Assignment 2 Neighbourhood Processing and Filters

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Introduction

This report will look at neighbourhood processing, low-level filters and their applications in image processing. To explore neighbourhood processing, we will look at correlation and convolution. To discuss low-level filters, we will look at Gaussian filters and Gabor filters. Finally, in applications in image processing, we will look at noise in digital images, image denoising, edge detection and foreground-background separation.

1 Neighbourhood Processing

Question 1

1. Correlation represents the similarity between signals. Convolution represents the impact of one signal on another signal. Both operators treat the mask **h** the same. The correlation operator leaves the image **I** unchanged. The convolution operator however, mirrors local regions of **I** about the origin.

2. Correlation and convolution operators are equivalent when a mask **h** is centrosymmetric.

2 Low-level filters

Question 2

Some 2D Gaussian kernels can be broken down to a 1D Gaussian in the x direction and a 1D Gaussian in the y direction. These will give the same result as the 2D Gaussian kernels, however their complexity will be linear $O(n)$ instead of quadratic $O(n^2)$. This breaking down of the 2D Gaussian can only be done with separable kernels. This is a special matrix kernel that can be separated into the outer product of two vectors.

Question 3

The second order Gaussian kernel is also called the Laplacian of Gaussian. It highlights the changes in intensity, so it is used for edge detection in an image. The parts of the image that do not change in intensity will get zero values.

Question 4

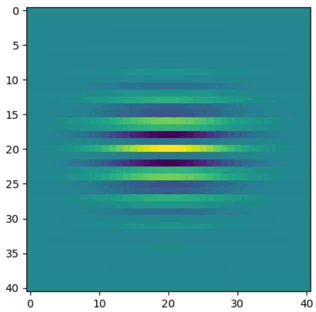
λ is the wavelength of the sinus. This means that a bigger λ makes the Gabor filter wider.
θ is a parameter that controls the orientation of the Gabor filter. When θ is zero, so the orientation is zero, the Gabor filter will be in the vertical position.
ψ is the phase offset of the complex sinusoidal. This is a value in degrees.
σ is the standard deviation in the Gaussian. This parameter controls the overall size of the Gabor filter.
γ is the aspect ratio of the Gabor filter. This parameter controls the height of the Gabor filter.

Question 5

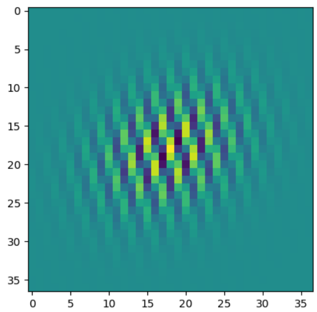
The parameters values that are used for the visualisations are : $\sigma = 5$, $\theta = \frac{\pi}{4}$, $\lambda = \frac{\pi}{4}$, $\psi = 0$, $\gamma = 0.75$ unless specified otherwise.

Theta

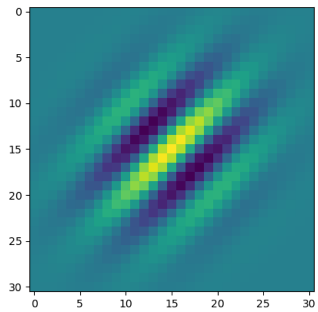
The σ is changed from $\frac{\pi}{2}$ to $\frac{\pi}{4}$.



(a) $\theta = \frac{\pi}{2}$



(b) $\theta = \frac{\pi}{3}$

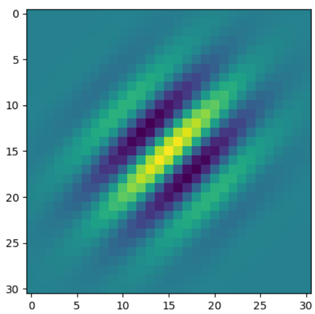


(c) $\theta = \frac{\pi}{4}$

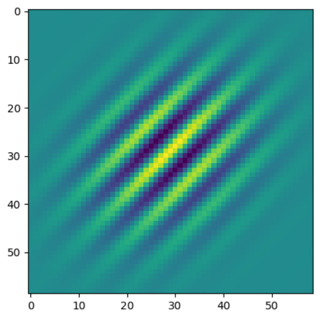
Figure 1: θ

Sigma

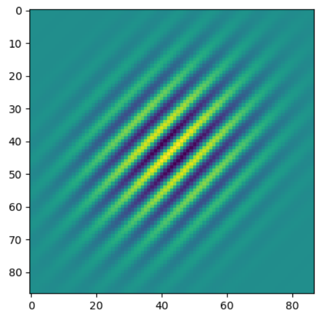
The σ is changed from 5 to 15.



(a) $\sigma = 5$



(b) $\sigma = 10$

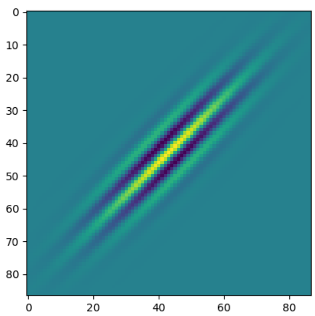


(c) $\sigma = 15$

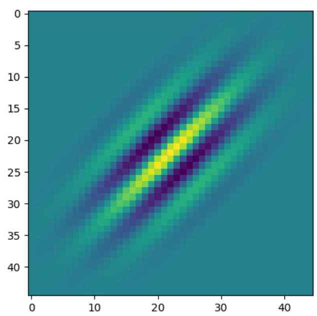
Figure 2: σ

Gamma

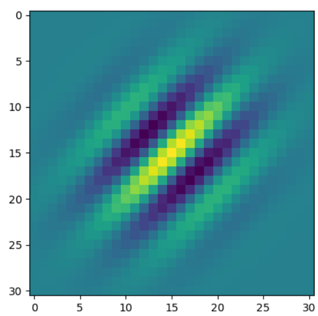
The γ is changed from 0.25 to 0.75.



(a) $\gamma = 0.25$



(b) $\gamma = 0.50$



(c) $\gamma = 0.75$

Figure 3: γ

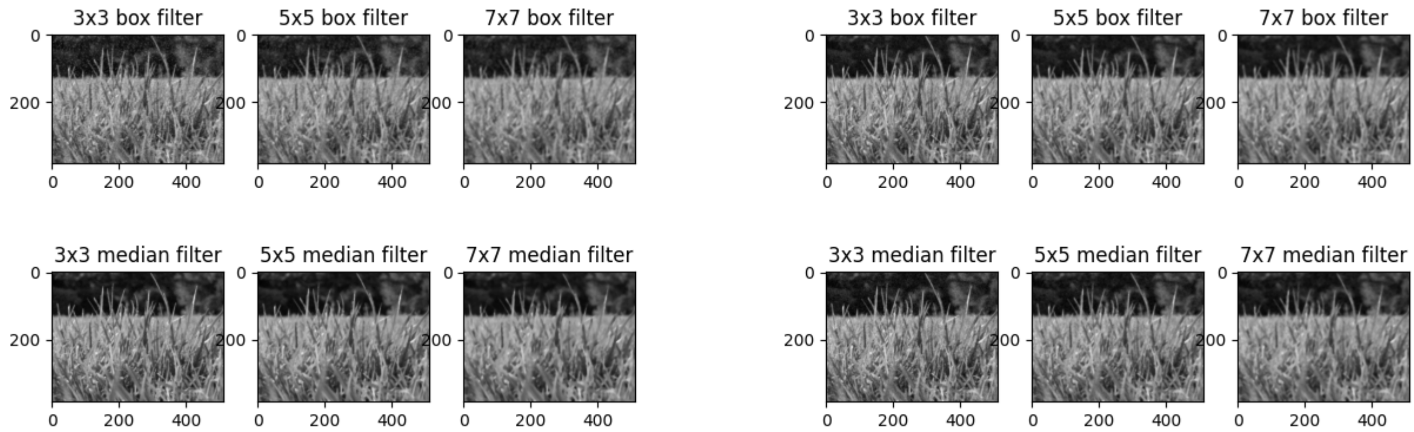
3 Applications in image processing

Question 6

3.1 Noise in digital images

1. PSNR (peak signal-to-noise ratio) represents the ratio of the maximum value of a signal and the noise that disturbs the measurement and affects the quality of the representation. A high value means less noise in signal.
2. 16.11 dB
3. 20.58 dB

Question 7



(a) saltpepper

(b) Gaussian image

Figure 4: Filters

1.

	3x3	5x5	7x7
Median	27.86	24.67	22.54
Box	23.39	22.63	21.41

Table 1: Saltpepper

	3x3	5x5	7x7
Median	25.53	23.94	22.24
Box	26.22	23.65	21.93

Table 2: Gaussian

2.

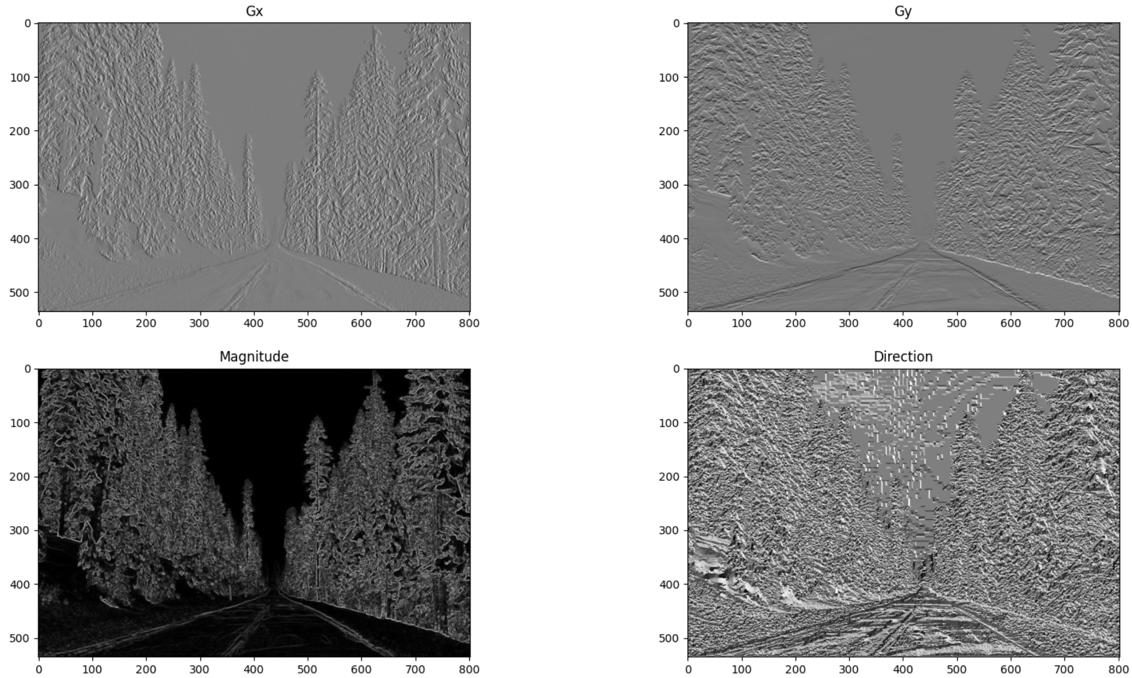
3. For saltpepper noise the median filter is best. For Gaussian noise the 3x3 box filter is best.

4. A Gaussian filter with a 3x3 kernel and a sigma of 1 yields the highest PSNR therefore this is the best option.
5. Increasing sigma assigns more weight to pixels further from the center pixel and decreases the weight of pixels close to the center. So with a higher sigma the smoothing pixels further from the center have more weight, this may cause extra noise since the pixels further from the center represent different objects.

Sigma	1	2	3	4
PSNR	26.81	26.38	26.29	26.29

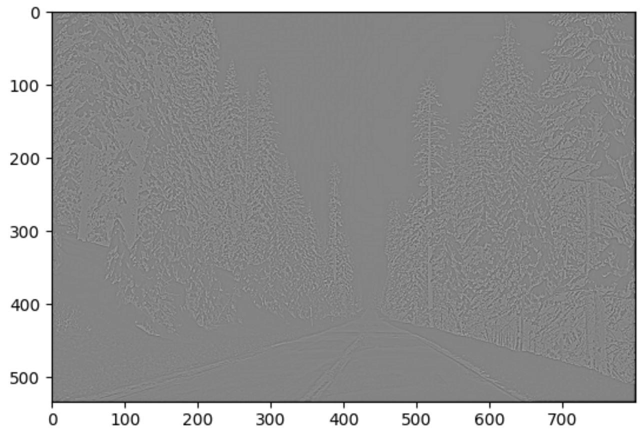
6. The median filter is a non-linear filter it removes noise by taking the median value (middle value of all ordered values in the kernel) of the filters pixel values. The box filter removes noise from an image by taking the average of pixel values in the filters domain. The Gaussian filter kernel has the shape of a Gaussian distribution, this means that it can be seen as a weighted average of the pixel neighbourhood. Where a higher weight is assigned to pixels close to the center pixel.

Question 8

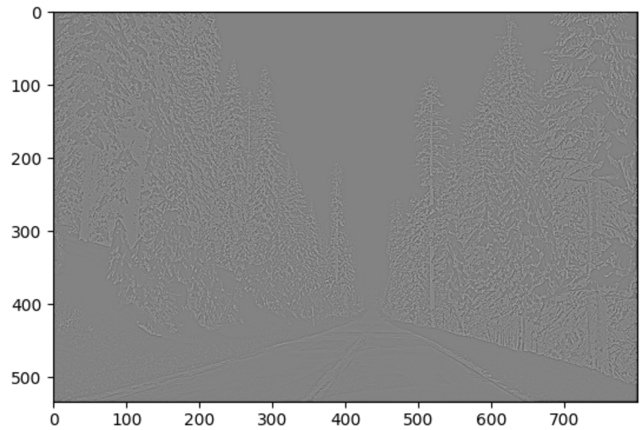


Gx shows the change in pixels values in the x direction, Gy shows the change in pixel values in the y direction, Direction shows the direction in which the pixel values increase the quickest, magnitude shows how fast the values increase.

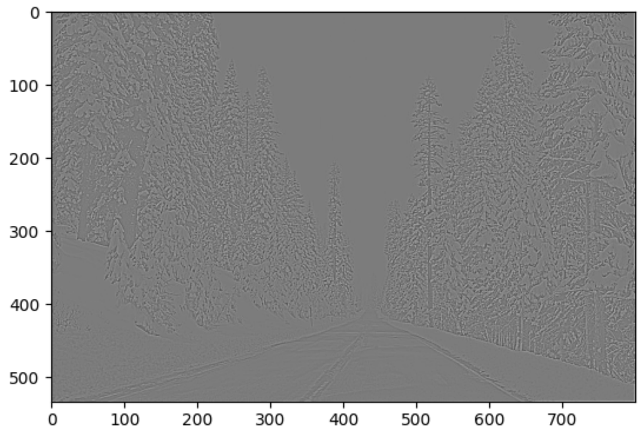
Question 9



(a) Smooth and apply Laplacian



(b) Directly apply LoG kernel



(c) Applying the DoG

Figure 5: Results of different LoG techniques.

1.

2. There is no difference between applying the Laplacian after the Gaussian (5a) and directly applying the LoG (5b), because convolution is associative, thus $(I * G_\sigma(x, y)) * L = I * (G_\sigma(x, y) * L)$. Because a Gaussian kernel is separable however, the first method is computationally faster than the second method. There is a difference between these two methods and the third method, i.e. applying the difference of Gaussians (DoG) kernel (5c). The DoG kernel is an approximation of the LoG with inverted signs. Convolving the image with the DoG thus results in the opposite of the image convolved with a LoG.

3. First convolving the image with a Gaussian before applying the Laplacian is not only needed to get the LoG, it also helps to denoise the image. Taking the derivative of a noisy image results in a noisy derivative which is not suited for purposes such as edge detection.

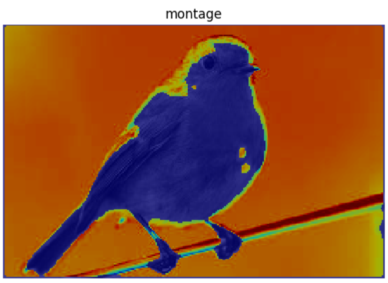
4. According to Hildreth and Marr (1980), the best ratio between σ_2 and σ_1 is approximately 1.6. Because a wide Gaussian has to be subtracted from a narrow Gaussian, there is a need for two standard deviations to describe both Gaussians.

5. To detect the road, it could be possible to apply a line finding algorithm to the LoG or DoG filtered image. Lines running alongside the road and meeting in the horizon can then be found and the road can be isolated.

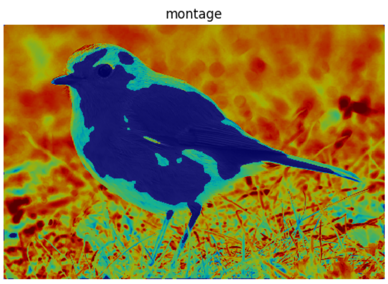
4 Foreground-background separation

Question 10

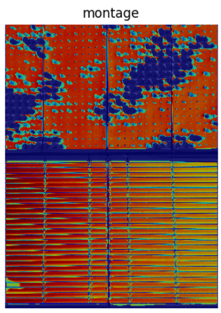
1. The Foreground-Background Segmentation Algorithm was executed using the given parameters for the filters in the Gabor-filterbank. To extend the background pattern in the images, wrap padding of an appropriate size was applied to each image before applying the Gabor filters. Furthermore, the standard deviation of the Gaussian kernels used to smooth the Gabor magnitude features was set to be twice the standard deviation used in the Gabor filter they were produced with (Jain & Farrokhnia, 1991). The magnitude matrices were 0-padded before applying the Gaussian smoothing filter.
   Out of the images, the ones containing the robin (fig. 6a and 6b) are segmented most successfully, where the best result is achieved with the picture of the robin with a blurry background (6a). The picture of the pattern on the outside of the Science Park building (fig. 6c) is also quite accurately segmented, with the only downside being the fact that a shadow is falsely considered to be on the foreground.
   Among the other images, the results are mixed. In the image of the dog (fig. 6d), the black dots in the background pattern are considered to be part of the foreground along with almost the whole dog and the shadow it casts on the floor. Furthermore, in the cows image (fig. 6e) only the dark sports on the cows are considered foreground and in the polar bear image (fig. 6f), only the green spots in between the flowers and the nose of the bear are considered background.



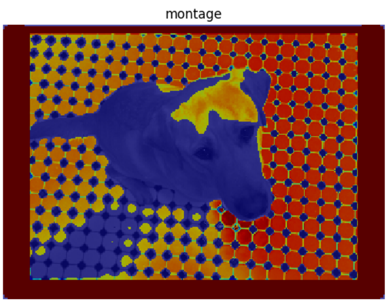
(a) Robin 1



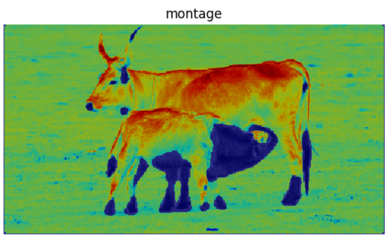
(b) Robin 2



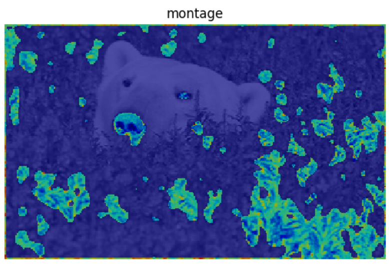
(c) SciencePark



(d) Kobi

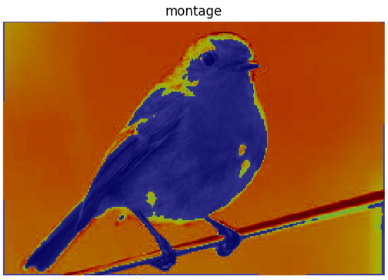


(e) Cows

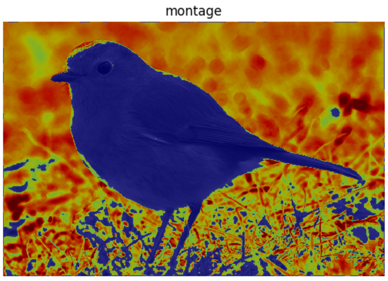


(f) Polar

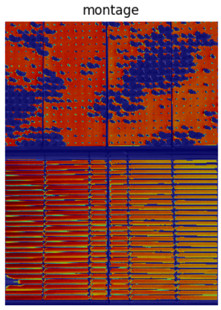
2. Changing λ or $\Delta\theta$ did not lead to significant improvement in segmentation. Changing σ however, did improve the results in the segmentation of some images. σ was changed from 1 and 2 to 0.4 and 0.8.
   The main improvements can be seen in the two robin images (7a and 7b), which are near perfectly segmented, as can be said of the Science Park image (7c). The polar bear image (7f), is also close to being perfectly segmented, since the nose is still considered to be part of the background. After the changes, a larger area of the dog's head is considered foreground (7d), which is an improvement. However, a larger part of the shadow is also considered foreground. Although not in their entirety, the cows are better distinguished from the background.
   The lower values of sigma presumably leads to more smoothing of the background than the foreground, especially when the background consists of grass. Since a blurry background led to better segmentation in the robin image, this could be the reason for better performance.



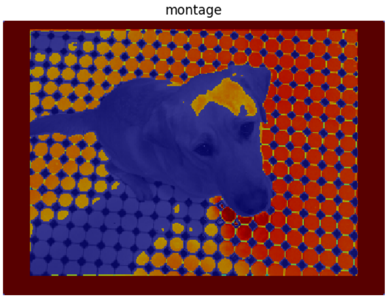
(a) Robin 1



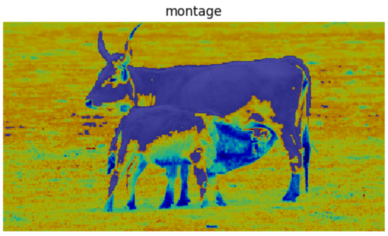
(b) Robin 2



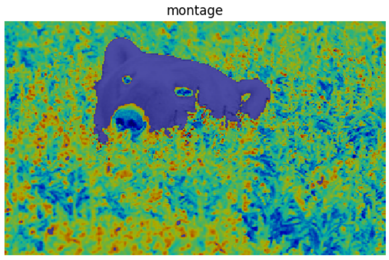
(c) SciencePark



(d) Kobi



(e) Cows



(f) Polar

3. Not smoothing the magnitude images will result in a noisy segmentation, which visually corresponds to more pixels in the background being assigned to the foreground cluster. Smoothing decreases local peak intensities, reducing differences between values making them more suitable for K-Means clustering.

Conclusion

In this assignment we learned about how different image kernels work. We saw that these kernels can be used to detect edges, by using filters such as a Sobel or LoG filter to compute the derivatives of an image. Furthermore, Gabor filters can be used to separate the fore- and background of an image.

References

Hildreth, E., & Marr, D. (1980). Theory of edge detection. *Proceedings of Royal Society of London*, *207*(187-217), 9.

Jain, A. K., & Farrokhnia, F. (1991). Unsupervised texture segmentation using gabor filters. *Pattern recognition*, *24*(12), 1167–1186.