SOLUTIONS MANUAL

Version 4.4c

2023

*DIGITAL IMAGE PROCESSING & ANALYSIS*

*Digital Image Enhancement,*

*Restoration and Compression*

*Edition 4*

Chapters 6 and 7

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***Solutions for Chapter 6: Image Enhancement***

1. a) spatial and frequency/sequency, b) Image enhancement techniques are employed to emphasize, sharpen and/or smooth image features for display and analysis. *Image enhancement* is the process of applying these techniques to facilitate the development of a solution to a computer imaging problem. Consequently, the enhancement methods are application-specific and are often developed empirically.

2. The type of techniques include *point operations*, where each pixel is modified according to a particular equation that is not dependent on other pixel values, *mask operations*, where each pixel is modified according to the values in a small neighborhood (subimage), or *global operations*, where all the pixel values in the image are taken into consideration.

3. a) point operations, b) The *mapping equation* changes the pixel's (gray level) values based on a mathematical function that uses brightness values as input., c) A slope greater than one stretches the scale, which enhances contrast; while a slope less than one compresses the gray scale thus reducing contrast. d) Gray scale modification works by remapping the pixel brightness values. Usually, the contrast in increased for gray level ranges of interest, thus allowing for improved visible detail. Additionally, we may decrease the contrast for the gray scale we are not interested in.

4.

*E[I(r,c)]*

Modified Gray Level Values

0 50 100 255

255

*I(r,c)* – Original Gray Level Values

100

50

5.

*E[I(r,c)]*

Modified Gray Level Values

0 50 100 255

255

*I(r,c)* – Original Gray Level Values

150

50

6.

*E[I(r,c)]*

Modified Gray Level Values

0 100 200 255

255

*I(r,c)* – Original Gray Level Values

150

50

7.

*E[I(r,c)]*

Modified Gray Level Values

0 128 255

255

*I(r,c)* – Original Gray Level Values

128

Slope = -1

8.a)

*E[I(r,c)]*

Modified Gray Level Values

0 35 50 128 255

255

*I(r,c)* – Original Gray Level Values

128

8b)

*E[I(r,c)]*

Modified Gray Level Values

0 50 75 128 255

255

*I(r,c)* – Original Gray Level Values

128

9.a)

*E[I(r,c)]*

Modified Gray Level Values

0 50 100 255

255

*I(r,c)* – Original Gray Level Values

150

50

10. a) Gamma correction is used to compensate for that fact imaging equipment, such as cameras, displays and printers typically react according to a power-law equation. b) The gamma correction equation reverses the mathematical function of the power law equation

11. a) Range compression is useful when the dynamic range of the input data is very large, b) used in remapping Fourier spectra for display

12.a)



b) 

c) 

13. This is necessary if most of the pixel values in the histogram cover a small range, but there are a few values at the extremes. In this case, a stretch will not accomplish anything (see Fig 6.2-11) since the gray values span the entire range in the original image. By allowing for clipping we can get stretch the main group of pixels in the “small range” and improve contrast..

|  |  |
| --- | --- |
| Gray Level | Number of Pixels |
| 0 | 0 |
| 1 | 5 |
| 2 | 10 |
| 3 | 15 |
| 4 | 8 |
| 5 | 5 |
| 6 | 0 |
| 7 | 0 |

 14.

 

|  |  |
| --- | --- |
| Gray Level | Number of Pixels |
| 0 | 1 |
| 1 | 0 |
| 2 | 5 |
| 3 | 5 |
| 4 | 0 |
| 5 | 0 |
| 6 | 12 |
| 7 | 2 |

 15.



16.

|  |
| --- |
| Mapping Table 1 |
|  O | H |
|  0 | 1 |
| 1 | 2 |
| 2 | 2 |
| 3 | 2 |
| 4 | 3 |
| 5 | 5.2 |
| 6 | 5.8 |
| 7 | 7 |
| Mapping 2 |
| OS | HS |
|  0 | 0 |
| 1 | 0 |
| 2 | 1 |
| 3 | 3 |
| 4 | 5 |
| 5 | 6 |
| 6 | 7 |
| 7 | 7 |

|  |
| --- |
| Histogram Specification Mapping Table |
| O | M |
| 0 | 2 |
| 1 | 3 (round up) |
| 2 | 3 (round up) |
| 3 | 3 |
| 4 | 3 |
| 5 | 4 |
| 6 | 5 |
| 7 | 6 |

|  |
| --- |
| Final Histogram |
| 0 | 0 |
| 1 | 0 |
| 2 | 5 |
| 3 | 10 |
| 4 | 11 |
| 5 | 3 |
| 6 | 6 |
| 7 | 0 |

17. Use small block sizes. This will effectively be an adaptive contrast enhancement method which will modify the gray values based on the local histogram within the specified window.

18. CVIPtools.

19. CVIPtools. b) The *Value* selection performs an HSV color transform and then uses the *Value* (brightness) band.

20. CVIPtools. b-e) the histograms will *resemble* the specified histogram, but will not look exactly like them. In some cases, the similarity will be vague. Compare the original and the output histogram, and you can see that it was remapped using the specified one as guide. They are not exact due to the quantized nature of the values. e) the ramp results look similar to the sin(0.005\*x). Answers to other questions will vary depending on the images and values selected.

21. a) To avoid blocky artifacts, b) for speed and computstionaly efficiency

22. a) Contrast limited adaptive histogram equalization. It is a method to perform local enhancement via histogram equalization. b) It allows for limiting large peaks in the histogram, and large contrast changes, c) Specify a block size and a clipping limit. Use the clipping limit to modify the image histogram before generating the histogram equalization mapping table. The clipping limit is used as a maximum and any values in the histogram that exceed it are redistributed.

23. a) *ml* = 3.08, 

center pixel value = 

b) 

c) 

d) 

24. CVIPtools

25. a) Because the human visual system can perceive thousands of colors in a small spatial area, but only about 100 gray levels. Additionally, color contrast can be more dramatic than gray level contrast, and various colors have different degrees of psychological impact on the observer, b) spatial and frequency. Spatial: intensity slicing, divide the gray level range into subranges and map each subrange to a fixed color specified by RGB values. Frequency: Perform a Fourier transform on the image, and then apply a lowpass, bandpass, and highpass filter to the transformed data. These three filtered outputs are then inverse transformed and the individual outputs are used as the RGB components of the color image.

26.

|  |  |
| --- | --- |
| Input gray level ranges | Output RGB triples |
| 0 - 3 | 15,0,0 |
| 4 - 7 | 0,15,0 |
|  8 - 11 | 0,0,15 |
| 012 -15 | 15,15,0 |



27. CVIPtools. a) color image results, b) In both cases the image will be gray, not color. Depending on the image, and the shape selected, the contrast will be changed. c) color image output, different form (a), d&e) various answers depending on colors selected

28. CVIPtools. a) Colors vary, but mostly red and green (some purple), with light areas red and dark areas typically mostly green. b) Mostly blue, green and yellow. c) Various answers, highly dependent on the image, the cutoffs and the colors chosen.

29. CVIPtools. b&c) yes, you should see some correlation, the degree depends on the original image histogram and the mapping equations, d) they will be similar if the input image histograms are similar – areas of similar input gray levels will be the same color(s).

30. 1) Extract high frequency information, 2) combine high frequency image and the original image, 3) improve contrast. EXAMPLES: 1) edge detector, frequency domain highpass filter, perform a Fourier transform and extract phase information, 2) multiply them, add them, OR them, 3) histogram equalization or histogram stretch

31. CVIPtools. Should be able to recreate the images.

32. CVIPtools. d) adding edge information (high frequency) to original boosts them, creating a sharpening effect. The edge detection image may need to be remapped to BYTE before adding to a BYTE image. Often we need postprocessing via histogram modification to improve contrast. The phase image itself typically has a lot of noise, so it is difficult to eliminate that – edge preserving, smoothing can help – Kuwahara, anisotropic diffusion filters.

33. a)



b) 1) a natural log transform (base e), 2) the Fourier transform, 3) Filtering, 4) the inverse Fourier transform, and 5) the inverse log function – the exponential.

c) This filter will boost the contributions from R(r,c) (assumed to be high freq), while attenuating those from L(r,c) (assumed to be low freq).

34. CVIPtools. With experimentation, better results can be obtained, but it is subjective.

35. a) The unsharp masking algorithm has been used for many years by photographers to enhance images. It sharpens the image by subtracting a blurred (lowpass) version of the original image. This was accomplished during film development by superimposing a blurred negative onto the corresponding positive film to produce a sharper result. b) The original image is lowpass filtered, followed by a histogram shrink to the lowpass filtered image. The resultant image from these two operations is then subtracted from the original image, and the result of this operation undergoes a histogram stretch to restore the image contrast. This process works because subtracting a slowly changing edge (the lowpass filtered image) from faster changing edges (in the original), has the visual effect of causing overshoot and undershoot at the edges, which has the effect of emphasizing the edges. By the scaling the lowpassed image with a histogram shrink we can control the amount of edge emphasis desired.

36. CVIPtools. As the range between the lower and upper limit increases, more edge only information appears in the output image. Note: If the HSL color transform is used: extract Lightness band and perform unsharp masking on it, convert it back to FLOAT data type, then re-assemble the color bands and do the inverse HSL transform.

37. CVIPtools. Various answers depending on algorithm developed. Improvement expected due to more information and experience.

38. a) :To give an image a softer or special effect, or to mitigate noise effects, b) Image smoothing is accomplished in the spatial domain by considering a pixel and its neighbors and eliminating any extreme values with median filters or by averaging with neighboring pixels with mean filters. In the frequency it can be done with a lowpass filter.

39. a) They are all positive to perform some form of averaging, b) with an arithmetic mean filter all the coefficients are the same, whereas with a Gaussian filter they decrease as we move away from the center pixel., c) remapping after the convolution operation, usually to BYTE, d) more blurring occurs as we increase the filter mask size

40. a) It is blurred and has a painted effect, b) the pseudomedian flter

41. The FFT frequency ranges from 0 to N/2-1 and DCT frequency ranges from 0 to N-1. This is due to the fact that they have different implied symmetry; for an N×N image the DCT is actually 2N×2N, whereas the FFT is N×N. The FFT frequency terms are complex, so there are actually two values for each term. Thus, if we use the same frequency cutoff, then with the DCT we are actually retaining only half as many terms.

42. CVIPtools. a-c) Should look similar due to similar function – lowpass filter effect. Difference between FFT and spatial filters will appear in the form of lines in the spectra from the finite spatial filter size. d) Same as (a-c) and Gaussian spectrum is “smoother” than other spatial filters, due to gradual falloff of coefficients.

**Supplementary Exercises**

1. a) L = 9, so M = 10//2 = 5, so MAXIMIN = MAX[18,21,2,2,2] = 21

MINIMAX = MIN[32, 122,122,122,122]=32

PSEUDOMEDIAN = ½(21) + ½ (32)=26.5

b) ½ (75) + ½ (112) = 93.5, c) ½ (12) + ½ (32) = 22, d) ½ (100) + ½ (133) = 116.5

2. a) Region 1: mean = 2.33, σ=2; Region 2: mean = 3.22, σ=1.56

Region 3: mean = 3.22, σ=1.56; Region 4: mean = 2.33, σ=2

Therefore output = 3.22

b) Region 1: mean = 17.67, σ=3.5; Region 2: mean = 18.44, σ=7.58

Region 3: mean = 42.22, σ=14.94; Region 4: mean = 37.44, σ=16.82

Therefore output = 17.67

c) Region 1: mean = 2.44, σ=1.42; Region 2: mean = 3.33, σ=0.5

Region 3: mean = 2.77, σ=0.44; Region 4: mean = 1.78, σ=0.83

Therefore output = 2.77

3.

|  |
| --- |
| Mapping Table 1 |
|  O | H |
|  0 | 1.55 |
| 1 | 2.33 |
| 2 | 3.11 |
| 3 | 4.82 |
| 4 | 5.6 |
| 5 | 5.6 |
| 6 | 6.06 |
| 7 | 7 |
| Mapping 2 |
| OS | HS |
|  0 | 0.77 |
| 1 | 1.55 |
| 2 | 2.33 |
| 3 | 3.88 |
| 4 | 5.44 |
| 5 | 6.22 |
| 6 | 7 |
| 7 | 7 |

|  |
| --- |
| Histogram Specification Mapping Table |
| O | M |
| 0 | 1 |
| 1 | 2 |
| 2 | 3  |
| 3 | 4 |
| 4 | 4 |
| 5 | 4 |
| 6 | 5 |
| 7 | 6 |

|  |
| --- |
| Final Histogram |
| 0 | 0 |
| 1 | 10 |
| 2 | 5 |
| 3 | 5 |
| 4 | 16 |
| 5 | 3 |
| 6 | 6 |
| 7 | 0 |

4. a) As the block size is increased more of the original image is retained and the black border on the image border gets larger. b) You get the original with the details enhanced. c) The one that works the “best” is image dependent and depends on the how you define “best”. d) The results are not necessarily the same. If they are the same it is because the relative histograms of the two images are similar. If not, it is because the relative histograms of the two images are different.

5. Answers are opinion based, but should be supported with valid reasoning. One possible answer is that smoothing is missing, and *Gray level mapping II* is more useful than what is available under *Utilities*.

6. a) A histogram stretch works the best, with clipping from 1% to 3% (0.01 to 0.03). b) The block artifact is 16×16. The row and column values can be checked on the original image, but it is easier to crop out a few blocks where the grid is easy to see and stretching it on the screen and then checking the row or column values.istogram stretch works the best

7. a) With the lower clip percent the dark areas do not show as much detail. b) Block artifacts appear.

8. a) More details in the dark areas with a higher clip percent., b) More details in the dark areas with a higher clip percent, c) with smaller block sizes, smaller details appear, also the images appear less real and looks like low frequencies are gone – no large color blocks.

9. CVIPtools. Another method is histogram specification – uosng the defaults the sin() works the best and tanh() second best.

*Solutions for Chapter7: Image Restoration and Reconstruction*

1. a) . Image restoration requires knowledge of the degradation process and uses a model to reverse the distortion. Image enhancement takes advantage of the human visual system’s response and creates an image looks better, so does not model the “distortion”. b) They are alike in that both processes seek to improve the image for viewing.

2. 1) blurring caused by motion or atmospheric disturbance, 2) geometric distortion caused by imperfect lenses, 3) superimposed interference patterns caused by mechanical systems, 4) noise from electronic sources

3. a) See fig 7.1-1, b) Sample degraded images and knowledge of the image acquisition process are inputs to the development of a degradation model. After this model has been developed the next step is the formulation of the inverse process. This inverse degradation process is then applied to the degraded image, *d(r,c)*, which results in the output image, . This output image, , is the restored image which represents an estimate of the original image, *I(r,c).* Once the estimated image has been created, any knowledge gained by observation and analysis of this image is used as additional input for the further development of the degradation model. This process continues via a feedback loop, until satisfactory results are achieved.

4. a) , b) , c) No, other models can be defined; specifically a multiplicative noise model where the noise function is not added to the image but is multiplied by the image. A model should be found that matches the process under study, but the model given here is applicable to most images.

5. a) *Noise* is any undesired information that contaminates an image. b) 1) periodic noise, such as form mechanical vibration, 2) quantization (sampling) noise, in both space and brightness or film grain noise, 3) electronic fluctuations causing thermal noise, 4) malfunctioning pixel elements in the camera sensors, 5) faulty memory locations, 6) timing errors in the digitization process, 7) faulty optics, dust on lenses, etc, c) Gaussian noise caused by natural phenomena such as random electronic fluctuations; salt-and-pepper type noise is typically caused by malfunctioning pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. Uniform noise is useful, since it can be used to generate any other type of noise distribution, and is often used to degrade images for the evaluation of image restoration algorithms since it provides the most unbiased or neutral noise model. Negative exponential noise occurs in laser-based images. Radar range and velocity images typically contain noise that can be modeled by the Rayleigh distribution. Gamma noise is another exponential noise model, which can be used to model natural phenomena. d) Rayleigh, e) negative exponential, f) Periodic noise in images is typically caused by electrical and/or mechanical systems. This type of noise can be identified in the frequency domain as impulses corresponding to sinusoidal interference (see Figure 7.2-6).

6. A portion of the image is selected that has a known histogram, and that knowledge is used to determine the noise characteristics. If we subtract the known histogram, what is left is the noise model. The easiest subimage to use is one that should be a constant gray value.

7. CVIPtools. *Note: answers are image dependent, but these are typical.* a,b) With a variance of 25, the histogram retains the shape of the original image histogram, but is smoother; with a variance of 800 the histogram takes on the Gaussian shape as the noise dominates. c) yes, it appears Gaussian, d) they have similar shape, but the noise only histogram is smoother, (e) e-b) With a variance of 25, the histogram retains the shape of the original image histogram, but is smoother; with a variance of 800 the histogram is even smoother, but still has the shape of the original. e-c) yes, it appears as negative exponential noise, e-d) they have similar shape, but the noise only histogram is smoother, (f) f-b)With a variance of 25, the histogram retains the shape of the original image histogram, but is smoother; with a variance of 800 the histogram is even smoother, but still has the shape of the original. f-c) yes, it appears Gaussian, f-d) they have similar shape, but the noise only histogram is smoother

8. a) order filters, mean filters, and adaptive filters. b) Mean filters will blur the image, but are simple to implement and fast; order filters will also blur the image and are relatively easy to implement but not typically as fast as mean filters (depending on the type); adaptive filters generally provide the best results and minimize blurring, but are more computationally intensive and complex., c) In most cases, the adaptive filters will work the best. This is because they modify their behavior based on the underlying pixel characteristics, usually measured by local image statistics.

9. a) 119, 99, 10, b) 255, 100, 12, c) 111, 0, 9, d) 183, 50, 10.5, e) 118, 98.4, 10.4

10. CVIPtools.

11. a) 132.2, 87.2, 10.4, b) 120.1, 98, 10.2, c) 168.54, 98.2, 10.7, d) 127.4, 58.93, 7.9, e) 124.2, 98.1, 10.3, f) 124.2, 98.1, 10.5, g) 144.1, 92.5, 10.5

12. CVIPtools. Yes, noise mitigation can be seen in the image spectra by the smoothing, or lowpass filtering effect. Because noise dominates at high frequencies, LP filters will help mitigate noise effects.

13. *Subimage1*:σn2 = 100; σl2 = 2,132.4444; ml = 132.2222

MMSE output: 121.5

*Subimage2:* MMSE output: 97.9, *Subimage3*: MMSE output: -113

14. a) Better at retaining edges, especially with much noise, b) Better at retaining edges and corners, especially with much noise, c) It retains more of the original image details, while still removing noise, but it is more complex so requires more computational time.

15. a) Examples include poor lens focus and motion of the camera. . A *spatially-invariant* degradation affects all pixels in the image the same, the pixel’s location does not affect the distortion. b) Examples include imperfections in a lens or movement of individual objects in the scene. . *Spatially-variant* degradations are dependent on spatial location and are more difficult to model.

16. Point Spread Function. b) It must be linear and spatially-invariant, c) uniform, with a constant blur in a linear direction, and Gaussian, where the blur function is shaped like a Gaussian which decreases over space (see Fig 7.4-1), d) After the PSF is determined, a model is developed to reverse the process. The application of the inverse model is called *deconvolution*. When the exact degradation function is unknown, which is typically true in practice, then the process is referred to as *blind deconvolution* and the PSF must be estimated.

17. a) Optical Transfer Function and Modulation Transfer Function; the OTF usually refers to the response of the optics in an imaging system, and the MTF refers to the response of the entire imaging system, including the optics. Some authors will use these terms interchangeably. These both refer to the response in the frequency domain, and represent the Fourier transform of the PSF. b) Images are typically NOT stationary. The stationary attribute is a mathematical property of the frequency content of a signal. A stationary signal has frequency content that does not change in space (or time). For an image this means the frequency content is reasonably the same throughout the image. This is not true; for example, at object edges there is much more high frequency energy than in areas of constant color (or gray level). Finely textured areas have much more high frequency energy than coarse textures.

18. a) Noise energy tends to be equally distributed across the spectrum, while real images tend to have energy concentrated in the low frequency regions. The inverse filter is derived based on the assumption of no noise. Thus, with noise, the high frequency energy from the noise will tend to swamp out the image signal.  Also see answer 19b below.

19. a)



The power spectrum ratio is the related to the signal-to-noise ratio inverted. b)

Spatial Frequency

N/2

−N/2

0

Wiener Filter

Response

Inverse Filter Response

Since high frequency energy is primarily caused by noise, the attenuation of the distorted signal in the high frequency range by the wiener filter achieves better results with noise than the inverse filter which boosts the distorted signal at high frequencies.

20. CVIPtools. a) Without noise the inverse filter can perform as good as the inverse filter, because the wiener becomes an inverse filter without noise. b) The wiener filter results are

much better with noise in the image. c) with noise variances of 800, the results are much worse than with noise variance of 100.

21. a) The constrained least squares (CLS) filter provides an alternate to the practical Wiener filter by replacing the power spectrum ratio with a function that varies with frequency. This filter was initially developed to eliminate some of the artifacts caused by Wiener filters. This is done by including a smoothing criterion in the filter derivation, so that the result will not have undesirable oscillations (these appear as "waves" in the image), as sometimes occurs with other frequency domain filters. b-c) CVIPtools

22. CVIPtools. . a) Without noise the inverse filter can perform as good as the inverse filter, because the wiener becomes an inverse filter without noise. b) The wiener filter results are

much better with noise in the image. c) with noise variances of 800, the results are much worse than with noise variance of 100.

23. a) 

b) , c) , When  , this filter becomes a standard Wiener filter, and when  , this filter becomes the inverse filter. As  is adjusted, the results vary between these two filters, with larger values providing more of the Wiener filtering effect

d) , , e) , .

24. CVIPtools. Results as good can be obtained because parameters can be set to make them the same. It is possible to obtain better results, because we have more parameters to control and experiment with.

25. CVIPtools. Results as good can be obtained because parameters can be set to make them the same. It is possible to obtain better results, because we have more parameters to control and experiment with.

26. a) *Block-by-block* or *subimage-by-subimage* processing is used in the frequency domain. With this approach the image is divided into blocks, typically between 8×8 and 32×32 pixels, and then the results are combined. b) The *blocking effect* or *blocking artifact* appears in images as false lines between image blocks. This is caused by the adaptive filter characteristics changing at block boundaries, which may create artificial brightness changes at block boundaries. c) 1) Post-processing the object boundaries with lowpass filters can help to mitigate these effects, 2) Overlap the subimages by using a window function, which allows neighboring subimages to slowly merge instead of abruptly change at the boundaries.

27. CVIPtools. a) It is possible to improve, but not easy, try notch filters and frequency restoration filters. b) Periodic noise can be easily removed with these filters.

28. a) 1) spatial transform and 2) gray level interpolation. b) Gray level interpolation is necessary since pixel row and column coordinates provided by the spatial transform are not necessarily integers. To find the corresponding gray value, the surrounding values in the distorted image must be used for interpolation to obtain an approximation to “correct” value. c) The *nearest neighbor method* has the advantage of being easy to implement and computationally fast. With the nearest neighbor approach, object edges will tend to appear jagged or blocky. The *neighborhood average method* will provide a better output image with smoother object edges, but the result will be slightly blurry and it is more computationally intensive. *Bilinear interpolation* provides the best visual results, but is the most complex and thus has the longest processing time and is the most difficult to implement.

29. The values correspond to these coordinates in the distorted image: 



30. The values correspond to these coordinates in the distorted image: 

a) 

b) 

31. a) 

b) 

32. CVIPtools. c) bilinear interpolation is best, but most computationally intensive. Nearest neighbor has blocky artifacts, and neighborhood average is slightly blurry.

33. CVIPtools. c) bilinear interpolation is best, but most computationally intensive. Nearest neighbor has blocky artifacts, and neighborhood average is slightly blurry.

**Supplementary Exercises**

1. Sort the inner 3x3 -> [125, 132, 143, 144, 146, 176, 187, 189, 199]. The median value is 146, minimum is 125, max is 199. The median is between min and max so we go to level 2. The current value, 199, is not between min and max, so we output the median, 146.

2. Sort the inner 3x3 -> [125, 132, 143, 144, 146, 176, 189, 199, 255]. The median value is 146, minimum is 125, max is 255. The median is between min and max so we go to level 2. The current value, 199, is between min and max, so we output the current value, 199.

3. Sort the inner 3x3 -> [143, 144, 176, 187, 255, 255, 255, 255, 255]. The median is 255, the min is 143, the max is 255. The median is not between min and max so we increase the window size to 5x5 and sort->

[0,0,0,27,111,111,113,119,125,125,125,125,143,144,155,176,186,187,188,255,255,255,255, 255,255]

Median is 143, min is 0, max is 255. Current value is 255, so output the median, 143.

4. a) Yes, noise only images are typically stationary. This means that random subimages cropped from the original image will have spectra that are similar. Such as these from random Gaussian noise subimages:

 

b) No, typical real images are not stationary. If random subimages are cropped from an image, their spectra will not necessairly be similar. For example these spectra from random subimages cropped from a real image:

 

5. a) [ 34, 37, 45, 47], b) [10, 20, 31, 43, 31, 19, 9], c) [32, 39, 42, 50]

6. a) $\left[\begin{matrix}\begin{matrix}34&37\\34&37 \end{matrix}&\begin{matrix}45&47\\45&47\end{matrix}\\\begin{matrix}34&37\\34&37\end{matrix} &\begin{matrix}45&47\\45&47\end{matrix}\end{matrix}\right]$

b) $\left[\begin{matrix}\begin{matrix}43&31\\31&43\end{matrix}&\begin{matrix}19&9\\31&19\end{matrix}\\\begin{matrix}20&31\\10&20\end{matrix} &\begin{matrix}43&31\\31&43\end{matrix}\end{matrix}\right]$

c) $\left[\begin{matrix}\begin{matrix}32&32\\39&39\end{matrix}&\begin{matrix}32&32\\39&39\end{matrix}\\\begin{matrix}42&42\\50&50\end{matrix} &\begin{matrix}42&42\\50&50\end{matrix}\end{matrix}\right]$

7. For the maximum widow size of 7x7, the mean ≈ 5.45 and σl2 ≈ 6.38, so the local-variance ratio = 5.0/6.38 = 0.784.

The 5x5 mean is 6.28 and variance is 6.127, so = 5.0/6.127 = 0.816.

The 3x3 mean is 7.44 and variance is 6.527, so = 5.0/6.527 = 0.766

a) 0.784 is not less than the threshold of 0.5, so the output is the MMSE from the 7x7, which is 6.89 ≈ 7

b) 0.784 is not less than the threshold of 0.6, so the output is the MMSE from the 7x7, which is 6.89 ≈ 7

c) 0.784 is not less than the threshold of 0.7, so the output is the MMSE from the 7x7, which is 6.89 ≈ 7.

8. a) [ 20, 12, 12, 20]; [5,10,11, 12, 11, 10, 5], [20, 12, 12, 20]

b) *0 degrees backprojection* $\left[\begin{matrix}\begin{matrix}20&12\\20& 12\end{matrix}&\begin{matrix}12&20\\12&20\end{matrix}\\\begin{matrix}20&12\\20&12\end{matrix} &\begin{matrix}12&20\\12&20\end{matrix}\end{matrix}\right]$

*45 degrees backprojection* $\left[\begin{matrix}\begin{matrix}12&11\\11&12\end{matrix}&\begin{matrix}10&5\\11&10\end{matrix}\\\begin{matrix}10&11\\5&10\end{matrix} &\begin{matrix}12&11\\11&12\end{matrix}\end{matrix}\right]$

*90 degrees backprojection*$\left[\begin{matrix}\begin{matrix}20&20\\12&12\end{matrix}&\begin{matrix}20&20\\12&12\end{matrix}\\\begin{matrix}12&12\\20&20\end{matrix} &\begin{matrix}12&12\\20&20\end{matrix}\end{matrix}\right]$

Superimpose or sum these three, we get the following for our approximate reconstructed image:

$$\left[\begin{matrix}\begin{matrix}52&43\\43&36\end{matrix}&\begin{matrix}42&45\\35&42\end{matrix}\\\begin{matrix}42&35\\45&42\end{matrix} &\begin{matrix}36&43\\43&52\end{matrix}\end{matrix}\right]$$

We can see that the resulting image retains the general shape of the original shape, but with a loss of contrast. The implications is that the backprojections need to be properly scaled.