Lab 2 - Neighborhood Processing & Filters

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1 Introduction

This lab was for us to get familiar with the fundamentals of image processing. In the sections of this assignment, we first try neighborhood processing and introduce low-level filters commonly used to analyze images. After that, we will see how these mathematical concepts relate to practice by working through fundamental tasks such as denoising and segmentation. By the end of this assignment, we will have an overall understanding of the following;Gaussian and Gabor filters, Edge detection and image denoising, Texture-based image segmentation.

2 Neighborhood Processing

Question 1.

1. The correlation operator looks for a relation of a point (pixel) with points to the right and/or below it, whereas convolution looks a points to the left and/or above it.

2 .The two operations are equal when an image is symmetric around a pixel.

3 Low-level filters

3.1 Gaussian Filters

3.1.1 1D Gaussian Filter

3.1.2 2D Gaussian Filter

Question 2.

In essence the two operations are equal. That is, they give the same result. However, if possible, computational cost is reduced when first performing horizontal 1D convolution followed by 1D vertical convolution. For a kernel of size K, performing (2) entails $2 * K$ calculations per pixel, whereas performing (1) entails K^2 calculations per pixel. This is method is only possible if the kernel is separable.

3.1.3 Gaussian Derivatives

Question 3.

The second order derivate of the Gaussian Kernel is of interest to design since it is useful to help detect blobs in an image or for edge detection.

3.2 Gabor Filters

3.2.1 1D Gabor Filters

3.2.2 2D Gabor Filters

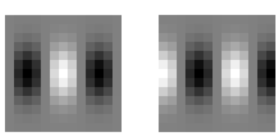
Question 4.

λ: The wave length of the sinusoidal wave.
θ: Rotation parameter, can change the direction of the Gabor filter. That is, when $\theta = 0$, the filter will respond to only horizontal features.
ψ: The phase offset
σ: The width of the Gaussian envelope. That is, how wide the Gaussian signal is until the signal is zero.
γ: regulates to what extend the Gaussian signal is elliptical.

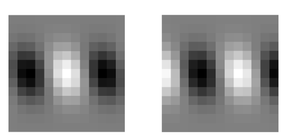
Question 5.

Figure 1: Effect of θ

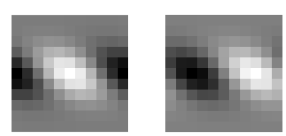
(a) $\theta = 0$



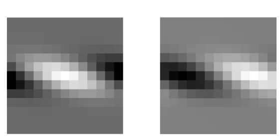
(b) $\theta = pi/8$



(c) $\theta = pi/4$



(d) $\theta = pi/3$



(e) $\theta = pi/2$

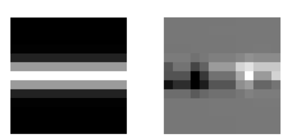
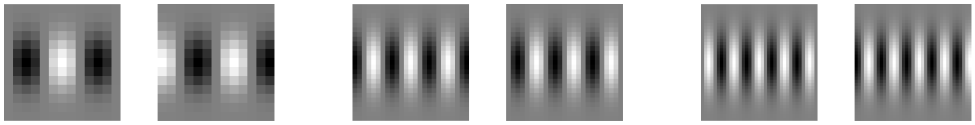


Figure 2: Effect of σ

(a) $\sigma = 1$ (b) $\sigma = 2$ (c) $\sigma = 3$



(d) $\sigma = 4$ (e) $\sigma = 5$

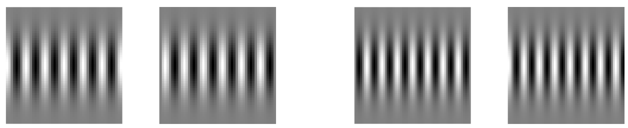
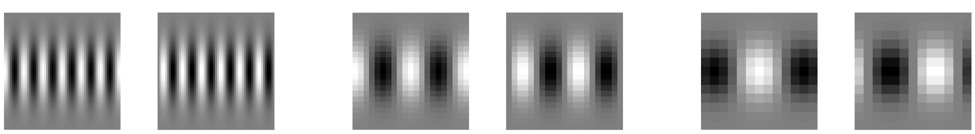
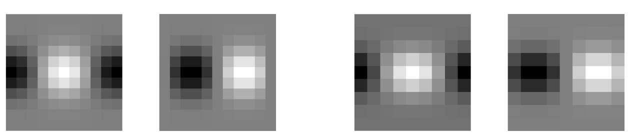


Figure 3: Effect of γ

(a) $\gamma = 0.1$ (b) $\gamma = 0.3$ (c) $\gamma = 0.5$



(d) $\gamma = 0.7$ (e) $\gamma = 0.9$



4 Applications in image processing

4.1 Noise in digital images

4.2 Image denoising

4.2.1 Question 6

1.
PSNR between image1 and salt&pepper is 16.1079 dB.

2.
PSNR between image 1 and guassian is 20.5835 dB.

4.2.2 Question 7

1.

Figure 4: Salt and pepper image with different box filter denoise

Figure 5: Gaussian image with different median filter denoise

Figure 6: Salt and pepper image with different box filter denoise

Figure 7: Gaussian image with different median filter denoise

2.

Table 1: Tables of PSNR values of different denoise filters

	Box		median	
	Salt & Pepper	Gaussian	Salt & Pepper	Gaussian
3x3	23.39	26.32	27.69	25.46
5x5	22.64	23.66	24.50	23.80
7x7	21.42	21.99	22.37	22.08

In the table can be seen that when enlarging the kernel size for every filter, that for every different filter the PSNR value decreases in this case. For the PSNR is accepted that how higher the value, how better the quality of the image is in comparison to the. So increasing the kernel size decreases the performance of the filters in terms of PSNR.

3.

For the Salt and Pepper noise the median filter with kernel size 3x3 is the best performing filter with a PSNR of 27.69 dB. The salt and pepper noise is not large in pixel numbers but has more contrast to the other pixels than Gaussian noise, when removing this noise while choosing the median pixel from a 3x3 kernel you are most likely to remove the influence of this contrasting noise instead of the mean value.

For the Gaussian image the box filter with kernel size 3x3 is the best performing filter with a PSNR of 26.32 dB. The guassian image has more pixels with noise but less contract to the pixels than salt&peppers noise, when removing this noise with a box filter with a 3x3 kernel you are most likely to decrease the difference between some gray noise and the image.

4.

For the gaussian we choose for a 3x3 kernel, this kernel seemed best performing with the other filtering methods and is therefore used. Furthermore is a 3x3 kernel, a small size, better for images with small features such as grass and with fast changing color patterns.

Figure 8: Gaussian image with gaussian 3x3 filter with different sigma

Table 2: My caption

	Gaussian
0.25	20.58
0.5	24.29
1	26.60
2	26.15
3	26.04

5.

The influence of the sigma or standard deviation is that the PSNR increases from 0.25 to 0.5 to 1 and then decreases from 1 to 2 to 3. So, the filter reaches his best performance with a standard deviation of 1 and then decreases in performance again.

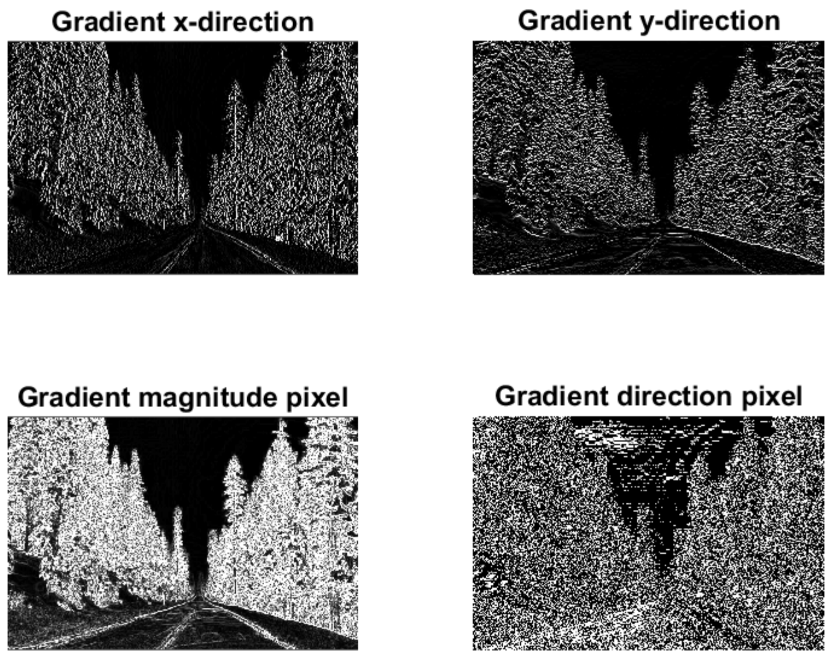
6.
In figure 9 can be seen that although performing in the same ballpark with the PSNR score (26.60 vs 26.32) the visual difference between these 2 images is visible. The box filter with a 3x3 kernel has a smoother appearance and a less visible noise.

Figure 9: Comparison of gaussian and box filter

4.2.3 Question 7

1.

Figure 10: Edge detection



4.3 Edge detection

4.3.1 Question 8

Figure 11: Edge detection

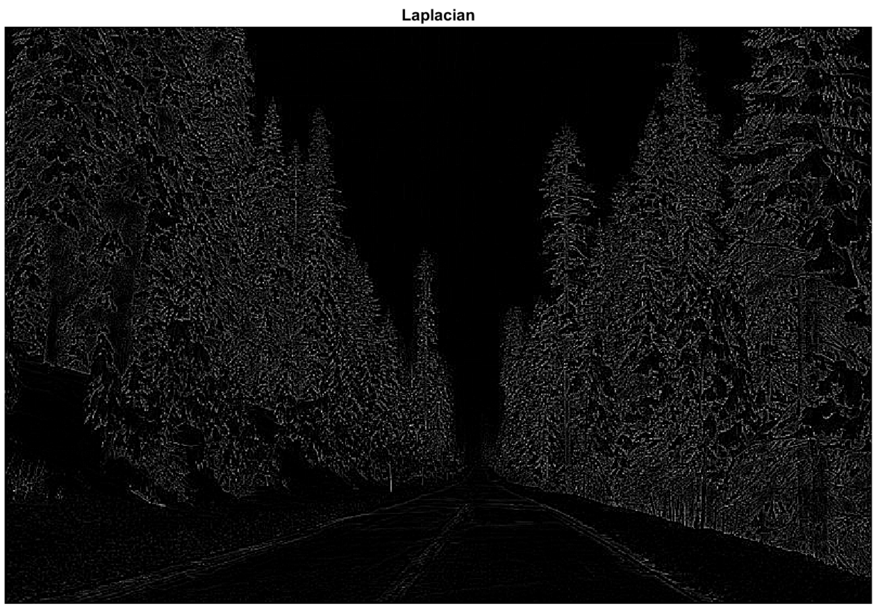


Figure 12: Edge detection

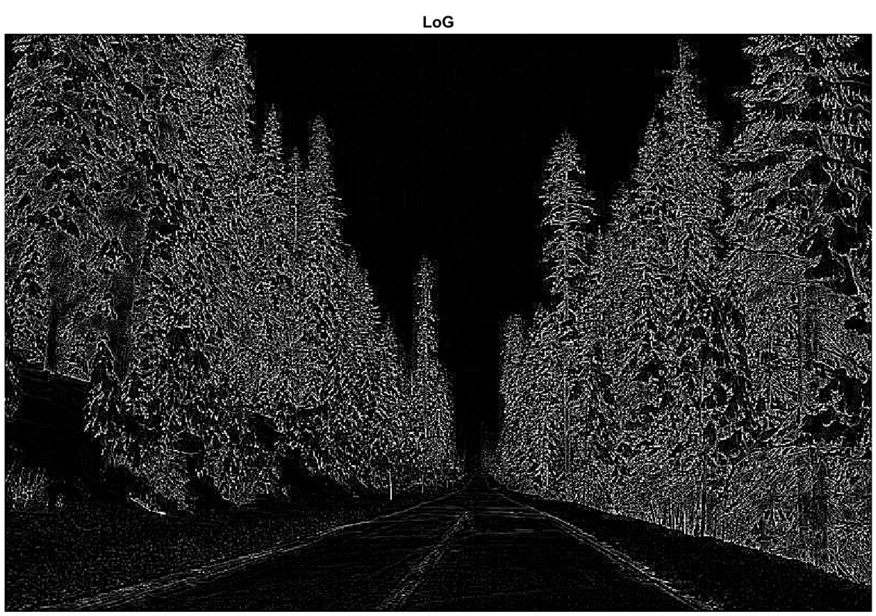


Figure 13: Edge detection

2.
The difference between the 3 methods is seen in intensity of the edge colors. The LoG method creates more noise but brighter edges, the Laplacian method creates less noise but lower intensity edges. The DoG method creates smoother edges but also lower intensity edges. The values of the sigma's can be altered for different results.

3.
Fisher et al [1] reasons that "Because these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise." Because this sensitivity to noise the Gaussian filter is used to reduce this for better results.

4.
Marr et al[1] describe the golden ratio as 1.6 between sigma1 and sigma 2, we have chosen the values sigma1 as 3 and sigma2 as 0.5. For this picture this seemed to create less noise and reasonable visible edges. The golden ratio is of course not used here, but without qualitative measures for this, the best ratio and values are very subjective. What is working for a human observer for edges can also be not a good setting for a shape detection algorithm.

5.
All the three methods in comparison to the first order derivative methods are better performing with cleaner edges and less noise. Also the intensity of the colors is a big difference, with high intensity in the first derivative method.

6.
Object recognition algorithms and software to recognize the road and outline extraction software to remove the background from the object(road).

4.4 Foreground-Background Separation

Question 10.

1.
Kobi: the lighter spot on the head of Kobi is considered background, because it is close to the color of the floor. Polar: with the polar bear it is hard to include the black nose in the foreground. Probably since it is not surrounded by the white fur of the bear in the image and therefore mistakenly assigned

to background.
Robin: For both Robins the legs are cut off from the foreground. Probably because there are few pixels with the legs around it (the legs are skinny). Cows: the head of the drinking calf is considered background. Probably because it is very dark compared to the rest of the cows. SciencePark: the separation seems merely based on the darkness of the circles in the upper half of the image.

2.
Since we include the whole spectrum of values of θ, no need to use that. Changing to smaller steps, doesn't really help as well.
Kobi: Parameter tuning does not help the separation concerning the bright spot on the dogs head.
Polar: A higher σ leads to bigger foreground area, which will include the nose. However it does also include parts of the flowers. λ hardly has influence. So we keep original parameter values
Robin: Increasing the λ works well for both Robins. Same holds for decreasing σ. Combining both adds to the effect. `sigmas = [0.1, 0.2]` and `lambdas = 2.^(0:(n-2)) * lambdaMin * 10`
Cows: Tuning Parameters doesn't improve separation. So we keep original parameter values
SciencePark: Tuning Parameters doesn't improve separation. (Moreover, don't know what we're looking at). So we keep original parameter values

3.
For all images, we hardly see any difference in the magnitude images. We found it impossible to conclude anything.

References

[1] Theory of Edge Detection. // D. Marr; E. Hildreth. // Proceedings of the Royal Society of London. Series B, Biological Sciences, Vol. 207, No. 1167. (Feb. 29, 1980), pp. 187-217.

[2] Laplacian/Laplacian of Gaussian // ©2003 R. Fisher, S. Perkins, A. Walker and E. // wolfart.https://homepages.inf.ed.ac.uk/rbf/HIPR2/log.htm