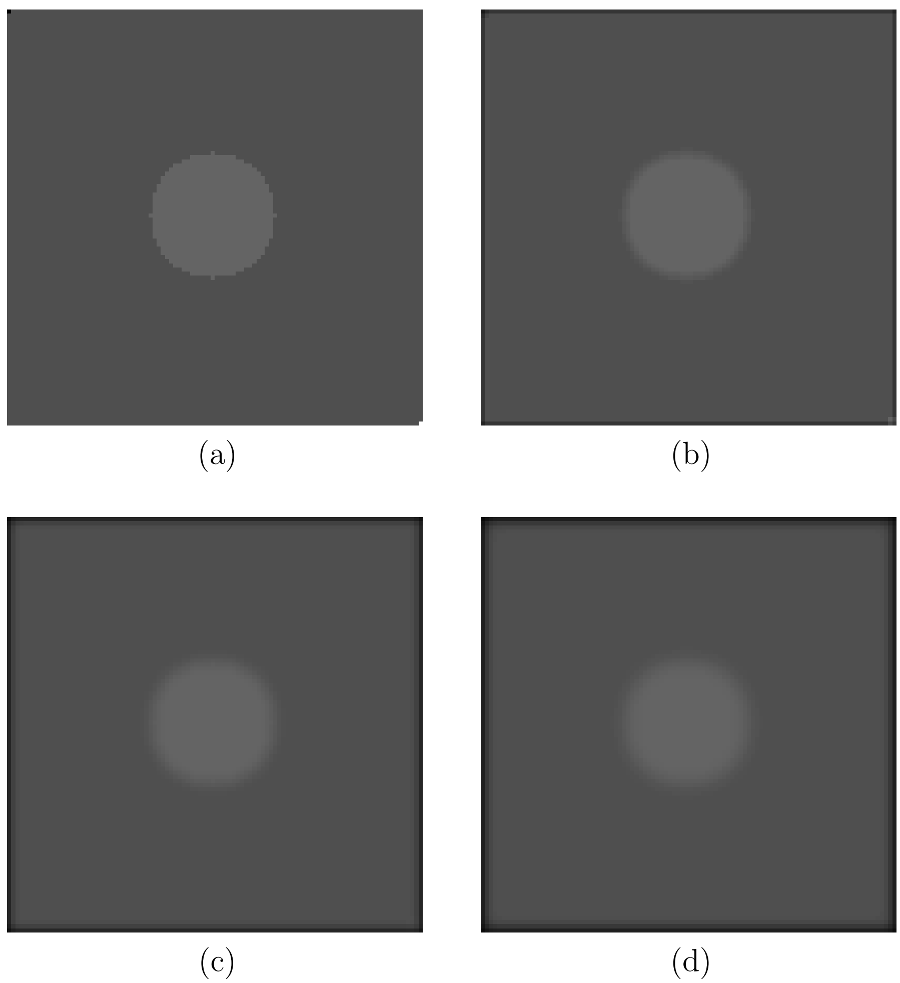
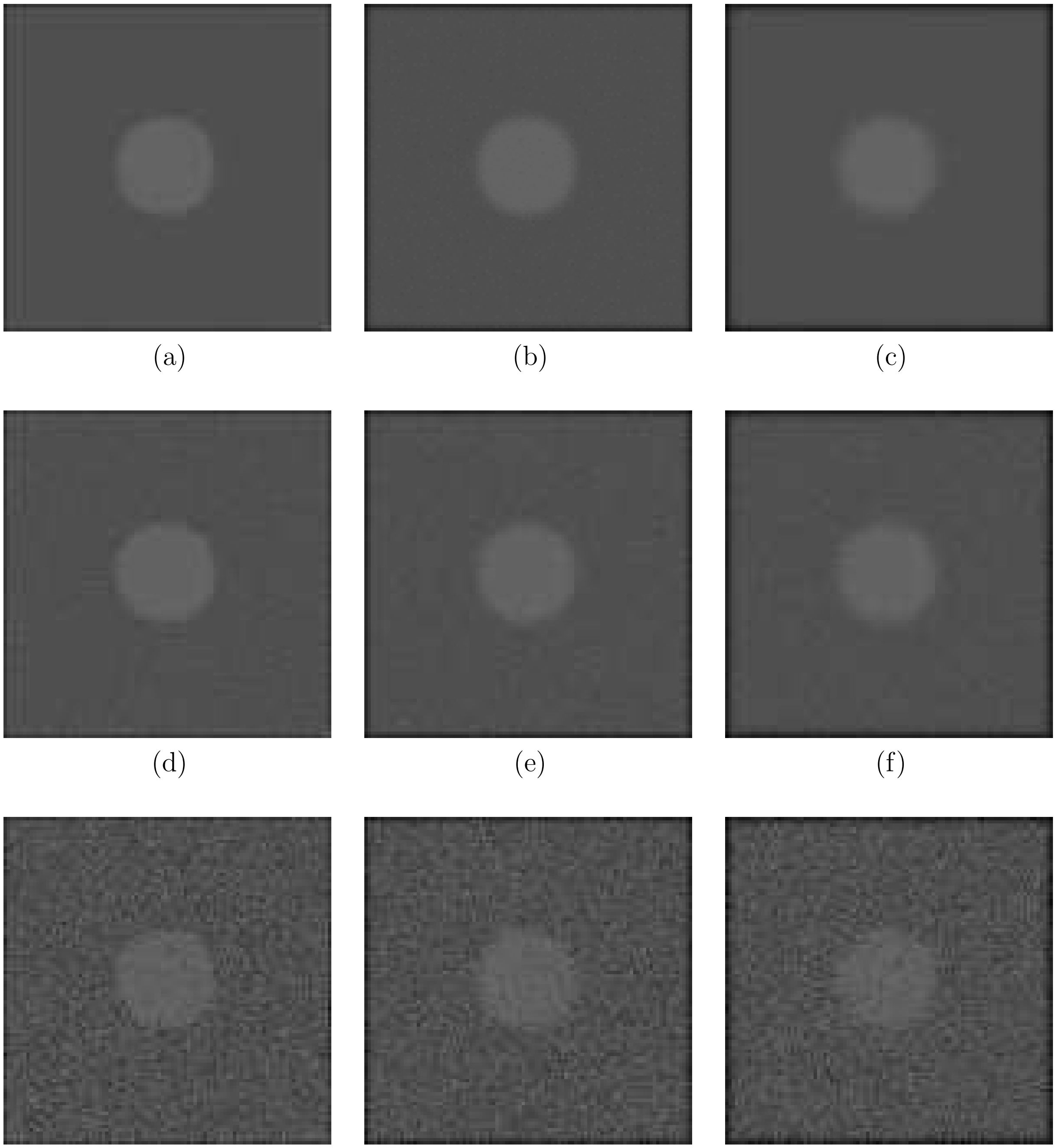


Figure 1: Test Image of size 100 pixels x 100 pixels: (a) original test image. (b) Test image in (a) filtered once by 3x3 mean filter. (c) Test image in (a) filtered 3 times by 3x3 mean filter. (d) Test image in (a) filtered 5 times by 3x3 mean filter.

By applying 3x3 mean filter, although the object on a uniform background is readily distinguishable in the filtered images, the increasing number of applications of the 3x3 mean filter quickly degrades the quality of the image by blurring the edges. In Figure 1(b) the sharp edges of the circle in the original image is blurred and and the circle looks more smooth.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 2: Effect of adding additive Noise - with Gaussian noise (μ=0,normalized σ^2=0.0001): (a) Filtered image in 1(b); (b)Filtered image in 1(c); (c) Filtered image in 1(d); with Gaussian noise (μ=0,normalized σ^2=0.001): (d) Filtered image in 1(b); (e) Filtered image in 1(c); (f) Filtered image in 1(d); with Gaussian noise (μ=0,normalized σ^2=0.01): (g) Filtered image in 1(b); (h) Filtered image in 1(c); (i) Filtered image in 1(d).

When applying a mean filter mask to the image, it is zero-padded close to the edges to maintain the convolution result as the same size of the image . This causes a false representation of the data around the edges of the image. Consequently, a single line black border is visible in all the edges of the filtered image. The sharp white pixel at the most lower right corner is blurred due to mean filtering and that pixel also affected the neighboring pixels by increasing the gray level values of those pixels. The same thing happended to the upper left corner dark pixel except that it has reduced the gray level values of the neighboring pixels (not visible in the report).

After applying the mean filter 3 times on the test image (Figure 1(c)) the resulted image is significantly blurred and the difference between the circle and the background is reduced. The corner white and black pixels are totally buried in the introduced black borders which have lower to higher gray level values from the outer edge to the inner as a result of constraining the convolution result to the same of the original image size. The same effect is visible at a larger extent in the 5 times mean filtered image in Figure 1(d). and the circle at the center is totally hazzy and blurred.

So, the application of the 3x3 mean filter five times represents the worst-case in terms of image quality and is clearly visible from the presented figures. In the cases of relatively low levels of noise, the effects are not highly perceptible. The object is still distinguishable from the background and is consistently blurred. In the presence of higher levels of noise (σ^2=0.01), all the images in Figure 2(g), 2(h) and 2(i) are degraded in such an extent that it has become difficult to distinguish the object's edges. Without prior knowledge about the object's shape, it would be difficult to identify the shape as being a disc. Speckle noise is of multiplicative type and adding this noise affects the images in a different manner though that is not clearly distinguishable in the images here because of lack of details in the images. The effect of adding Speckle noise is illustrated in Figure 3 and similar affect is visible as described before. But, images are less affected by same level Speckle noise than Gaussian noise because of signal dependency of the speckle noise.

	${\sigma_\eta}^2 = 0.0001$		${\sigma_\eta}^2 = 0.001$		${\sigma_\eta}^2 = 0.01$	
Filter Iterations	MSE	NMSE	MSE	NMSE	MSE	NMSE
mean x 1	34.3455	0.0052	43.3119	0.0065	127.7474	0.0192
mean x 3	85.1875	0.0128	94.3869	0.0142	176.9485	0.0266
mean x 5	128.1369	0.0192	137.1035	0.0206	222.1529	0.0334

Table 1: MSE for images with Gaussian Noise, mean $\mu = 0$, normalized variance, σ^2

	${\sigma_\eta}^2 = 0.0001$		${\sigma_\eta}^2 = 0.001$		${\sigma_\eta}^2 = 0.01$	
Filter Iterations	MSE	NMSE	MSE	NMSE	MSE	NMSE
mean x 1	33.8823	0.0051	39.2399	0.0059	94.0584	0.0141
mean x 3	85.1489	0.0128	91.0033	0.0137	144.0835	0.0216
mean x 5	127.6576	0.0192	133.3233	0.0200	185.7838	0.0279

Table 2: MSE for images with Speckle Noise, normalized variance σ^2

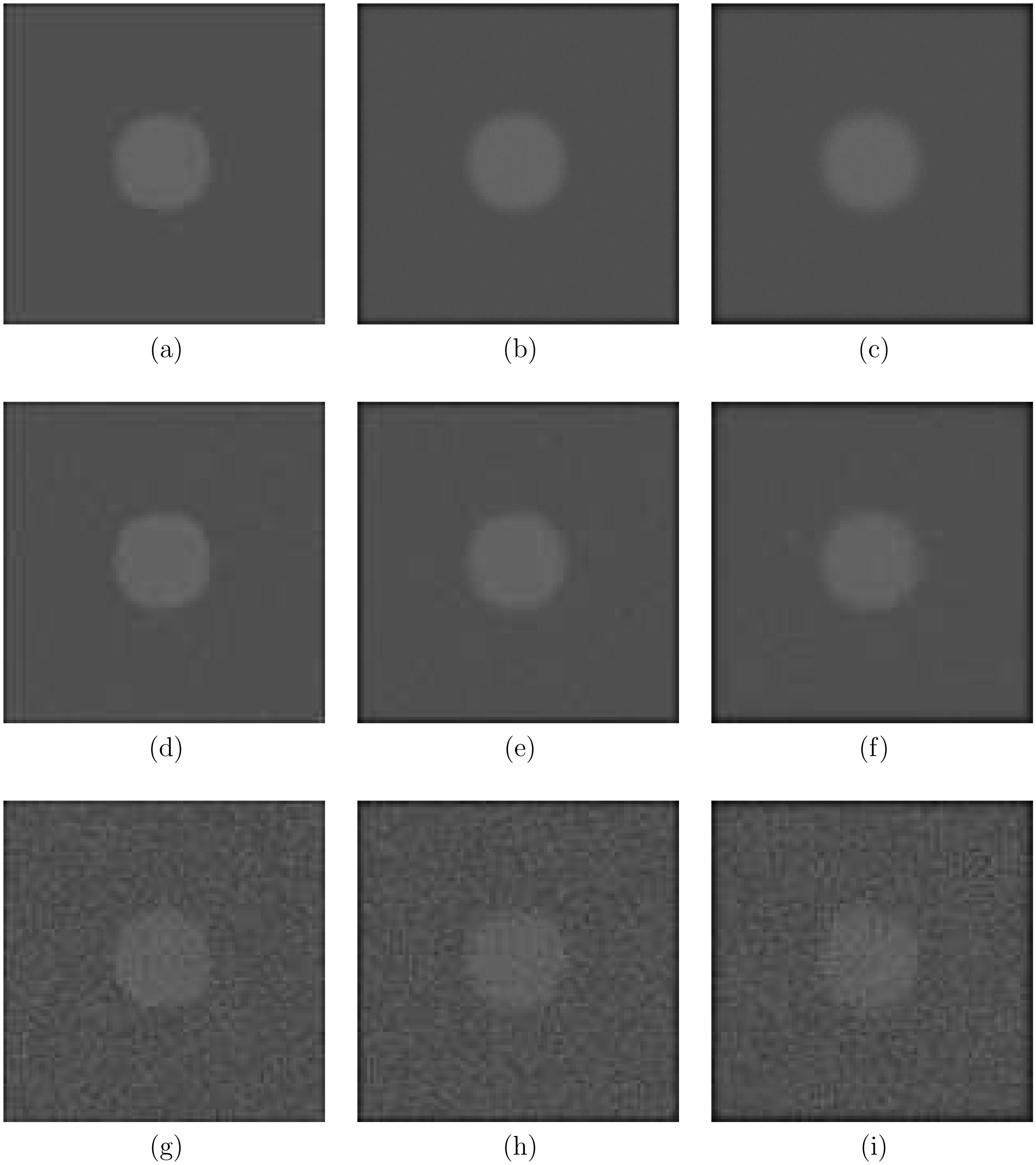


Figure 3: Effect of adding multiplicative noise - with Speckle noise (normalized σ^2=0.0001):(a) Filtered image in 1(b) ; (b)Filtered image in 1(c); (c) Filtered image in 1(d); with Speckle noise (normalized σ^2=0.001): (d) Filtered image in 1(b); (e) Filtered image in 1(c); (f) Filtered image in 1(d); with Speckle noise (normalized σ^2=0.01): (g) Filtered image in 1(b); (h) Filtered image in 1(c); (i) Filtered image in 1(d)

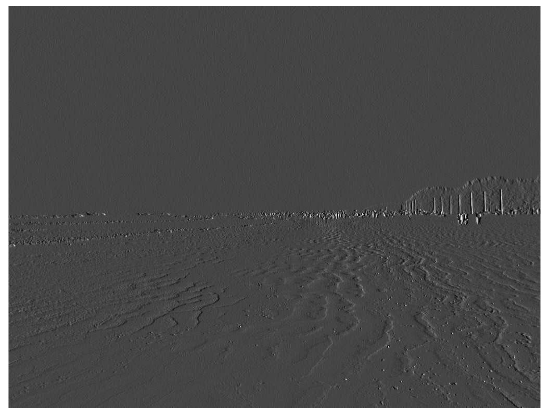
In contrast, in Table 1, for a normalized variance of Gaussian noise, σ^2=0.001, the MSE for one iteration of the mean filter is 43.31, and it quickly decreases to 94.39 for 3 iterations and to 137.10 with 5 iterations of the mean filter. Similarly, for five applications of the filter and a normalized noise variance of σ^2=0.0001, the MSE is 128.14 and increases with higher levels of noise to 222.15 for a variance of σ^2=0.01. In table 2, for a normalized variance of Speckle noise, σ^2=0.001, the MSE for one iteration of the mean filter is 39.24, and it quickly decreases to 91.00 for 3 iterations and to 133.32 with 5 iterations of the mean filter. Similarly, for five applications of the filter and a normalized noise variance of σ^2=0.0001, the MSE is 127.66 and increases with higher levels of noise to 185.78 for a noise variance of σ^2=0.01. Compared to Gaussian, the MSE is almost same for low noise levels for mean filtering but as the noise level is increased along with iteration number the Speckle noise has less degraded the image in terms of MSE and NMSE.

Although the various levels of noise and the different number of iterations of the mean filter affect the MSE accordingly, there is also another artifact in the images which contribute to the image errors due to zero padding. This biases the MSE results, compounding the errors due to the noise and effects of blurring.To obtain a more accurate result of the MSE, the border could be eliminated in the calculation of the error.

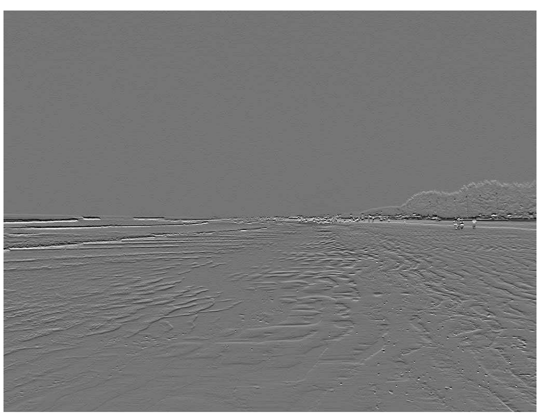
Lab Exercise:04

Edge detection and edge extraction in an image is an important task in image processing and image analysis. For purpose of edge detection the most simple operations are the horizontal and vertical derivatives and the laplacian. The horizontal derivative can be obtained by convolving the original image with the mask $[-1, 1]$. After applying this mask, the edges present in the horizontal direction can be detected i.e this operation detects edges that are not oriented horizontally in the image.

(a)



(b)



(c)

(d)

Figure 1: (a) Original (Smooth edges) image; (b) original image processed with horizontal difference operator, display range [-15, 40] out of [-116 200]; (c) original image processed with vertical difference operator, display range [-32, 38] out of [-128 152]; (d) original image processed with Laplacian difference operator, display range [-20, 55] out of [-352 220].

The results of this operation on an image containing smooth edges and weaker definition of features and the other image with sharp edges and strong definition of features are presented in part (b) of Figures 1 and 2 respectively. By examining part (b) of Figure 1, we can see that the vertically oriented edges have been detected. Due to weaker definition of edges only some waves, the sign of water on the sand and the moving people and vertical columns at the right side are detected. There is no presence of horizontally oriented edges. On the other hand, in part (b) of Figure 2 all the horizontal edges and window borders are wiped out or suppressed by this operation. As the sharp corners of the building are not totally horizontally oriented but much inclined, they are also detected. The vertical pillar or column is perfectly detected and enhanced.

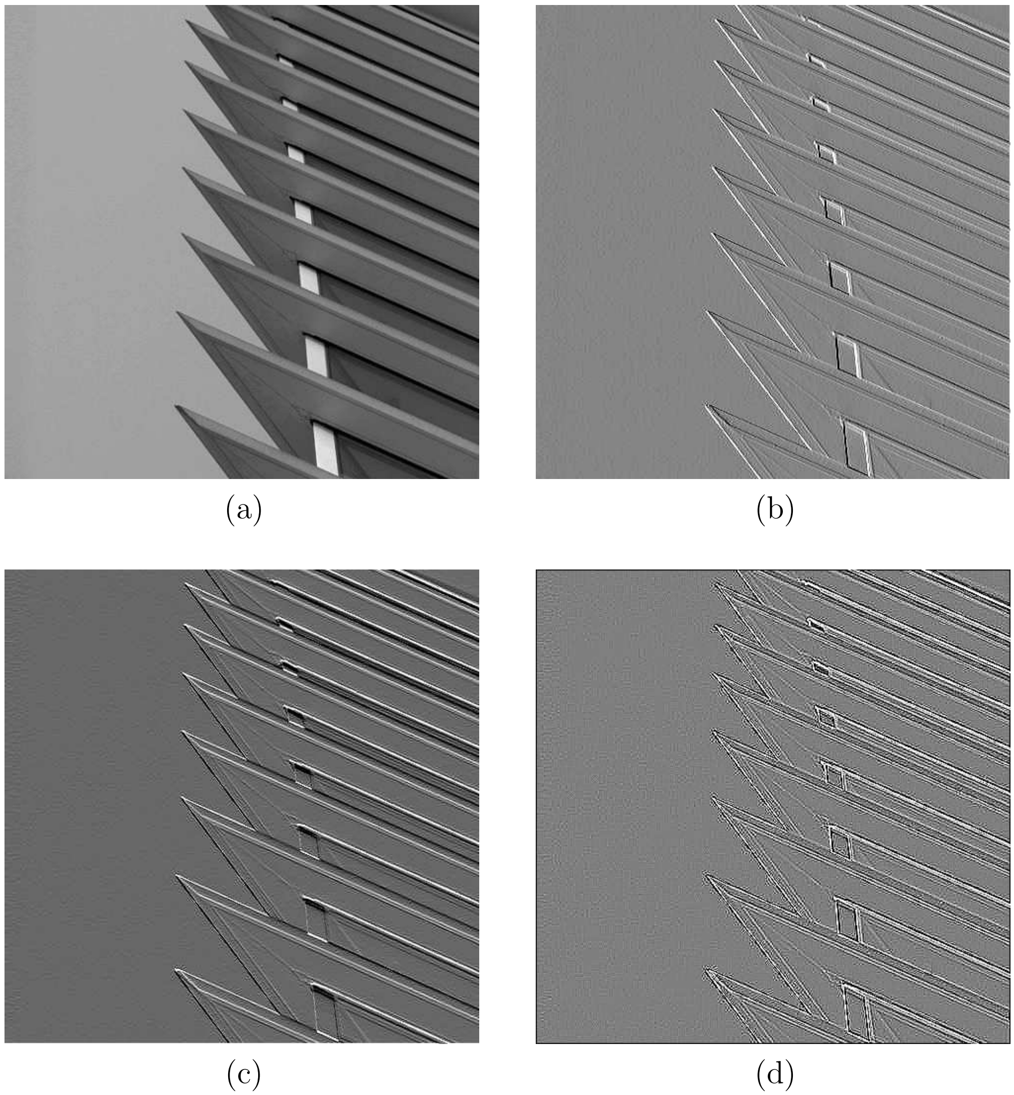


Figure 2: (a) Original (Sharp edges) image; (b) original image processed with horizontal difference operator, display range [-39, 36] out of [-156 144]; (c) original image processed with vertical difference operator, display range [-28, 41] out of [-112 164] ; (d) original image processed with Laplacian difference operator, display range [-37, 30] out of [-308 308].

The vertical derivative was obtained by convolving the image with $[-1, 1]^T$. The results are presented in part (c) of Figures 1 and 2. This operation detects edges that are not oriented vertically in the image. Examining part (c) of Figure 1, there are many weak vertical edges can be seen and the edges of the sharp waves, the horizontally oriented patterns and trees on the background have been detected. Note that, the vertical columns at the (far end) right side of the images are not visible. In Figure 2 we can see that there are few columns that are perfectly vertical or horizontal. Most are oriented at some oblique angle and the vertical derivative operator has detected these sharp edges. Compared to Figure 2(b) the other edges of the corners are enhanced here and the edges of the vertical pillar or column are suppressed.

The Laplacian operation was obtained by convolving the image with the 3x3 mask

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}.$$

Laplacian is an omnidirectional operator and it detects edges in all direction. As it as aprrox-iamtion of second derivative operation, the intensity information is totally lost and all the dc frequency components are removed. However, after performing masking with laplacian there would be two edges visible consisting of a sharp positive and negative value at the place of edges in the image.The results of laplacian operation are presented in part (d) of Figures 1 and 2. Compared to other two operations presented earlier, the results are less strongly emphasized than in the individual application of the horizontal and vertical derivate operators. And in part (d) of Figures 1 and 2, there are some slightly disjoint border visible around the image. This arises due to use of zero-padding in the regions of the border when the Laplacian operator is applied. However, the prominent or strong edges in all directions are still very clearly detected in both the figures. Due to loss of intensity information the images are of low contrast with dull gray appearance without any details.

Lab Exercise: 05

Mean and median filters are widely used filters in the field of signal and image processing. In the presence of Gaussian noise, the mean filter and the median filters for all three neighborhoods given performed reasonably well for the case of image containing smooth features due to the fact that the variation within the neighborhood is relatively small and the image components are constant. The 5x5 square neighborhood median filter introduced significant blurring and also caused elimination of small objects though it has suppressed much noise compared to the others. Visually the difference among the effects of all the four filtering are barely distinguishable in Figure 1. In terms of MSE, the 5x5 Square neighborhood median filter performed the best and the 4 connected median filter performed worst among all the four filters as can be seen from Table 1.

Filter Type	Gaussian Noise	Salt-and-pepper Noise
Unfiltered	646.4092	168.9336
8-Connected Median	115.0897	4.1486
4-Connected Median	189.2159	1.3810
5x5 Square Median	56.8186	12.2651
3x3 Mean	84.4541	31.5278

Table 1: Smooth features: MSE for noisy images filtering using median and mean filters. Gaussian noise (μ=0,normalized σ^2=0.01) and Salt and Pepper noise (normalized σ^2=0.01) used.

Filter Type	Gaussian Noise	Salt and Pepper Noise
Unfiltered	585.5154	164.3455
8-Connected Median	121.8913	11.5215
4-Connected Median	185.6759	7.5668
5x5-Square Median	85.7416	23.9242
3x3-Mean	105.5941	56.8485

Table 2: Sharp Edges: MSE for noisy images filtering using median and mean filters. Gaussian noise (μ=0,normalized σ^2=0.01) and salt-and-pepper noise (normalized σ^2=0.01) used.

In case of Salt and Pepper noise, all three median filter perfomed excellent to remove noise from the image of smooth features as seen from Figure 2. The mean filter could not remove noise totally in the image though it has introduced some blurring of the salt and pepper noise. Actually, median filter always performs well to remove noise with long tailed PDF (resulting in outliers). This statement is verified in terms of MSE also as found from the Table 1. In terms of MSE the 4-connected median filter performed the best and the mean filter has the worst performance.

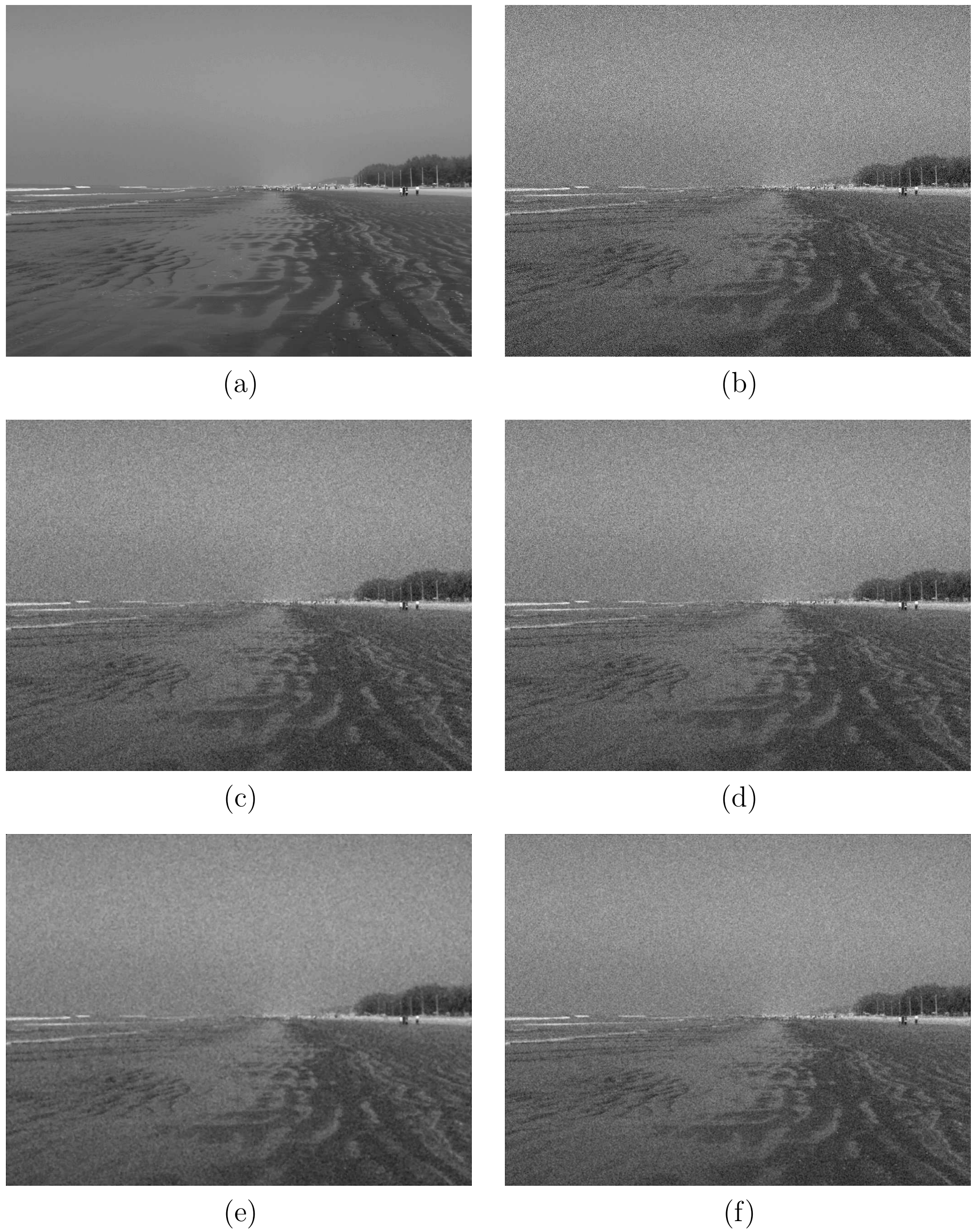


Figure 1: (a) Original image; (b) Original image with Gaussian noise, zero mean and normalized σ^2=0.01; (c) Result of median filtering using 8-connected neighborhood; (d) Result of median filtering using 4-connected neighborhood; (e) Result of median filtering using 5x5 square neighborhood; (f) Result of 3x3 mean filtering.

In presence of Gaussian noise, the effect of filtering is more evident in the image containing sharp edges. The median filter with 5x5 neighborhood performed best in terms of noise removal and the mean filter also performed well though it has introduced little blurring around the edges present in the image with some loss of fine details and textures. All the three median filter has caused some clipping effect at some of the sharp corners and this effect is barely perceptible in the images presented in the report.

(a)

(b)

(c)

(d)

(e)

(f)

Figure 2: (a) Original image; (b) Original image with salt-and-pepper noise, normalized σ^2=0.01; (c) Result of median filtering using 8-connected neighborhood; (d) Result of median filtering using 4-connected neighborhood; (e) Result of median filtering using 5x5 square neighborhood; (f) Result of 3x3 mean filtering.

In addition, the 5x5 square median filter has eliminated the small objects like the lines parallel to the edges of the building extensions. Due to zero padding around the corners all the corner pixels of the image are darker in case of median filtering. By examining table 2 it is obvious that the mean and the median filters performed in a similar manner as in case of image of smooth features in presence of gaussian noise (in terms of MSE). But all the filters (especially the mean filter) have shown comparatively good performance for image with smooth features in presence of gaussian noise.

In case of salt and pepper noise, the median filters performed very well by removing almost all the noise as seen from Figure 4 (c),(d) and (e). The characteristic of removing very small objects for large neighborhood is still visible in the Figure4 part (e). Though all the images are visually very similar in quality for the three median filters.

As expected, the mean filter could not remove salt and pepper noise significantly and in addition, it has blurred the eedges and reduced the variability of gray level values. The mean filter also affected some close neighbors of the salt or pepper containing pixels (the effect of outliers). In terms of MSE as seen from table 2 the best performance is obtained by 4 connected neighborhood median filtering and mean filter has performed the worst.

In contrast, mean filter can eliminate gaussian noise well for image containing less gray level variability among the neighboring pixels and can smooth images. Despite of clipping at the corners and elimination of small object, the nonlinear median filter with small neighborhood performs really well and showed excellent result in removing salt and pepper noise. Due to nonlinearity, the distortion near the sharp edges is barely perceptible in the images other than part(e) of figures 3 and Figure 4.

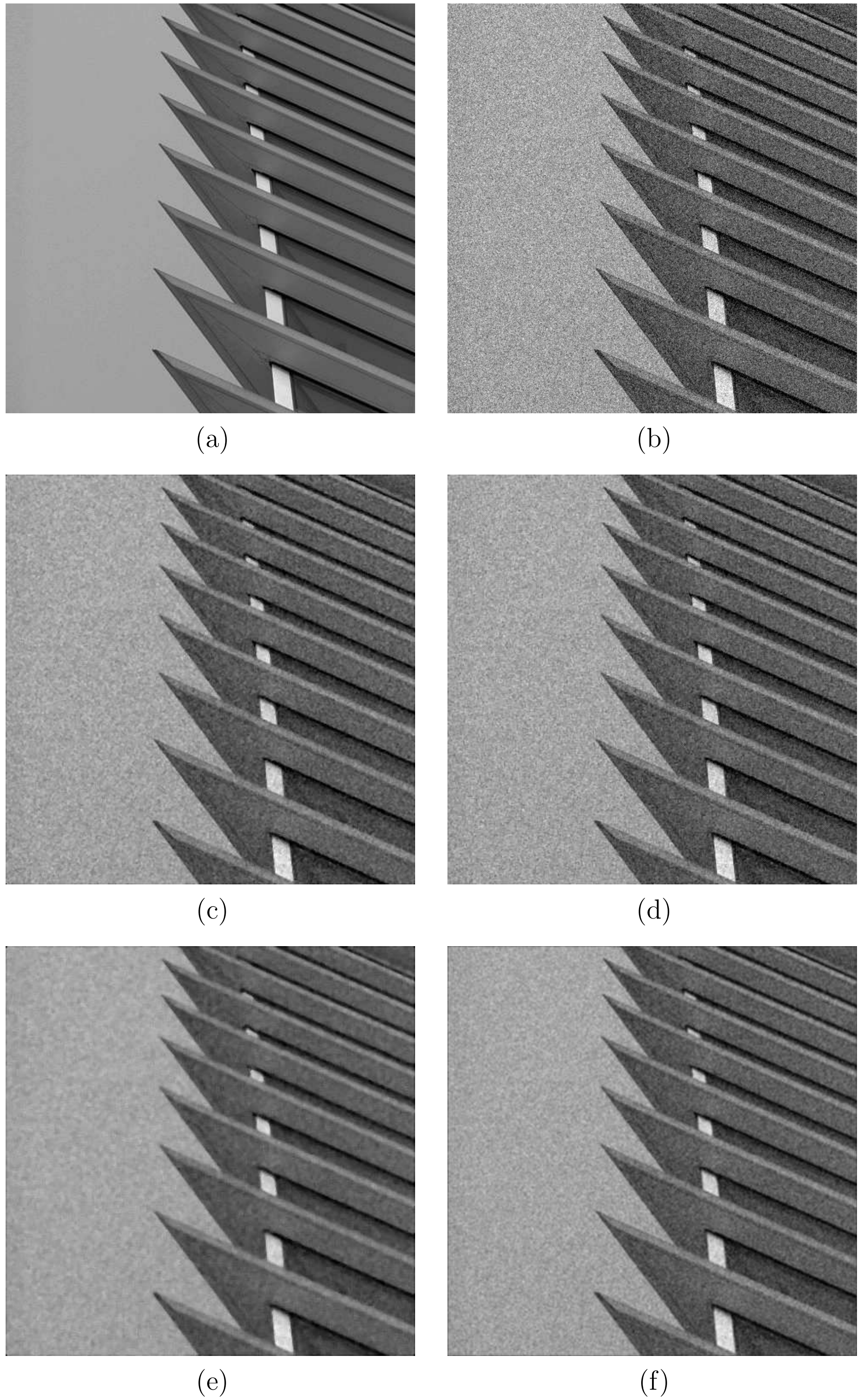


Figure 3: (a) Original image; (b) Original image with Gaussian noise, zero mean and normalized σ^2=0.01; (c) Result of median filtering using 8-connected neighborhood; (d) Result of median filtering using 4-connected neighborhood; (e) Result of median filtering using 5x5 square neighborhood; (f) Result of 3x3 mean filtering.

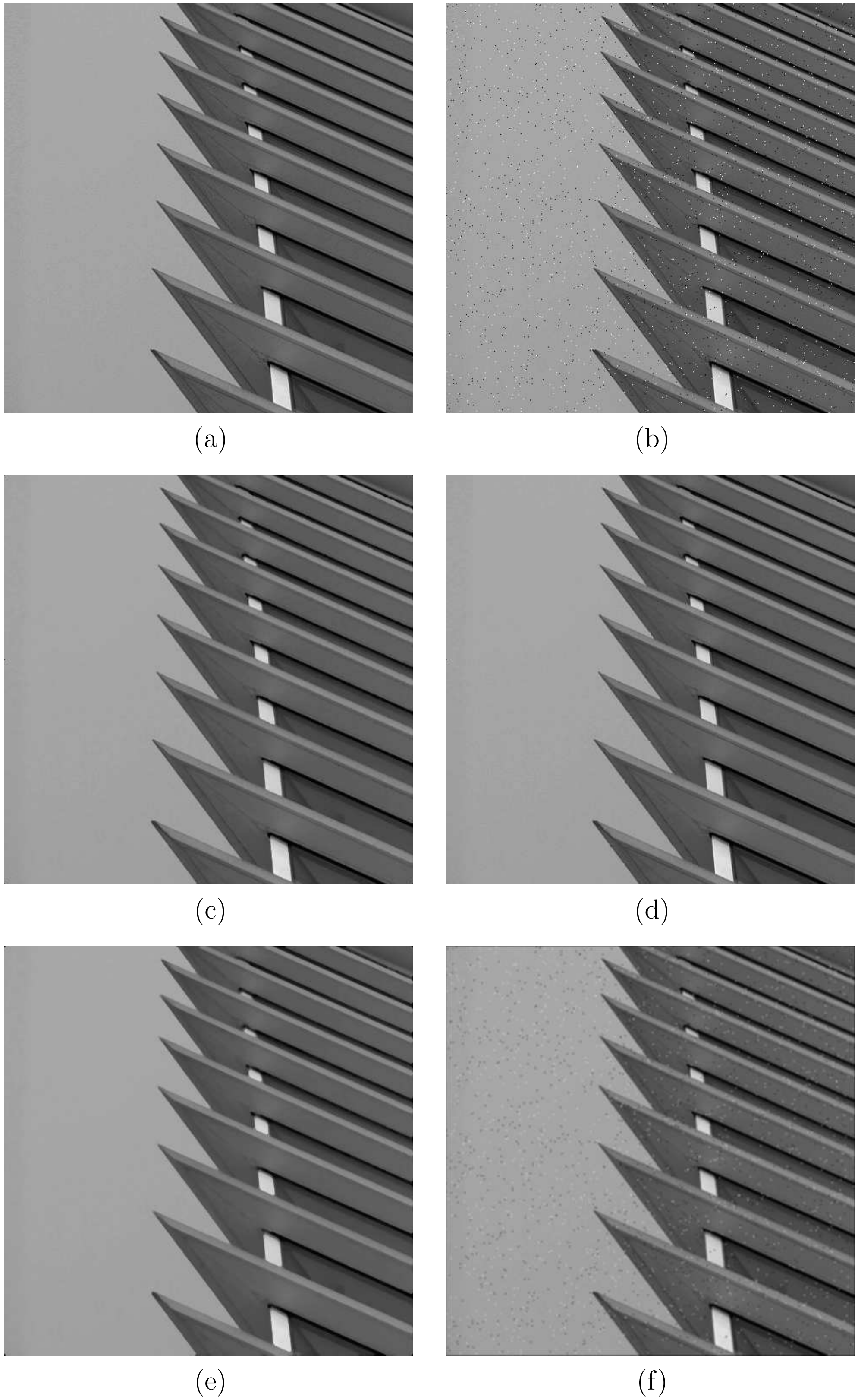
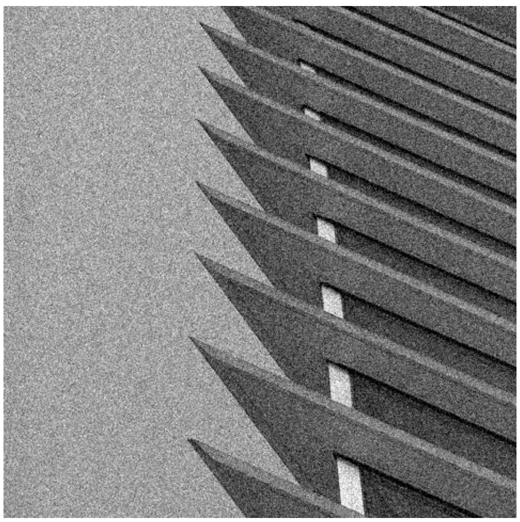


Figure 4: (a) Original image; (b) Original image with salt-and-pepper noise, normalized σ^2=0.01; (c) Result of median filtering using 8-connected neighborhood; (d) Result of median filtering using 4-connected neighborhood; (e) Result of median filtering using 5x5 square neighborhood; (f) Result of 3x3 mean filtering.

Lab Exercise: 06

Two noisy images from previous lab exercise have been selected and are displayed in Figure 1(a) and 1(b). The first image is with additive Gaussian noise, μ=0, normalized σ^2=0.01 and the second image is with multiplicative Salt and Pepper noise, normalized σ^2=0.01.



(a)

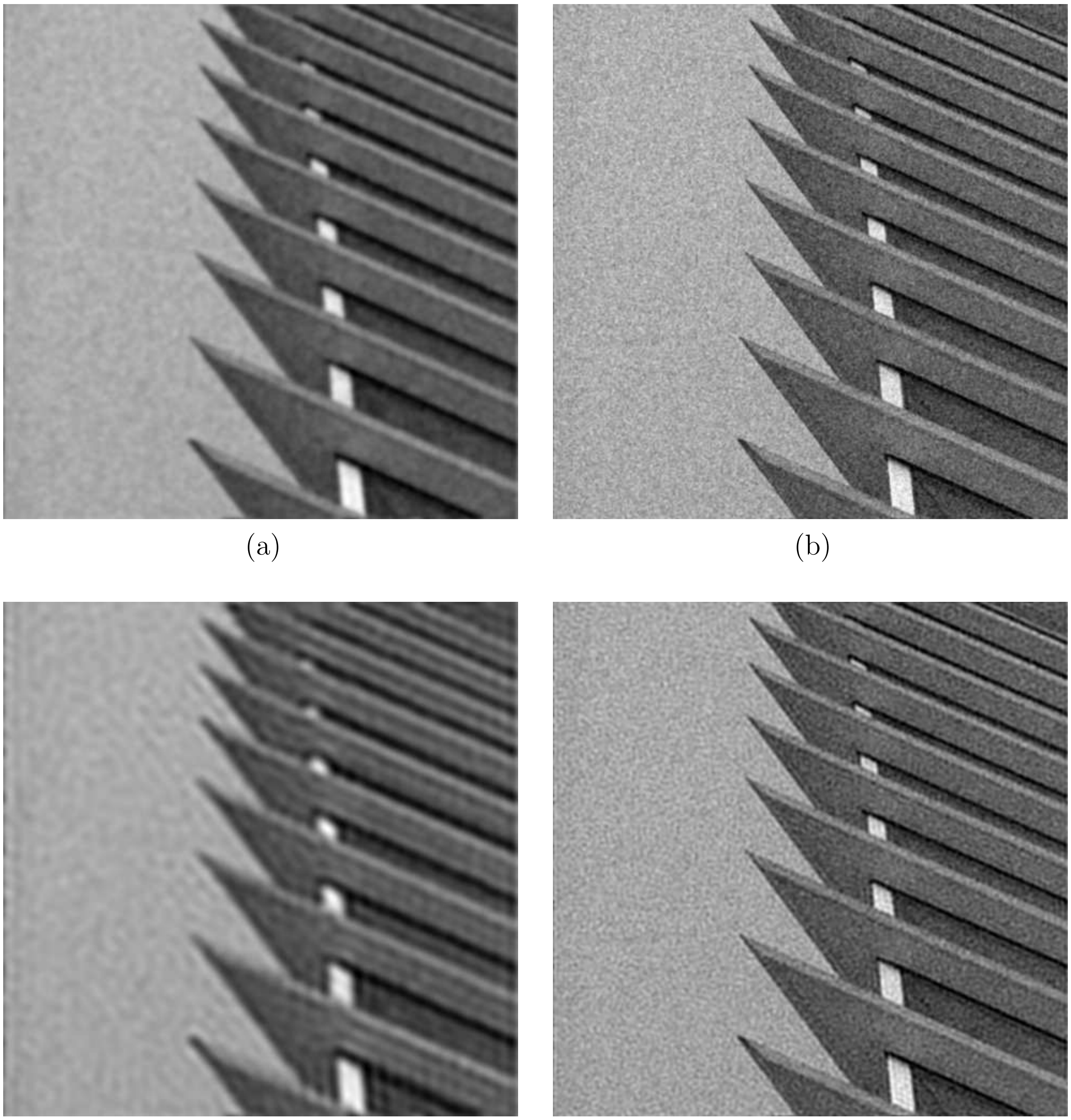
(b)

Figure 1: (a) Original image with additive Gaussian noise, μ=0, normalized σ^2=0.01; (b) Original image with Salt and Pepper noise, normalized σ^2=0.01

In Figure 2, the filtered versions of the noisy image in part (a) of Figure 1 is displayed. At first a cutoff frequency of D_o=0.15 was applied for both Butterworth filter of second order and for ideal lowpass filter. The effect of filtering is shown in part (a) and (c) of figure 2. As there are sharp edges present in the image a very low cutoff frequency of the filters have affected the image significantly. Due to low pass filtering with such a low cutoff frequency has caused huge blurring and smoothing of the image.

Butterworth filter has removed all the fine details and textures from the image and also reduced the noise significantly. The ideal low pass filter has worked resonably well in terms of noise removal but it has also caused huge ringing artifacts due to sharp transition from passband to stopband. The ringing artifact is so severe in the image in Figure 2 (c) that the quality of image has reduced significantly compared to the noisy image. The blurring and ringing effect is not so severe when a cutoff frequency of D_o=0.40 applied. The butterworth filter has performed well without causing significant blurring as seen in Figure 2 (b). The ideal low pass filter worked very well though there are still ringing artifacts visible and the blurring effect is higher as compared to the butterworth filter. (see Figure 2(d)). For both the images, due to high cut off frequency the noise is not totally removed.

The application of the lowpass filters has resulted in the suppression of noise in image containing smooth features, as seen in parts (a)-(d) of Figure 3. In case of cutoff frequency D_o=0.15 the ideal filter has resulted in a little blurrier image than the result of Butterworth lowpass filtering due to the ringing effect as seen in part (c) Figure 3. As there is not much sharp edges present in the image the ringing artifacts are not so severe in the image. There are some ringing artifacts visible by the sides of sharp waves. Here, the ideal low pass filter has performed well in terms of Salt and Pepper noise removal than the Butterworth filter .



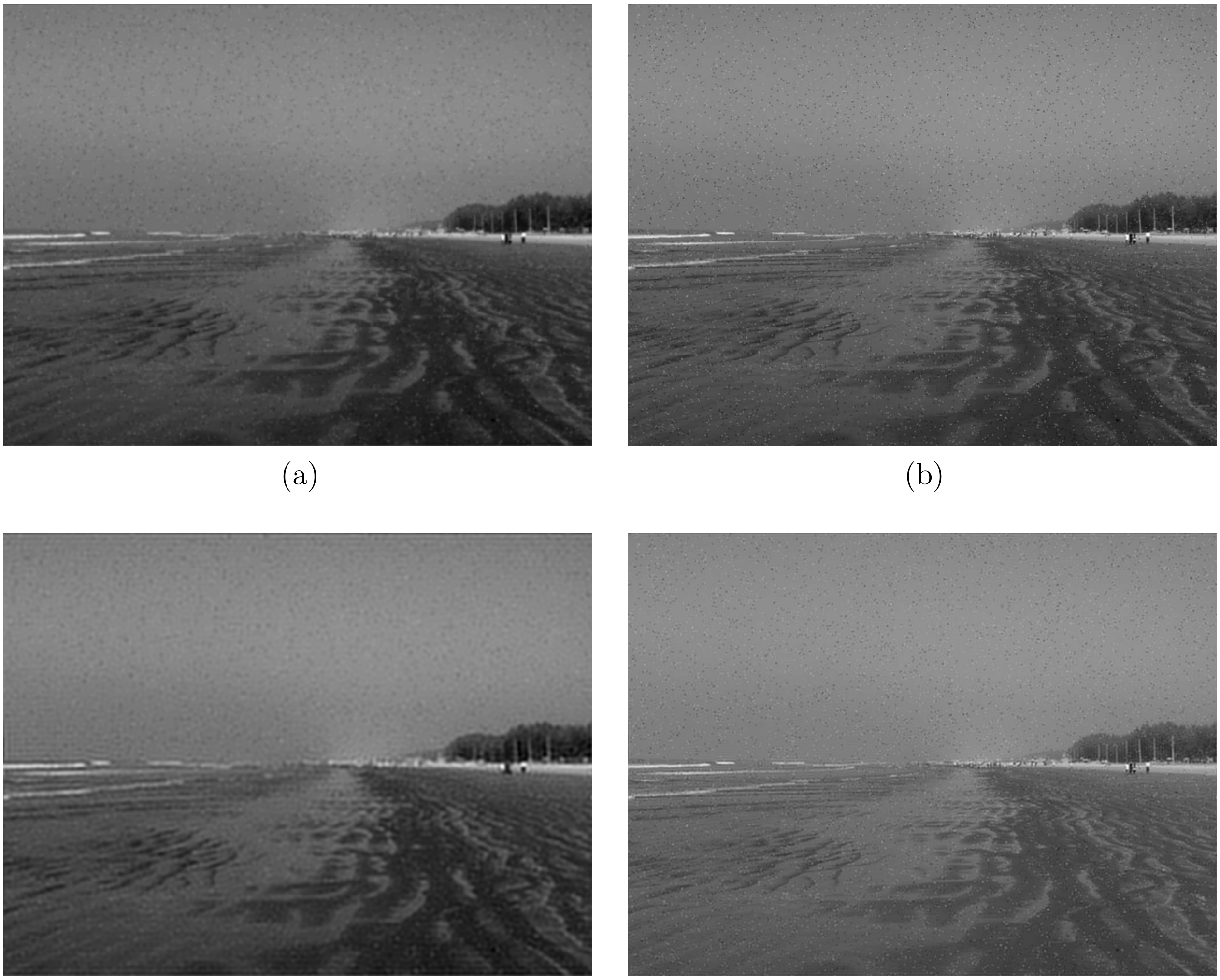
(a) (b)

(c) (d)

Figure 2: (a) Noisy image in Figure 1(a) filtered with Butterworth lowpass filter (D_o=0.15); (b) Noisy image in Figure 1(a) filtered with Butterworth lowpass filter(D_o=0.4); (c) Noisy image in Figure 1(a) filtered with ideal lowpass filter(D_o=0.15); (d) Noisy image in Figure 1(a) filtered with ideal lowpass filter(D_o=0.4).

In parts (b) and (d) of Figure 3 for cutoff frequency of D_o=0.40, it is clearly seen that

Butterworth filter has poor performance while removing Salt and Pepper noise than that of the ideal filter. Though the Salt and Pepper sharp spots are blurred due to lowpass (integration) effect, but still both the filters are not suitable for removing this type of noise.



(a) (b) (c) (d)

Figure 3: (a) Noisy image in Figure 1(b) filtered with Butterworth lowpass filter (D_o=0.15); (b) Noisy image in Figure 1(b) filtered with Butterworth lowpass filter(D_o=0.4); (c) Noisy image in Figure 1(b) filtered with ideal lowpass filter(D_o=0.15); (d) Noisy image in Figure 1(b) filtered with ideal lowpass filter(D_o=0.4).

So, from the discussion, it is evident that ideal lowpass filter gives rise to many undesired components in the filtered image and for that reason a slow transition butterworth filter is preferable to eliminate high frequency noise. And to eliminate Salt and Pepper noise, the median filter with small neighborhood is more effective.

Lab Exercise:07

The image in Figure 1(a) represents an example of sharp edges and in Figure 1 (b),(c) and (d) the effect of unsharp mask, the Laplacian and the subtractive Laplacian operation are shown respectively.

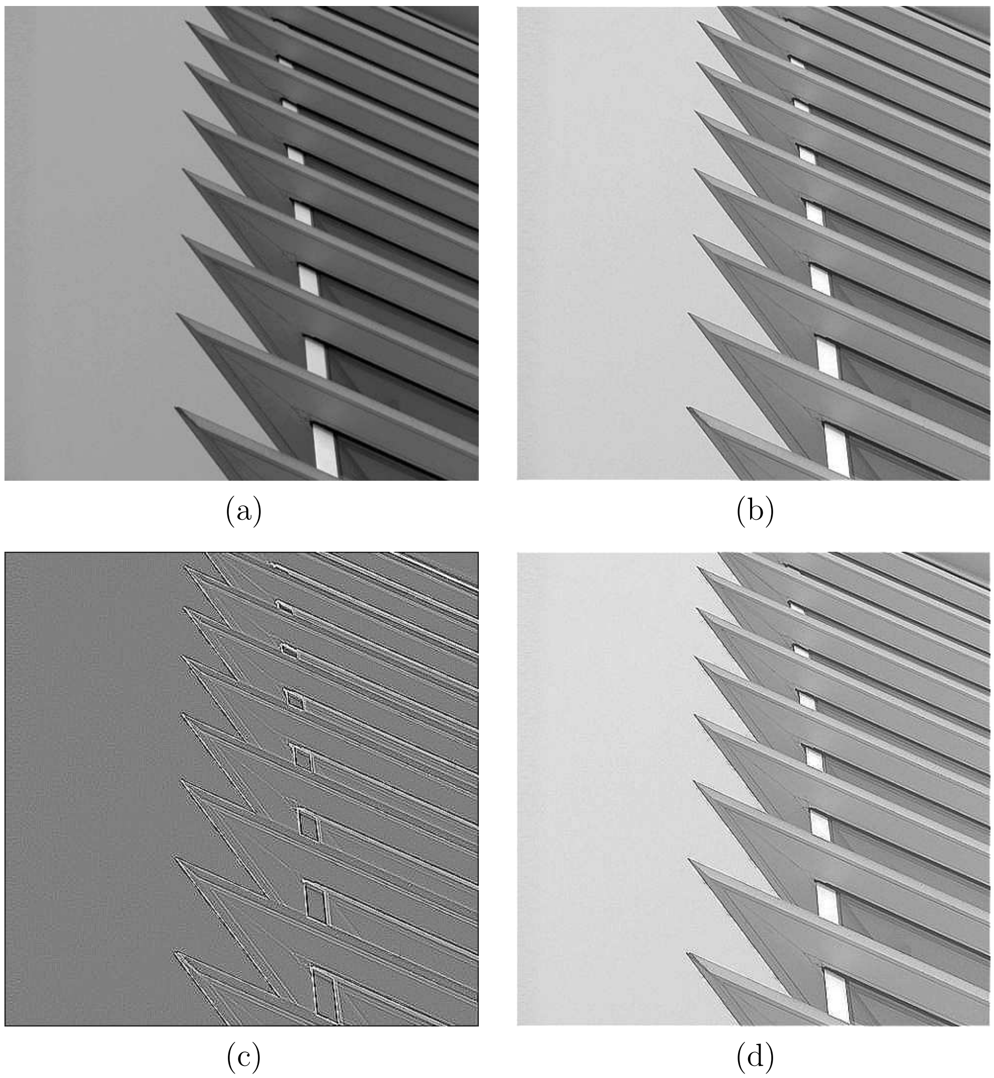
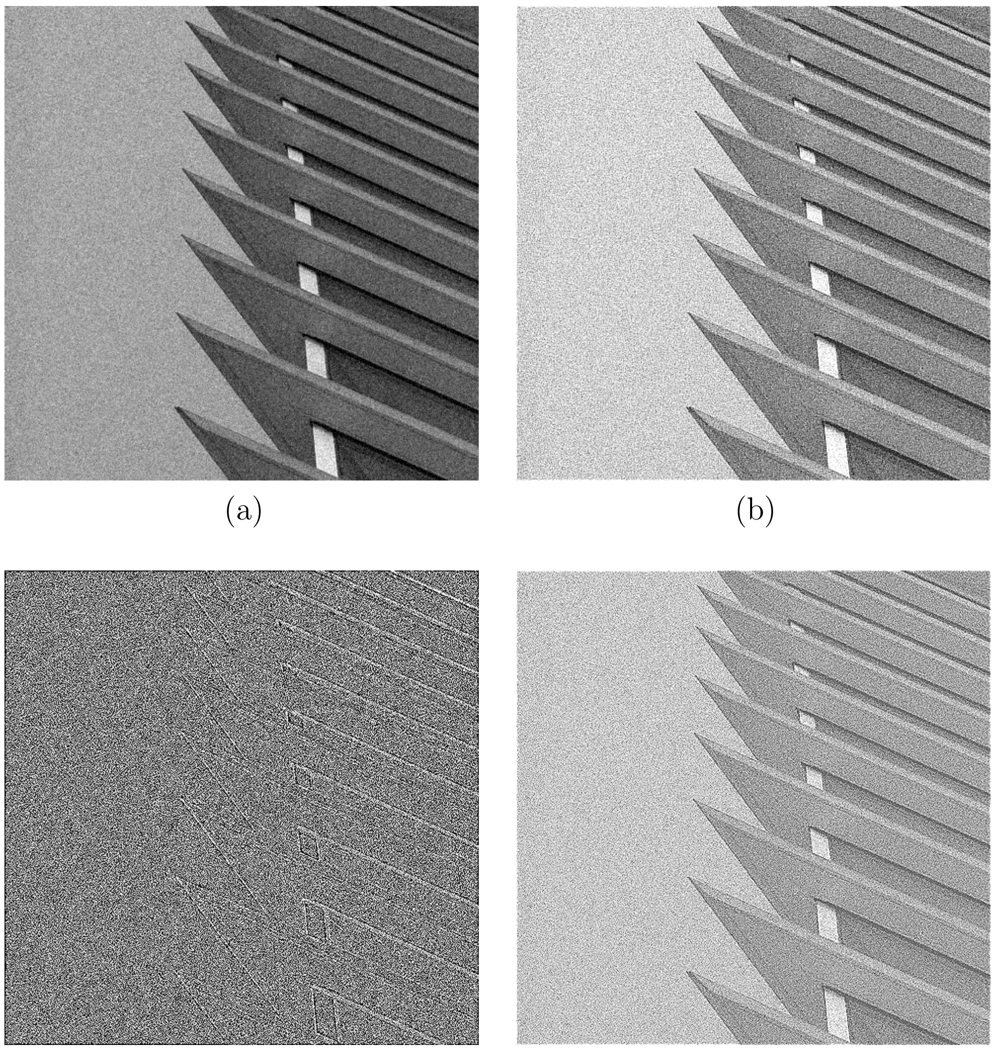


Figure 1: (a) Original image; (b) Unsharp mask applied to original image, display range [-40 200] out of [-48,301]; (c) Laplacian applied to original image, display range [-50 50] out of [-308,308]; (d) Subtractive Laplacian applied to original image, display range [-100 200] out of [-283,481]

The unsharp operation has almost produced the same output as the input with edge enhancement and there is no net change in average intensity in the image. The subtracting Laplacian operator also has preserved the intensity in the image. The unsharp masking and subtracting laplacian both operators have emphasized certain edges that are unnoticeable in the original image, such as the parallel lines near the sides of the edges are clearly visible now.

The Laplacian has extracted the edges in all directions but the intesity information and all the details are totally lost, leaving only the high positive and negative values corresponding to the edges of the image. Consequently, it's difficult to distinguish whether the building has lower gray level values than the background because the operator sets all homogeneous regions (i.e low frequency components) to zero whereas the subtracting laplacian has enhanced the edges with maintaining the almost same image quality. For subtracting laplacian the edges are sharpened in the image and the image is made little bit noisier than image with the unsharp masking operation.



(a) (b)

(c) (d)

Figure 2: (a) Original image with additive Gaussian noise, with zero mean and normalized σ^2=0.005; (b) Unsharp mask applied to noisy image, display range [-50 200] out of [-86,350]; (c) Laplacian applied to noisy image, display range [-50 50] out of [-427,390]; (d) Subtractive Laplacian applied to noisy image, display range [-100 200] out of [-380,643]

But all these operation has given rise to some overshoot and undershoot artifacts around the edges which is more evident in Figure 1(c). There is also a subtle border surrounding the image that arises from zero-padding when the operator is applied near the edge of the image.

In the presence of noise, as shown in (b),(c) and (d) of Figure 2, noise is also emphasized along with the edges by the operators. In the presence of noise, the unsharp masking has given a good result and in case of laplacian, the operator is still able to extract the strong edges but it has resulted an image containing granular like components that looks like more noisy and grainy than the original noisy image. The subtracting laplacian operation has also been affected by the noise.

In presence of noise the disturbing artifacts around the edges are not so prominent but the border line artifact is still visible in the images.

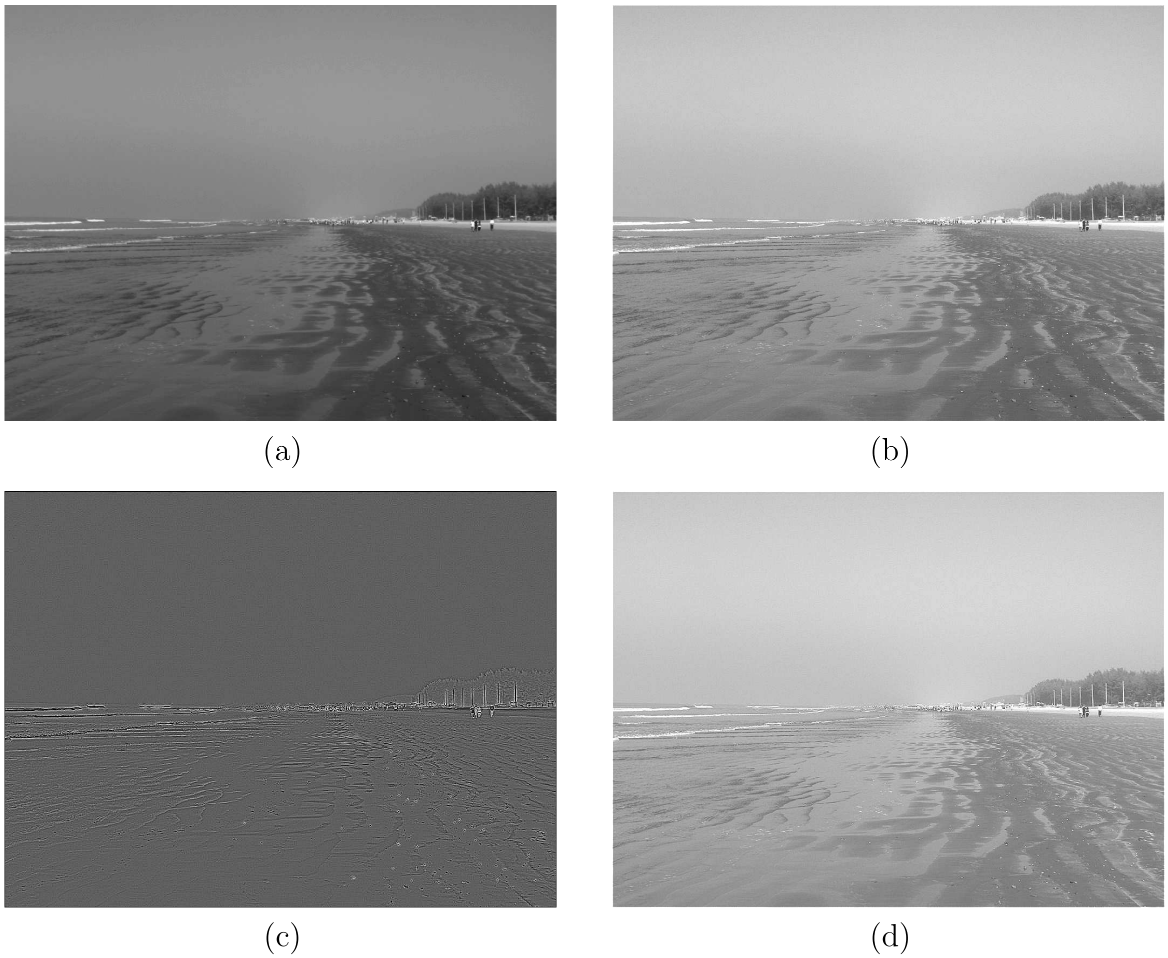


Figure 3: (a) Original image ; (b) Unsharp mask applied to image in (a), display range [-5 200] out of [-7,357]; (c) Laplacian applied to image in (a), display range [-30 50] out of [-350,211]; (d) Subtractive Laplacian applied to image in (a), display range [-50 200] out of [-157,597]

The three operators are also applied on image with smooth features and are presented in Figure 3. As there is not much sharp edges present in the image the Laplacian operator has detected the edges in all directions with removing all the intensity information from the image.The unsharp masking operator and the subtracting laplacian operator have maintained the same image quality and enhanced edges which is not clear in the image displayed here. The effect of these operations on the noisy smooth image is not presented here because in absence of strong edges the whole image gets corrupted by noise producing no meaningful result.

In presence of high level of noise these operations might not be able to produce good and desired outputs and will result in boosting of high frequency noise components.

Lab Exercise: 08

For the image containing sharp edges, a normalized cutoff frequency of 0.5 and 0.1 is applied individually and the effect of filtering are displayed in Figure 1. Then the same filters are applied on the same image added with the Gaussian noise of zero mean and normalized variance 0.01 and is displayed in Figure2.

As seen in Figure 1 and 2, the regions in between the edges and background (i.e the areas that correspond to high frequencies) are strongly contrasted. In all cases of highpass filtering, the edges are strongly pronounced or enhanced. In presence of Gaussian noise, the filtered images have noisy or grainy appearance as seen from Figure 2.

The Butterworth filters are calculated for order n=2. The parameters for the high-emphasis Butterworth filter, using the definition provided in the text, are κ_1=0.2 and κ_2=1.0.

For the images in part (a),(c) and (e) of Figure 1, a normalized cutoff frequency of 0.5 was applied. In the case of the ideal highpass filter, as shown in part (e) of Figure 1, there are noticeable ringing effect that degraded the quality of the image. Part (a) depicts the image after applying the Butterworth highpass filter and the filtered image is free of the ringing effect. For both the cases, the details or intensity information is lost. Part (b) represents the image after the application of the high-emphasis Butterworth filter which has enhanced the sharp edges and this image differs from other two due to the fact that the low frequency components are not eliminated but suppressed while boosting the high frequency contents. So, here the high emphasis filter mostly enhances the edges while the other two extract edges for this case.

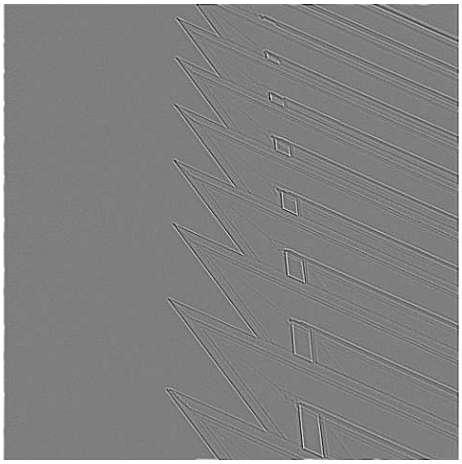
For the images in part (b),(d) and (f) of Figure 1 a normalized cutoff frequency of 0.1 is applied and the results obtained are more clear and easier to interpret. Having such a low cut off frequency has allowed the images to contain more low frequencies and so the details are more visible. All three filters have produced almost same result by giving rise to high positive and negative values around the edges. The Butterworth filters are almost free from ringing artifacts but the ideal filtered image is degraded in quality for prominent ringing effect. And for all the images there is a artifact near around the border of the image resulting from zero padding which is clearly perceptible at the right side border of the images.

In contrast to the images without noise, the filters has performed worse with added Gaussian noise as can be seen from Figure 2. Using a higher D_o=0.5 has degraded the quality of edge enhancement, particularly in the application of the ideal filter, as seen in part(e). Due to noise boosting the edges are totally lost and nothing is visible. The Butterworth high emphasis filter also produces noisy coarse image and the edge enhancement is not very prominent (see Figure 2(c)). In the case of Butterworth highpass filter the edges are perceptible but still the image has become of coarse nature due to noise (see Figure 1(g)).

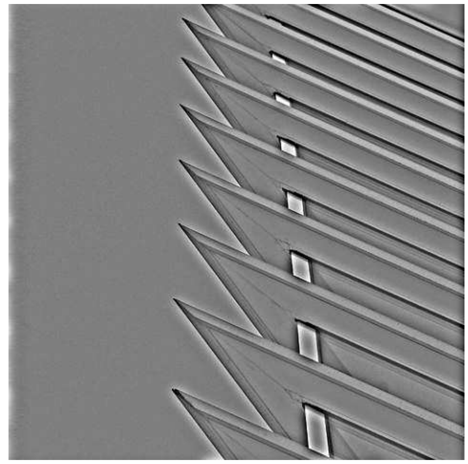
Despite the presence of noise in images the strong edge enhancement activities are still visible with D_o=0.1 as seen in part (b),(d) and (f) of Figure 2. In the case of the ideal and the Butterworth filter, almost all intensity informations are lost. In the regions of background and the part of the building aside from the edges, appear to have the same gray level values though there is high positive and negative values around the edges. However, with the high-emphasis

Butterworth filter, the relative image intensity is retained. Ringing effect is still visible in the ideal high pass filtered image .

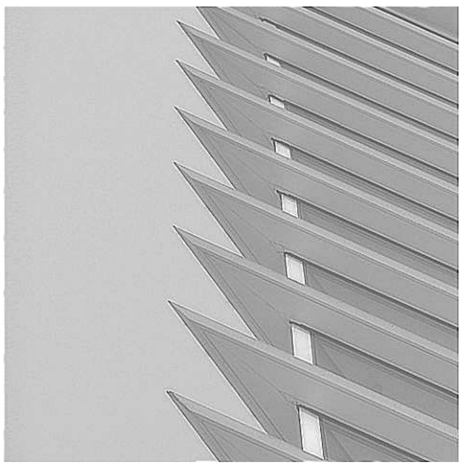
For the image containing smooth features, a normalized cutoff frequency of 0.2 is applied and the results with the original image and the noisy image are displayed in Figure 3. The Butterworth highpass filter has performed well in terms of edge extraction. But for the noisy images the edges are not clearly visible for all three cases. The Butterworth high emphasis filter has almost maintained the intensity level with the original image but the noisy image got corrupted and has become of coarse nature. The ideal filter has significant ringing artifact and almost nothing is visible in the filtered noisy image.



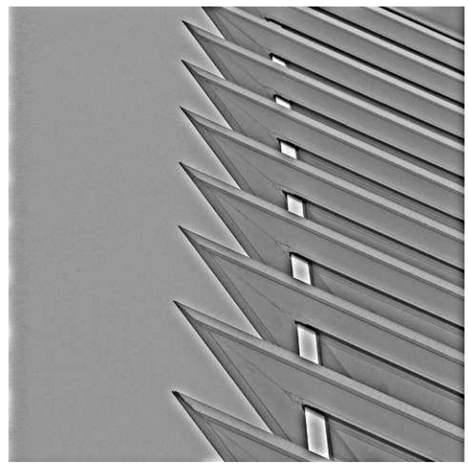
(a)



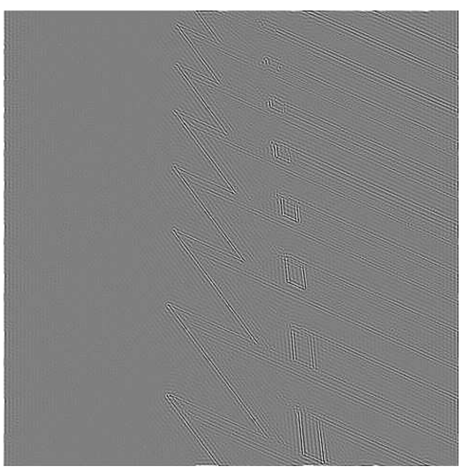
(b)



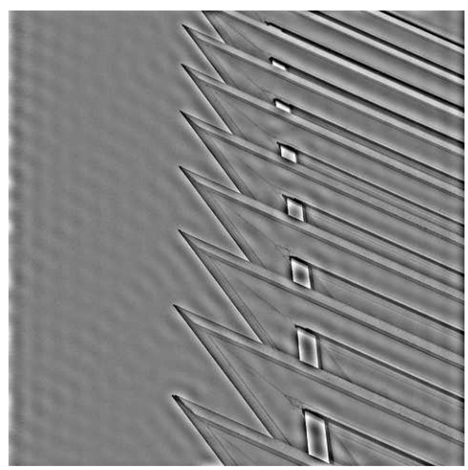
(c)



(d)

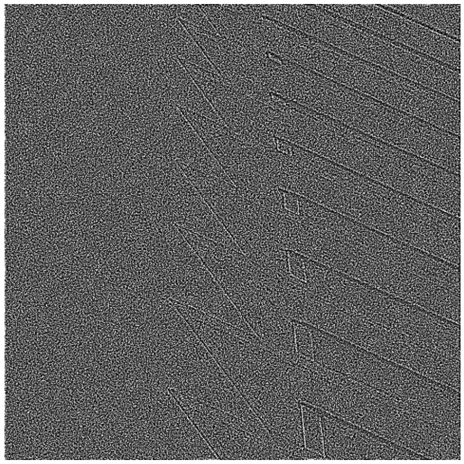
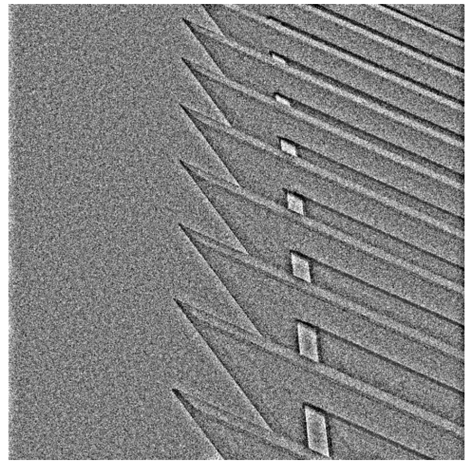


(e)

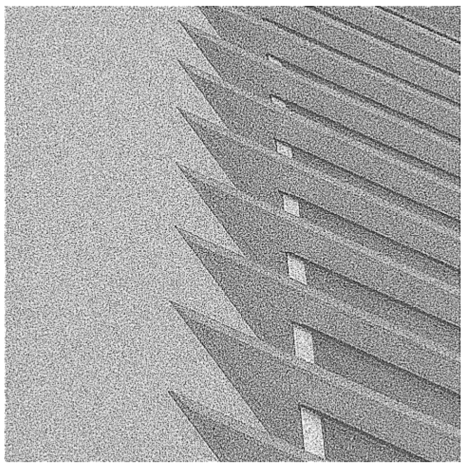
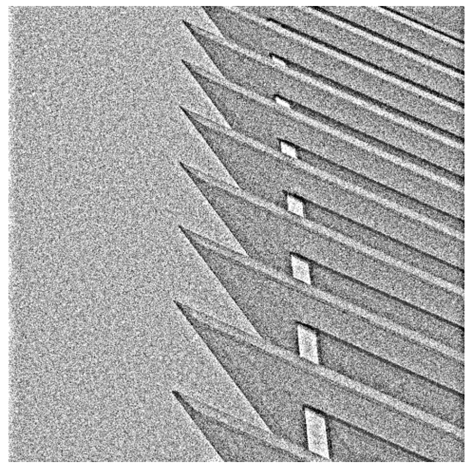


(f)

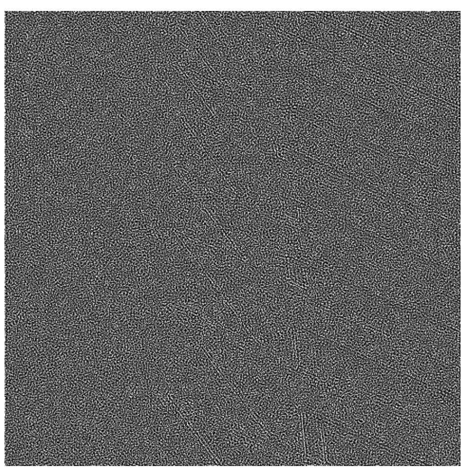
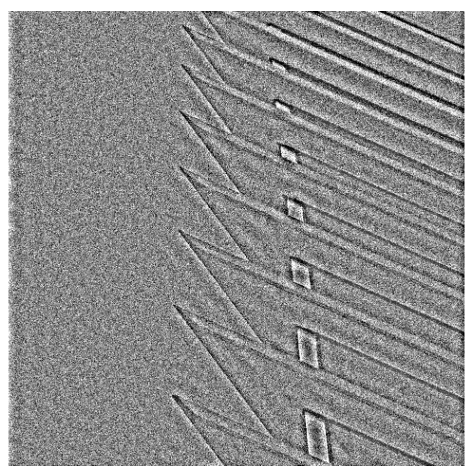
Figure 1: Original image filtered with (a) Butterworth highpass filter(D_o=0.5) , display range [-40, 40] out of [-64, 61]; (b) Butterworth highpass filter(D_o=0.1) , display range [-70, 70] out of [-111, 115] (c) Butterworth high-emphasis filter(D_o=0.5,κ_1=0.2,κ_2=1.0) , display range [-40, 50] out of [-62, 103]; (d) Butterworth high-emphasis filter(D_o=0.1,κ_1=0.2,κ_2=1.0) , display range [-70, 100] out of [-109, 161]; (e) Ideal highpass filter (D_o=0.5), display range [-30, 30] out of [-57, 53]; (f) Ideal highpass filter (D_o=0.1) , display range [-70, 70] out of [-117, 118]

(a) (b)

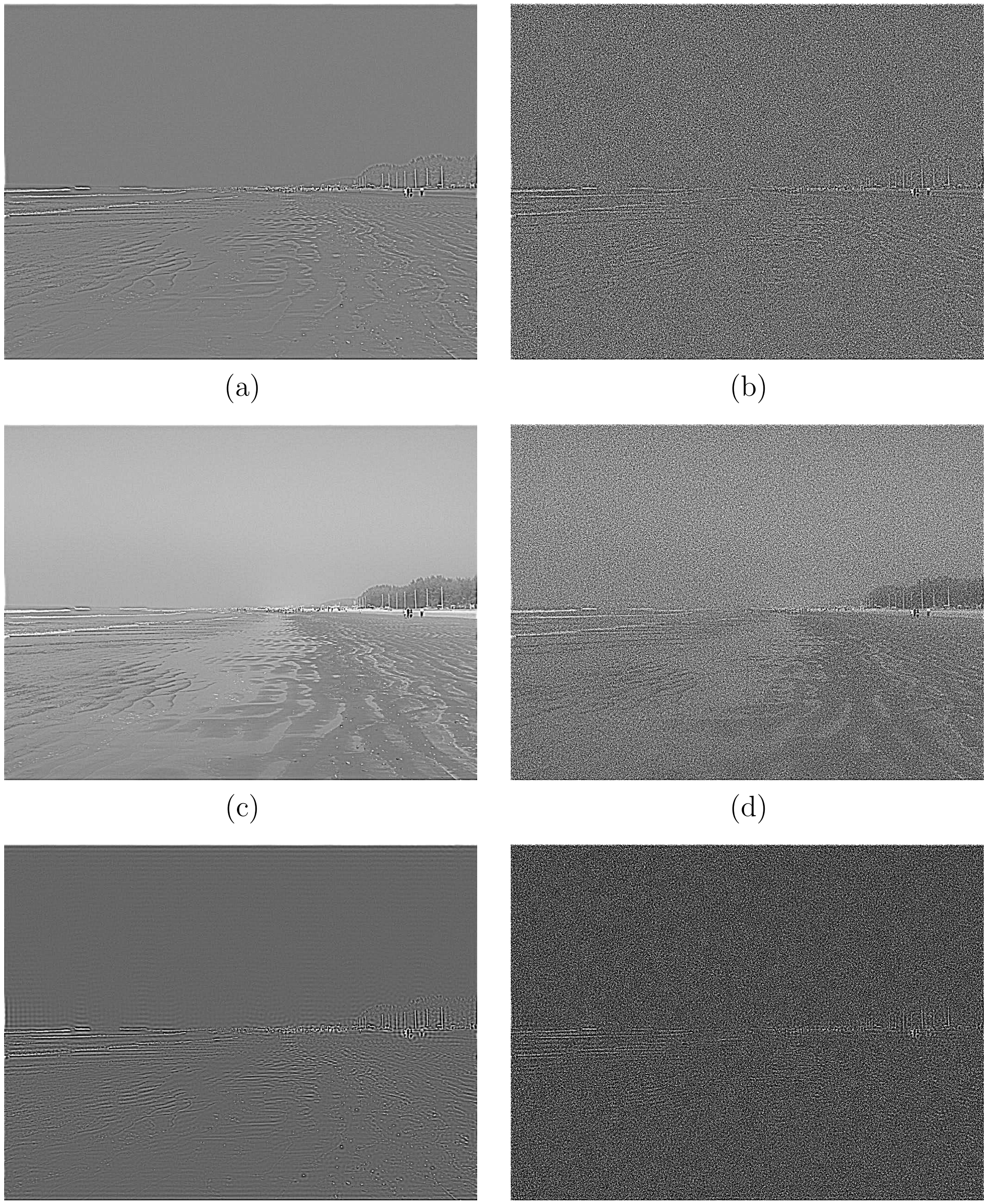



(c) (d)

(e) (f)

Figure 2: Noisy image (with additive Gaussian noise of zero mean and normalized σ^2=0.01) filtered with (a) Butterworth highpass filter(D_o=0.5) , display range [-20, 40] out of [-96, 100]; (b) Butterworth highpass filter(D_o=0.1) , display range [-80, 80] out of [-140, 142] (c) Butterworth high-emphasis filter(D_o=0.5,κ_1=0.2,κ_2=1.0) , display range [-30, 50] out of [-88, 140]; (d) Butterworth high-emphasis filter(D_o=0.1,κ_1=0.2,κ_2=1.0) , display range [-80, 80] out of [-140, 191]; (e) Ideal highpass filter (D_o=0.5), display range [-20, 40] out of [-101, 105]; (f) Ideal highpass filter (D_o=0.1) , display range [-80, 70] out of [-133, 150]



(a) (b) (c) (d) (e) (f)

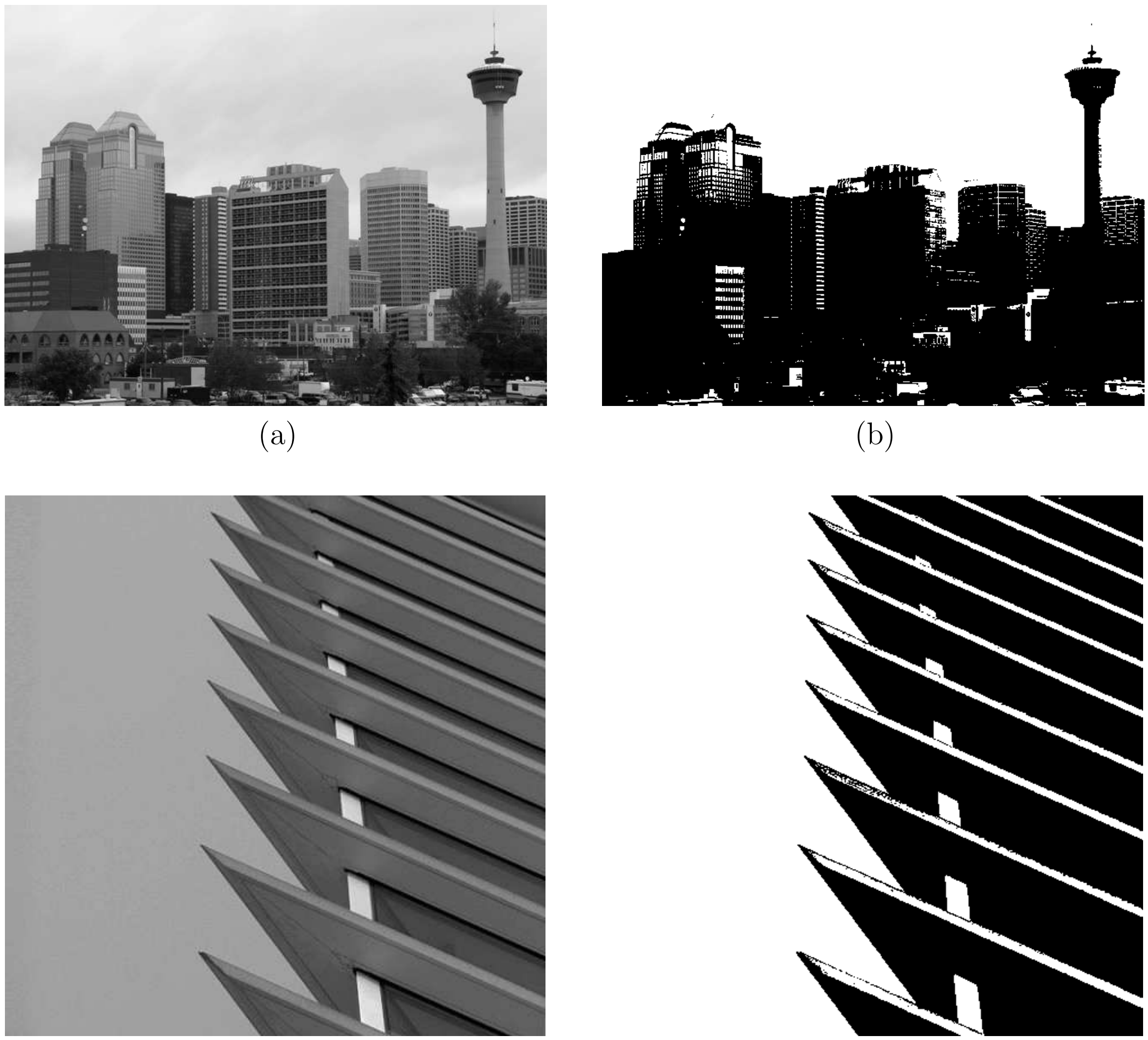
Figure 3: Original image filtered with (a) Butterworth highpass filter(D_o=0.2) , display range [-30, 30] out of [-90, 150]; (c) Butterworth high-emphasis filter(D_o=0.2,κ_1=0.2,κ_2=1.0) , display range [-20, 50] out of [-79, 199]; (e) Ideal highpass filter (D_o=0.2), display range [-20, 30] out of [-95, 151]; and noisy image (with additive Gaussian noise of zero mean and normalized σ^2=0.01) filtered with (b) Butterworth highpass filter(D_o=0.2) , display range [-20, 30] out of [-132, 146]; (d)Butterworth high-emphasis filter(D_o=0.2,κ_1=0.2,κ_2=1.0) , display range [-20, 70] out of [-127, 196]; (f) Ideal highpass filter (D_o=0.2) , display range [-10, 40] out of [-137, 160].

Lab Exercise: 09

The image in Figure 1(a) is thresholded and binarized using a normalized threshold of 0.5588. The resulting image is shown in part (b). The background sky in the main image has higher gray level value than the buildings. The reason fo selecting this image is to examine the capability of global thresholding with intrinsic variability of gray levels. From the resulted image it is evident that the thresholding has not performed so well in terms of object detection and segmentation. The operation has only detected objects where there is a sharp and high transition in gray level values between the object and its background. For that reson the tower and some bright portions in the image are detected and most of the things are buried in black regions. The opeartion performed well in obtaining the window structures at the upper side of the two high buildings at the left of the image. In original image that region has same gray level values and the window structures are not very clear.

A normalized threshold of 0.4706 was calculated using the graythresh command in Matlab and was used to binarize the image seen in part(c) of Figure 1. The result is shown in part (d). Here the threshold and binarization procedure were able to separate the objects from the background and the operation has separated the vertical column and the sides of the building extensions from other parts of the building and the background. This is reasonable because there exist good contrast between object and background in the original image. The only drawback is some dark effects on the detected sidee which can be removed by further processing.

For both sets of images, at first edge detection and then binarization together may improve the segmentation of the objects from their background. Multi level thresholding, mathematical morphology, region growing and many other procedures can be used to segment the desired objects in the images. So, there need some preprocessing and/or some postprocessing to improve the segmentation.



(a) (b)

(c) (d)

Figure 1: (a) Original image of city center; (b) Result of thresholding (a) at normalized level, 0.5588; (c) Original image of sharp edge; (d) Result of thresholding (c) at normalized level, 0.4706.

Lab Exercise: 10

In figure 1(a) the original image is displaayed and the results of the Prewitt operators are shown in (b)-(e) of Figure 1. The lines or edges oriented at $0°$, $45°$, $90°$, and $135°$ have been detected individually by these opeartors. As can be seen, the $0°$ detects edges that are oriented vertically and removes horizontally-oriented edges, and the opposite effect is seen with the $90°$ operator. The vertical columns detected by $0°$ opeartor at the left side (Figure 1(b)) can not be seen in Figure 1(c) while the horizontally oriented waves are detected by $90°$ opeartor. As for the other two operators, $45°$ and $135°$, features oriented at oblique angles have been detected and the ones that are either horizontal or vertical are suppressed. The Figures in part (d) and (e) look similar except for the fact that which edge is detected or enhanced by one operator is eliminated or suppressed by the other. For the gradient magnitude opearation obtained by combining the horizontal and vertical prewitt opeartions, as seen in Figure 1(f), almost all the edges are detected in all directions. The result is promising in terms of edge boundary detection though the depth of the objects are not perceptible and only the outlines of the edges are visible. For all the opeartions, the areas of constant gray level values produced zero output and caused loss of intensity information.

In Figure 2, it can be seen that the various Prewitt direction operators did excellent jobs of detecting, or rather eliminating the appropriate edges from the image. In (b), the horizontal operator has eliminated the horizontally oriented features . The vertical operator has removed or suppressed the vertical columns and edges and enhanced the other edges that are not detected by horizontal opeartion. In the image in part (d), the details that were oriented at approximately $45°$ have been removed. Similarly, on the right-hand side of image (e), the features oriented at approximately $135°$ have been eliminated and the edges or lines that are not much perceptible in Figure 2(d) are significantly enhanced. The gradient magnitude opeartion in Figure 2(f) has showed similar result as in Figure 1(f).

Compared to lab exercise 4, results of edge detection using the Prewitt operators are more clear than those of using the first order horizontal or vertical derivative opeartion. Those oparators are based upon the values of two pixels that made those opeartors more susceptible to noise or spurious pixel values. But the prewitt operators provide more robust and reliable edge detection. In addition, there is no double border visible here around the edges like the effect of laplacian opeartion and the edges can be extracted or eliminated at any particular orientation. The gradient magnitude opeartion can be used for edge detection where the object boundary at all orientations are desired. An edge-linking procedure could also be incorporated to join the edges and more clearly present the objects in the image.

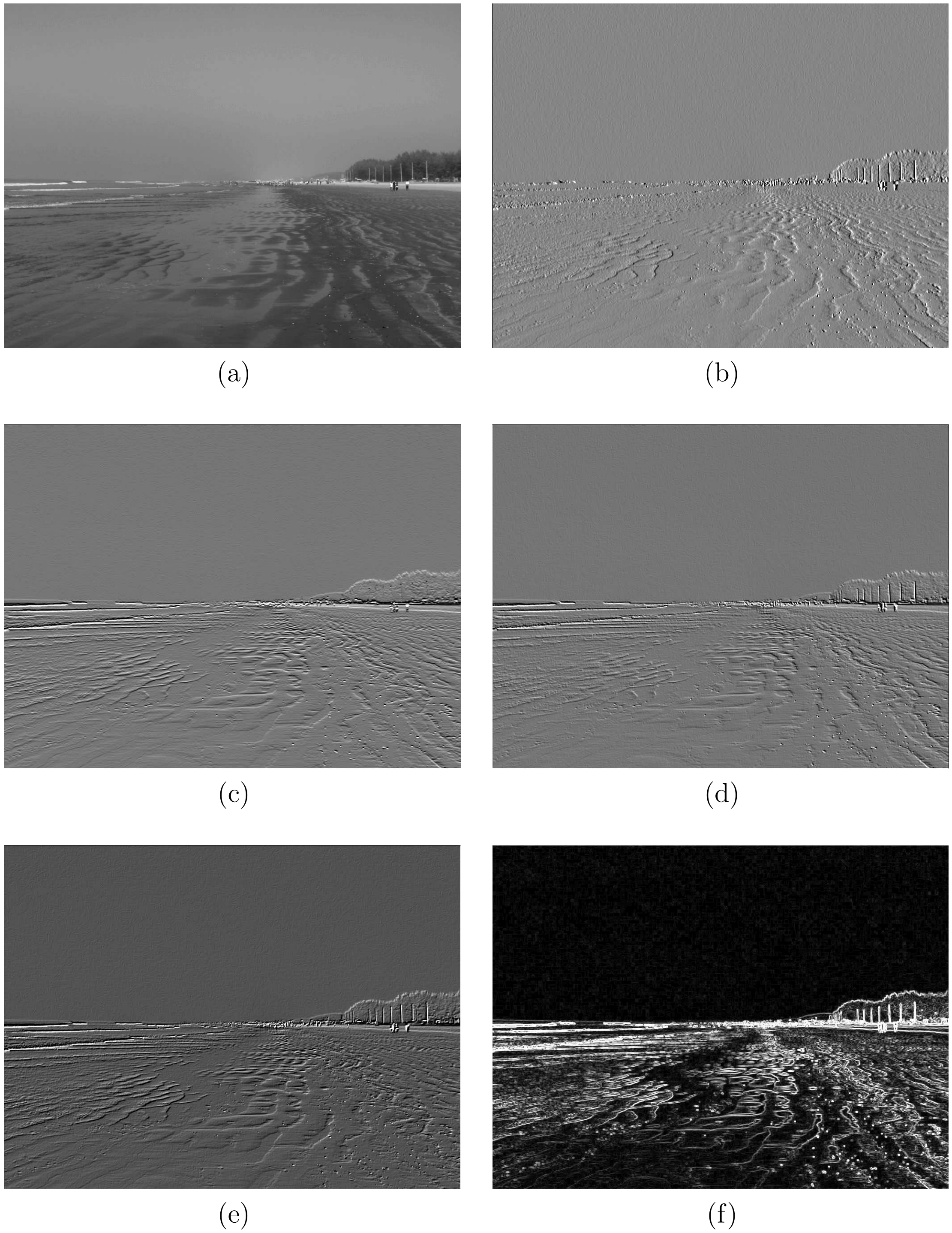


Figure 1: (a) Original image; (b) Result of horizontal Prewitt operator, display range [-67 60] out of [-666 601]; (c) Result of vertical Prewitt operator, display range [-100 116] out of [-499 581]; (d) Result of 45° Prewitt operator, display range [-87 104] out of [-437 520]; (e) Result of 135° Prewitt operator display range [-49 103] out of [-490 410]; (f) Magnitude of the gradient, display range [0 67] out of [0 666].

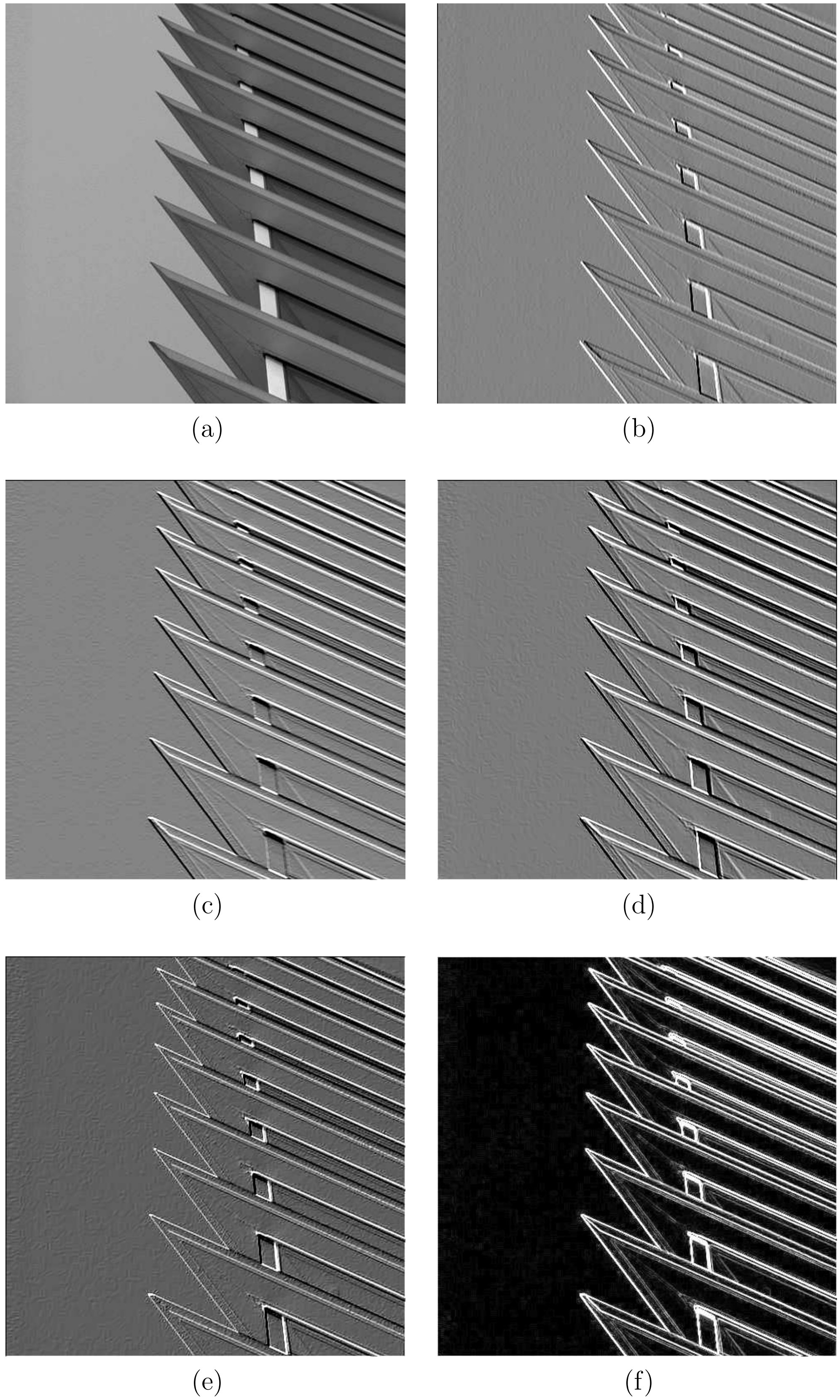


Figure 2: (a) Original image; (b) Result of horizontal Prewitt operator, display range [-134 125] out of [-535 500]; (c) Result of vertical Prewitt operator, display range [-122 115] out of [-486 461]; (d) Result of 45° Prewitt operator, display range [-77 83] out of [-387 417]; (e) Result of 135° Prewitt operator display range [-46 79] out of [-462 315]; (f) Magnitude of the gradient, display range [0 107] out of [0 535]