Advanced Machine Learning – Assignment #1

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Question 1

1.d

All following comments will relate to Fig.1, in which we specify the numbers of the figures also used in the following argument.

In the first figure, we obtain a 2D gaussian filter applying separately a 1D gaussian filter on the x-axis and the y-axis. It is possible because the gaussian filter is separable, it means that a 2D gaussian filter can be written as the product of two 1D gaussian filters along the axis, and because the convolution is a linear operation.

The separability of the gaussian filter allows us to reduce the computational complexity with respect to directly applying a 2D gaussian filter: this because the application of a 2D gaussian filter with size N on a picture of pXp pixels has a p^2N^2 computational complexity, instead the application of two 1D gaussian filters on the same image has a linear complexity with respect to the size of the filter, $2p^2N$.

In the second figure, we apply a 1D gaussian filter to smooth the signal along the x-axis and, then, we apply a derived gaussian filter along the y-axis to emphasize the horizontal edges. Regarding the third figure, we know that convolution is a linear operation, which means that for the commutative property the order in which we apply the filters does not matter: for this reason the third figure is identical to the second one.

For the fifth and sixth images the reasoning is the same as for the pair of images 2 and 3, the difference is in the application of the Gaussian filter and the derived gaussian filter, respectively, along the y axis and the x axis. The application of this filter allows us to emphasize the vertical edges.

The fourth figure is the result of the application of two Gaussian filters derived along the vertical and horizontal axes, it provides us a gradient of the picture, useful for identifying edges with different inclinations.

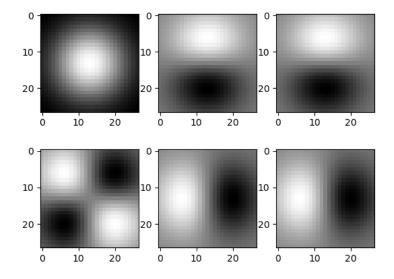


Figure 1: Impulse responses of 6 different filters. From the first row and from left to the right, we have: (1) first Gx, then Gx^T ; (2) first Gx, then Dx^T ; (3) first Dx^T , then Gx^T ; (6) first Gx^T , then Gx^T ; (6) first Gx^T , then Gx^T .

1.e

In Fig.2 and Fig.3 we show, in order, the application of a Gaussian filter derived along the horizontal direction, a Gaussian filter derived along the vertical direction and, finally, the magnitude of the gradient, given by the norm l2 of the two filtered images previously obtained. Therefore we can see how, in the same order, each filter identifies respectively the vertical edges, the horizontal edges and, finally, all the edges within the image.

It is foundamental to smooth an image, in this case through a Gaussian filter, before applying the derivative operation as this allows us to cut all the high frequencies characterizing the image, for example frequencies due to noise or tiny edges that do not constitute the boundaries of objects in the image, such as surface textures.

Furthermore, we note how, thanks to the linearity of the convolution, it is possible to derive the Gaussian filter and then directly apply this derived Gaussian filter to the image instead of applying the two filters separately: this allows us, once again, to reduce the computational complexity of the operation.

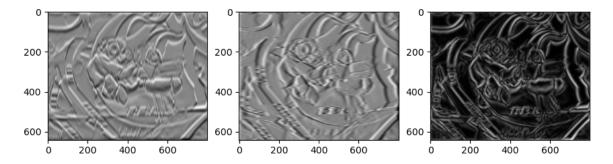


Figure 2: In order, filtered picture obtained applying Dx, Dx^T and the magnitude of the gradient.

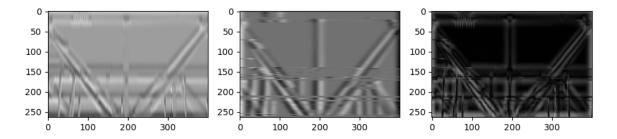


Figure 3: In order, filtered picture obtained applying Dx, Dx^T and the magnitude of the gradient.

Question 3

3.cThe following table shows the ability that different types of distances, histograms and number of bins have in recognizing and comparing images.

Hist. type	Dist. type	# Bins	# correct over 100
RGB	Intersect	30	72
RGB	Intersect	10	70
RGB	Intersect	50	70
RGB	Intersect	5	69
RG	Intersect	30	65
RG	Intersect	50	65
RG	Intersect	5	63
RG	Intersect	10	62
RGB	Chi2	5	61
RGB	Chi2	10	60
RG	Chi2	5	58
DxDy	Intersect	10	58
DxDy	Intersect	30	58
DxDy	Intersect	50	58
RGB	L2	5	<i>57</i>
RG	L2	5	55
RGB	L2	10	54
RG	Chi2	10	53
RG	L2	10	52
DxDy	Intersect	5	50
RG	Chi2	30	42
DxDy	Chi2	30	41
DxDy	Chi2	10	40
DxDy	L2	30	40
DxDy	Chi2	5	39
DxDy	L2	5	39
DxDy	L2	10	39
RG	L2	30	39
RGB	Chi2	30	38
DxDy	Chi2	50	38
DxDy	L2	50	38
RG	Chi2	50	35
RGB	L2	30	34
RG	L2	50	31
RGB	Chi2	50	30
RGB	L2	50	30
Table 1			

It is possible to immediately notice how the first eight positions are occupied by the intersect distance. Subsequently RGB with intersect gives higher values for each number of bins, followed by RG and DxDy. However, considering the intersect distance, it can be seen that there is no substantial variation in correctness, in fact RGB with intersect remains between 69% and 72% correctness for each bin size analyzed. Typically, the lowest performance is achieved by increasing the bins to 50, often combined with L_2 distance. It is important to note that DxDy histograms never exceed 58% of correctness, therefore the other types of histograms are preferable.

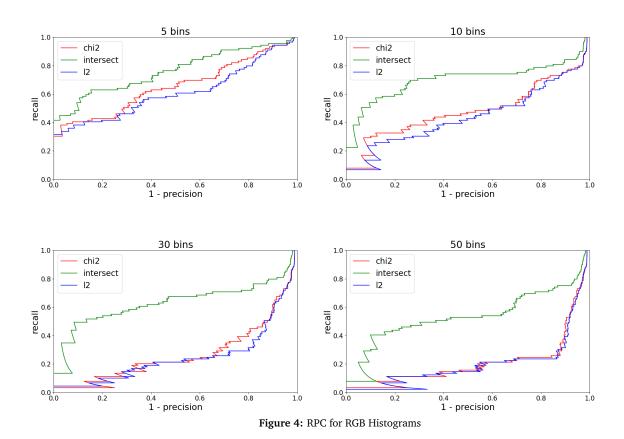
Question 4

4.b

From the figures below it is possible to observe the different plots as the number of bins and the type of histogram vary. From these graphs it is clear how the best performances are obtained with the RGB histogram, as we have also been able to verify in point 3c. Also, the distance which gives us the best performance is the intersect.

So, in general, it is possible to say that the distances L_2 and χ^2 are less performing than the intersect distance, as verified in *Table1* where their performance is actually lower.

On the other hand, it is possible to note that in the plots concerning the *Dxdy histogram* there is no prevalence of distance measurement. In fact, the three measures start at the bottom and then grow very slowly all together.



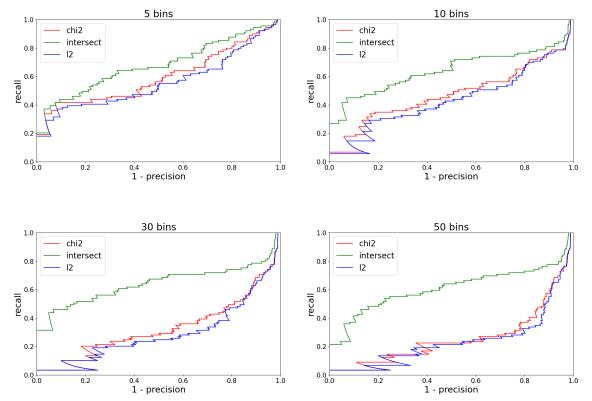


Figure 5: RPC for RG Histograms

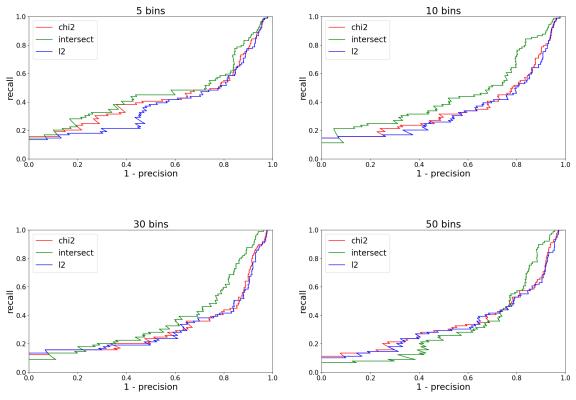


Figure 6: RPC for DxDy Histograms