Universitat Politècnica de Catalunya
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Master in Artificial Intelligence

Computational vision

Feature detection and matching (I)

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1 Question 1

Take at your own choice several keypoints that have been detected at different scales. Using the theory given in the lectures, comment on the reasons of why do you think that a keypoint has been detected at that position and at that particular scale. You may repeat the experiment with another image (such as 'river1') to understand what a significant keypoint is.

When running the keypoint detection function `vl_sift` on the image `river1`, 1816 keypoints are detected. We hand-picked several keypoints to demonstrate why they were picked. The selected keypoints can be seen in figure 1. Keypoints were selected in different areas of the image and at different scales, ranging from 2.3 for keypoint D to 13.6 for keypoint A. While this is just a small part of all detected keypoints, they represent a variety of different points at different locations with different scales.

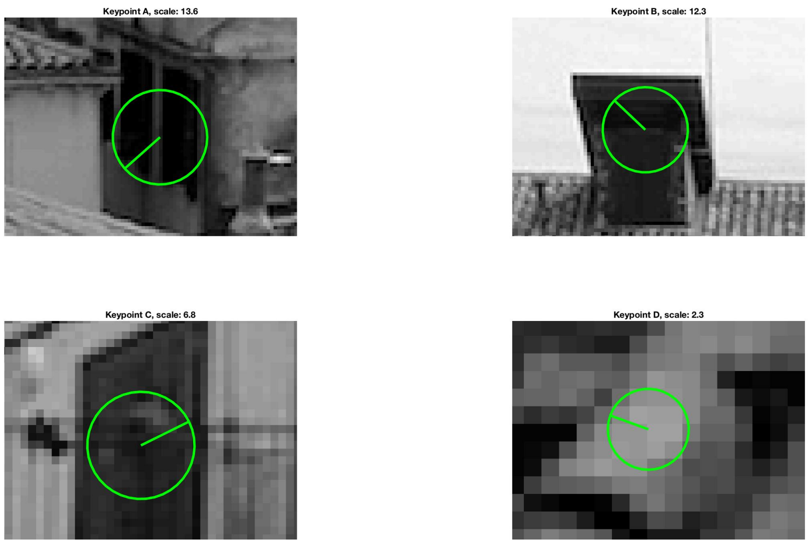

Figure 1: Example keypoints

Keypoint A was detected at the position of a window on the corner of a house. The scale of 13.6 represents the width of this window. For this scale, there is a strong gradient around the selected keypoint, since the pixels around the window have a higher brightness.

Keypoint B was selected at the position of a roof hatch. The gradient for this scale is strong since the ceiling around the hatch is much brighter. The scale of 12.3 more or less fits the width of the hatch, making it a strong candidate for a promising keypoint.

Similarly, keypoint C was detected at the position of a balcony door with a strong gradient between the dark door and the bright wall around it. Again, the scale of 6.8 corresponds to the door's width.

Keypoint D is at a much smaller level with a scale of only 2.3. It is located on a tile of one of the roofs. As we can see after zooming in on its location, there is a strong edge between the bright part of the tile and the shade around it. The scale is similar to the width of the bright part and when calculating the difference of Gaussians at this scale there will be a extreme difference towards surrounding pixels in the scale space.

2 Question 2

2:Which is the effect when using the peak threshold=0.01 on the 'roofs1' image? Comment the differences with respect to the previous result.

The peak threshold filters out keypoints whose extrema in the difference of Gaussian scale space are below a certain value. Increasing this threshold above the default value of 0 will effectively remove keypoints that lie in low contrast areas. This can be seen in figure 2.

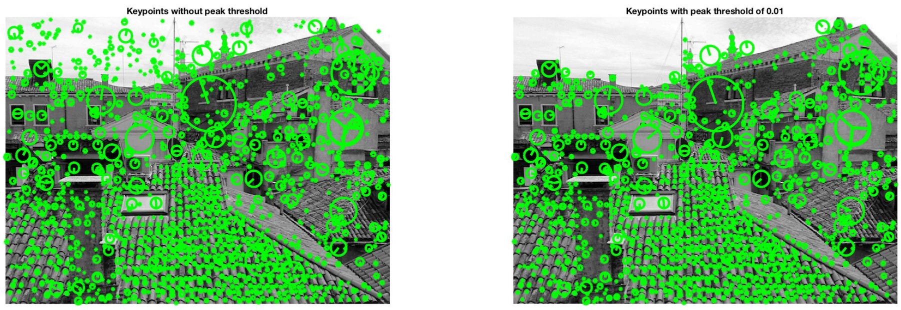

Figure 2: Comparison of peak threshold effects

As can be seen in figure 2, the keypoints located on the comparatively low-contrast sky will be filtered out by the threshold of 0.01. Figure 3 shows a zoomed in area in which the difference is notable the most.

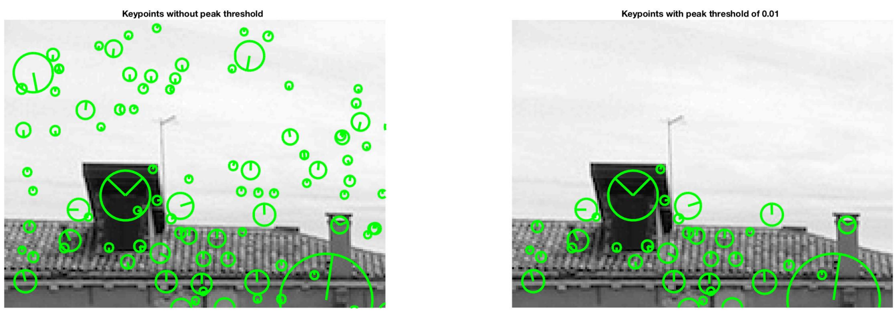

Figure 3: Detailed comparison of peak threshold effects

3 Question 3

Try to slowly increase or decrease the (peak) threshold. Comment why the number of detected keypoints decreases when the threshold is increased. Is this the expected behavior according to the way the threshold is defined?

Figure 7 shows the effects of increasing the peak threshold on the number of detected keypoints. For a threshold value of 0, 1816 keypoints are detected. For a threshold of 0.005, the number decreases to 1698. The number of keypoints keeps decreasing monotonously until it reaches 2 for a threshold of 0.09 and finally 0 for a threshold of 0.1.

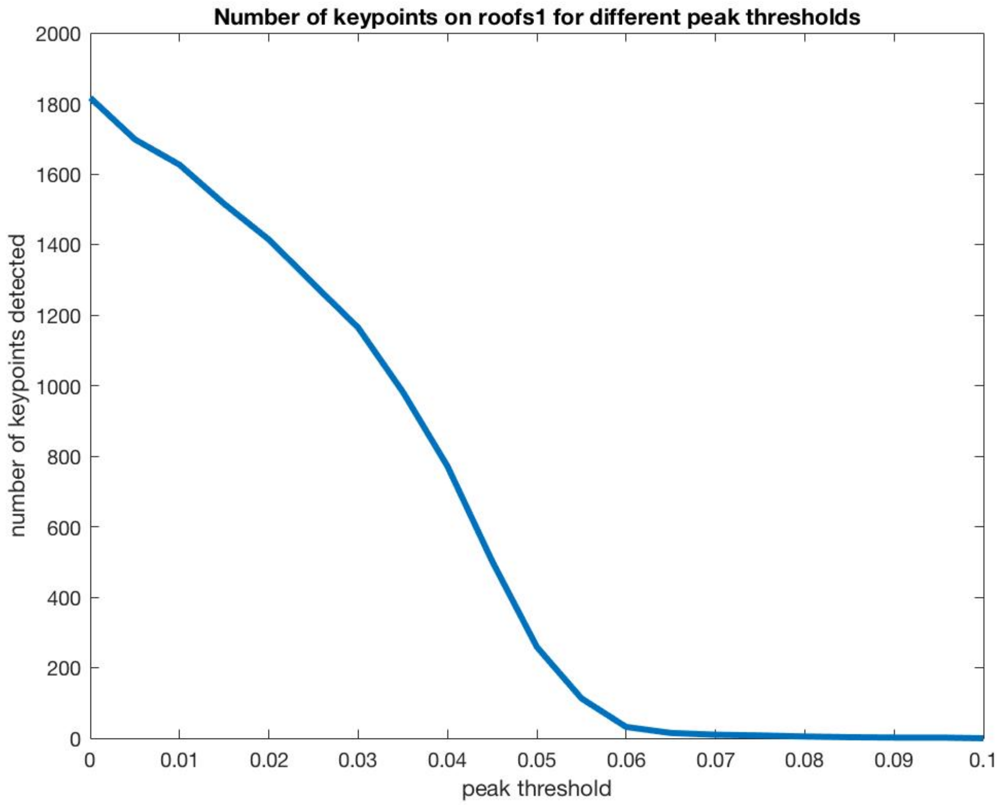

Figure 4: Relationship between peak threshold and number of detected keypoints

The number of detected keypoints decreases when increasing the threshold, since more and more keypoints with low extreme values of the difference of Gaussian in the scale space are filtered out, until finally there are none left. The peak threshold leads to the behavior we would expect.

Figure 5 shows the effects of increasing the peak threshold on the example image `roofs1`. Keypoints in areas with low contrast and thus low extrema are sorted out first. For a threshold of 0.01 keypoints in the low contrast sky almost entirely are sorted out. For a threshold of 0.04, keypoints on the roof tiles begin to disappear. For a threshold of 0.06 only a few keypoints in very distinct positions remain.

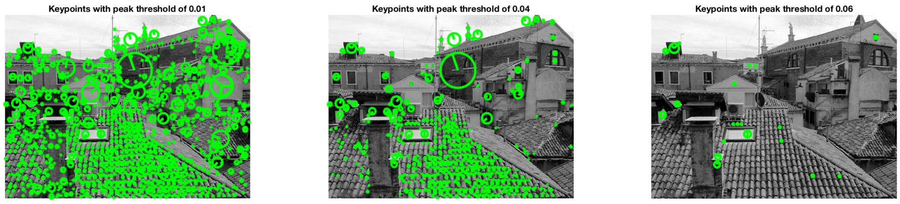

Figure 5: Effects of increasing the peak threshold

4 Question 4

Try to slowly increase or decrease the (edge) threshold. Comment why the number of detected keypoints decreases when the threshold is decreased. Is this the expected behavior according to the way the threshold is defined?

The edge threshold is used to filter out extrema of the difference of Gaussians that lie on an edge, i.e. that have a small curvature. Keypoints on edges can be moved along the edges with minor differences in their features and are thus not well suited to be selected. Figure 6 shows the effects of different levels of edge thresholds on the keypoints that are detected.

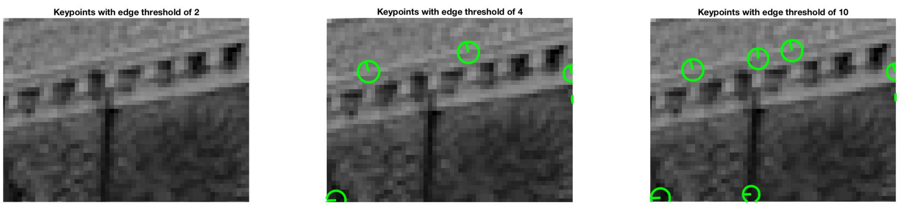

Figure 6: Effects of decreasing the edge threshold

As we can see in figure 6, low values of the edge threshold effectively remove keypoints that lie along edges. The edge threshold r is the ratio between the largest magnitude eigenvalue λ_{max} and the smaller one λ_{min} with $\lambda_{max} = r\lambda_{min}$. A small r means that both eigenvalues are relatively close to each other, which indicates a high curvature. With decreasing r we remove more and more keypoints on edges. This effect can be observed in figure 7: While there are no keypoints with a ratio r that is exactly 1, for increasing the edge threshold we allow more and more keypoints that lie on increasingly obvious edges. This fits to our expected behavior based on the way the threshold is defined.

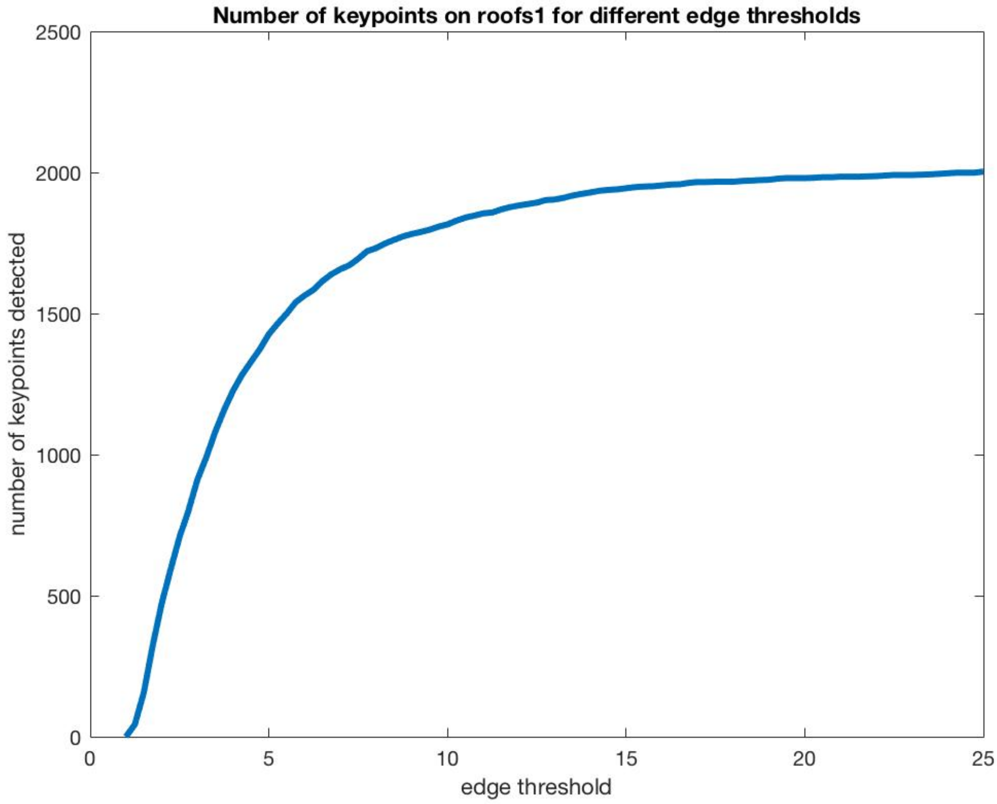

Figure 7: Relationship between edge threshold and number of detected keypoints