session 2:

Image Features

M. Kundegorski

13th December 2019

IAFIG-RMS - Bioimage Analysis With Python

Cambridge Bioinformatics Training Centre

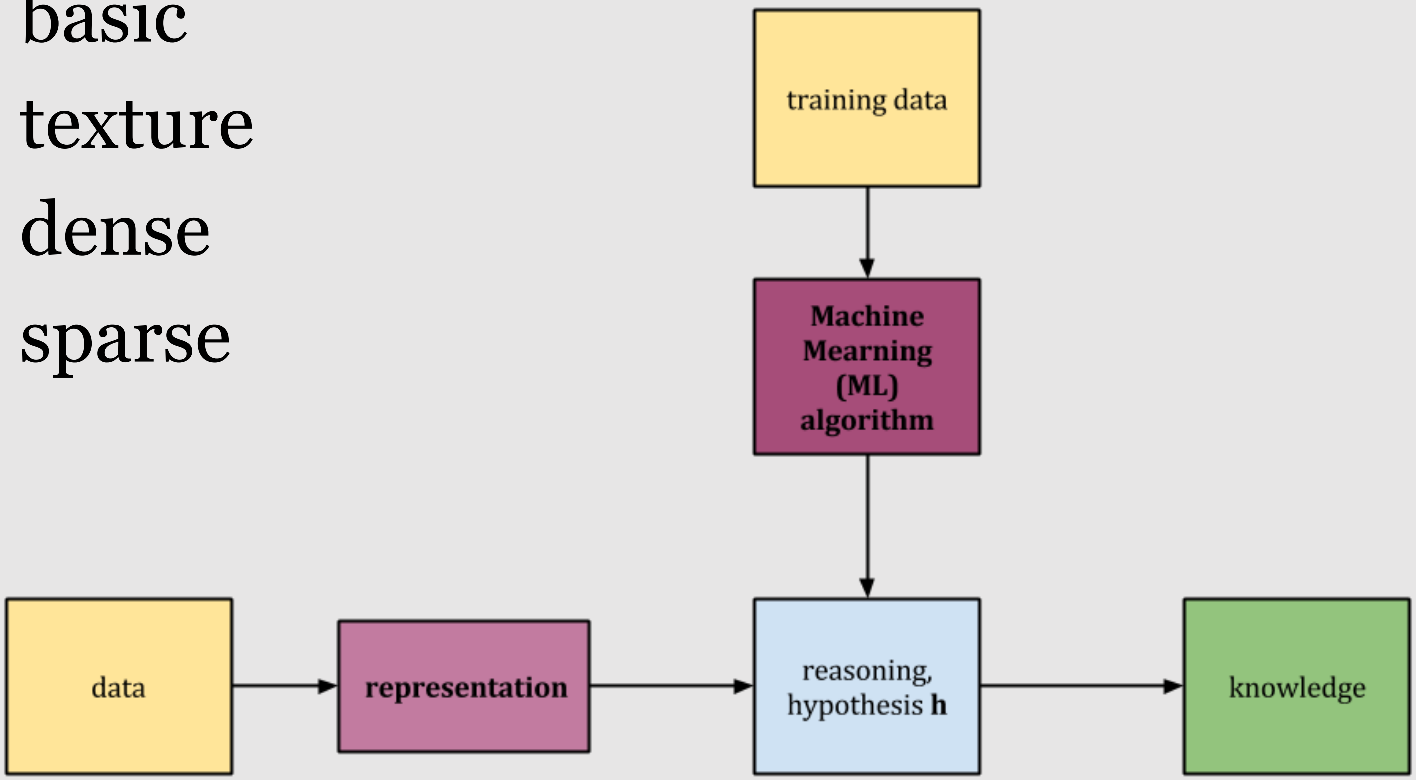
Royal Microscopical Society

Image features

Variety of ways to represent visual data

Types of Image Features

- basic
- texture
- dense
- sparse

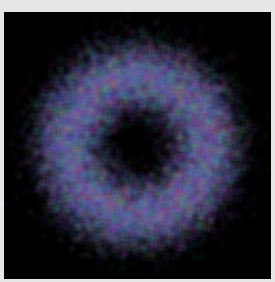
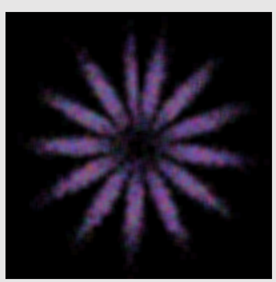
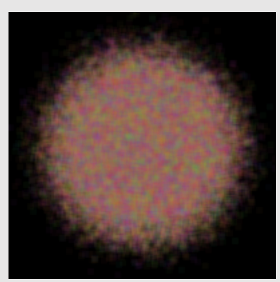


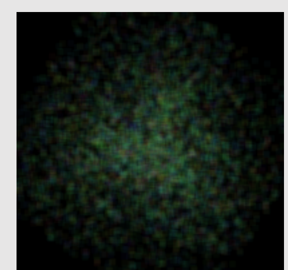
Machine Learning vs Image Analysis

- Many common uses
- Difference often in amount of “learning by example”
- Image features are technically an area of Image Processing devoted to Machine Learning

Basic features

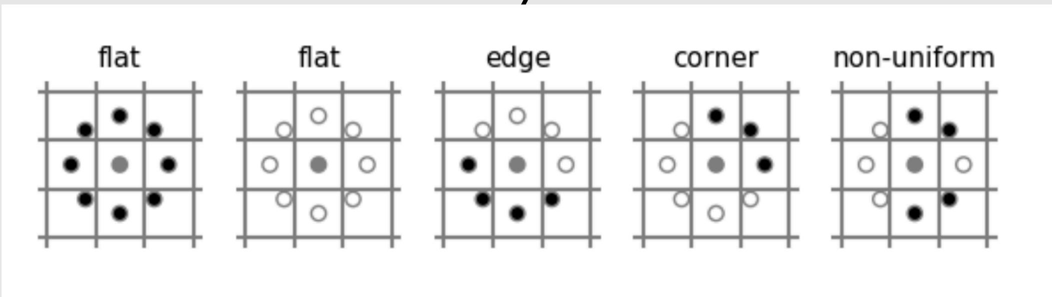
- colour statistics (over whole or part of the image)
- edges and gradients
- corners
- shapes (convolution/autocorrelation)

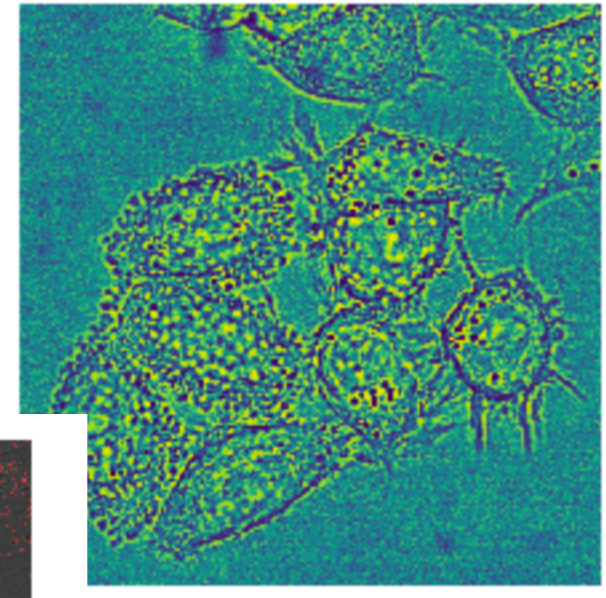




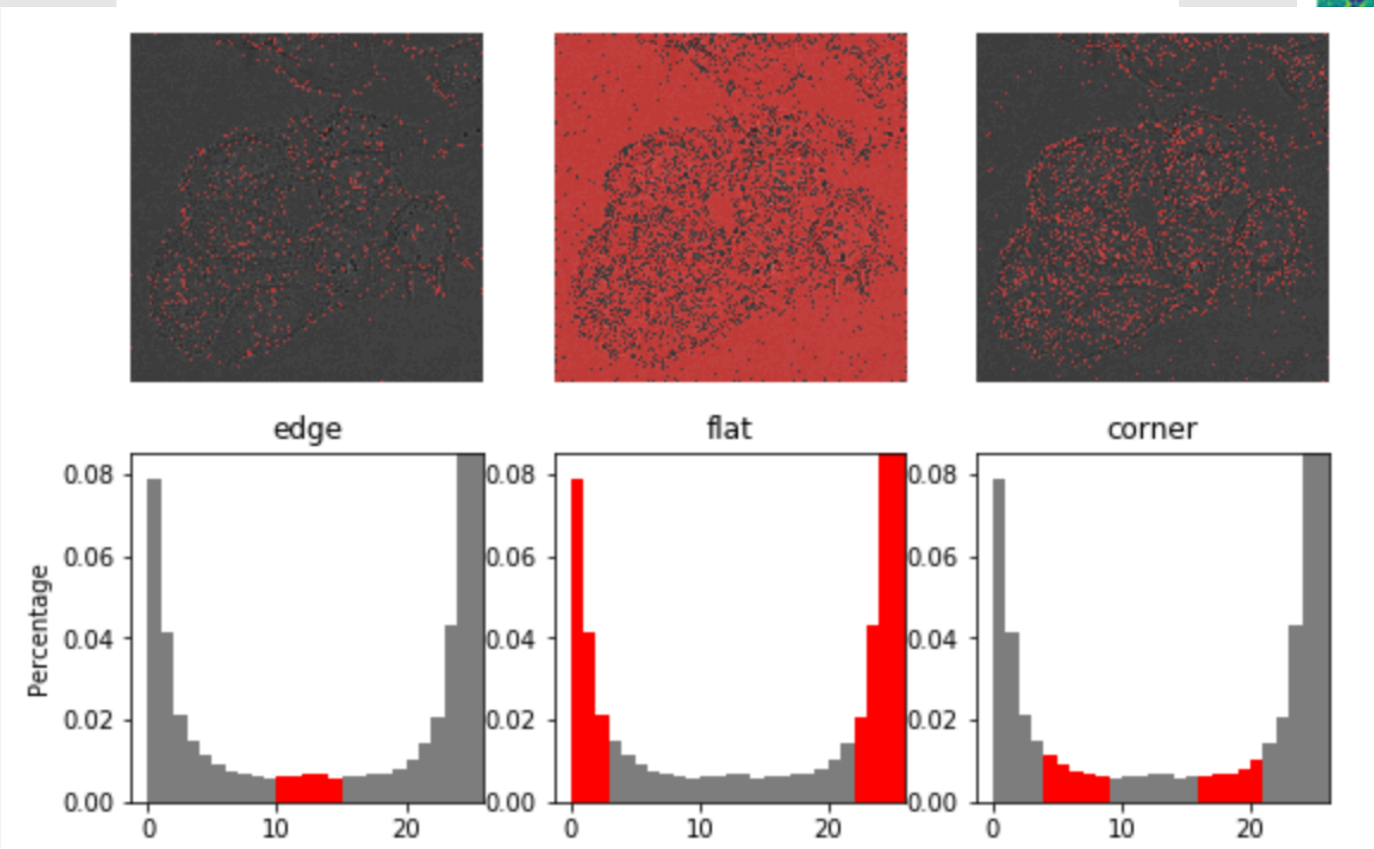


Texture features

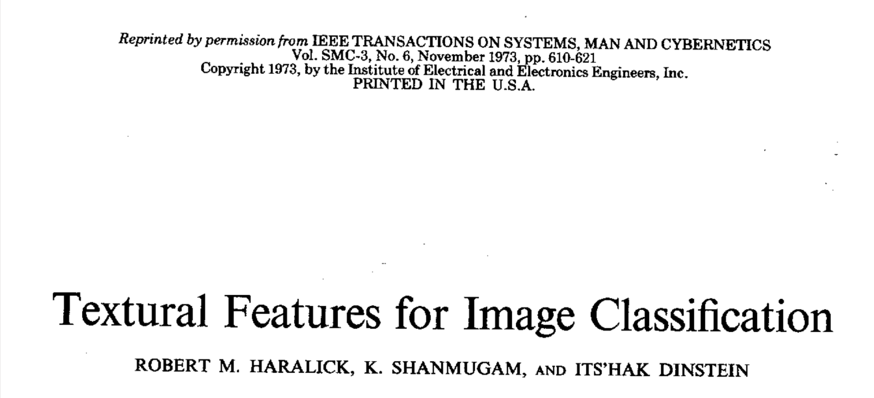
Local Binary Features







https://scikit-image.org/docs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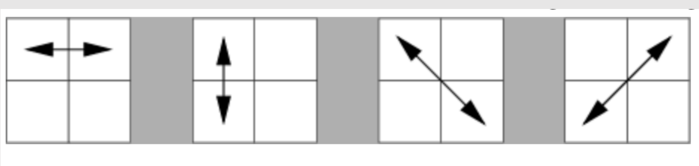
Vol. SMC-3, No. 6, November 1973, pp. 610-621

Textural Features for Image Classification

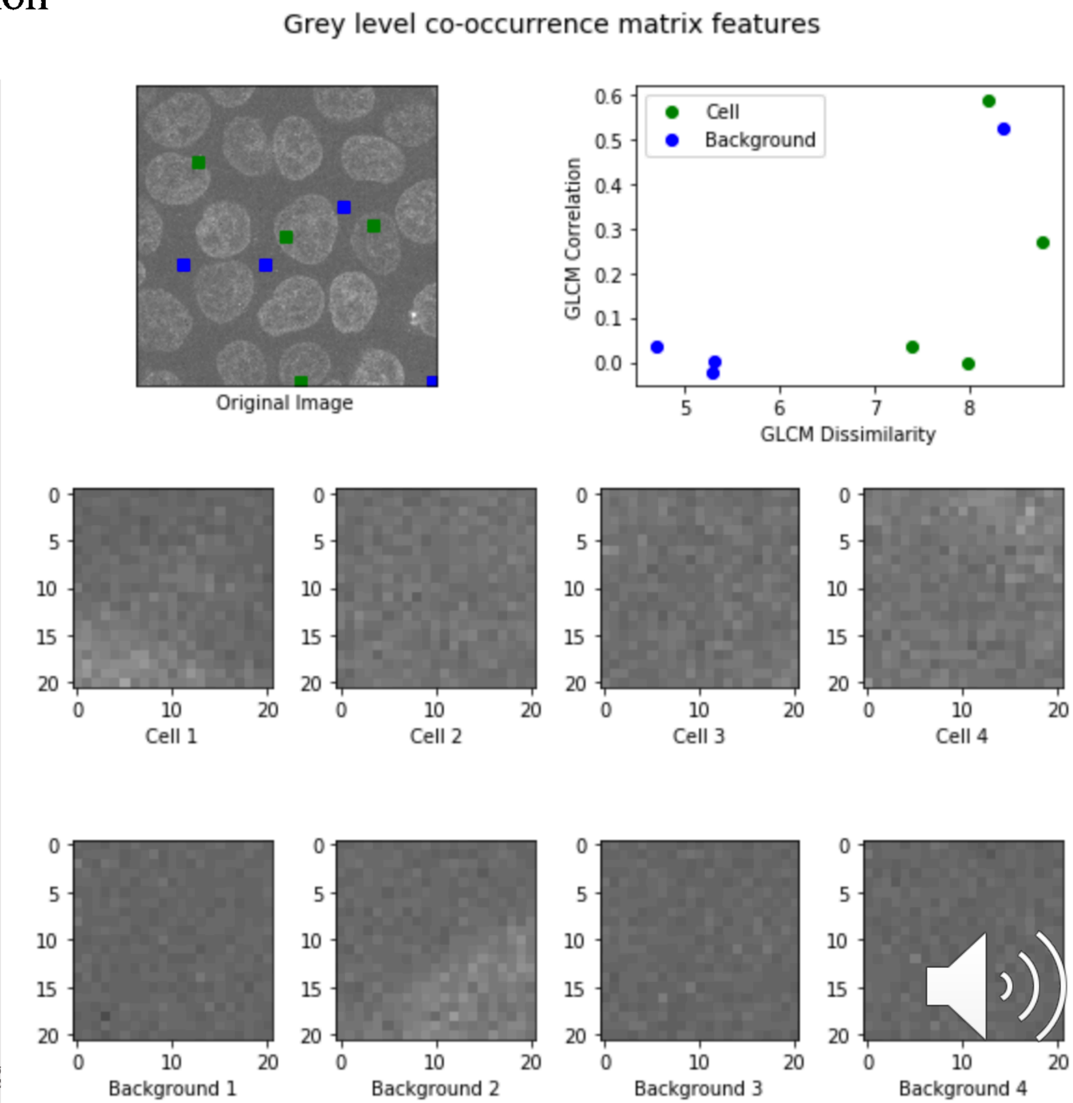
ROBERT M. HARALICK, K. SHANMUGAM, AND ITS'HAK DINSTEIN

Haralick Features

Element [*i*,*j*] of the matrix is generated by counting the number of times a pixel with value *i* is adjacent to a pixel with value *j*



source: http://murphylab.web.cmu.edu/publications/boland/boland_node26.html



Dense features

Haar-like features

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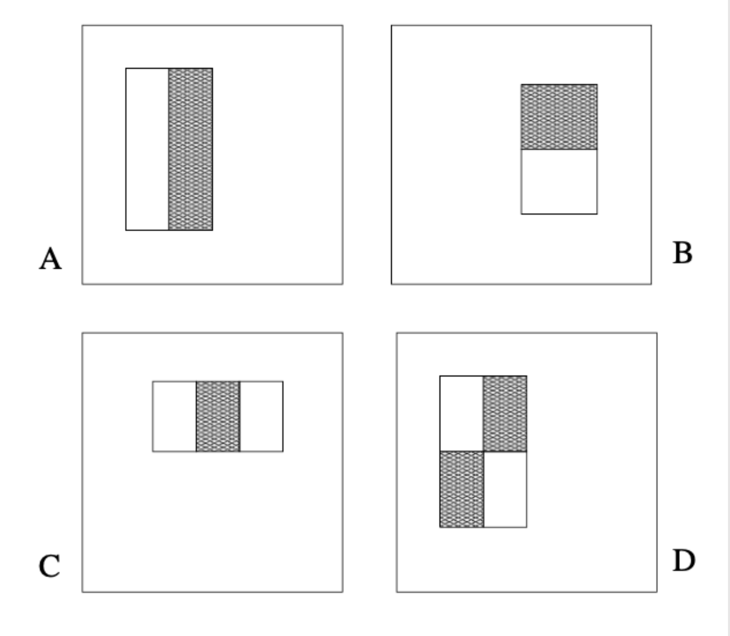
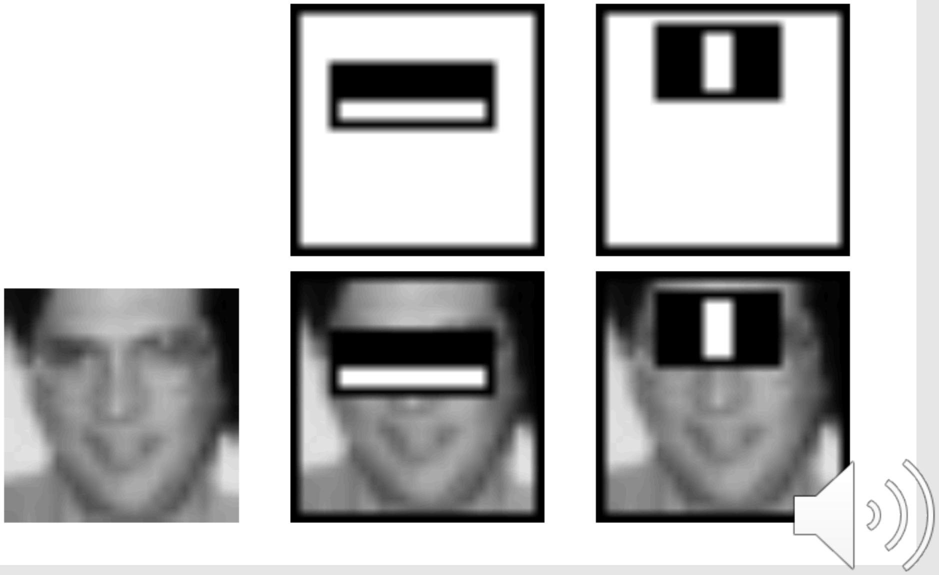
http://www.merl.com

Rapid Object Detection Using a Boosted Cascade of Simple Features

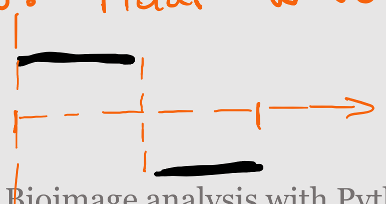
Viola, P.; Jones, M.

TR2004-043 May 2004





n.b. Haar wavelet:



Histograms of Oriented Gradients for Human Detection

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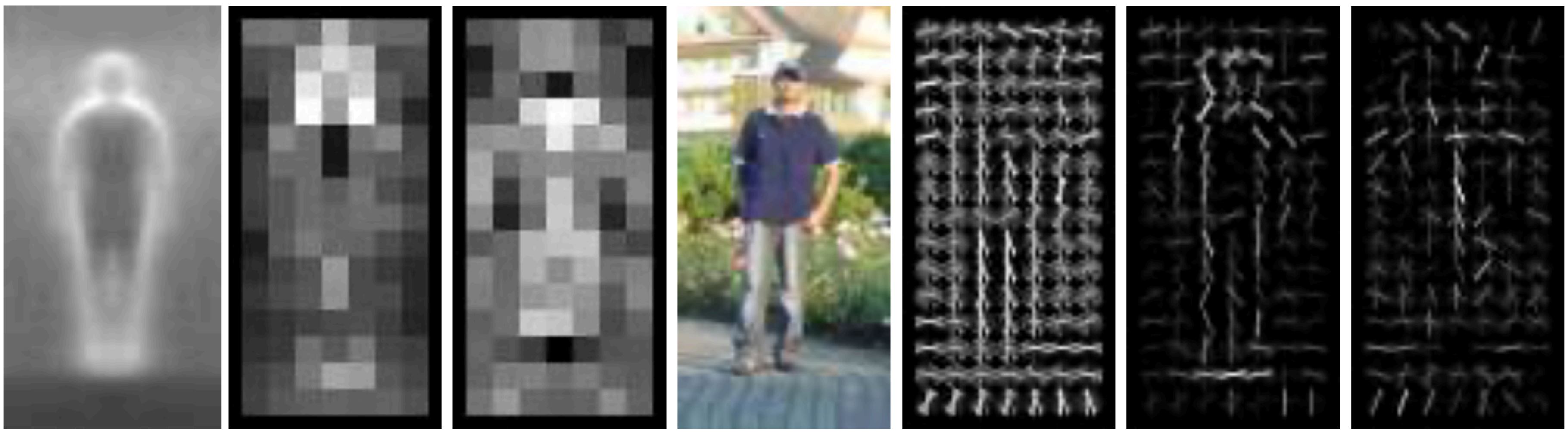
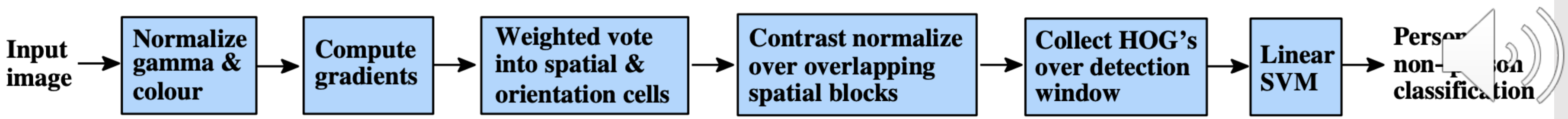


(a) (b) (c) (d) (e) (f) (g)

Figure 6. Our HOG detectors cue mainly on silhouette contours (especially the head, shoulders and feet). The most active blocks are centred on the image background just *outside* the contour. (a) The average gradient image over the training examples. (b) Each "pixel" shows the maximum positive SVM weight in the block centred on the pixel. (c) Likewise for the negative SVM weights. (d) A test image. (e) It's computed R-HOG descriptor. (f,g) The R-HOG descriptor weighted by respectively the positive and the negative SVM weights.



Original "publication"

U.S. Patent Jan. 28, 1986 Sheet 2 of 12 4,567,610

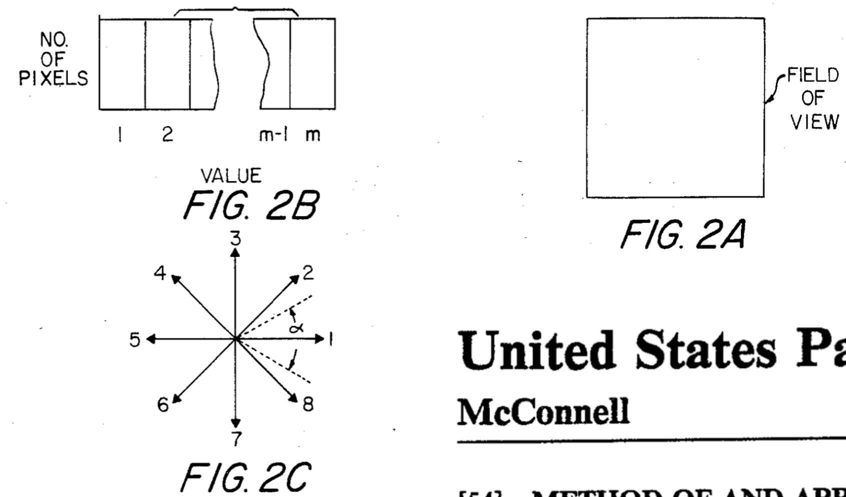


FIG. 2B

FIG. 2A

FIG. 2C

United States Patent [19]

McConnell

[11] **Patent Number:** **4,567,610**

[45] **Date of Patent:** **Jan. 28, 1986**

[54] **METHOD OF AND APPARATUS FOR PATTERN RECOGNITION**

[75] Inventor: **Robert K. McConnell**, Arlington, Mass.

[73] Assignee: **Wayland Research Inc.**, Wayland, Mass.

[21] Appl. No.: **400,948**

[22] Filed: **Jul. 22, 1982**

[51] **Int. Cl.**[4] **G06K 9/80**
[52] **U.S. Cl.** **382/18**; 382/30
[58] **Field of Search** 382/18, 30; 358/107

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Watanabe, "Pattern Recognition as a Quest for Minimum Entropy", *Pattern Recognition*, vol. 13, No. 5, 1981, pp. 381-387.

Primary Examiner—Leo H. Boudreau
Attorney, Agent, or Firm—Schiller & Pandiscio

[57] **ABSTRACT**

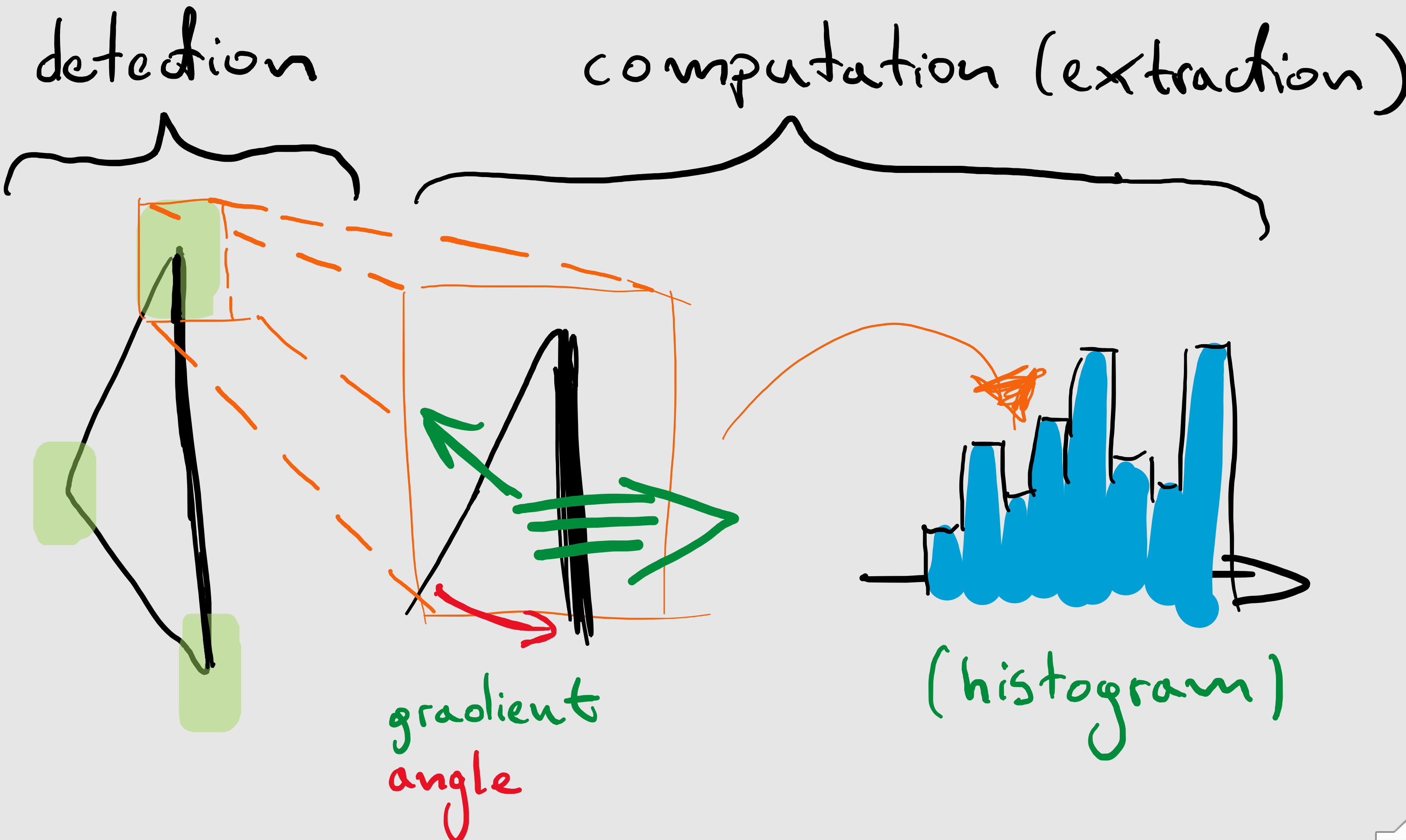
A method of and an apparatus for analysis of patterns both in static and dynamic modes. A test histogram is described in terms of the optimum code described for a reference histogram.

52 Claims, 33 Drawing Figures

Limitations:

- Rotational sensitivity
- Works at one scale only
- susceptible to parts change, deformations and other non-affine transformations

Sparse Features



SIFT

Object Recognition from Local Scale-Invariant Features

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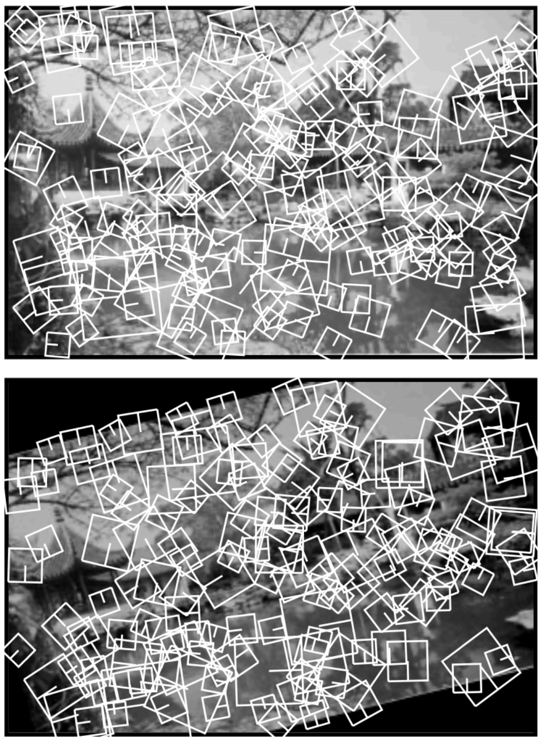
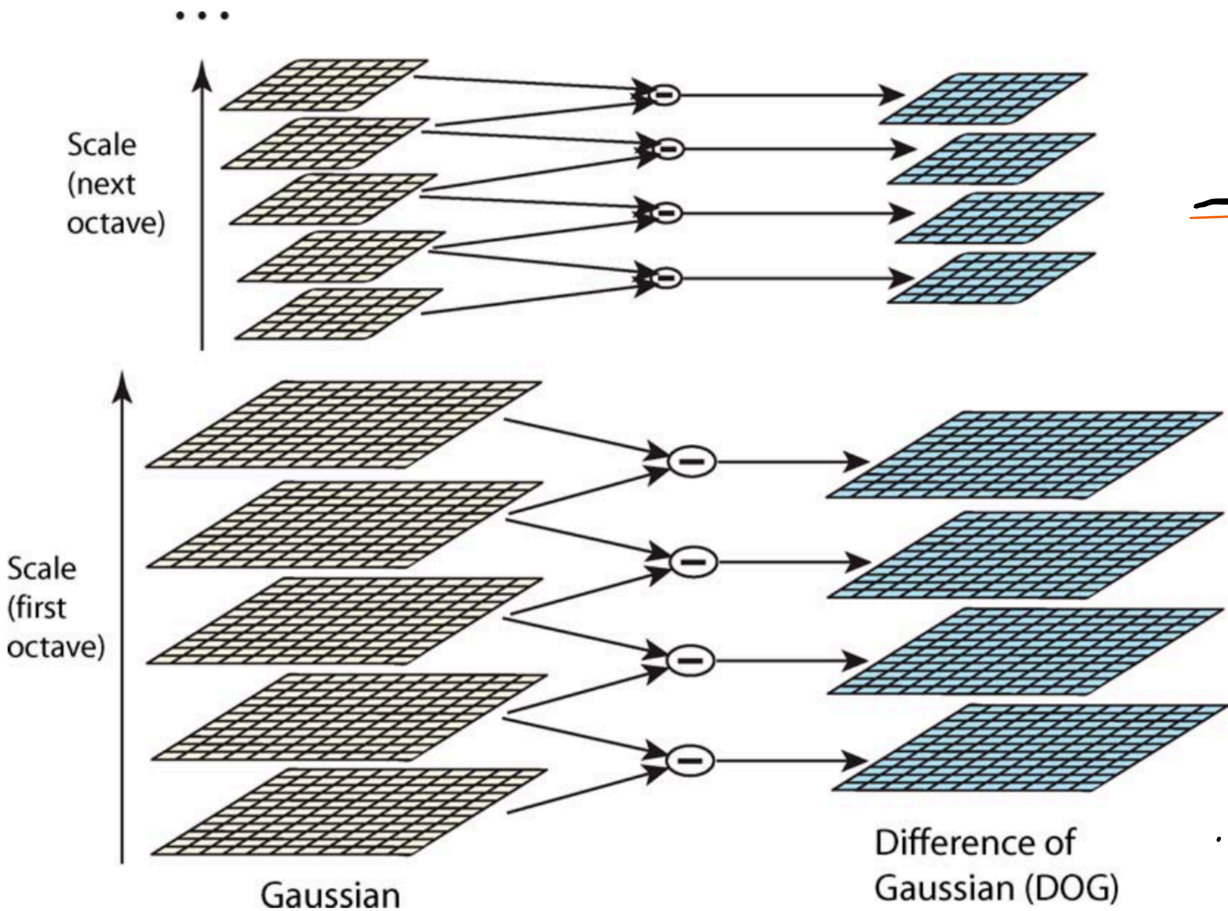


Figure 1: The second image was generated from the first by rotation, scaling, stretching, change of brightness and contrast, and addition of pixel noise. In spite of these changes, 78% of the keys from the first image have a closely matching key in the second image. These examples show only a subset of the keys to reduce clutter.

Figure 5: Examples of 3D object recognition with occlusion.



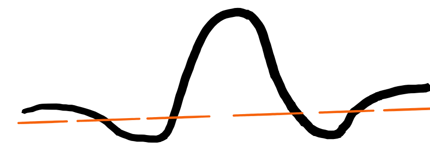


Figure 1. For each octave of scale space, the initial image is repeatedly convolved with Gaussians to produce the set of scale space images shown on the left. Adjacent Gaussian images are subtracted to produce the difference-of-Gaussian images on the right. After each octave, the Gaussian image is down-sampled by a factor of 2, and the process repeated.

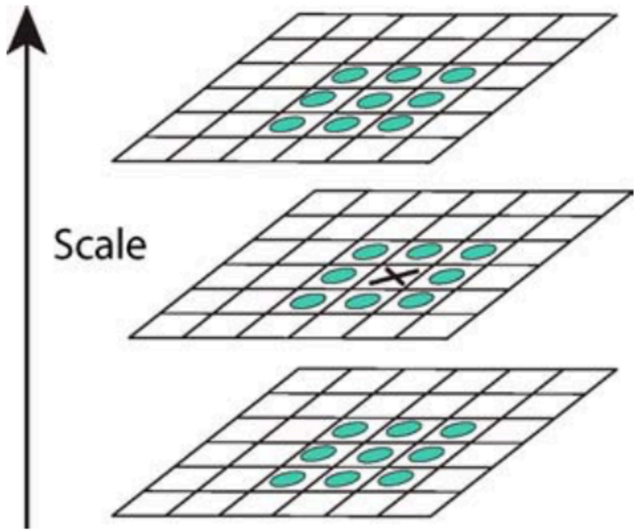


Figure 2. Maxima and minima of the difference-of-Gaussian images are detected by comparing a pixel (marked with X) to its 26 neighbors in 3 × 3 regions at the current and adjacent scales (marked with circles).

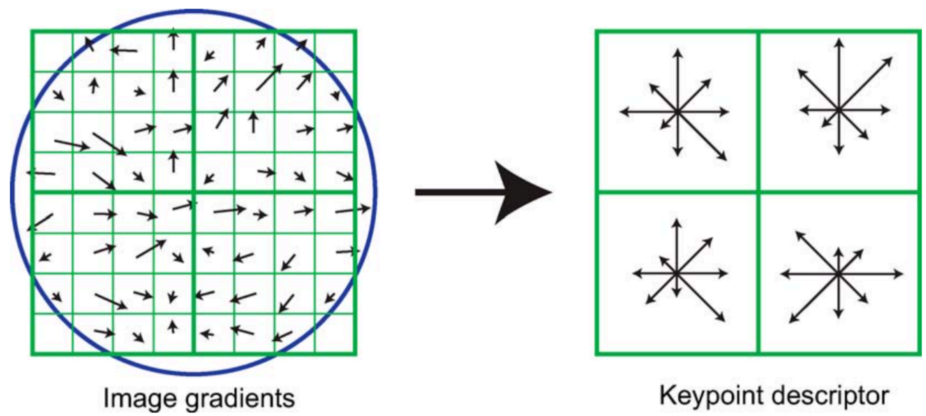


Figure 7. A keypoint descriptor is created by first computing the gradient magnitude and orientation at each image sample point in a region around the keypoint location, as shown on the left. These are weighted by a Gaussian window, indicated by the overlaid circle. These samples are then accumulated into orientation histograms summarizing the contents over 4x4 subregions, as shown on the right, with the length of each arrow corresponding to the sum of the gradient magnitudes near that direction within the region. This figure shows a 2 × 2 descriptor array computed from an 8 × 8 set of samples, whereas the experiments in this paper use 4 × 4 descriptors computed from a 16 × 16 sample array.

ORB

ORB: an efficient alternative to SIFT or SURF

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- Rotation invariant FAST + BRIEF
- Open Source

Machine Learning for High-Speed Corner Detection

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BRIEF: Binary Robust Independent Elementary Features*

Michael Calonder, Vincent Lepetit, Christoph Strecha, and Pascal Fua

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Keypoint detection

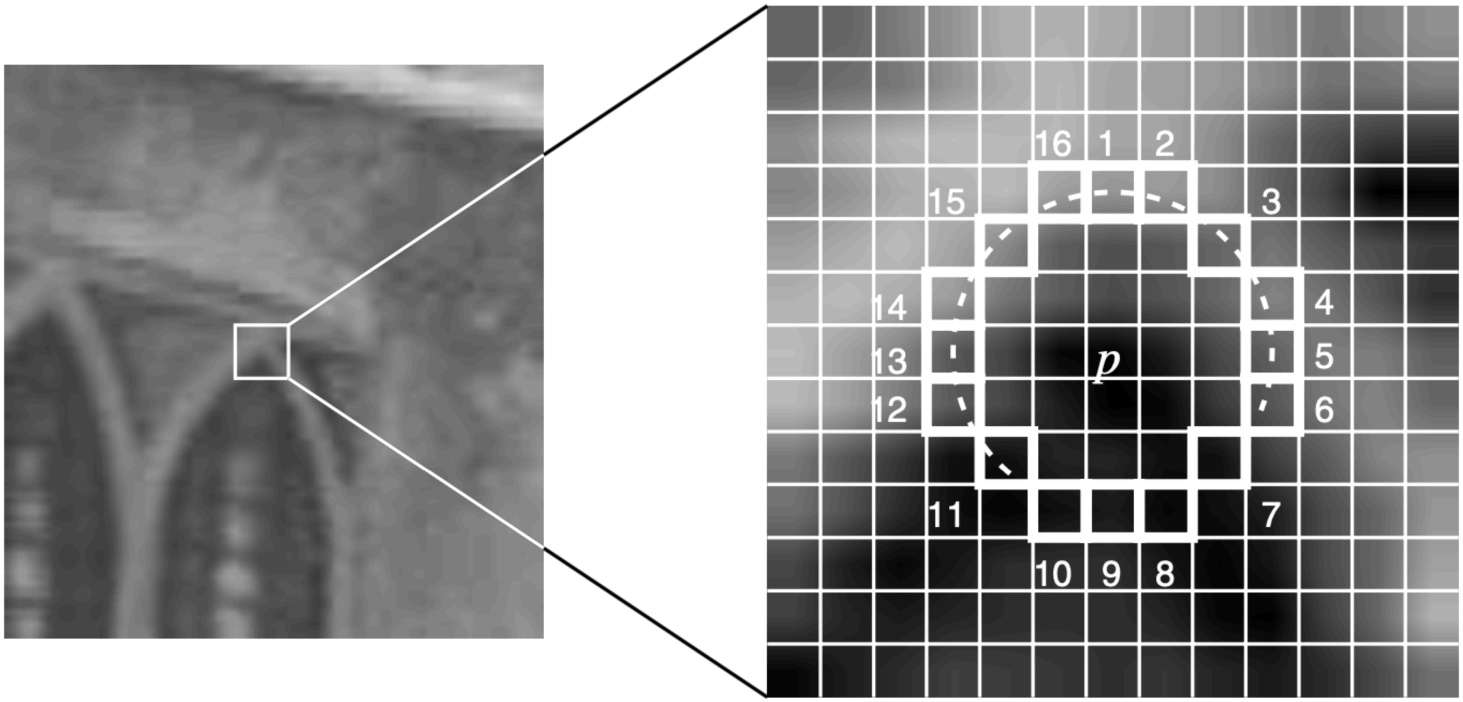
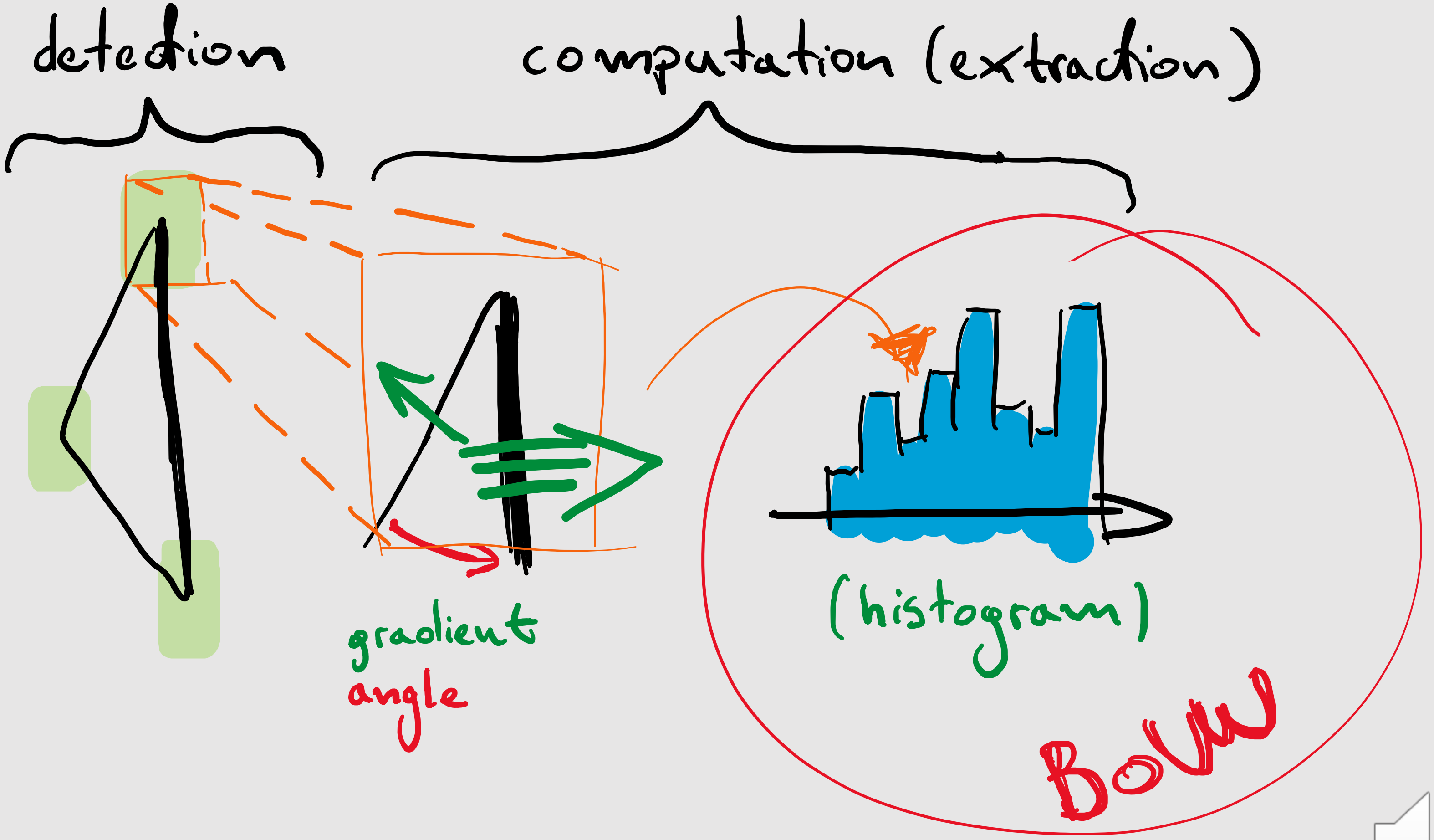
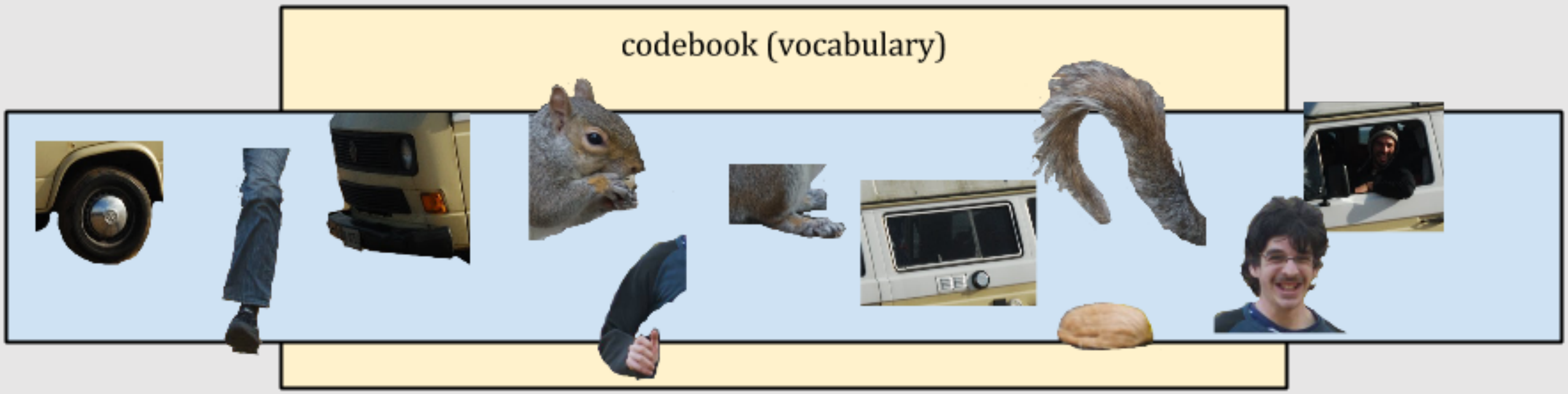


Fig. 1. 12 point segment test corner detection in an image patch. The highlighted squares are the pixels used in the corner detection. The pixel at p is the centre of a candidate corner. The arc is indicated by the dashed line passes through 12 contiguous pixels which are brighter than p by more than the threshold.

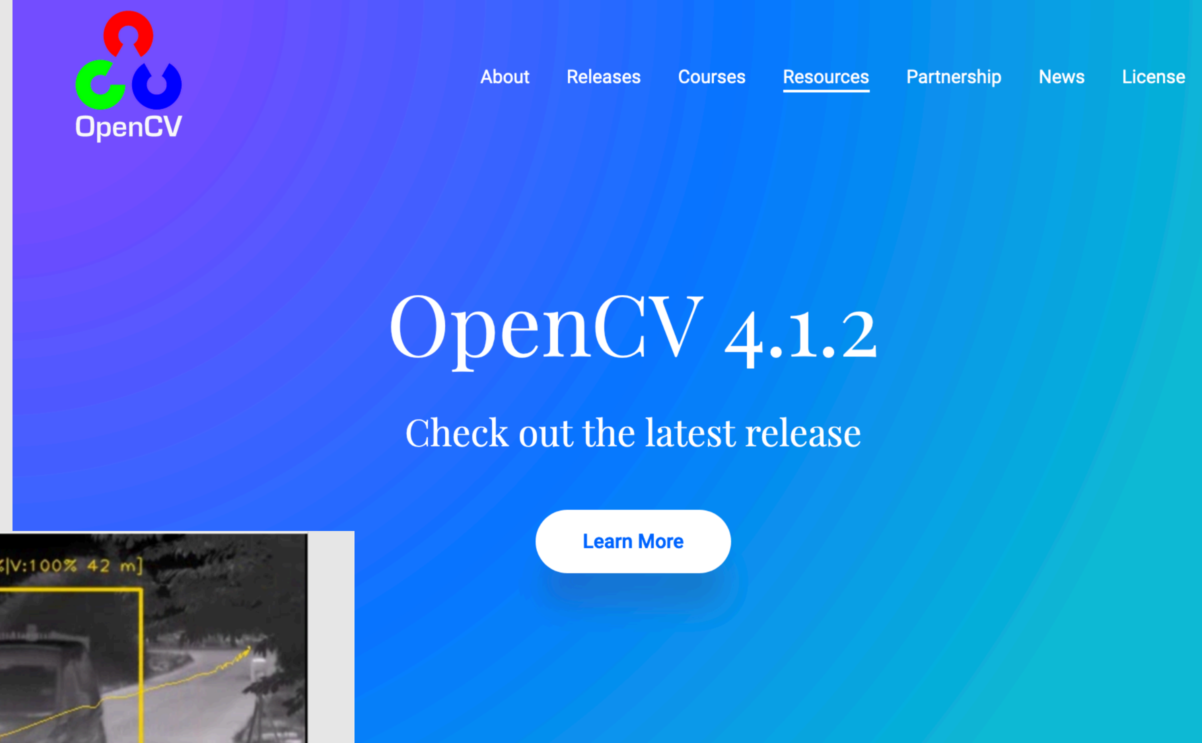
BoVW Feature points



Bag of Visual Words


codebook (vocabulary)

OpenCV C++ library



computer vision and robotics with Python bindings

OpenCV vs Scikit Learn

	OpenCV	**Scikit Learn**
Use	Industry and academia: from robotics to business analytics	Science and statistics
Language	C++/Java/Python	Python
Current version:	4.1.2	0.17
	Industry proven but at times poorly documented and inconsistent. Many well tested famous algorithms.	Excellent tutorials and examples, much easier to use and pythonesque.