

Medical Image Processing for Interventional Applications

Feature Descriptors – SIFT (Part 2)

Online Course – Unit 12

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Pattern Recognition Lab (CS 5)

Topics

SIFT – Key Point Localization

SIFT – Orientation Assignment

SIFT – Key Point Descriptor

Summary

Take Home Messages

Further Readings

SIFT – Scale Invariant Feature Transform

1. Scale-space extrema detection → feature detection
2. **Key point localization and filtering → feature selection**
3. Orientation assignment → local coordinate system
4. Computation of key point descriptor → encode local gradient distribution

Key Point Localization (cf. [Lowe, 2004](#))

- At each candidate location:
 - Fit 3-D quadratic to DoG scale-space to approximate extremum in **space and scale** with sub-pixel and sub-scale accuracy.

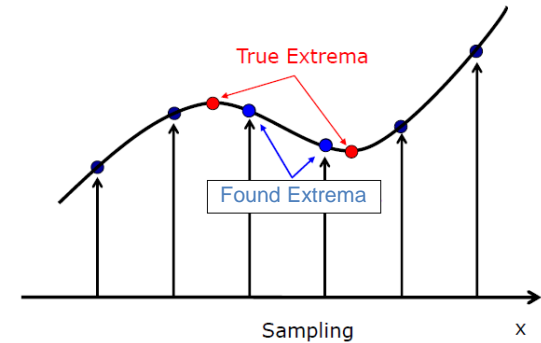


Figure 1: Curve fitting is used to find true extrema.

Key Point Localization (cf. [Lowe, 2004](#))

- At each candidate location:
 - Fit 3-D quadratic to DoG scale-space to approximate extremum in **space and scale** with sub-pixel and sub-scale accuracy.
 - Elimination of unstable interest points
→ Eigenvalues of Hessian matrix encode principal curvatures:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

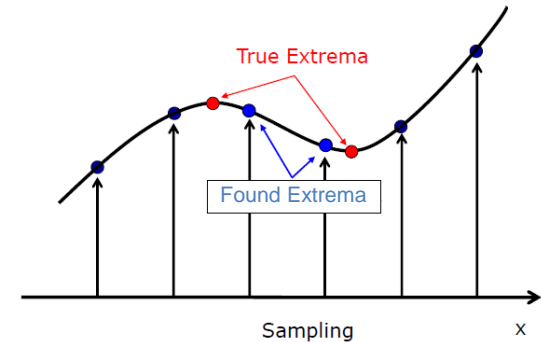


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$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

- Now we have a set of good points $\hat{x} = (\hat{x}, \hat{y}, \hat{\sigma})^T$.

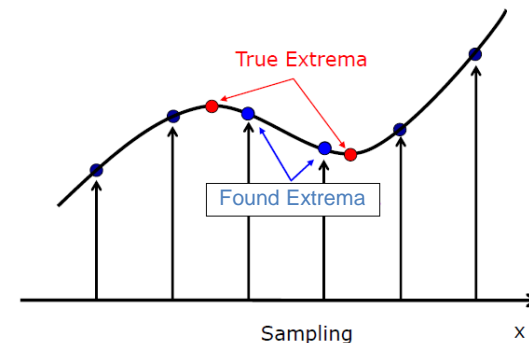


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Orientation Assignment (cf. [Lowe, 2004](#))

What about rotation invariance?

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$$\mathbf{g}(x, y) = \nabla f(x, y) = \begin{pmatrix} f_x(x, y) \\ f_y(x, y) \end{pmatrix}$$

- Gradient orientation:

$$\theta(x, y) = \tan^{-1} \left(\frac{g_y(x, y)}{g_x(x, y)} \right)$$

- Gradient magnitude:

$$\|\mathbf{g}(x, y)\| = \sqrt{g_x(x, y)^2 + g_y(x, y)^2}$$

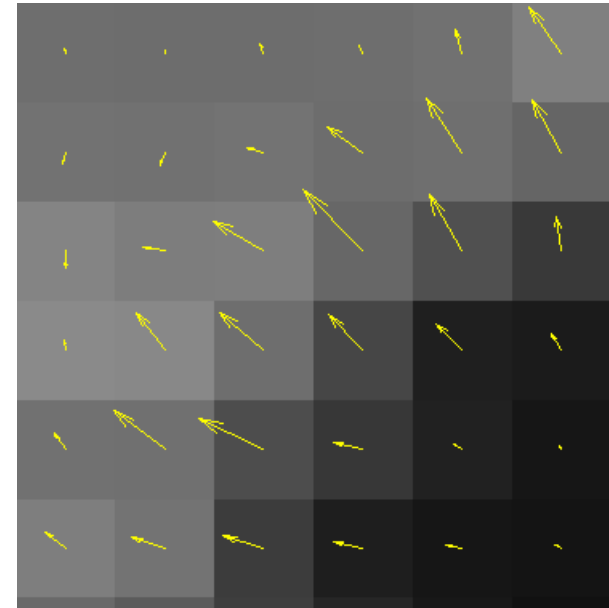
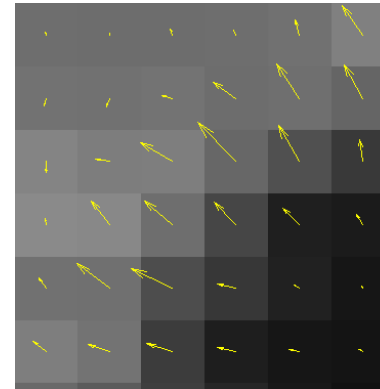
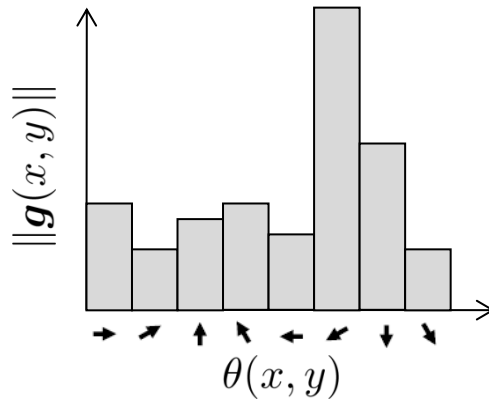


Figure 2: Gradient directions in a gray value image

Orientation Assignment (cf. [Lowe, 2004](#))

What about rotation invariance?

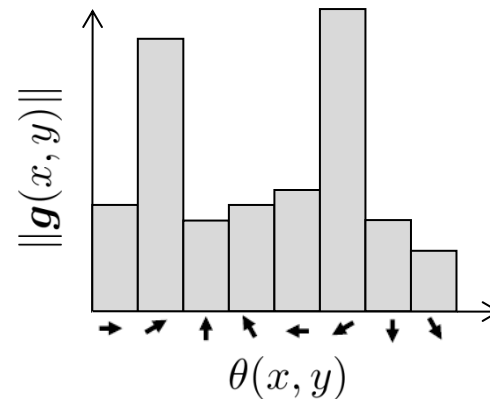
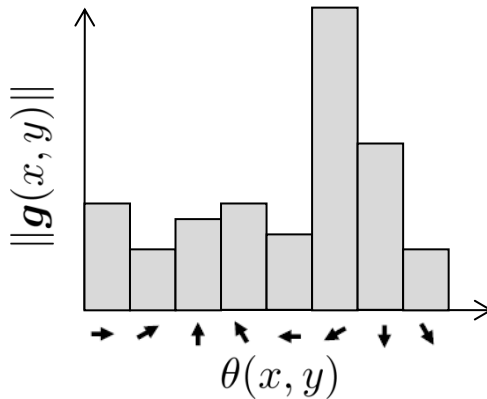
Idea: Select dominant local gradient direction → orientation histogram at key point scale.



Orientation Assignment (cf. [Lowe, 2004](#))

What about rotation invariance?

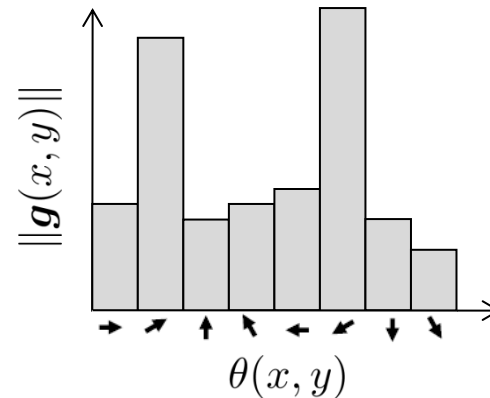
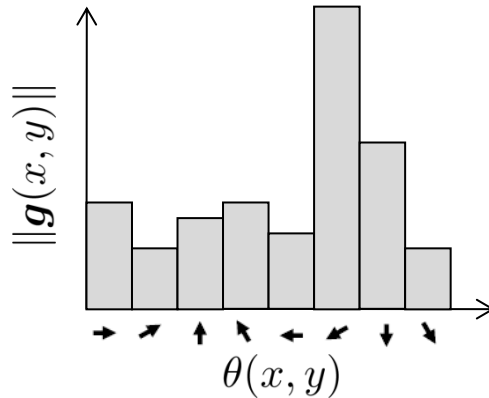
Idea: Select dominant local gradient direction \rightarrow orientation histogram at key point scale.



Orientation Assignment (cf. [Lowe, 2004](#))

What about rotation invariance?

Idea: Select dominant local gradient direction → orientation histogram at key point scale.



→ Separate key point is created for histogram maximum and any other direction within 80% of the maximum value.

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Scale and Rotation Invariant Frame

All future operations are performed on image data that has been transformed relative to the assigned orientation, scale and location for each feature, therefore providing invariance to these transformations is essential.

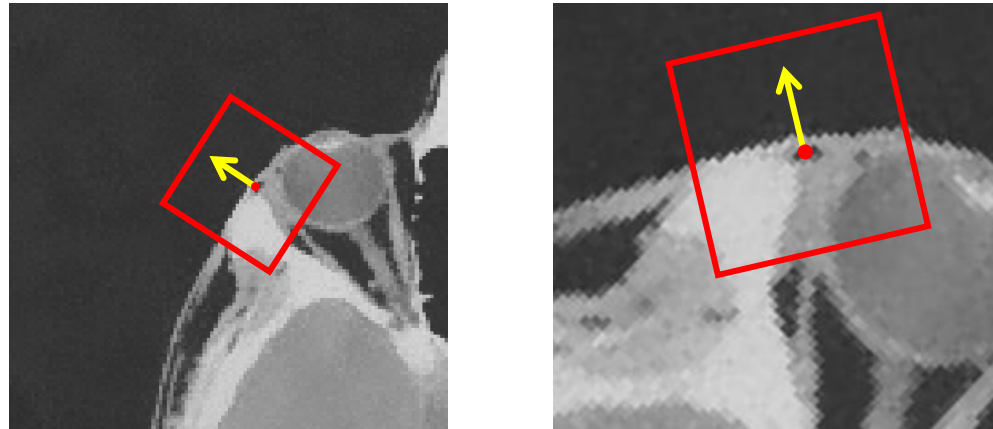
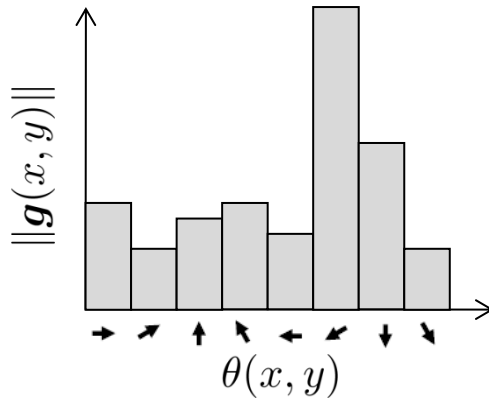
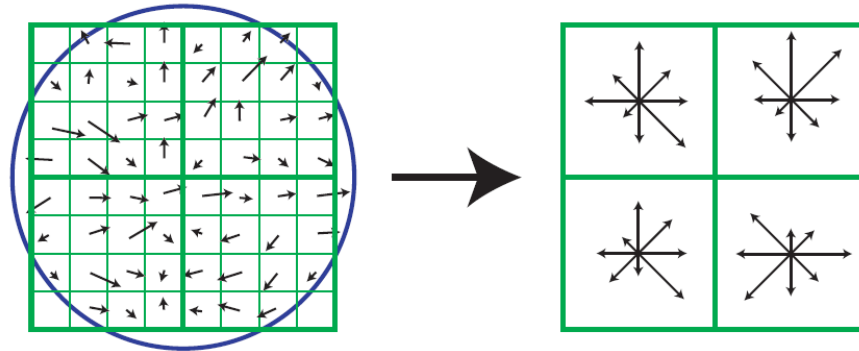
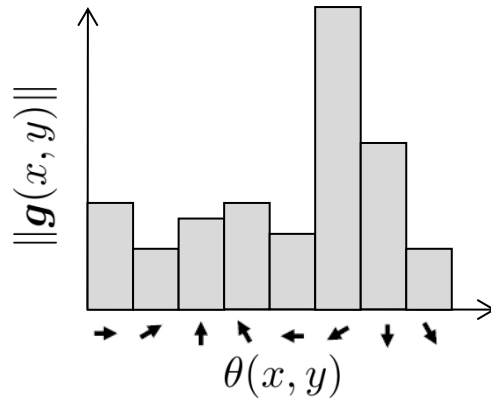


Figure 5: Same key point with different relative rotation and scale

SIFT Descriptor (cf. [Lowe, 2004](#))

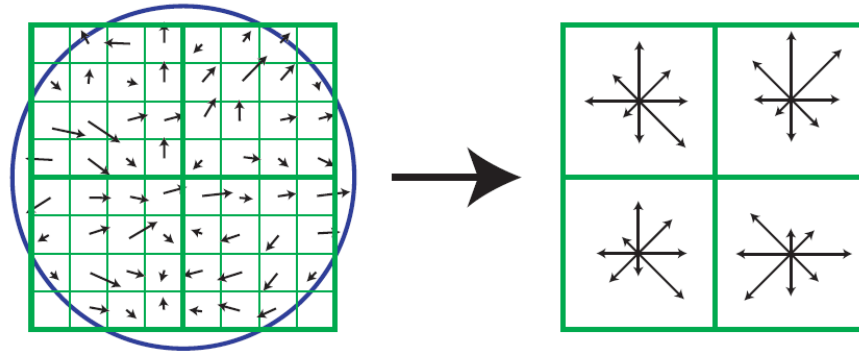
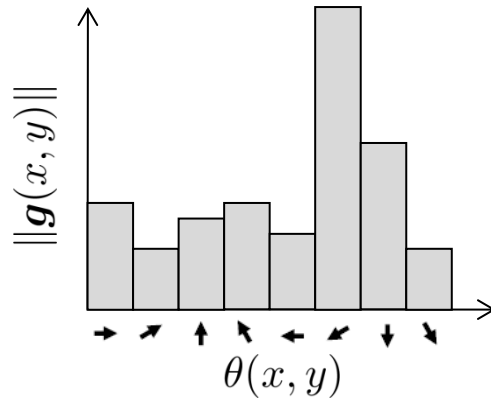


SIFT Descriptor (cf. [Lowe, 2004](#))



Benefits: Histogram representation of gradient distribution allows significant levels of local shape distortion and illumination change.

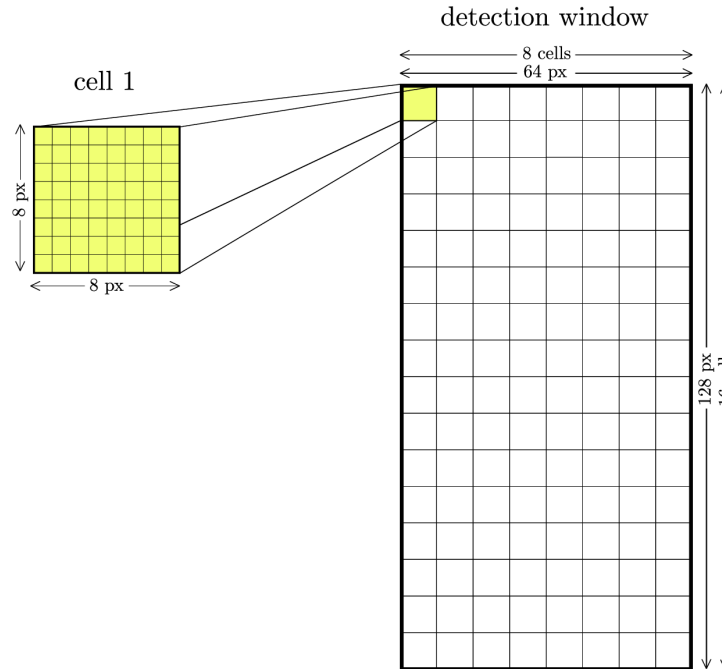
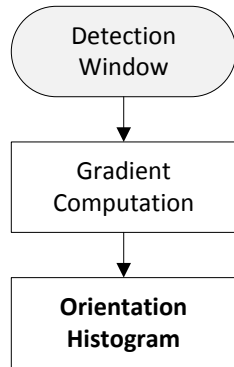
SIFT Descriptor (cf. [Lowe, 2004](#))



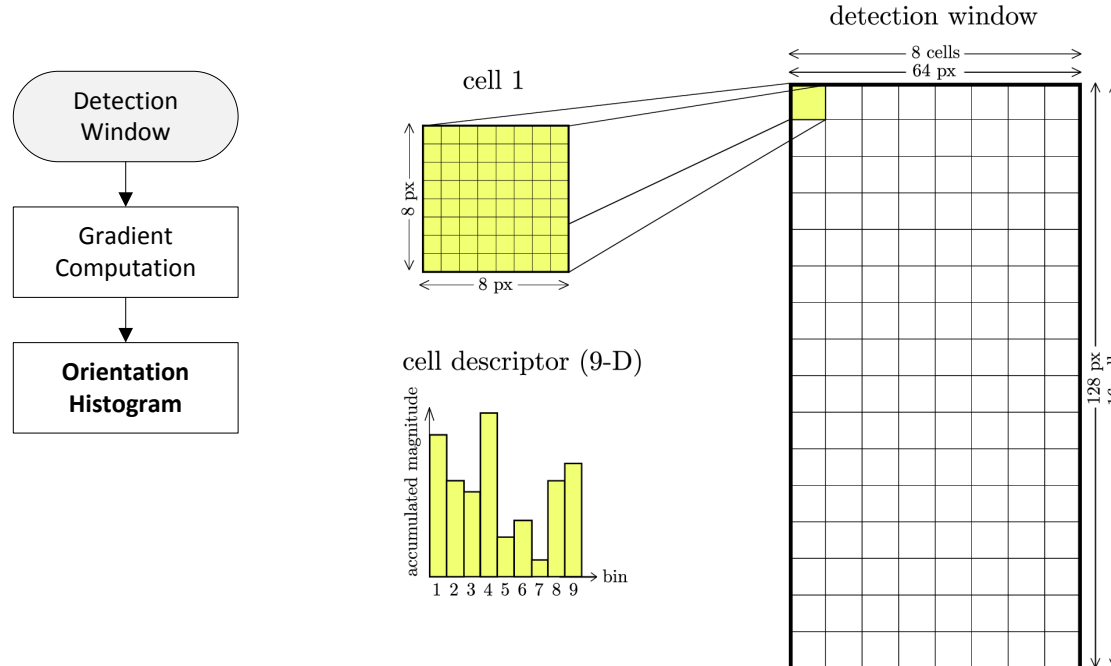
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→ Dimensionality?

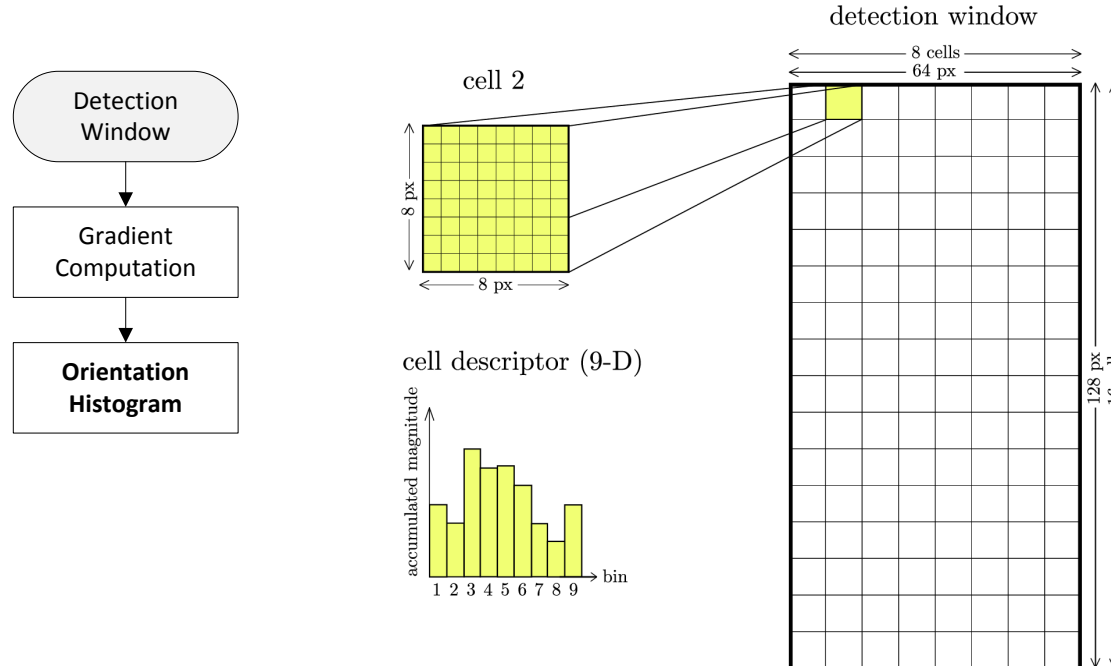
Orientation Histogram (cf. [Dalal and Triggs, 2005](#))



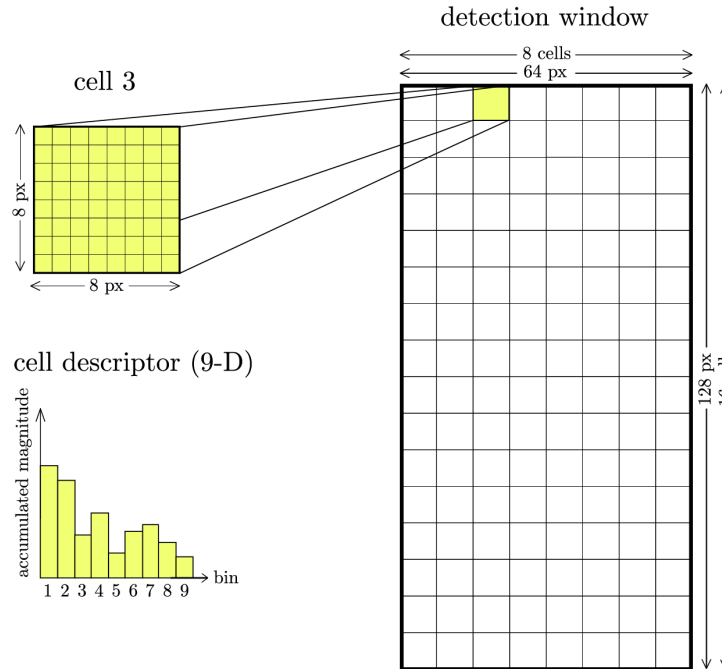
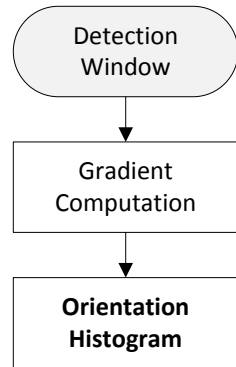
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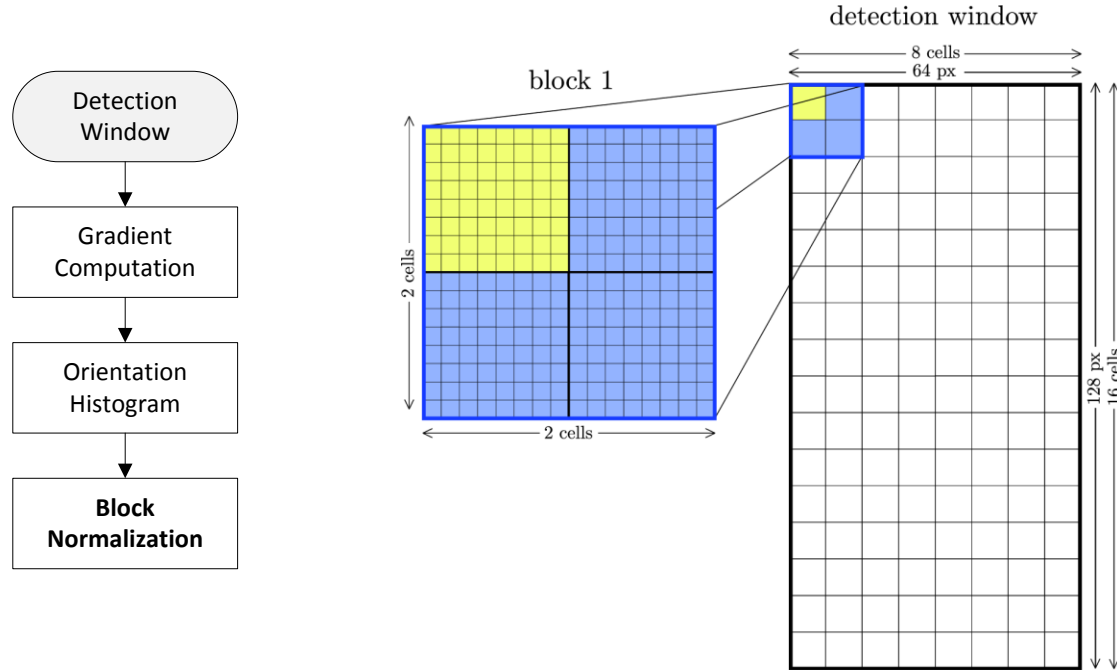
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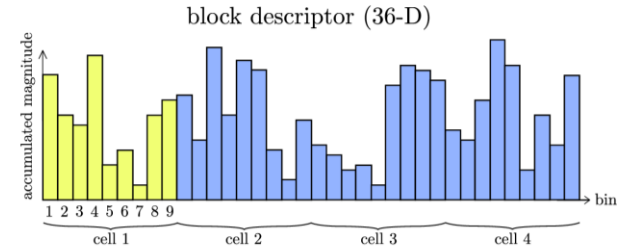
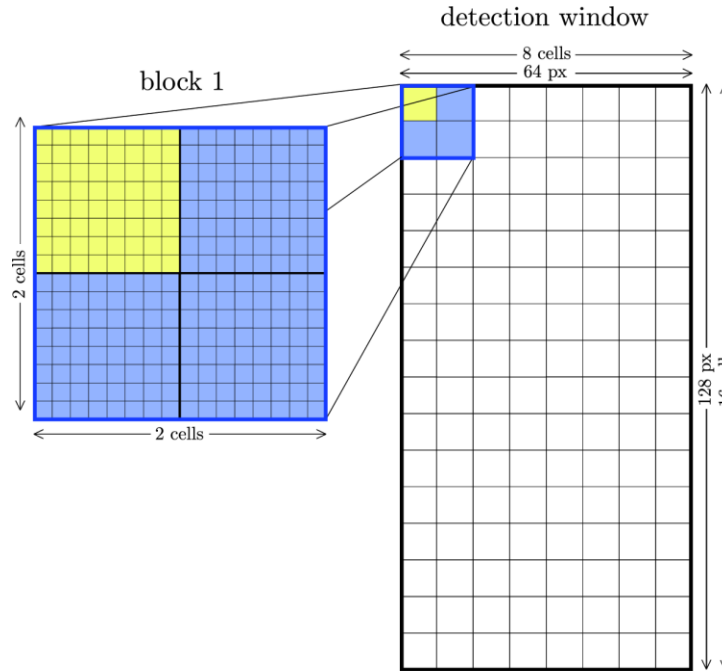
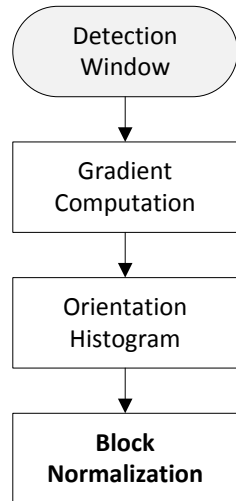
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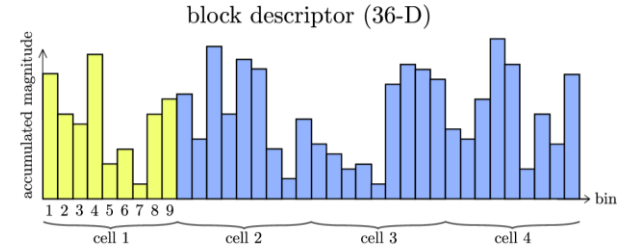
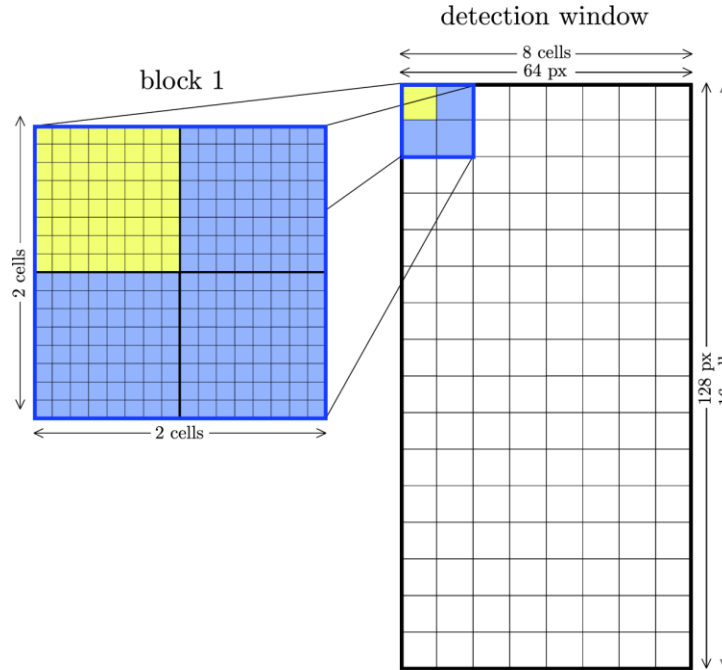
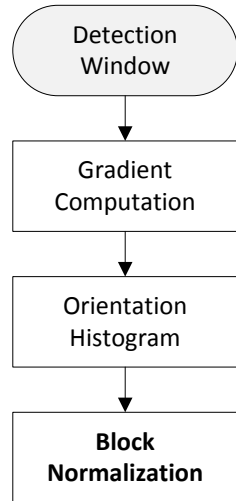
Block Normalization (cf. [Dalal and Triggs, 2005](#))



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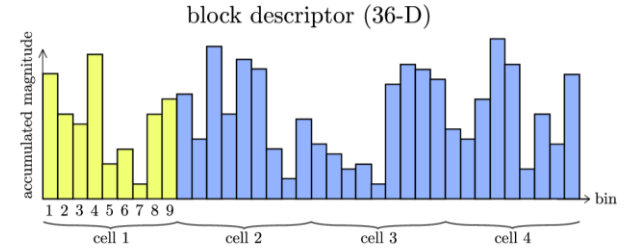
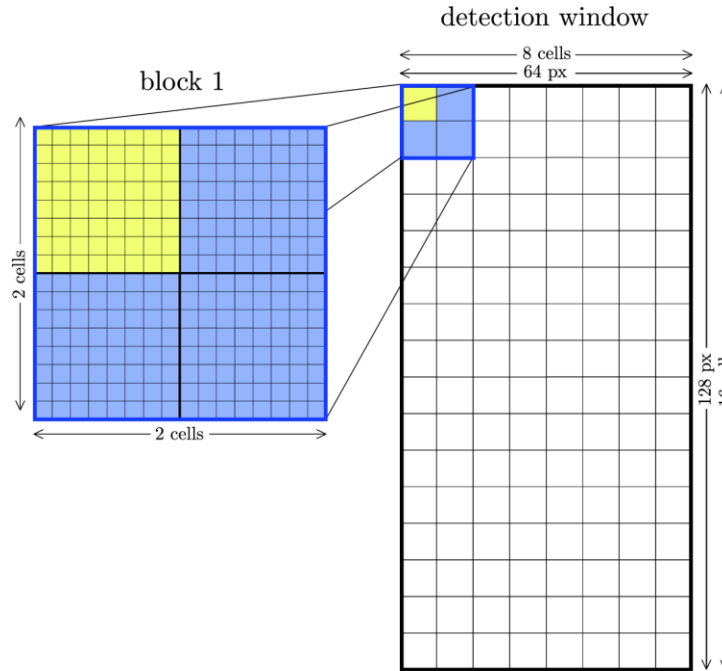
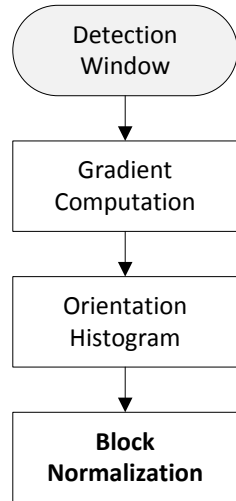


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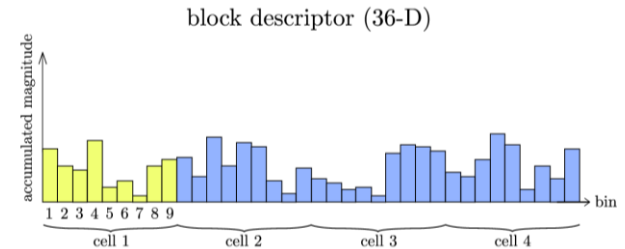


$$f \rightarrow \frac{f}{\sqrt{\|f\|_2^2 + \epsilon^2}}$$

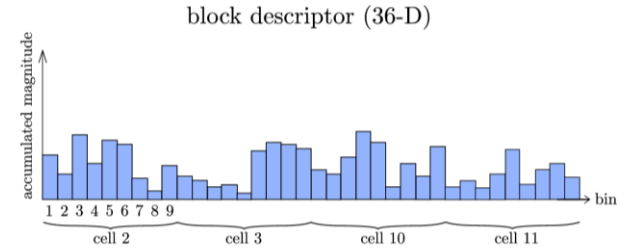
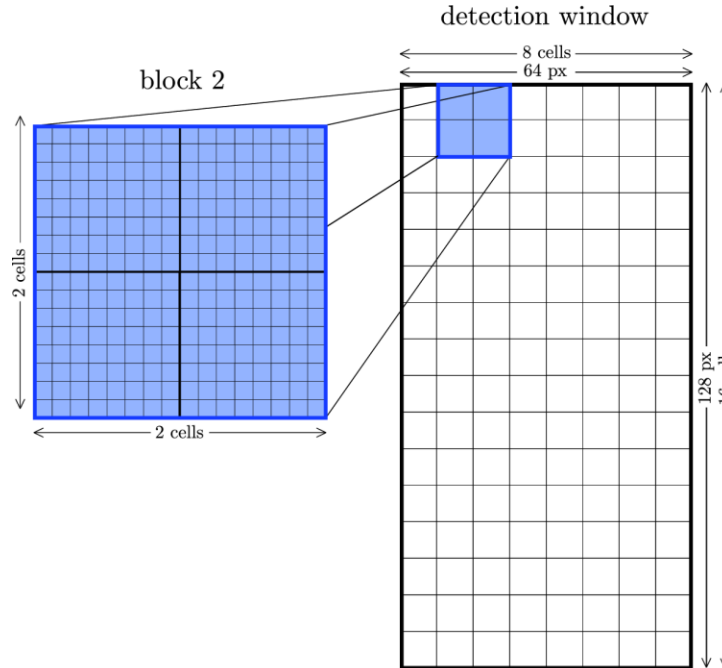
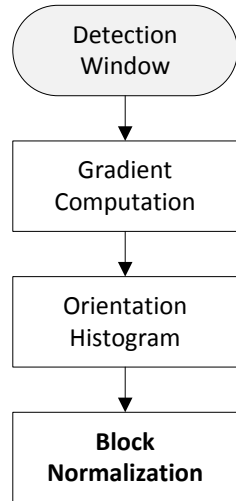
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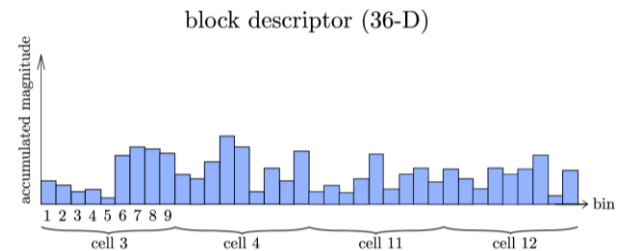
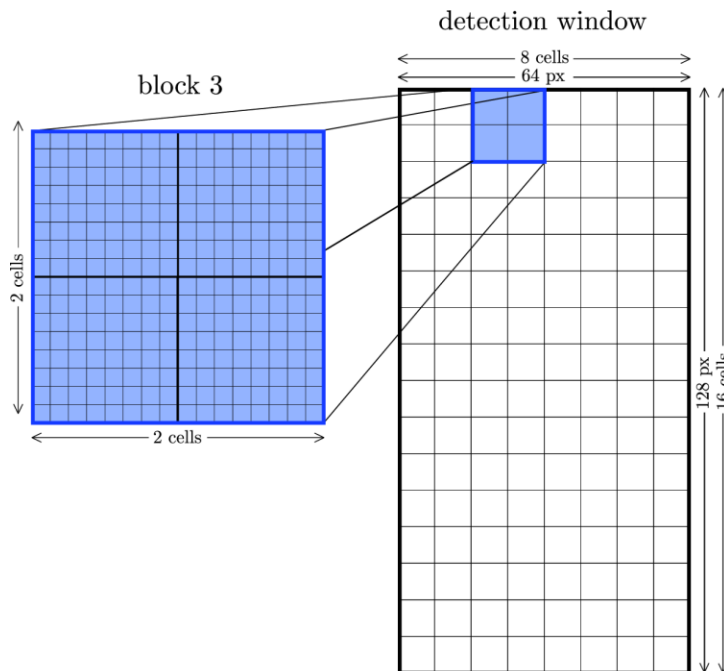
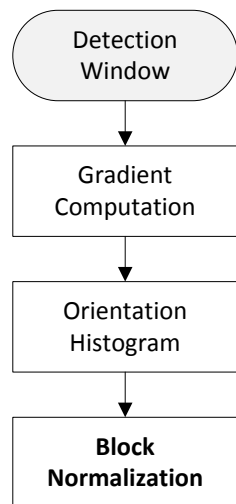
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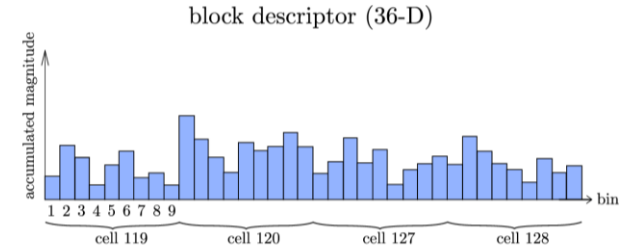
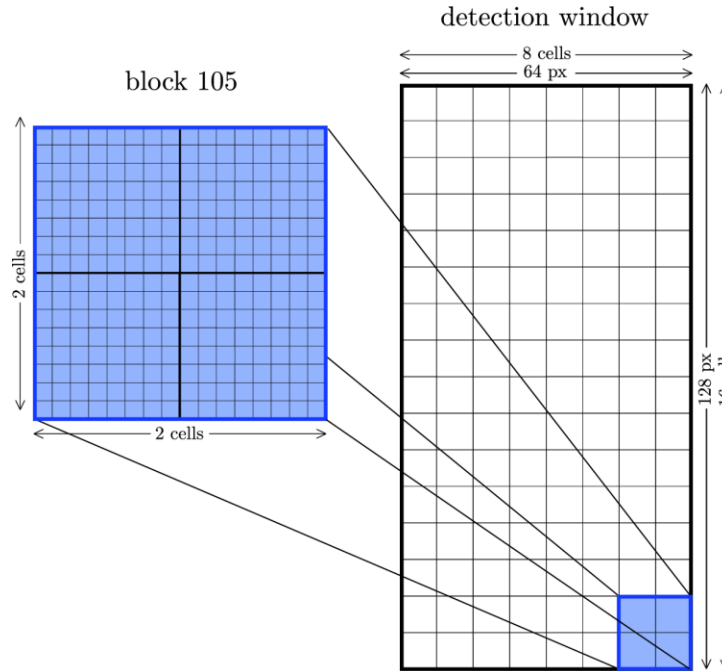
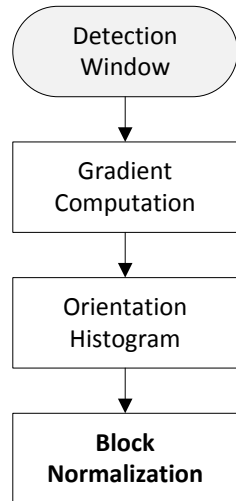
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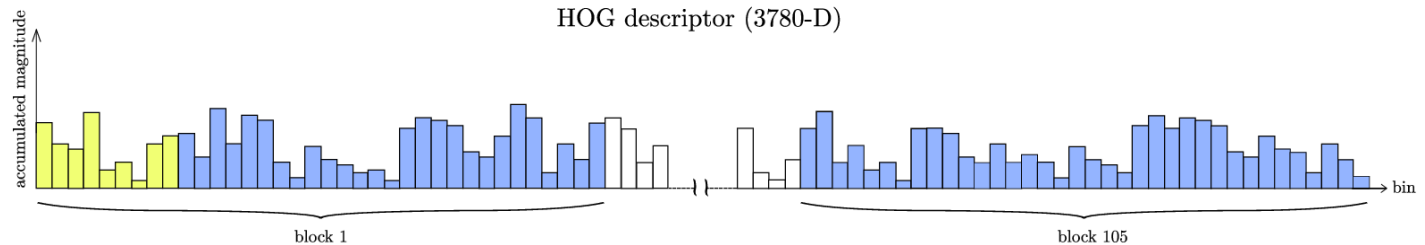
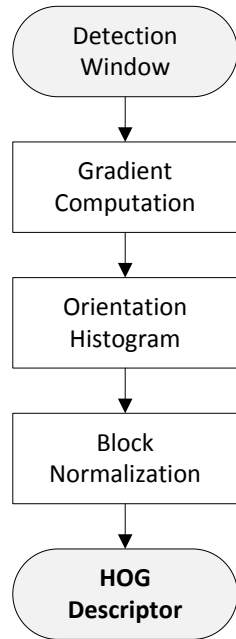
Block Normalization (cf. [Dalal and Triggs, 2005](#))



Block Normalization (cf. [Dalal and Triggs, 2005](#))



HOG Descriptor (cf. [Dalal and Triggs, 2005](#))



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- SIFT key points are determined by finding extrema from quadratic curve fits of the DoG results.
- Histograms of the gradient magnitude over different (discretized) gradient directions allow an orientation invariant assignment of key points.
- The final descriptor is a composition of block normalized histograms.

Credits:

We acknowledge the contributions of F.F. Li, E. Angelopoulou, D. Lowe, and A. Berg for their material in units 9-14 (on feature detectors/descriptors).

Further Readings

- David G. Lowe. “Distinctive Image Features from Scale-Invariant Keypoints”. In: *International Journal of Computer Vision* 60.2 (Nov. 2004), pp. 91–110. DOI: 10.1023/B:VISI.0000029664.99615.94
- Navneet Dalal and Bill Triggs. “Histograms of Oriented Gradients for Human Detection”. In: *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)*. Vol. 1. IEEE, June 2005, pp. 886–893. DOI: 10.1109/CVPR.2005.177