Medical Image Processing for Interventional Applications

Edge Detection and Structure Tensor

Online Course – Unit 6
Andreas Maier, Joachim Hornegger, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Edge Detection in Medical Image Processing

- Edge detection and computation of interesting points is a standard problem
  - in medical image processing,
  - and in image processing in general.

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  - noisy images,
  - low contrast images, where structures are hard to detect and require a high degree of experience.
- Edges appear where we observe high differences in intensities.
- Differences in intensities can be measured by the **gradient**:

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix} = \begin{pmatrix} f_x \\ f_y \end{pmatrix} .$$

CT Slice and Corresponding Gradient Image

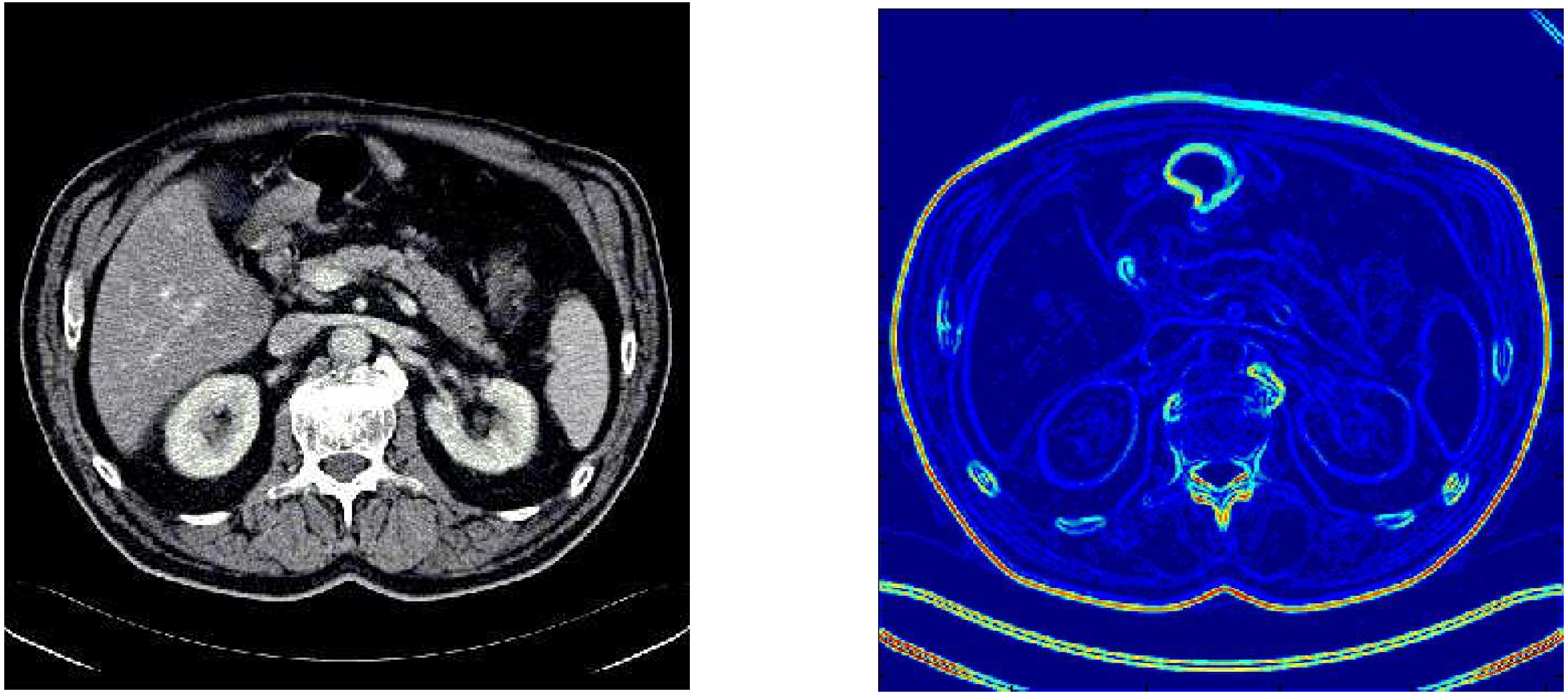

Figure 1: A CT slice (left) and its gradient image (right, gradient norm is color encoded)

Edge Detection and Gradients

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- An edge is supposed to be orthogonal to the gradient (which is often not true in practice).
- Derivatives are highly sensitive to noise (they are even ill-conditioned).
- Different discretizations exist, e.g.:
  - central differences,
  - the Sobel operator,
  - Nevatia-Babu,
  - and many more...

Computation of Discrete Derivatives

From the Taylor series expansion:

$$f(x+h) = f(x) + hf'(x) + O(h^2)$$

we get:

$$f'(x) = \frac{f(x+h) - f(x)}{h} + O(h).$$

Depending on the choice of h we get:

- forward differences, e.g. $h = 1$:

$$f'(x) \approx f(x+1) - f(x),$$

- backward differences, e.g. $h = -1$:

$$f'(x) \approx f(x) - f(x-1).$$

Differentiation and Smoothing

- Differentiation is mostly combined with low pass filtering, for instance, Gaussian filtering.
- We have two choices:
  - filtering with the Gaussian kernel K_σ followed by discrete differentiation of the filtered signal, where

$$K_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right),$$

  - convolution with first derivative of filtering kernel

$$\nabla f_\sigma = \nabla\left(K_\sigma * f\right) = \left(\nabla K_\sigma\right) * f.$$

Rule of thumb:
Always prefer the computation of derivatives in continuous space to differentiation in a discrete domain.

Topics

Edges and Gradients

Structure Tensor

Summary

- Take Home Messages
- Further Readings

Structure Tensor

An extension of the gradient information by using the **structure tensor** was introduced by Förstner and Gülch in 1987.

Applications of the structure tensor in low-level feature analysis are:

- edge detection,
- corner detection,
- texture analysis,
- optical flow,
- tracking.

Definition of Structure Tensor

Define the tensor product of gradients (gradient tensor) by:

$$\boldsymbol{J} = \nabla f \otimes \nabla f = \nabla f (\nabla f)^{\mathsf{T}} = \begin{pmatrix} f_x \\ f_y \end{pmatrix} (f_x, f_y) = \begin{pmatrix} f_x^2 & f_x f_y \\ f_x f_y & f_y^2 \end{pmatrix}.$$

The **structure tensor** is now defined by applying spatial averaging of the components of the gradient tensor with a Gaussian K_ρ:

$$\mathbf{J}_{\rho,\sigma} = K_\rho * (\nabla f_\sigma \otimes \nabla f_\sigma) \qquad \text{(element-wise convolution)},$$

where

$$\nabla f_\sigma = (\nabla K_\sigma) * f.$$

In this context, the “standard deviations” ρ and σ act as **regularization parameters**.

Comments on the Structure Tensor

Averaging is required:

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Properties:

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Let λ_1, λ_2 be the eigenvalues and $\boldsymbol{v}_1, \boldsymbol{v}_2$ be the respective eigenvectors of the structure tensor. The eigenvalues describe the average integrated contrast in the eigendirections:

- **flat area**: $\lambda_1 = \lambda_2 = 0$,
- **straight edge**: $\lambda_1 \gg \lambda_2 = 0$,
- **corner**: $\lambda_1 \geq \lambda_2 \gg 0$.

Example

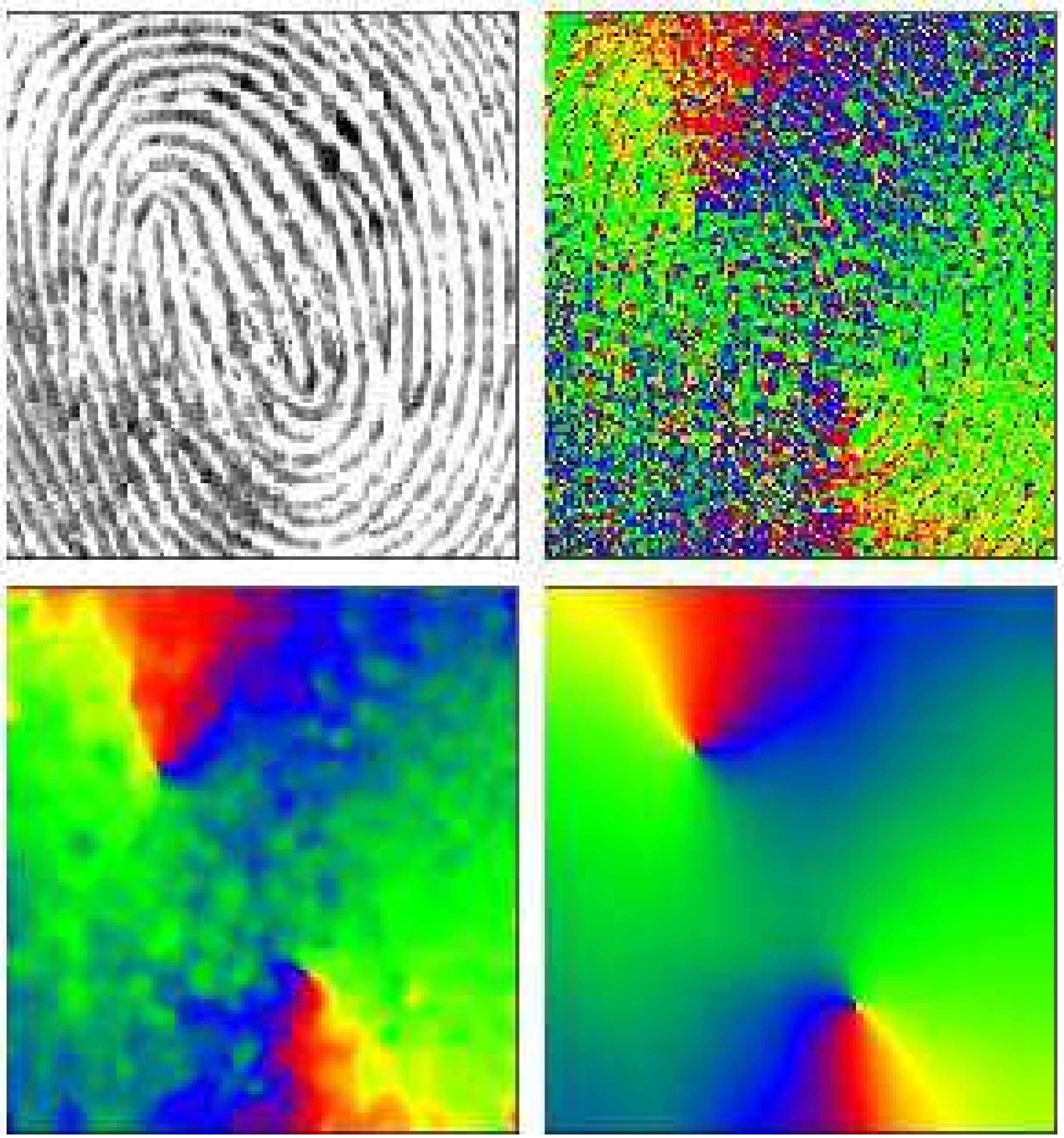

Figure 2: Original image (top left), direction of eigenvector with smaller eigenvalue for $\rho = 0$ (top right), $\rho = 4$ (bottom left), and $\rho = 26$ (bottom right) (image courtesy of Joachim Weickert)

Drawbacks of Structure Tensor

- Computation of the structure tensor violates the sampling theorem.
- Spatial averaging is done by Gaussian filtering that is not adapted to local structures.
- Corner detection has low accuracy.

Topics

Take Home Messages

- The detection of structures like edges and corners (of objects) in images is an important task, especially for interventional imaging.
- Local gradients and smoothed versions provide a mathematical basis for edge detection.
- Although it is not perfect, the structure tensor is an important tool to estimate local image structure.

Further Readings

The fundamentals of image processing including gradient computation, structure tensor, edge and corner detection, can be found in:

Bernd Jähne. *Practical Handbook on Image Processing for Scientific and Technical Applications*. 2nd ed. CRC Press, 2004

The idea of the structure tensor was first published by:

W. Förstner and E. Gülch. “A Fast Operator for Detection and Precise Location of Distinct Points, Corners and Centres of Circular Features”. In: *Proceedings of the ISPRS Intercommission Workshop on Fast Processing of Photogrammetric Data, Interlaken, Switzerland* (June 1987), pp. 281–305

A nice introduction and improvement of the structure tensor can be found in:

Ullrich Köthe. “Edge and Junction Detection with an Improved Structure Tensor”. In: *Pattern Recognition: 25th DAGM Symposium, Magdeburg, Germany, September 10-12, 2003. Proceedings*. Ed. by Bernd Michaelis and Gerald Krell. Vol. 2781. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2003, pp. 25–32. DOI: 10.1007/978-3-540-45243-0_4

Medical Image Processing for Interventional Applications

Vesselness Filter

Online Course – Unit 7

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Topics

Vessel Segmentation

- **Problem 1:** Vessels have different diameters.
  $\rightarrow$ We need to model different scales.
- **Problem 2:** Edges are only a weak model of vessels.
  $\rightarrow$ Structure tensor is insufficient for vessel modeling.

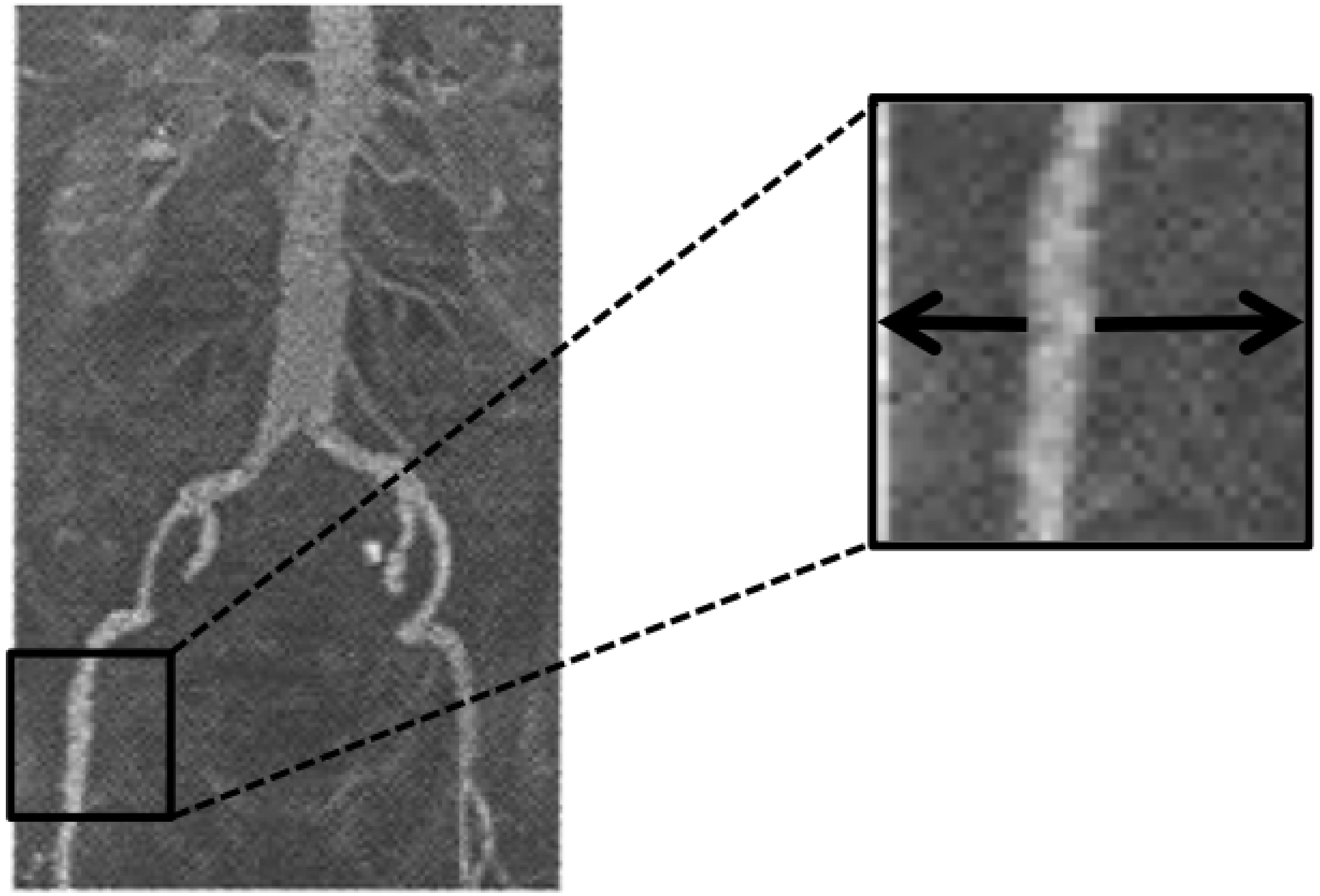


Figure 1: Example for a medical image containing vessels (left), detail on an area showing the edge property well (right)

Problem 1: Scale Modelling

Question: How big must the window/volume be?

- Solution using scale space with parameter s:

$$I(x,s) = I(x) * G(x,s), \quad G(x,s) = \frac{1}{\sqrt{2\pi s}} \exp\left(-\frac{\|x\|^2}{2s^2}\right)$$

- Derivative of Gaussians (in 1-D):

$$\frac{\partial}{\partial x} I(x,s) = I(x) * \frac{\partial}{\partial x} G(x,s)$$

Problem 2: Vessel Model

From the properties of the structure tensor we can determine:

- rank 0 $\rightarrow$ flat area,
- rank 1 $\rightarrow$ edge,
- rank 2 $\rightarrow$ corner.

But: Edges are not a good model of a vessel.

$\rightarrow$ Modeling of curvature seems better suited to tackle this problem.

Problem 2: Vessel Model

Approach: compute Hessian (here 2-D)

$$H_s = \begin{pmatrix} \frac{\partial^2}{\partial x^2} I(\boldsymbol{x}, s) & \frac{\partial^2}{\partial x \partial y} I(\boldsymbol{x}, s) \\ \frac{\partial^2}{\partial y \partial x} I(\boldsymbol{x}, s) & \frac{\partial^2}{\partial y^2} I(\boldsymbol{x}, s) \end{pmatrix}$$

This matrix looks very similar to the structure tensor, but the analysis of its eigenvalues yields:

- rank 0 $\rightarrow$ no curvature, i. e., **flat** or **linear** behaviour,
- rank 1 $\rightarrow$ curvature in one direction, i. e., a **tubular** structure,
- rank 2 $\rightarrow$ curvature in two directions, i. e., a **blob-like** structure.

Good Vessels in 2-D

Indication of a vessel (we assume sorting $|\lambda_1| \geq |\lambda_2|$):

$$|\lambda_1| > |\lambda_2| \qquad \wedge \qquad |\lambda_2| \approx 0$$

Vesselness measures:

$$R_B = \frac{\lambda_2}{\lambda_1} \qquad \text{(close to 0 if vessel)}$$

$$S = \sqrt{\lambda_1^2 + \lambda_2^2} \qquad \text{(high contrast if vessel)}$$

Probability map for vessels (β, c are control parameters, e. g., $\beta = 0.5$, and c depends on scaling):

$$V(\boldsymbol{x}, s) = \begin{cases} 0, & \lambda_1 > 0 \\ \exp\left(-\frac{R_B^2}{2\beta^2}\right)\left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right), & \text{otherwise} \end{cases}$$

Maximum over all scales:

$$V(\boldsymbol{x}) = \max_{s_{\min} < s < s_{\max}} V(\boldsymbol{x}, s)$$

3-D Case

Good vessels (we assume sorting $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|$):

$$|\lambda_3| \approx 0 \qquad \wedge \qquad |\lambda_2| \gg \lambda_3 \qquad \wedge \qquad \lambda_1 \approx \lambda_2$$

3-D vesselness:

$$R_B = \frac{|\lambda_3|}{\sqrt{|\lambda_1 \lambda_2|}} \qquad \text{(close to 0 if vessel)}$$

$$R_A = \frac{|\lambda_2|}{|\lambda_1|} \qquad \text{(close to 0 if surface point)}$$

$$S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2} \qquad \text{(high if vessel } \rightarrow \text{ contrast)}$$

3-D Case

Vesselness on scale s (probability map):

$$V(\boldsymbol{x}, s) = \begin{cases} 0, & \lambda_1 > 0 \text{ or } \lambda_2 > 0 \\ \left(1 - \exp\left(-\frac{R_A^2}{2\alpha^2}\right)\right) \exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right), & \text{otherwise} \end{cases}$$

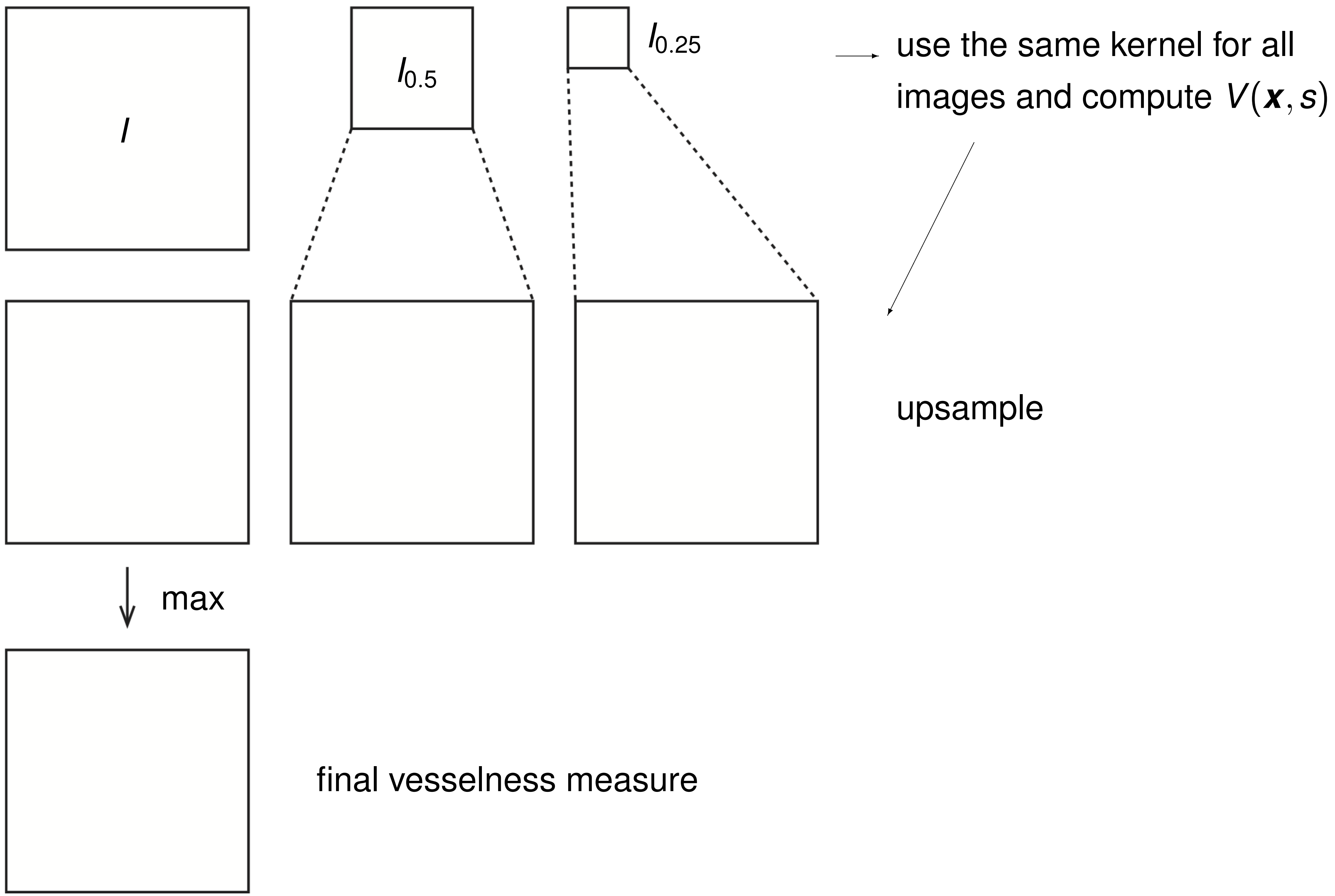
α, β, c are parameters to be selected by the user ($\alpha = \beta = 0.5$, c depends on contrast)

Maximum over all scales:

$$V(\boldsymbol{x}) = \max_s V(\boldsymbol{x}, s)$$

Faster Implementation

Instead of increasing s, downsample the image I to images I_d accordingly:
$\rightarrow$ less eigenvalue analyses
$\rightarrow$ faster computation for high resolution images



Topics

Vesselness Filter

- Vessel Segmentation
- Good Vessels in 2-D
- Faster Implementation

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- The Hessian and its eigenvalue analysis can be used to define a measure of vesselness.
- It is often more reliably than the structure tensor.
- The vesselness filter is well-known in medical imaging and can be considered a requisite.
- When implementing methods using scale-space, downsampling instead of computing several kernels can speed up your code.

Further Readings

- Alejandro F. Frangi et al. "Multiscale Vessel Enhancement Filtering". In: *Medical Image Computing and Computer-Assisted Intervention – MICCAI'98*. Ed. by William M. Wells, Alan Colchester, and Scott Delp. Vol. 1496. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 1998, pp. 130–137. DOI: 10.1007/BFb0056195
- A. Budai et al. "Robust Vessel Segmentation in Fundus Images". In: *International Journal of Biomedical Imaging* 2013.154860 (Sept. 2013), pp. 1–11. DOI: 10.1155/2013/154860

Medical Image Processing for Interventional Applications

Vesselness Examples

Online Course – Unit 8
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Topics

Applications of Vesselness

Take Home Message

Paper

Alejandro F. Frangi et al. “Multiscale Vessel Enhancement Filtering”. In: *Medical Image Computing and Computer-Assisted Interventation – MICCAI’98*. Ed. by William M. Wells, Alan Colchester, and Scott Delp. Vol. 1496. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 1998, pp. 130–137. DOI: 10.1007/BFb0056195

2-D Angiography

Figure 1: Part of a contrast X-ray image of the peripheral vasculature (left), calculated vesselness of the left image (middle-left), calculated vesselness after inversion of the grey-scale map (middle-right), image obtained by subtracting reference (without contrast) image from left image – shown here to facilitate visual inspection of the results of the filtering procedure (right) (source of images and description: Frangi‘s article cited on slide no. 3)

Fundus Imaging / Low Resolution Images

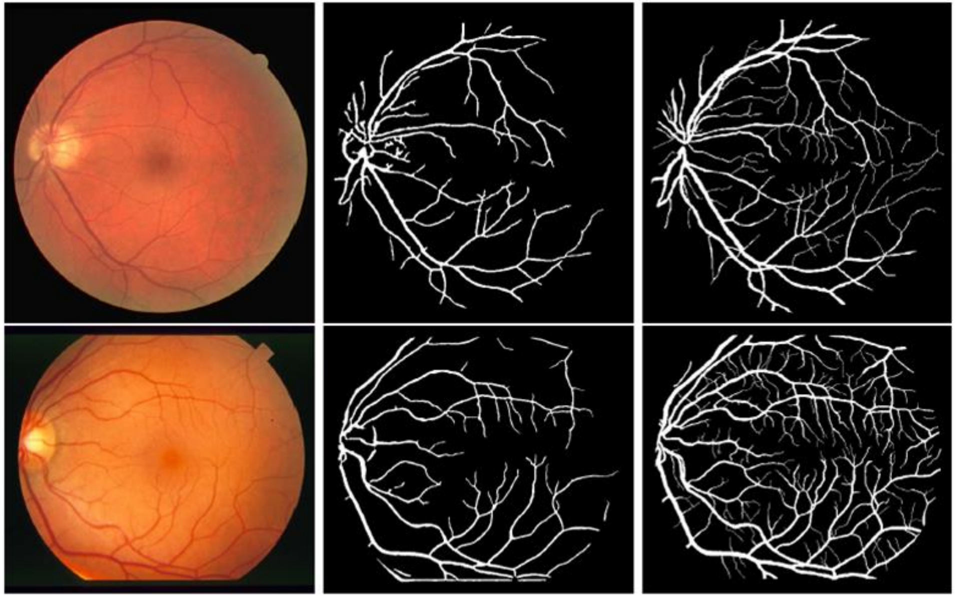

Figure 2: Example segmentation results on two public databases, from left to right: input fundus image, segmentation results, and gold standard images (Attila Budai, Pattern Recognition Lab, FAU)

Fundus Imaging / High Resolution Images

Figure 3: Source by Attila Budai, Pattern Recognition Lab, FAU

3-D MRI Angiography

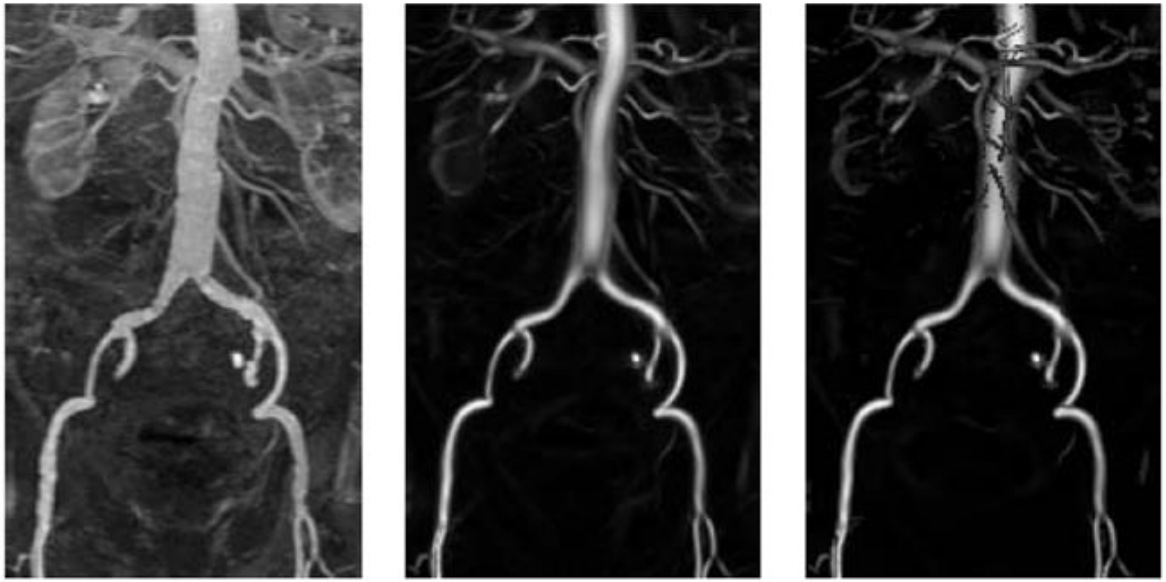

Figure 4: Original maximum intensity projection of a contrast (Gd-DTPA) MRA image (left); maximum intensity projection of vessel enhanced image →obtaining quite good background suppression (middle); closest vessel projection, facilitated by the filter‘s excellent background suppression (source of images and description: Frangi‘s article cited on slide no. 3)

3-D MRI Angiography

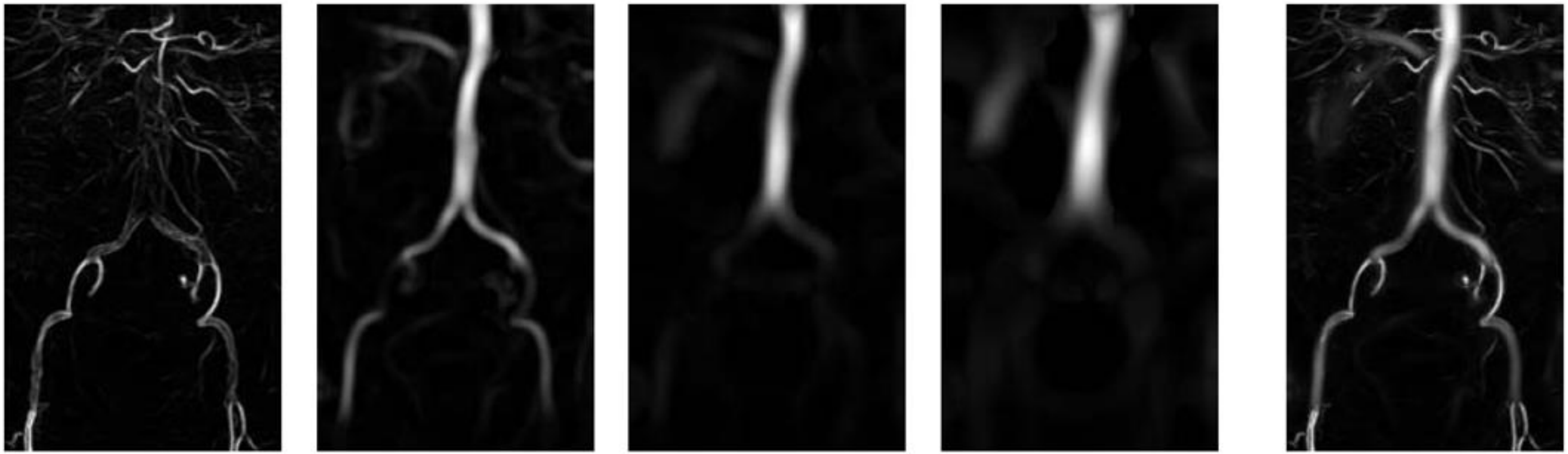

Figure 5: The first four images show the vesselness obtained at increasing scales. The last image is the result after the scale selection procedure. (source of images and description: Frangi‘s article cited on slide no. 3)

Topics

Applications of Vesselness

Take Home Message

Take Home Message

There are a lot of applications in medical imaging where vesselness measures are useful. In this regard, always recall Frangi‘s original work which is often cited when vesselness is used.

Medical Image Processing for Interventional Applications

Introduction to Feature Matching

Online Course – Unit 9

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TECHNISCHE FAKULTÄT

Topics

Feature Matching

Introduction

Requirements

Pipeline

Summary

Take Home Messages

Further Readings

Introduction: Stereo Vision in Image-guided Radiation Therapy

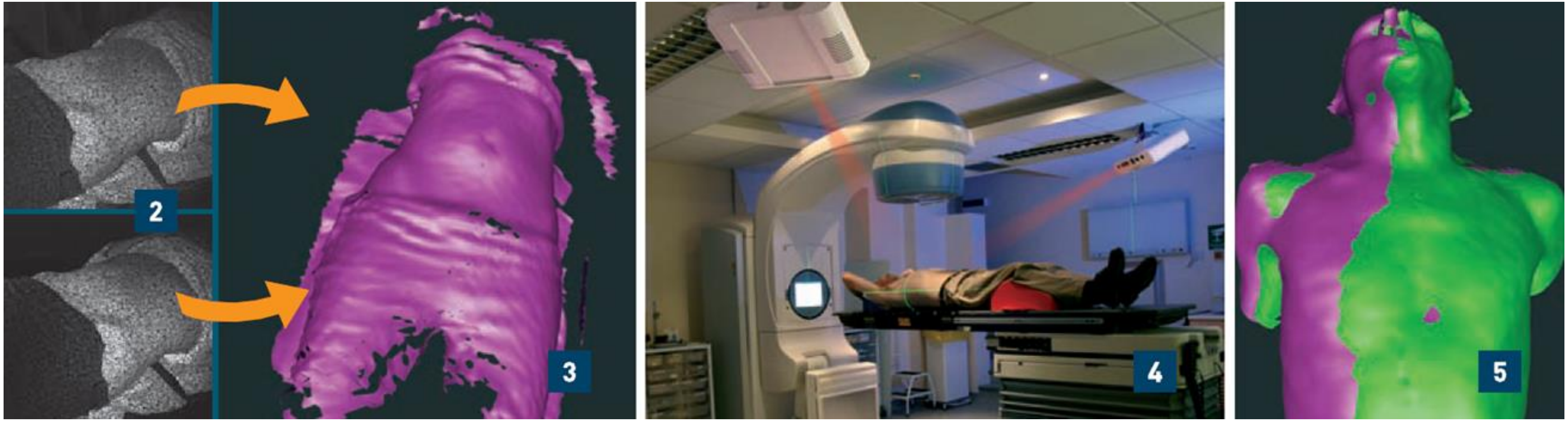


Figure 1: AlignRT system – overview of the workflow in image-guided radiation therapy (images courtesy of VisionRT)

Introduction: Stereo Vision in Image-guided Radiation Therapy

1. Identify pairs of corresponding points
2. Reconstruct depth by triangulation

Figure 2: VisionRT stereo imaging device (image courtesy of VisionRT)

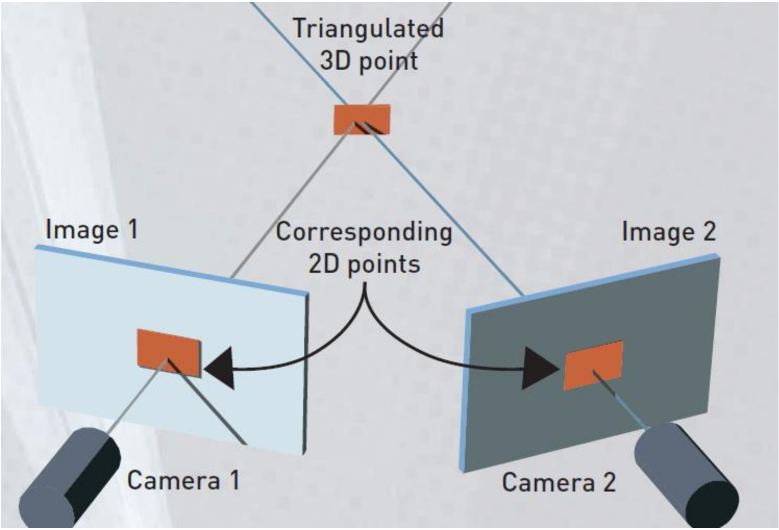


Figure 3: Epipolar geometry (image courtesy of VisionRT)

Introduction: Importance of features

Many computer vision applications are based on local features

Requirements and Invariances

What makes a feature suitable for matching?

Requirements and Invariances

What makes a feature suitable for matching?

- Locality

Requirements and Invariances

What makes a feature suitable for matching?

- Locality
- Invariance to transformations

Requirements and Invariances

What makes a feature suitable for matching?

- Locality
- Invariance to transformations
- Repeatability, quantity

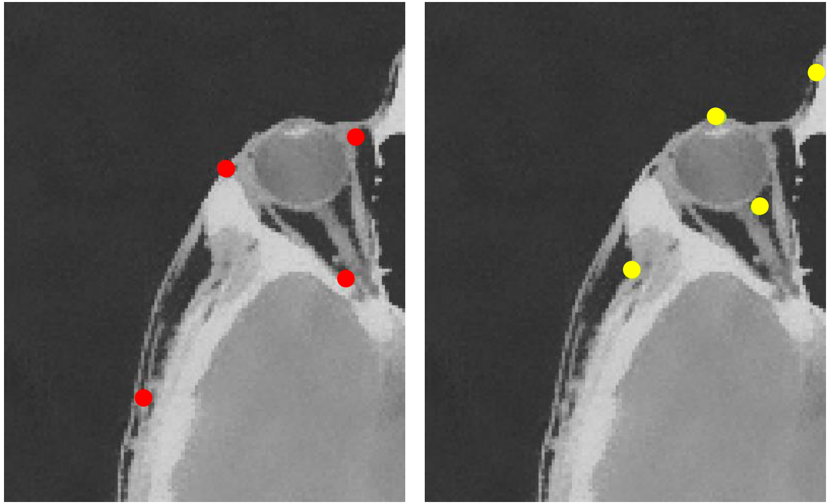


Figure 4: Local feature points

Requirements and Invariances

What makes a feature suitable for matching?

- Locality
- Invariance to transformations
- Repeatability, quantity
- Distinctiveness

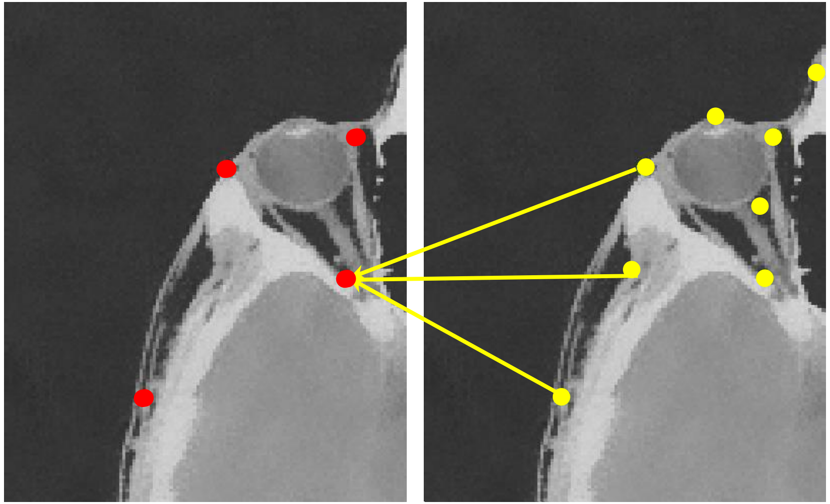


Figure 5: Matching trial

Requirements and Invariances

What makes a feature suitable for matching?

- Locality
- Invariance to transformations
- Repeatability, quantity
- Distinctiveness
- Robustness (illumination, viewpoint, noise, …)

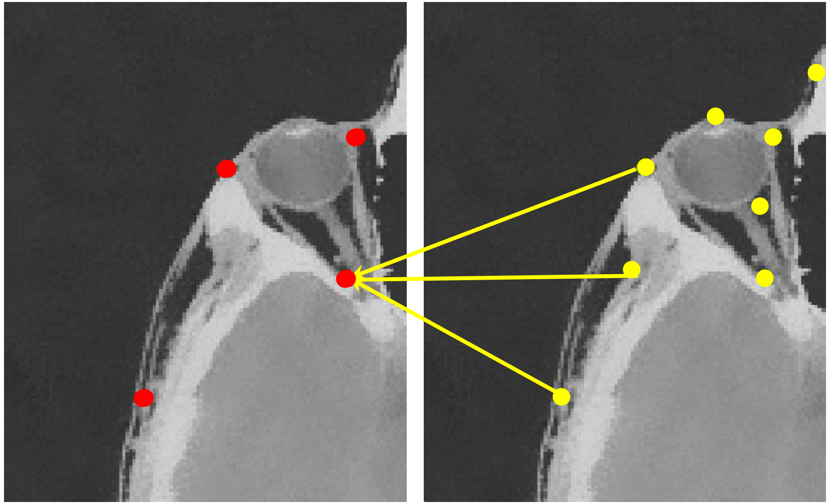


Figure 5: Matching trial

Feature Matching Pipeline

Matching cascade:

Image 1

Image 2

Feature Matching Pipeline

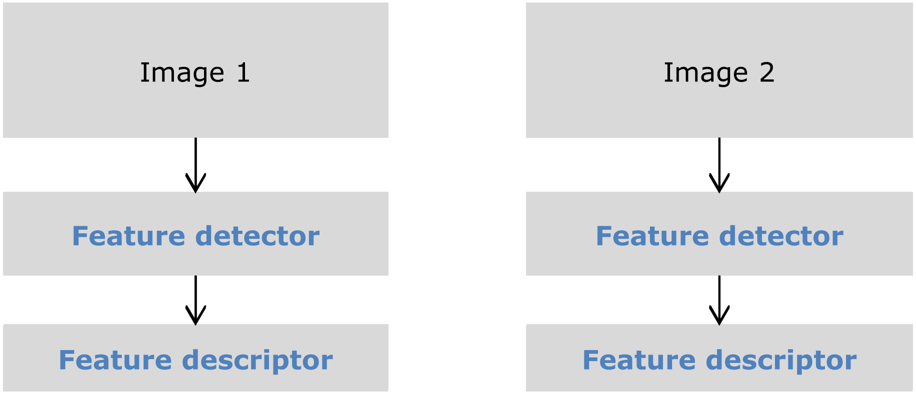
Matching cascade:

1. Identify potential interest points with low-level algorithms

Feature Matching Pipeline

Matching cascade:

1. Identify potential interest points with low-level algorithms
2. Compute high-level descriptor only at these locations



Feature Matching Pipeline

Matching cascade:

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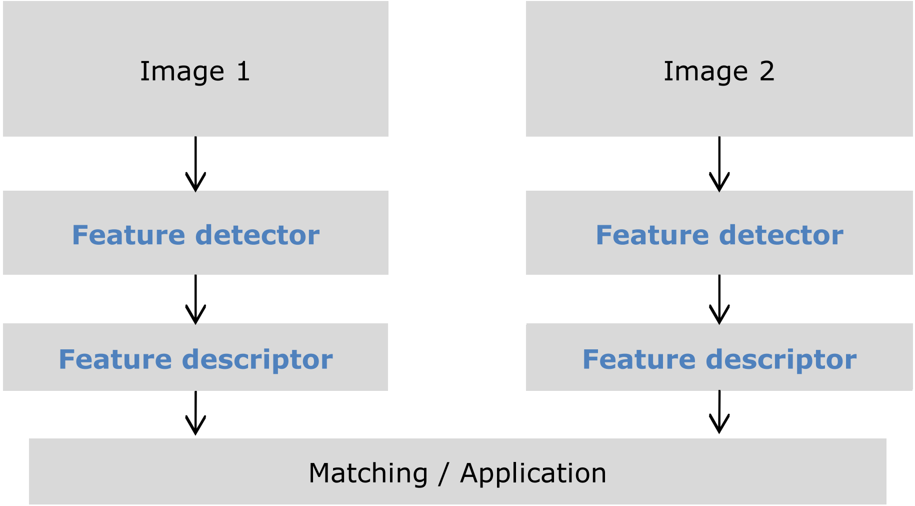

Feature Matching Pipeline

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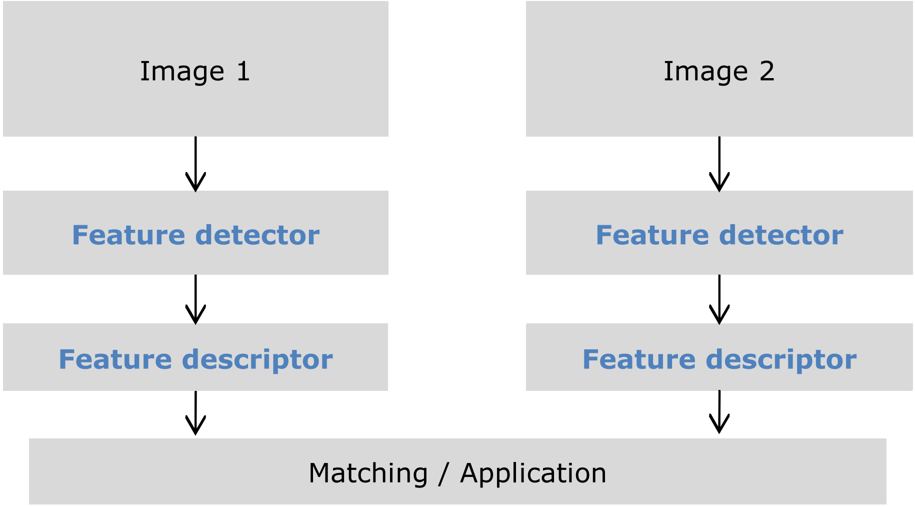

→ Minimizing the cost of feature extraction

→ Reducing the correspondence search space

Topics

Take Home Messages

- Imaging for interventional imaging involves tasks similar to computer vision tasks.
- Often two different images have to be matched, so distinct interest points have to be detected.
- Invariances of features w.r.t. locality and certain transformations is desired and most often necessary.

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
- Cordelia Schmid, Roger Mohr, and Christian Bauckhage. “Evaluation of Interest Point Detectors”. In: *International Journal of Computer Vision* 37.2 (June 2000), pp. 151–172. DOI: 10.1023/A:1008199403446
- D. Marr and E. Hildreth. “Theory of Edge Detection”. In: *Proceedings of the Royal Society of London B: Biological Sciences* 207.1167 (Feb. 1980), pp. 187–217. DOI: 10.1098/rspb.1980.0020

Medical Image Processing for Interventional Applications

Feature Detectors

Online Course – Unit 10

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Pattern Recognition Lab (CS 5)

Topics

Feature Detectors

Initial Considerations

Harris Corner Detector

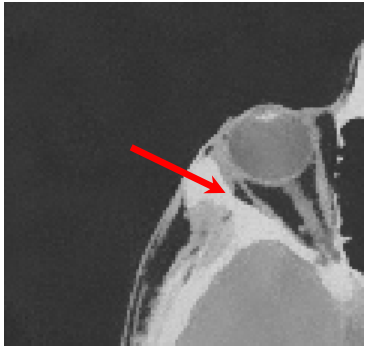
Summary

Take Home Messages

Further Readings

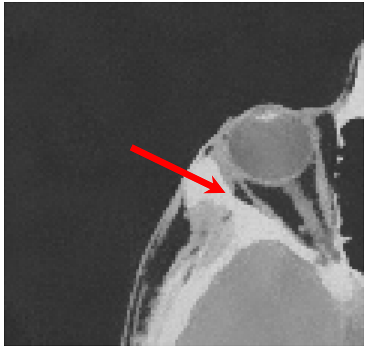
Feature Detectors

How to identify distinctive locations efficiently?

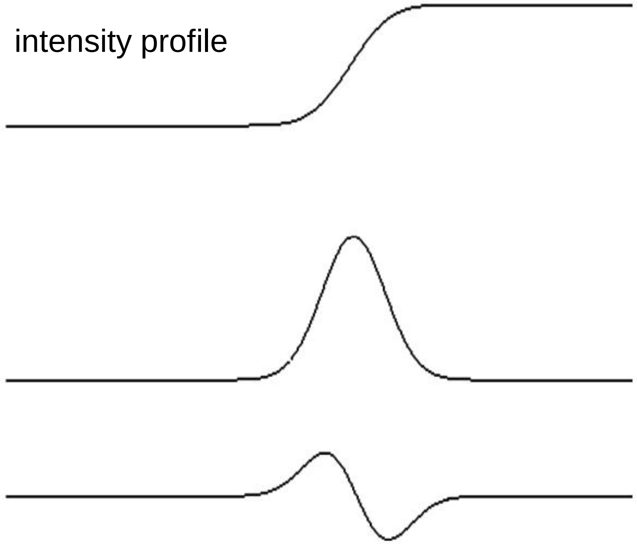


Feature Detectors

How to identify distinctive locations efficiently?



- First order derivatives
- Second order derivatives
- Structure tensor, Hessian matrix



Feature Detectors: Benchmark Study by Schmid, Mohr, and Bauckhage (2000)

Which one to choose?

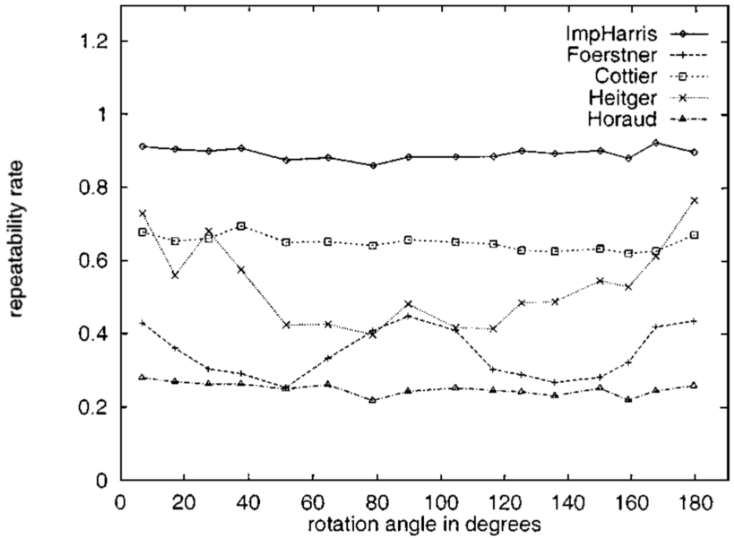


Figure 2: **Rotation** invariance

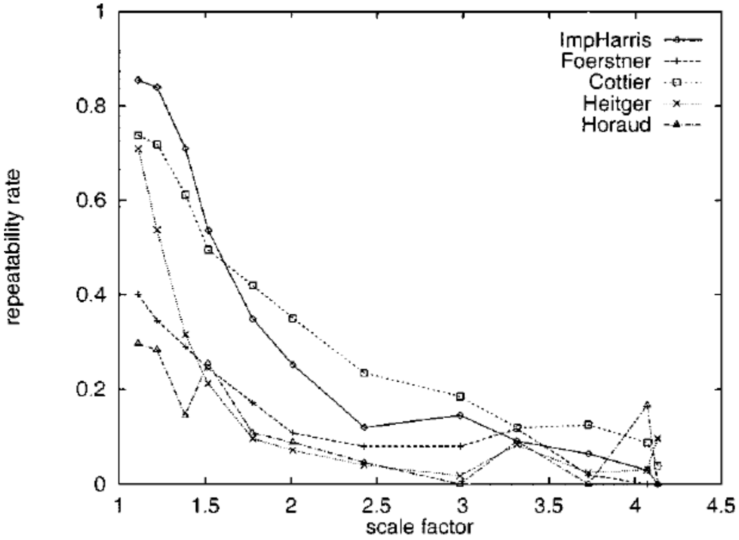


Figure 3: **Scale** invariance

Feature Detectors: Benchmark Study by Schmid, Mohr, and Bauckhage (2000)

Which one to choose?

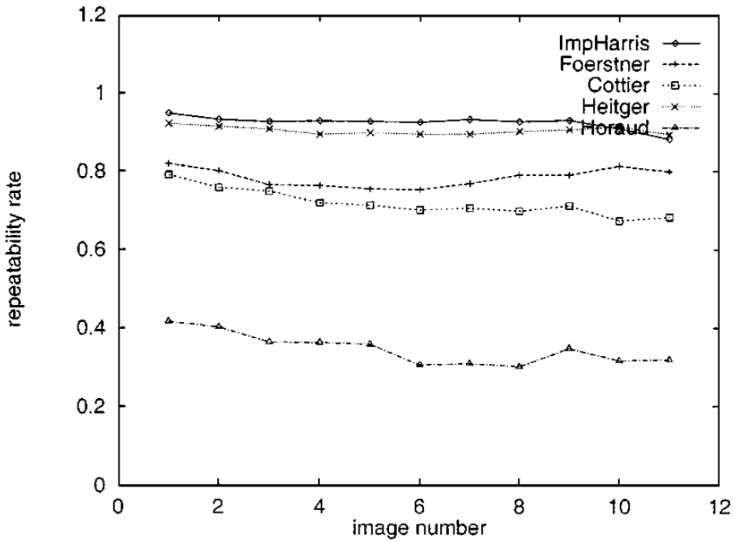


Figure 4: **Illumination** invariance

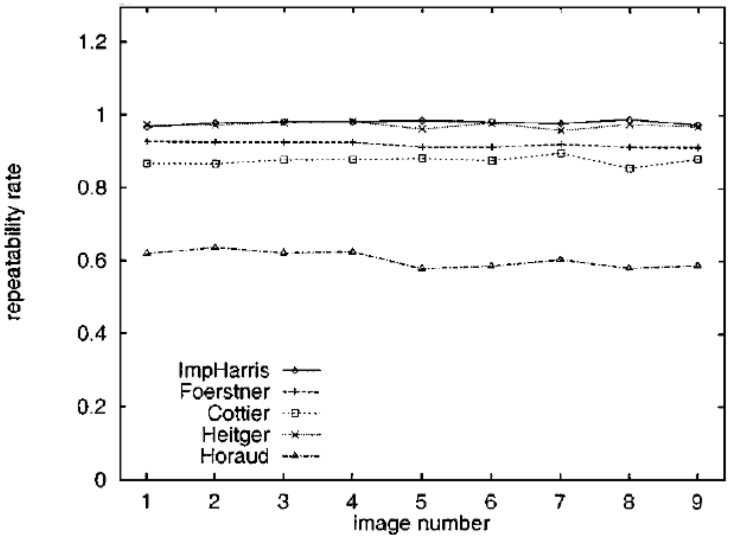


Figure 5: **Noise** invariance

Harris Corner Detector

Basic idea (Harris and Stephens, 1988): A corner point should have large intensity changes in all directions.

Gradient approximation:

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

Structure tensor (autocorrelation):

$$\begin{aligned}\mathbf{G}(x,y) &= \sum_{i=-k}^{k}\sum_{j=-k}^{k} w(x,y)\boldsymbol{g}(x+i,y+j)\boldsymbol{g}^T(x+i,y+j) \\ &= \sum_{i=-k}^{k}\sum_{j=-k}^{k} w(x,y)\begin{bmatrix} (g_x(\ldots))^2 & g_x(\ldots)g_y(\ldots) \\ g_x(\ldots)g_y(\ldots) & \left(g_y(\ldots)\right)^2 \end{bmatrix}\end{aligned}$$

Harris Corner Detector

Eigenvectors and eigenvalues of structure tensor $\mathbf{G}$ describe predominant directions of the gradient:

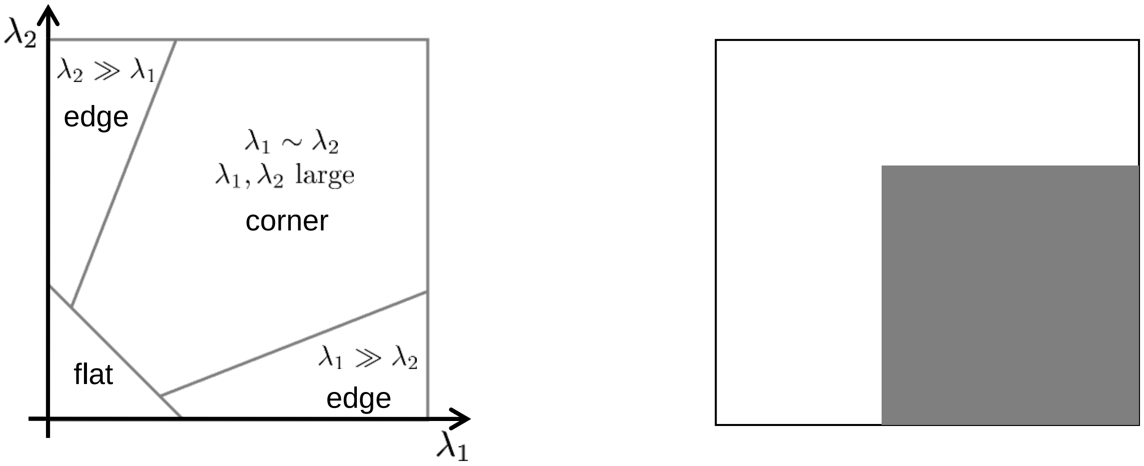
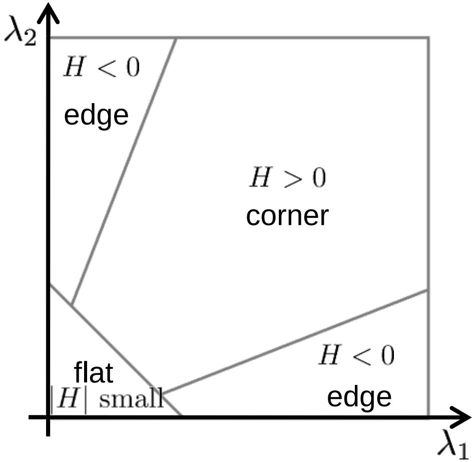


Figure 6: Schematic of relationship between feature categories and eigenvalues (left), example image with a corner, edges and flat areas (right)

Harris Corner Detector

Eigenvectors and eigenvalues of structure tensor $\mathbf{G}$ describe predominant directions of the gradient:

$$H(x, y) = \det(\mathbf{G}(x, y)) - \nu \left(\mathrm{tr}\left(\mathbf{G}(x, y)\right)\right)^2$$



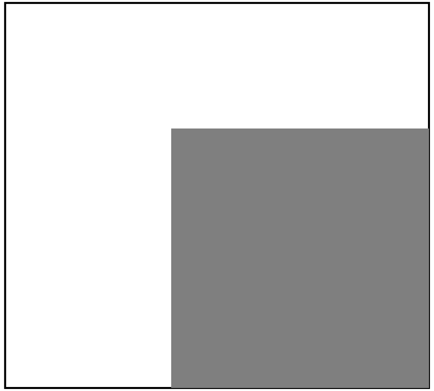
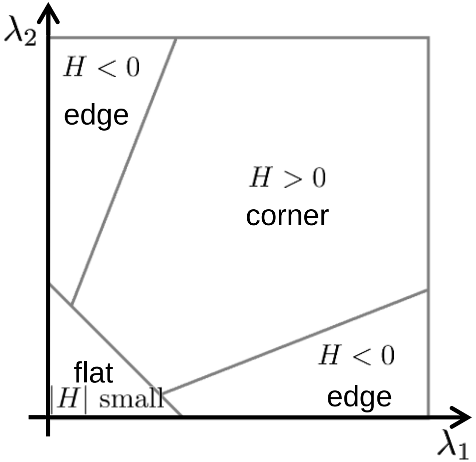


Figure 7: Structure described by value of H (left), example image with a corner, edges and flat areas (right)

Harris Corner Detector

Eigenvectors and eigenvalues of structure tensor $\mathbf{G}$ describe predominant directions of the gradient:

$$H(x,y) = \det(\mathbf{G}(x,y)) - \nu\left(\mathrm{tr}\big(\mathbf{G}(x,y)\big)\right)^2 = \lambda_1\lambda_2 - \nu(\lambda_1+\lambda_2)^2$$



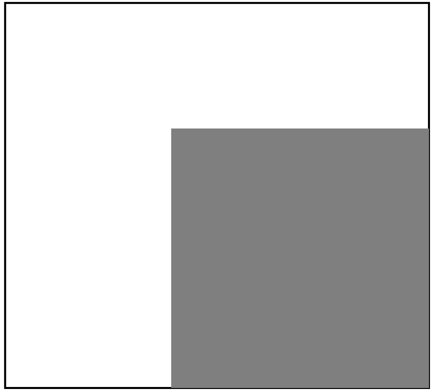


Figure 7: Structure described by value of H (left), example image with a corner, edges and flat areas (right)

Harris Corner Detector: Workflow

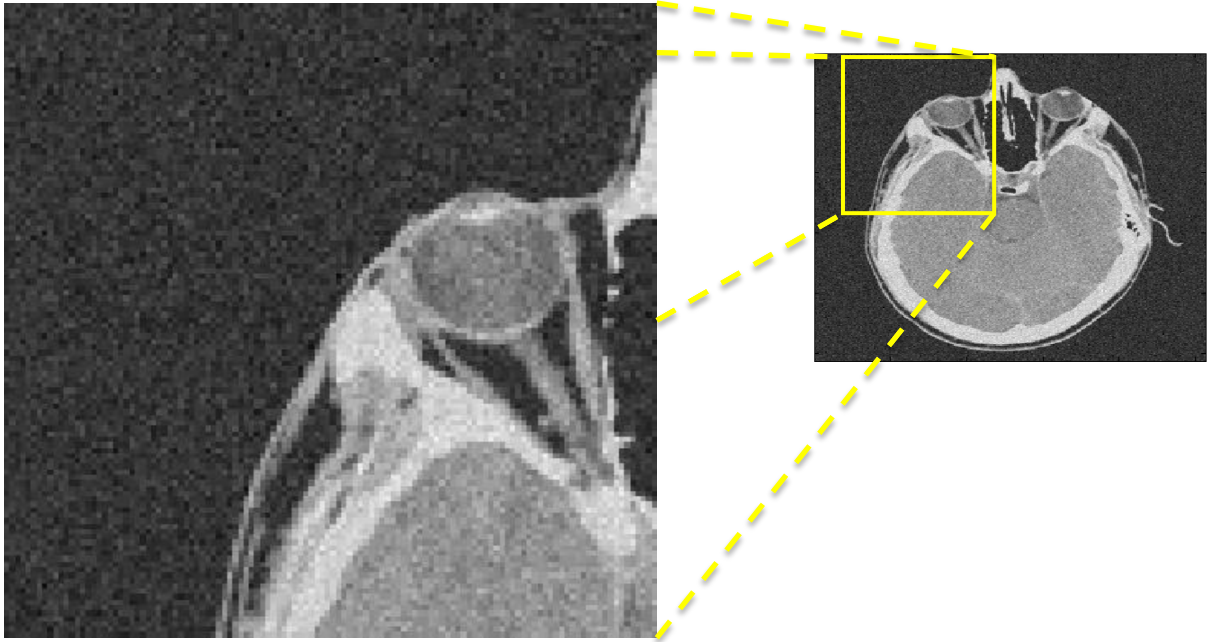


Figure 8: What about noise?

Harris Corner Detector: Workflow

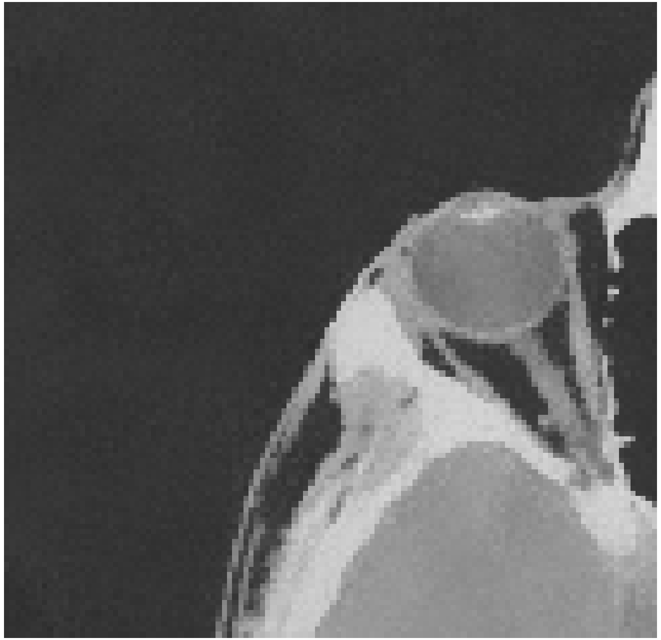


Figure 9: Edge-preserving denoising

Harris Corner Detector: Workflow

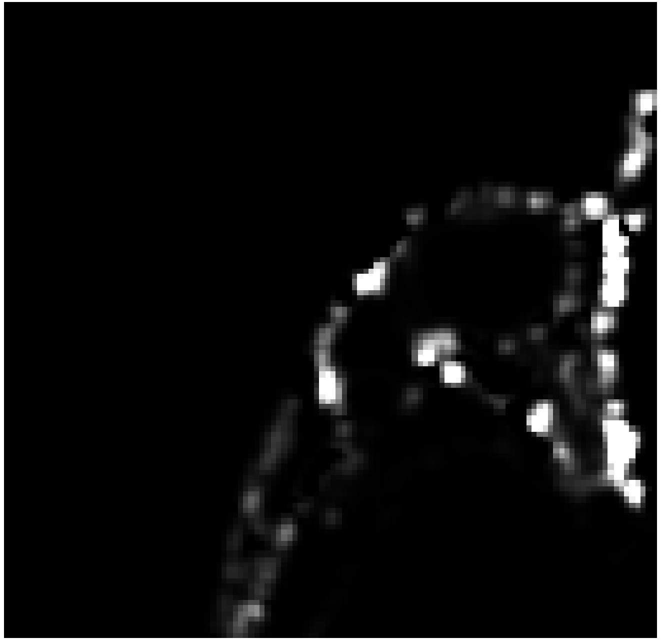


Figure 10: Corner response

Harris Corner Detector: Workflow

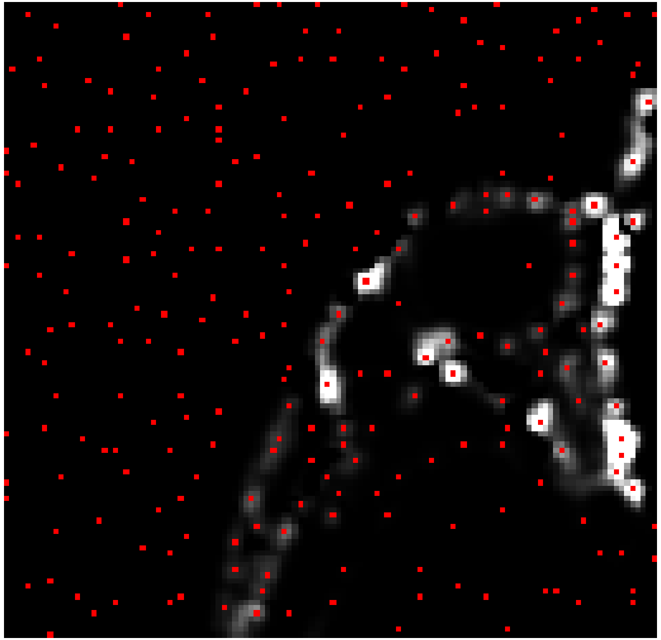


Figure 11: Corner localization, non-maximum suppression

Harris Corner Detector: Workflow

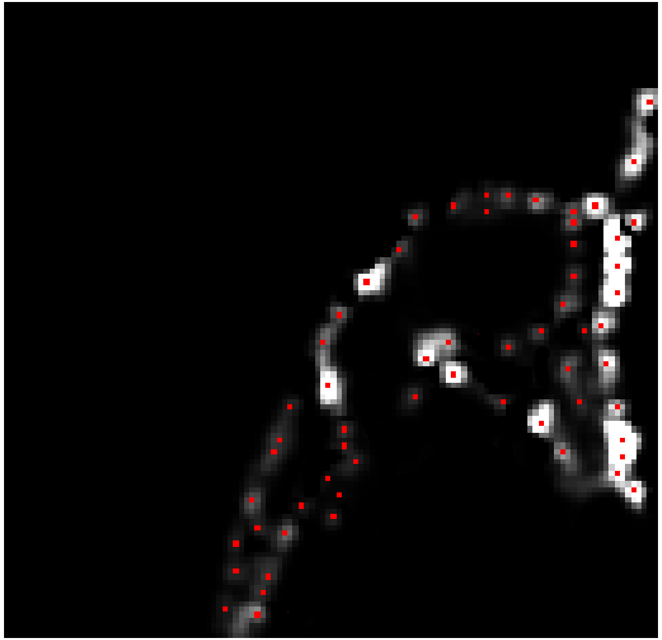


Figure 12: Corner selection

Topics

Feature Detectors

Initial Considerations

Harris Corner Detector

Summary

Take Home Messages

Further Readings

Take Home Messages

- An analysis of the derivatives in an image yields important information to build a feature detector.
- Best choose features which are invariant to certain transformations.
- The Harris corner detector utilizes the structure tensor to determine image points to be corners, edges or rather part of flat and homogeneous areas.

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

- Cordelia Schmid, Roger Mohr, and Christian Bauckhage. "Evaluation of Interest Point Detectors". In: *International Journal of Computer Vision* 37.2 (June 2000), pp. 151–172. DOI: 10.1023/A:1008199403446
- Chris Harris and Mike Stephens. "A Combined Corner and Edge Detector". In: *Proceedings of Fourth Alvey Vision Conference*. 1988, pp. 147–152

Medical Image Processing for Interventional Applications

Feature Descriptors – SIFT (Part 1)

Online Course – Unit 11

Andreas Maier, Sebastian Bauer, Frank Schebesch
Pattern Recognition Lab (CS 5)

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Feature Descriptors

SIFT – Feature Detection

- Scale Space
- Laplace of Gaussians (LoG)
- Difference of Gaussians (DoG)

Summary

- Take Home Messages
- Further Readings

Feature Descriptors

Basic principle: Describe the neighborhood of a key point in an invariant manner → feature vector.

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Types: intensity, color, frequency domain, texture, …

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Types: intensity, color, frequency domain, texture, …

Popular: analysis of local gradient distribution (SIFT, SURF, HOG, GLOH, RIFF …)

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

SIFT – Scale Invariant Feature Transform

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Topics

Feature Descriptors

SIFT – Feature Detection

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Summary

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SIFT – Scale-space Extrema Detection (cf. Lowe, 2004)

→ Feature detector

Challenge: scale invariance

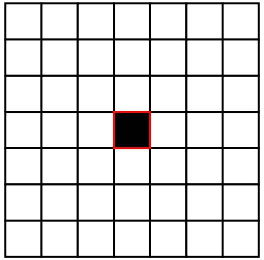


Figure 1: Feature detector fits object size

SIFT – Scale-space Extrema Detection (cf. Lowe, 2004)

→ Feature detector

Challenge: scale invariance

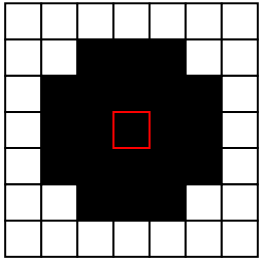


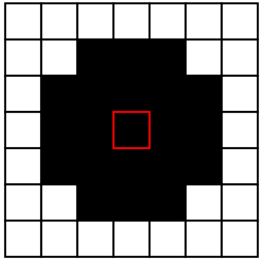
Figure 2: Different detector/object scales

SIFT – Scale-space Extrema Detection (cf. Lowe, 2004)

→ Feature detector

Challenge: scale invariance

What about Harris corner detector?



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SIFT – Scale-space Extrema Detection (cf. Lowe, 2004)

→ Feature detector

Challenge: scale invariance

What about Harris corner detector?

→ It works at a predetermined scale.

→ Which scale?

SIFT – Scale-space Extrema Detection (cf. Lowe, 2004)

→ Feature detector

Challenge: scale invariance

What about Harris corner detector?

→ It works at a predetermined scale.

→ Which scale?

Objects have characteristic scale where they 'make sense'.

→ Search over all scales and image locations!

Scale-space Representation

- Represent an image as one-parameter family of Gaussian-smoothed images
- Scale as a third image dimension (x, y, σ)

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y), \qquad G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

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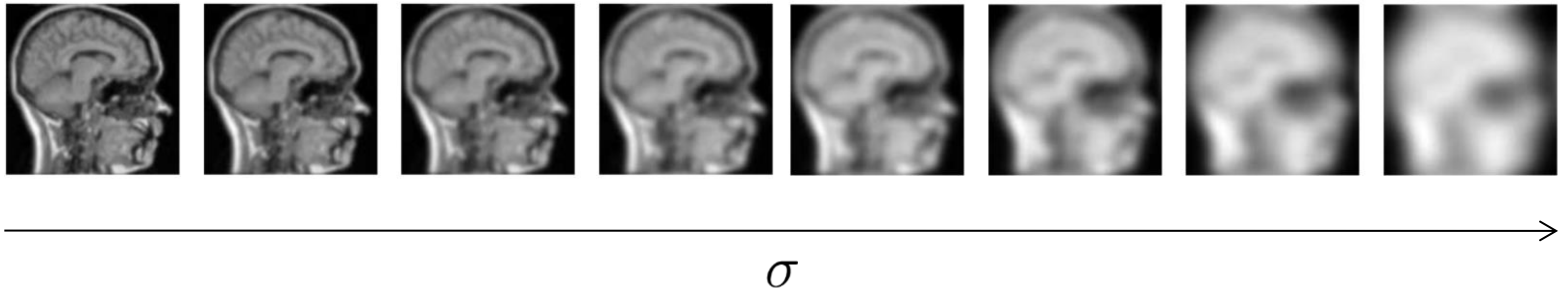

Laplacian of Gaussian (cf. Marr and Hildreth, 1980)

Laplacian of Gaussian (LoG):

$$\nabla^2\left(G(x, y, \sigma) * I(x, y)\right), \qquad G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

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Derivative theorem of convolution:

$$\nabla^2\big(G(x,y,\sigma) * I(x,y)\big) = (\nabla^2 G(x,y,\sigma)) * I(x,y)$$

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LoG/Marr-Hildreth operator:

$$\nabla^2 G(x,y,\sigma) = \frac{\partial^2 G(x,y,\sigma)}{\partial x^2} + \frac{\partial^2 G(x,y,\sigma)}{\partial y^2}$$

$$= -\frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)e^{-\frac{x^2+y^2}{2\sigma^2}}$$

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Laplacian of Gaussian (LoG):

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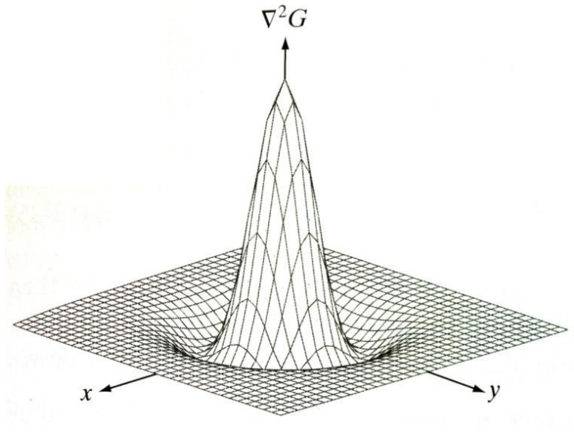

Figure 4: LoG mesh plot

LoG: Examples

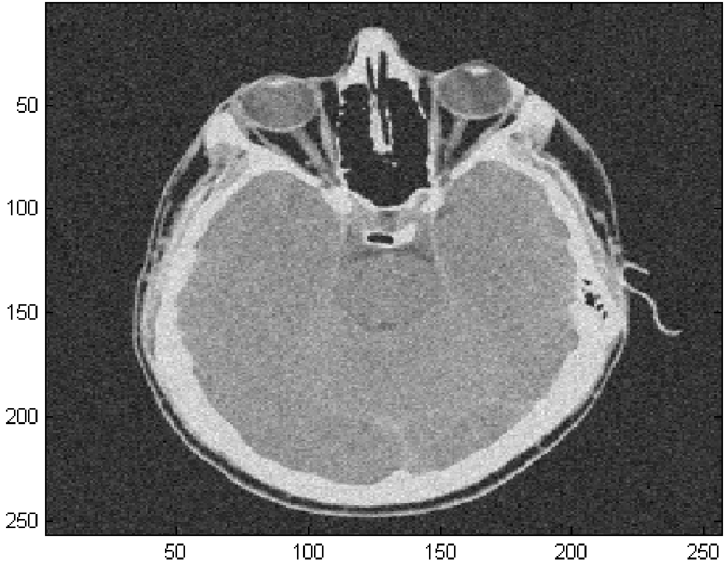

Figure 5: Noisy input

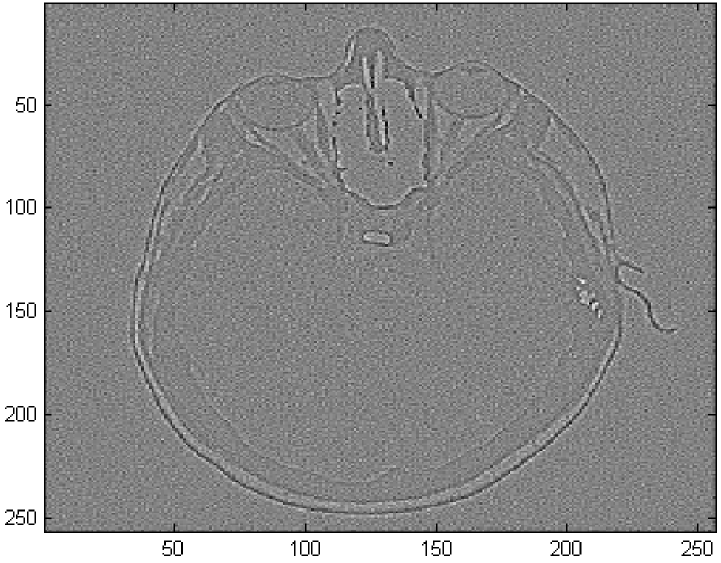

Figure 6: Laplace operator

LoG: Examples

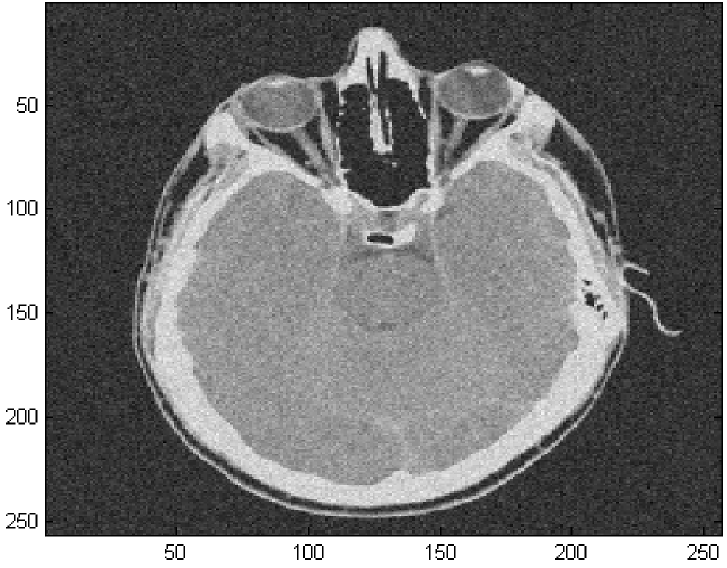

Figure 5: Noisy input

$\nabla^2 G(x, y, \sigma)$

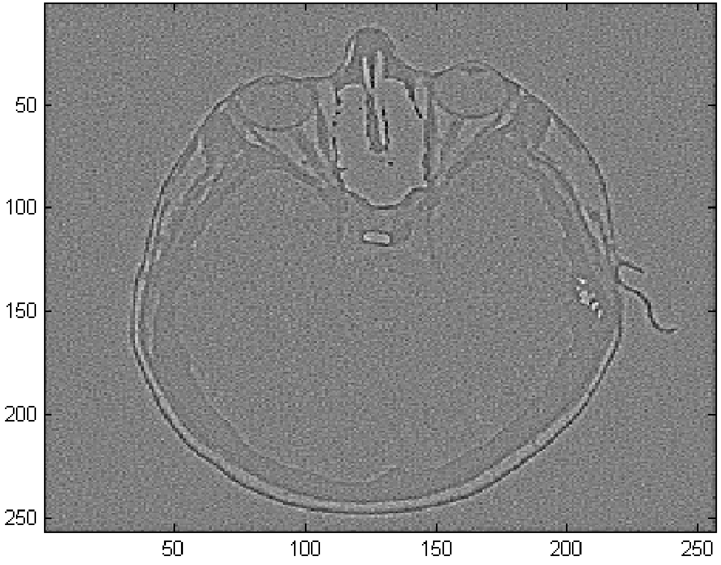

Figure 7: LoG operator, $\sigma = 0.5$

LoG: Examples

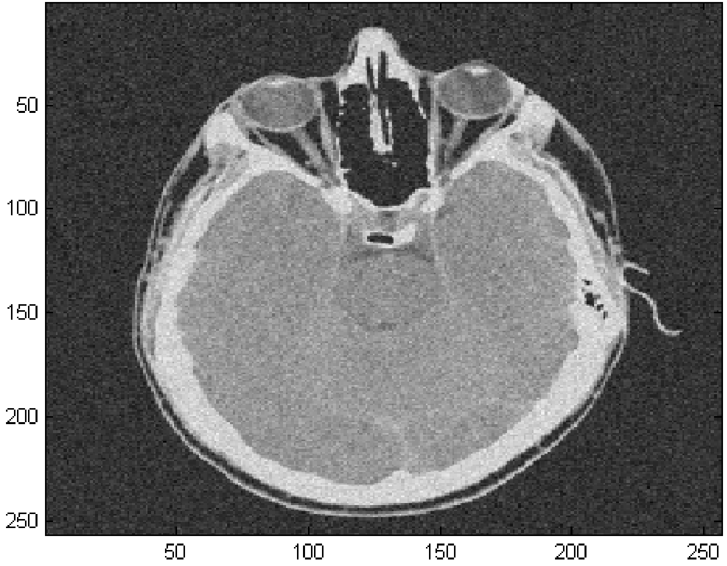

Figure 5: Noisy input

$\nabla^2 G(x, y, \sigma)$

Figure 8: LoG operator, $\sigma = 1$

LoG: Examples

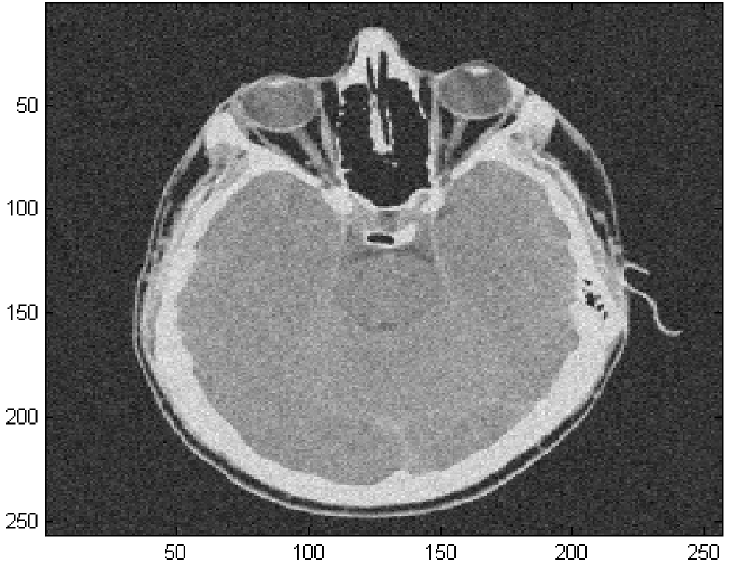

Figure 5: Noisy input

$$\nabla^2 G(x, y, \sigma)$$

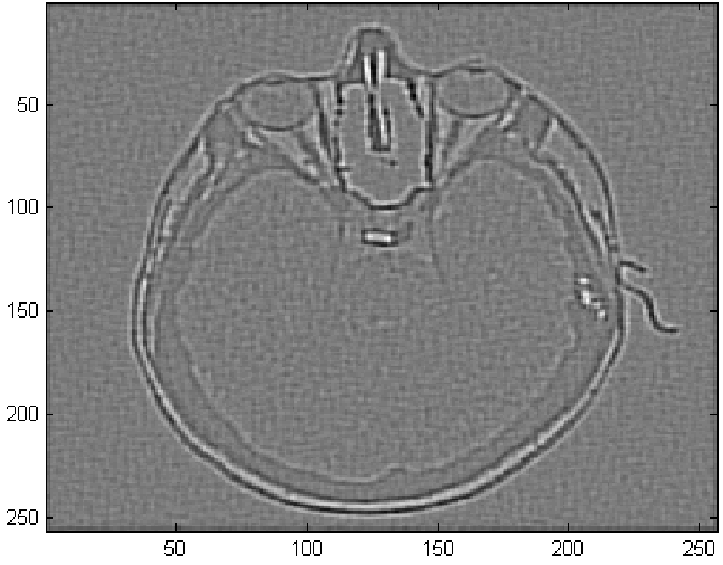

Figure 9: LoG operator, $\sigma = 2$

Difference of Gaussians (cf. Lowe, 2004)

Difference of Gaussians (DoG):

→ Approximation of scale-normalized LoG operator $\sigma^2 \nabla^2 G(x, y)$

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

$$\begin{aligned} D_k(x, y, \sigma) &= \big(G(x, y, k\sigma) - G(x, y, \sigma)\big) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma), \qquad 0 < k < +\infty \end{aligned}$$

Difference of Gaussians (cf. Lowe, 2004)

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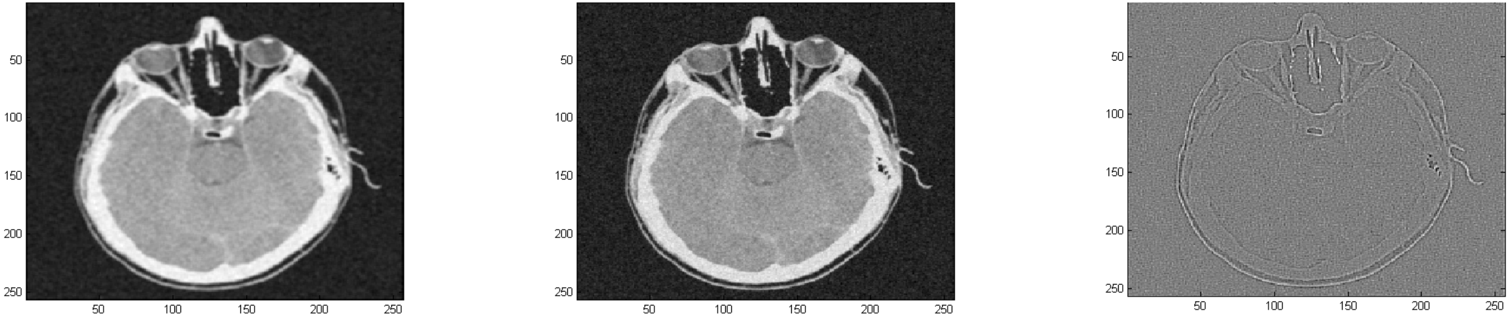

Figure 10: $L(x,y,k\sigma)$ on the left, $L(x,y,\sigma)$ in the middle, and $D_k(x,y,\sigma)$ on the right

Difference of Gaussians (cf. Lowe, 2004)

Difference of Gaussians (DoG):

→ Approximation of scale-normalized LoG operator $\sigma^2 \nabla^2 G(x,y)$

$$
\begin{aligned}
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D_k(x,y,\sigma) &= \big(G(x,y,k\sigma) - G(x,y,\sigma)\big) * I(x,y) \\
&= L(x,y,k\sigma) - L(x,y,\sigma), \qquad 0 < k < +\infty
\end{aligned}
$$

Interpretation in the frequency domain?

DoG Scale-space (cf. Lowe, 2004)

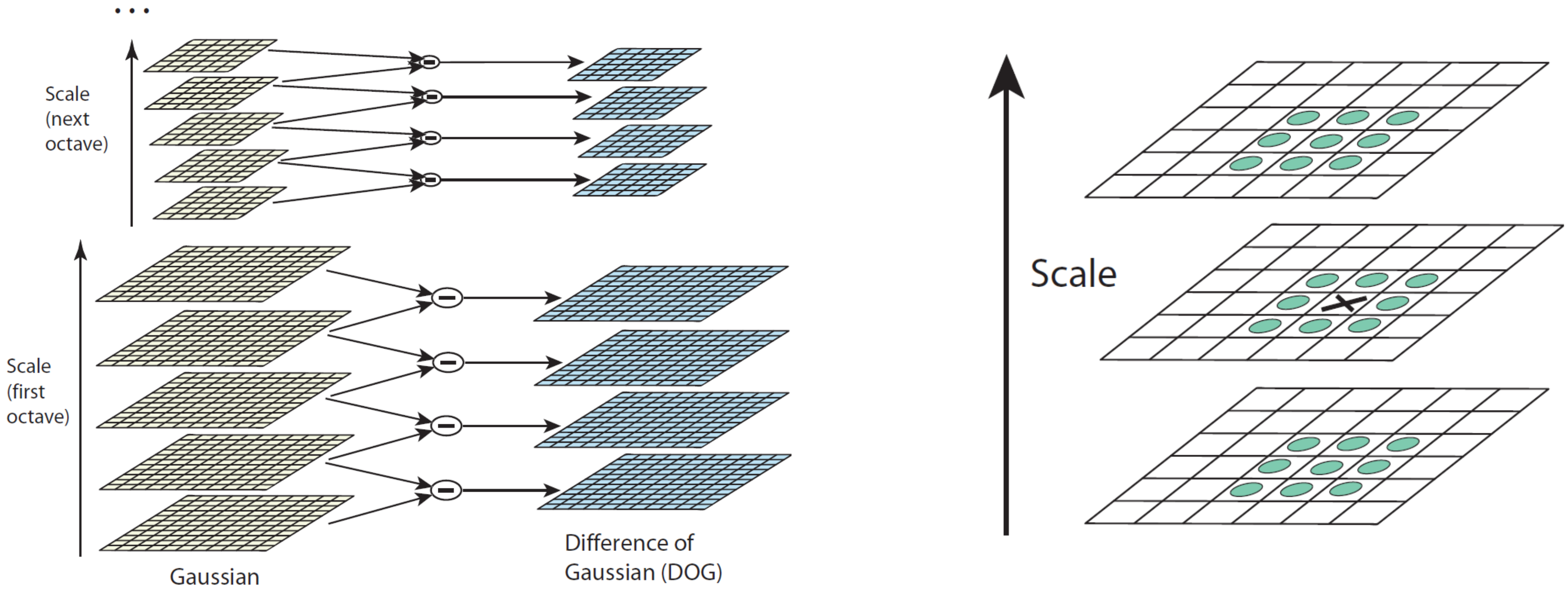


Figure 11: Detect local extrema **across scale and space** → characteristic scale σ

Topics

Feature Descriptors

SIFT – Feature Detection

- Scale Space
- Laplace of Gaussians (LoG)
- Difference of Gaussians (DoG)

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- Many feature descriptors are based on an analysis of the derivatives of an image.
- In order to make the feature detector scale invariant, this analysis is usually performed on different scales.
- The **s**cale **i**nvariant **f**eature **t**ransform (SIFT) utilizes differences of Gaussians (DoG) to detect extrema in scale-space.

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
- D. Marr and E. Hildreth. “Theory of Edge Detection”. In: *Proceedings of the Royal Society of London B: Biological Sciences* 207.1167 (Feb. 1980), pp. 187–217. DOI: 10.1098/rspb.1980.0020
- Chris Harris and Mike Stephens. “A Combined Corner and Edge Detector”. In: *Proceedings of Fourth Alvey Vision Conference*. 1988, pp. 147–152

Medical Image Processing for Interventional Applications

Feature Descriptors – SIFT (Part 2)

Online Course – Unit 12

Andreas Maier, Sebastian Bauer, Frank Schebesch
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.

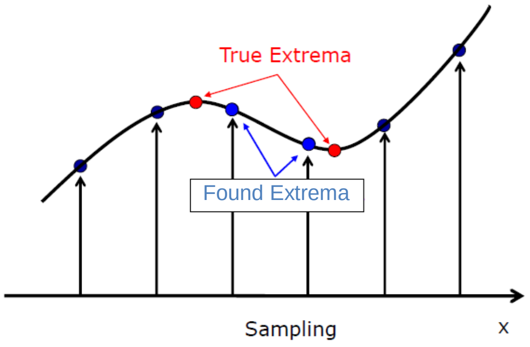


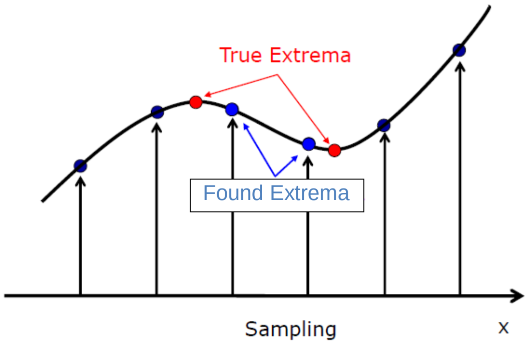
Figure 1: Curve fitting is used to find true extrema.

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:

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{D}_{xx} & \boldsymbol{D}_{xy} \\ \boldsymbol{D}_{xy} & \boldsymbol{D}_{yy} \end{bmatrix}$$



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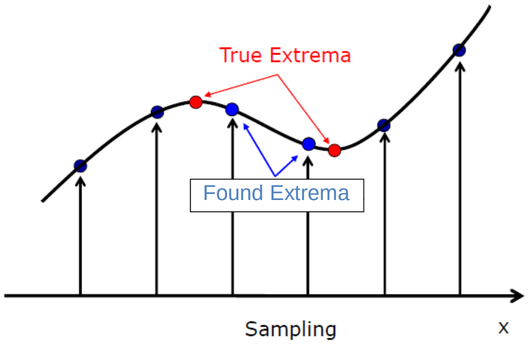

Figure 1: Curve fitting is used to find true extrema.

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

Topics

SIFT – Key Point Localization

SIFT – Orientation Assignment

SIFT – Key Point Descriptor

Summary

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Orientation Assignment (cf. Lowe, 2004)

What about rotation invariance?

Orientation Assignment (cf. Lowe, 2004)

What about rotation invariance?

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

- Gradient orientation:

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

- Gradient magnitude:

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

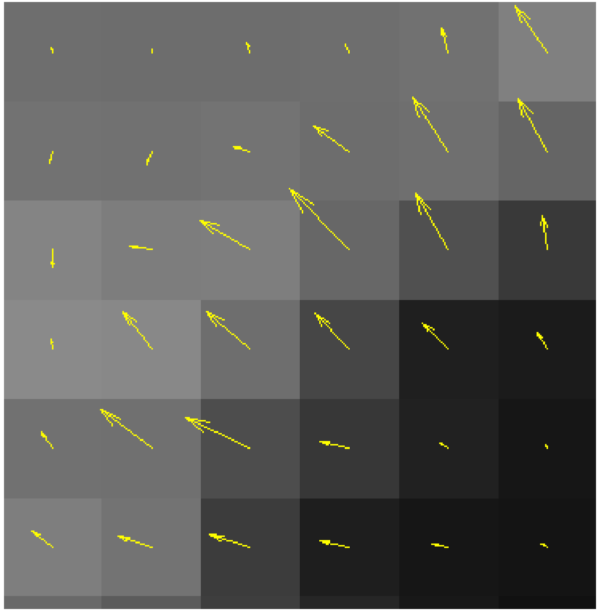
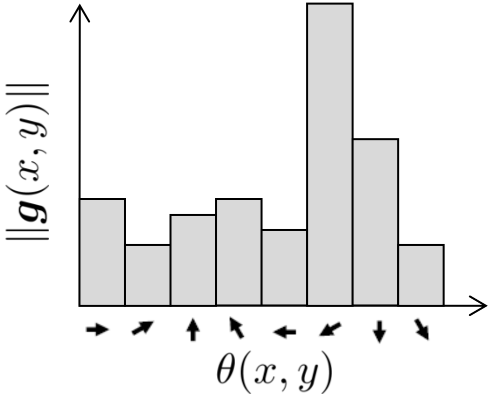


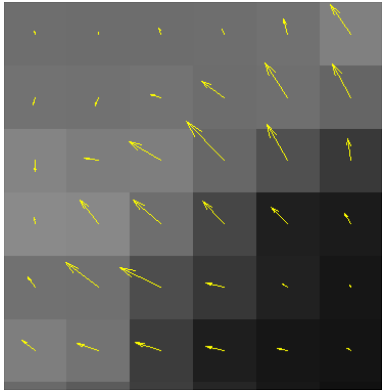
Figure 2: Gradient directions in a gray value image

Orientation Assignment (cf. Lowe, 2004)

What about rotation invariance?

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





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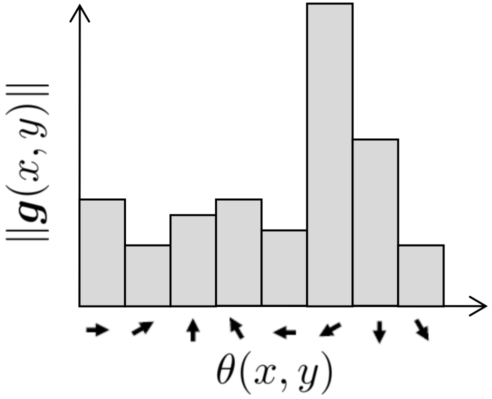

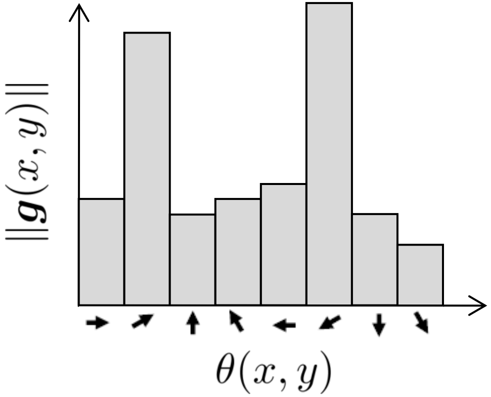

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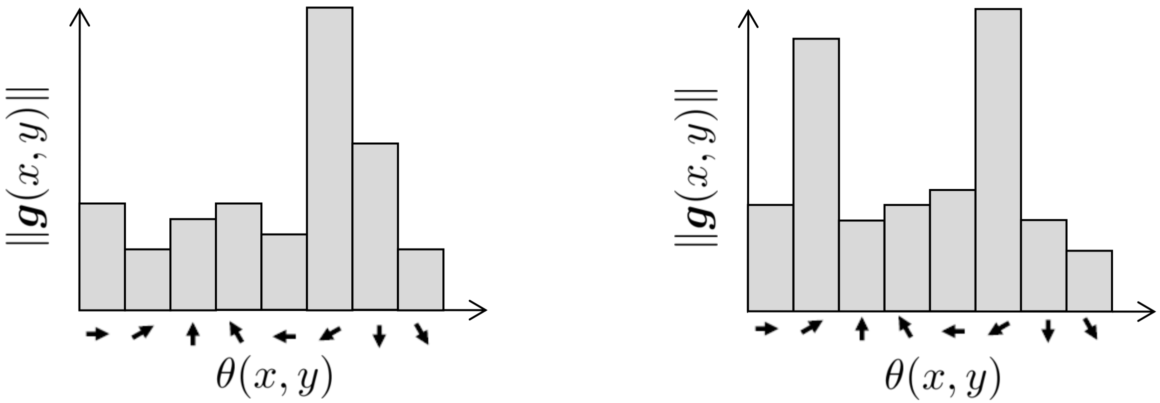
Idea: Select dominant local gradient direction → orientation histogram at key point scale.



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

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**

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.

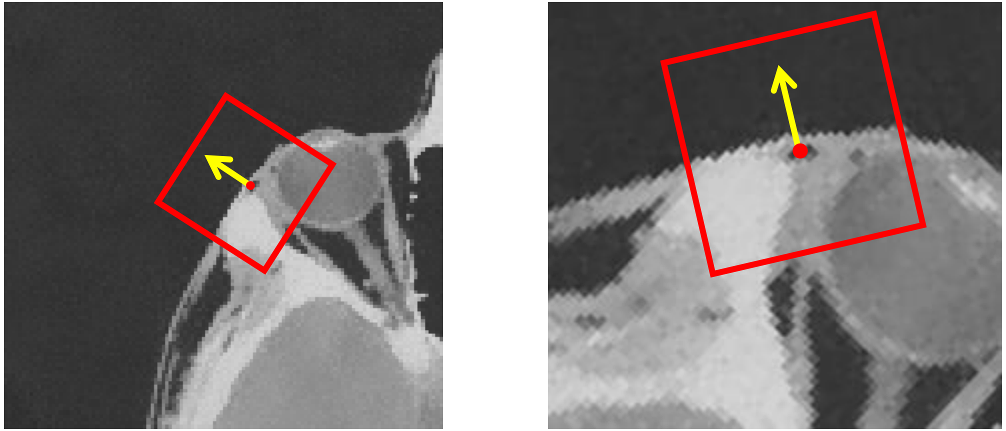
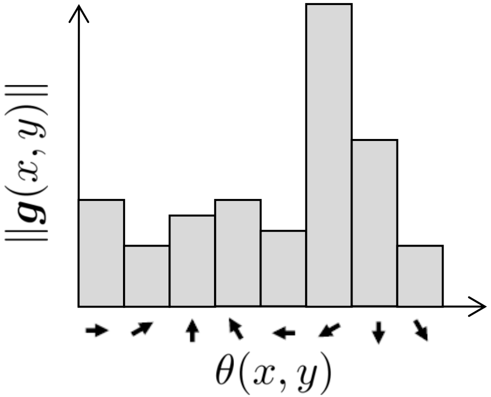
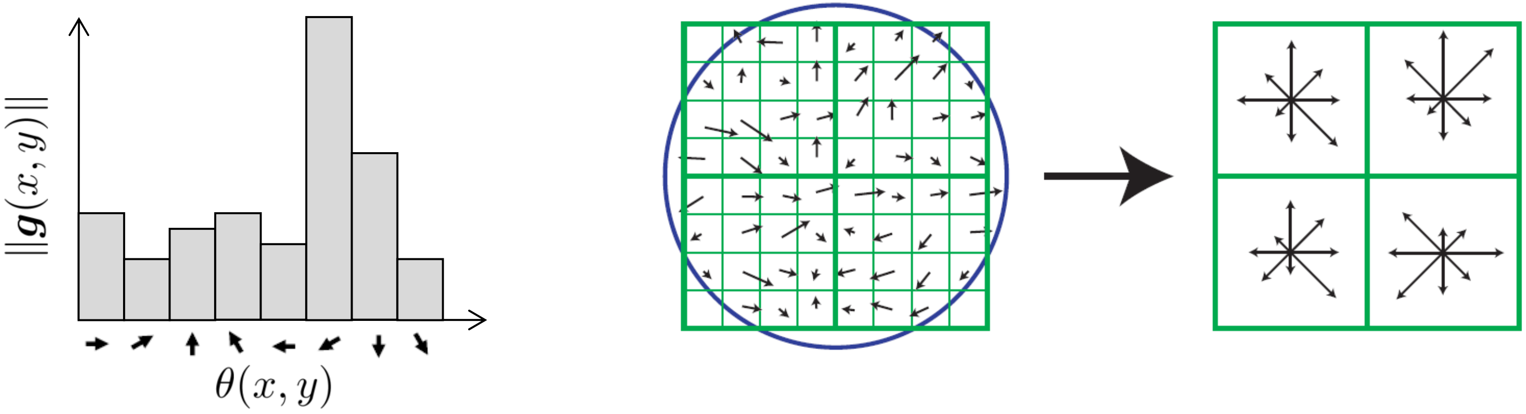


Figure 5: Same key point with different relative rotation and scale

SIFT Descriptor (cf. Lowe, 2004)

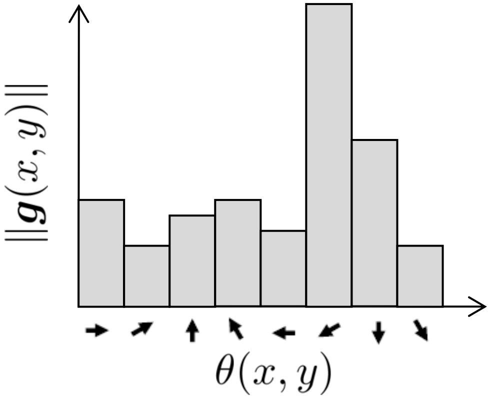


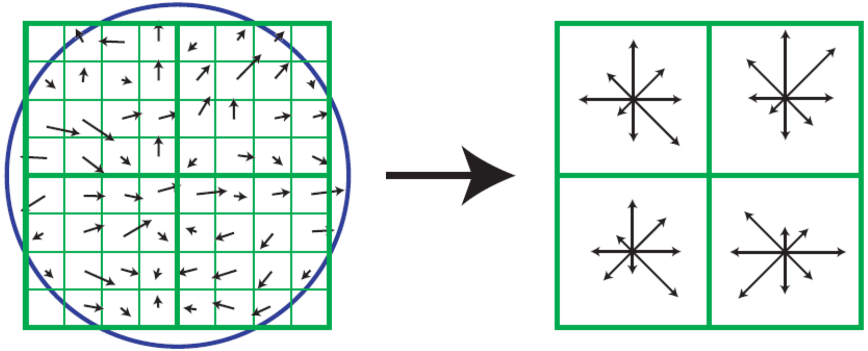
SIFT Descriptor (cf. Lowe, 2004)



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

SIFT Descriptor (cf. Lowe, 2004)



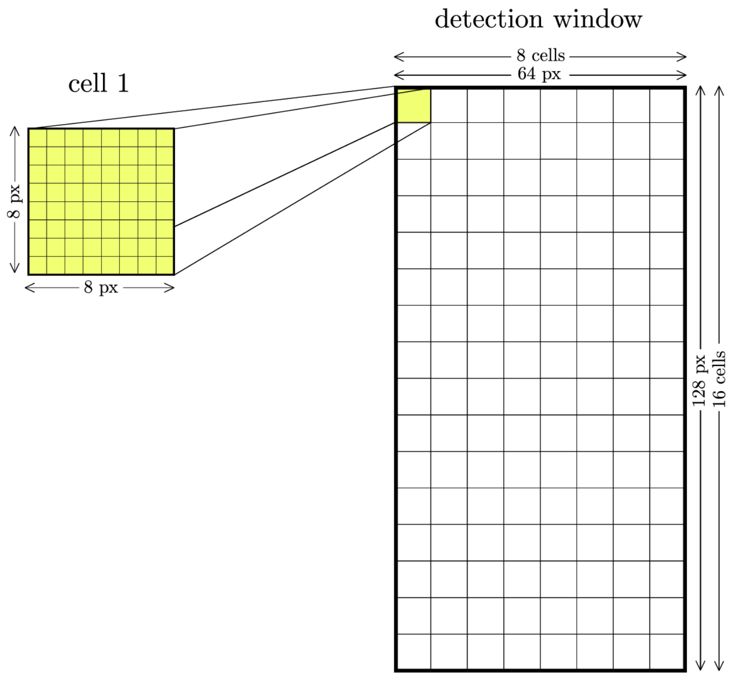


Benefits: Histogram representation of gradient distribution allows significant levels of local shape distortion and illumination change.

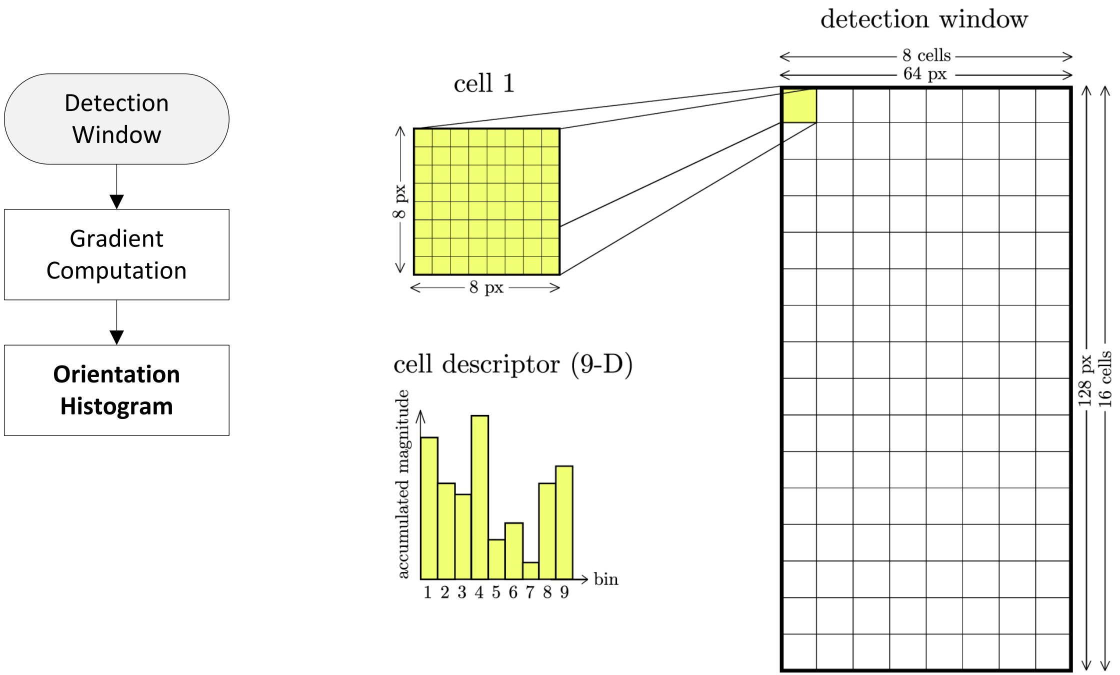
→ Dimensionality?

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

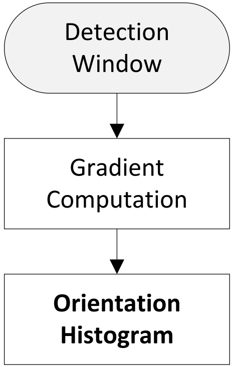
- Detection Window
- Gradient Computation
- **Orientation Histogram**

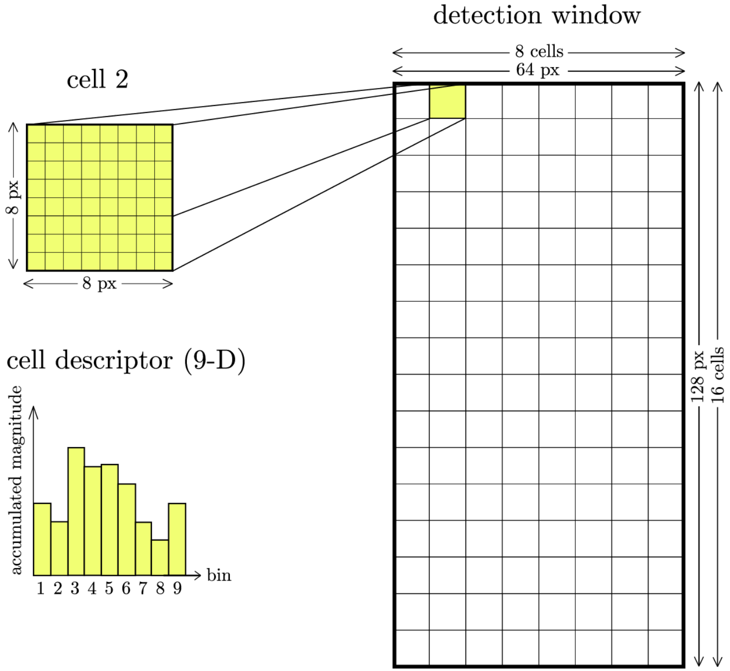


Orientation Histogram (cf. Dalal and Triggs, 2005)

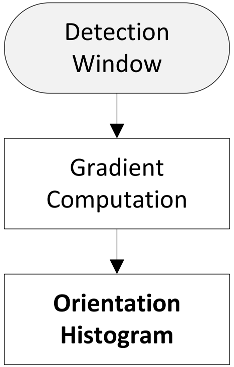


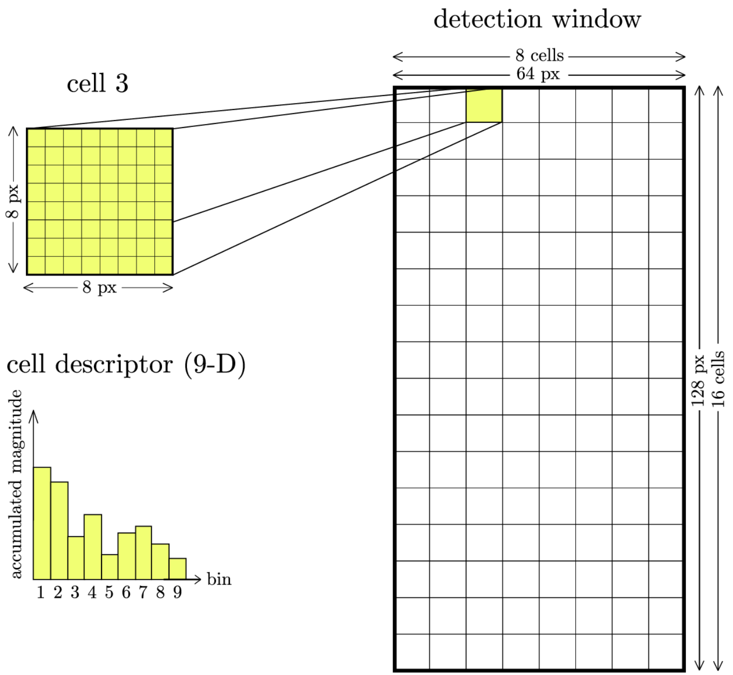
Orientation Histogram (cf. Dalal and Triggs, 2005)





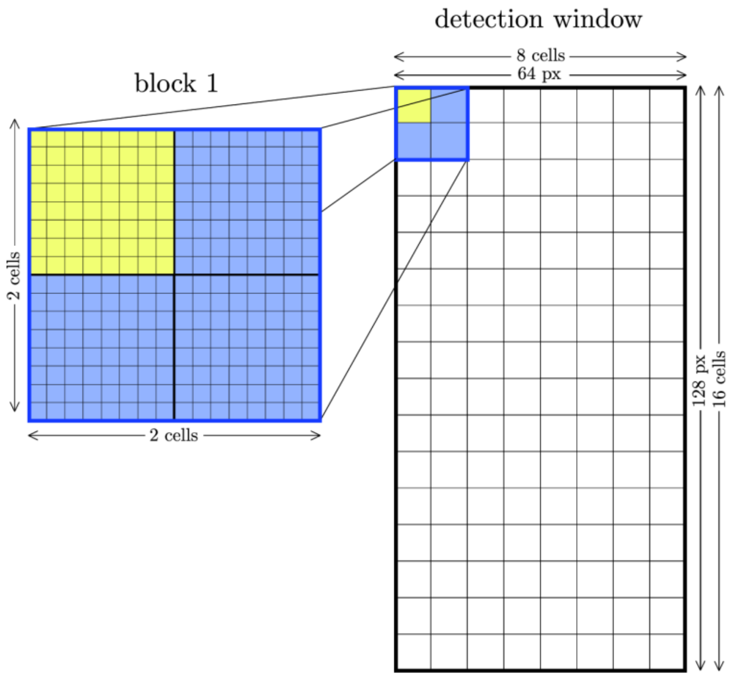
Orientation Histogram (cf. Dalal and Triggs, 2005)



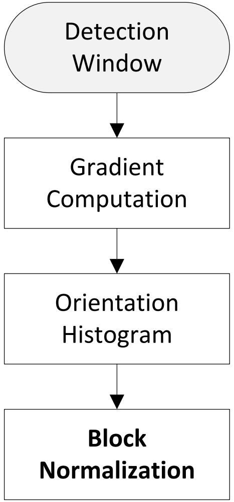


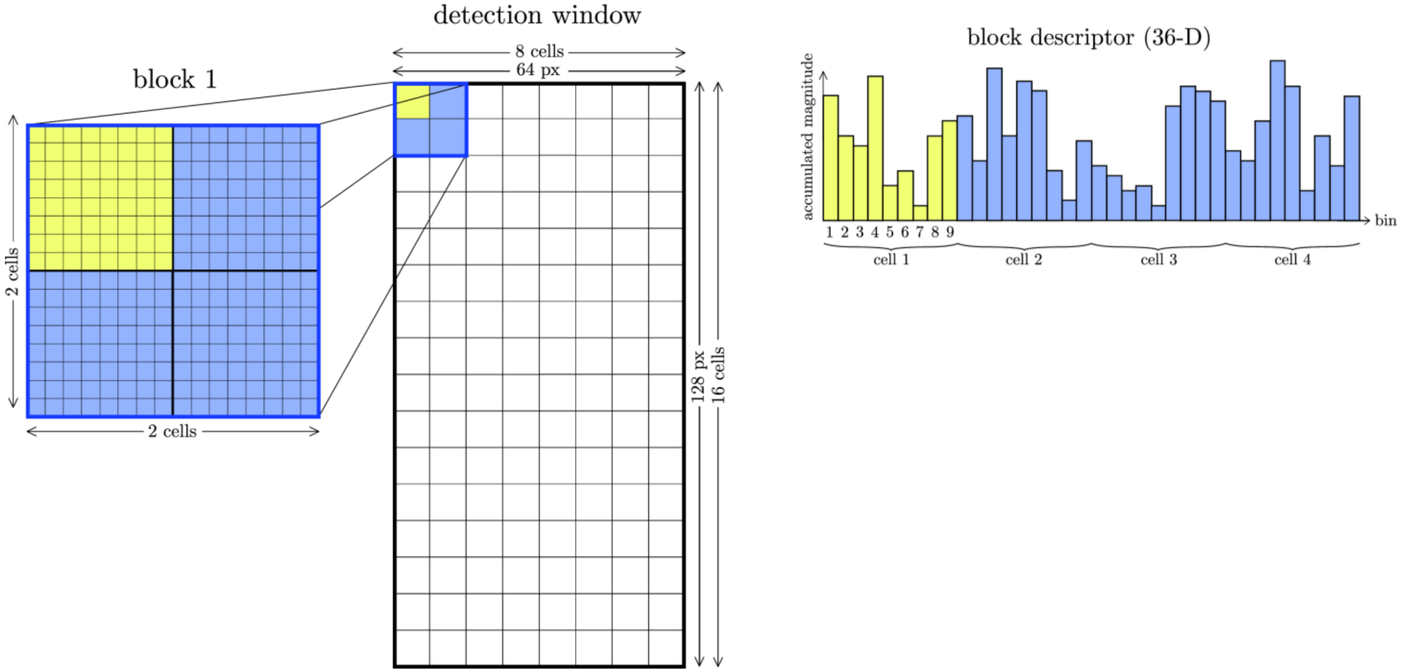
Block Normalization (cf. Dalal and Triggs, 2005)

Detection Window
↓
Gradient Computation
↓
Orientation Histogram
↓
Block Normalization

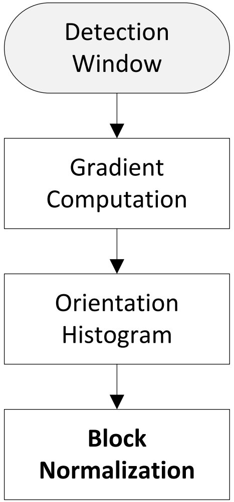


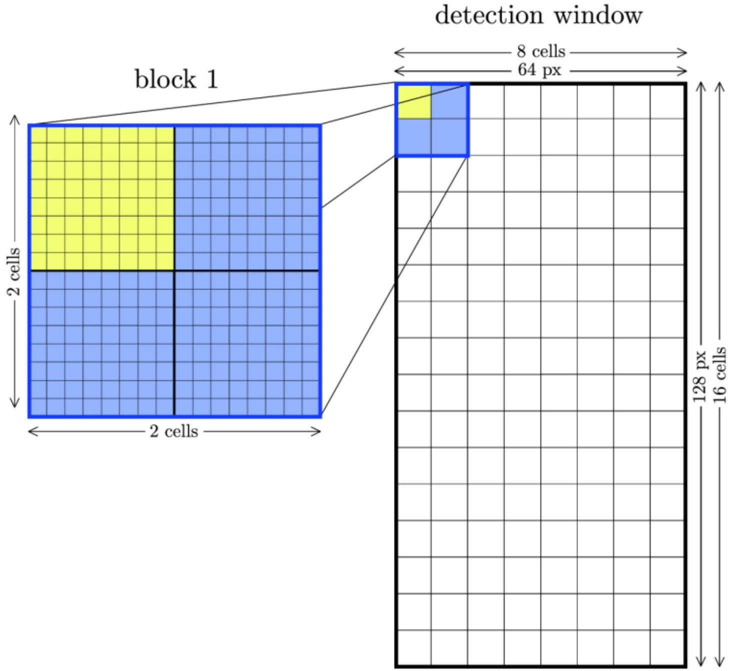
Block Normalization (cf. Dalal and Triggs, 2005)

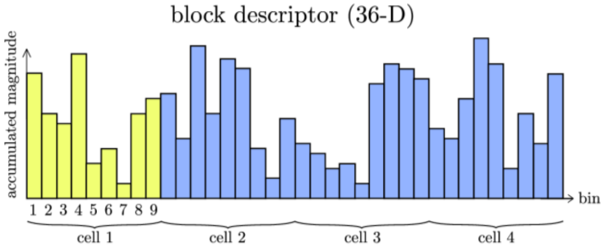




Block Normalization (cf. Dalal and Triggs, 2005)

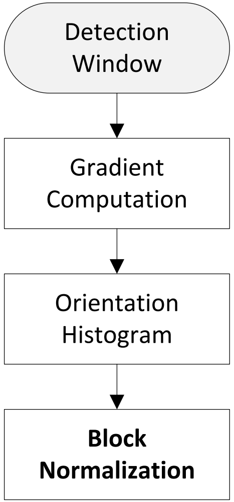


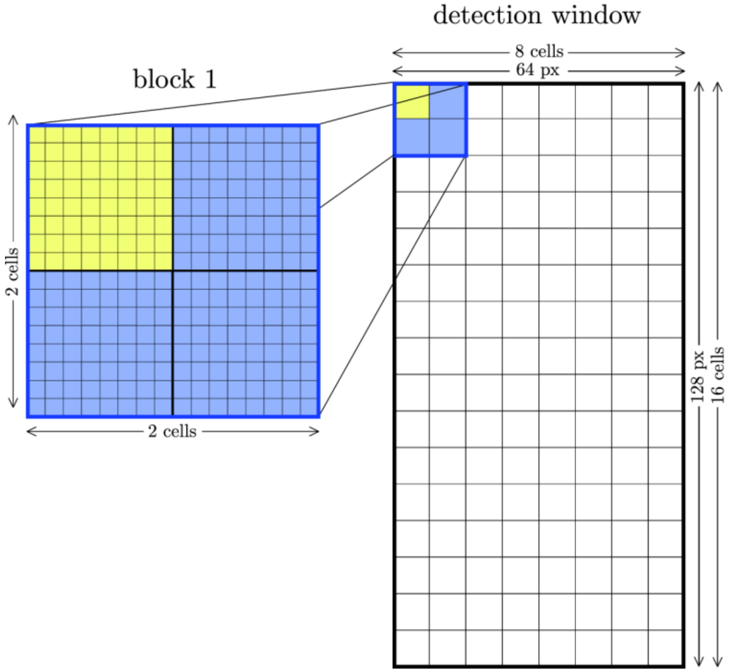


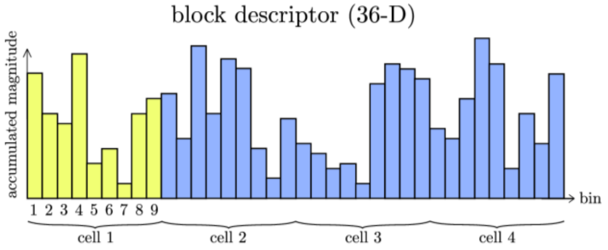


$$f \rightarrow \frac{f}{\sqrt{\|f\|_2^2 + \epsilon^2}}$$

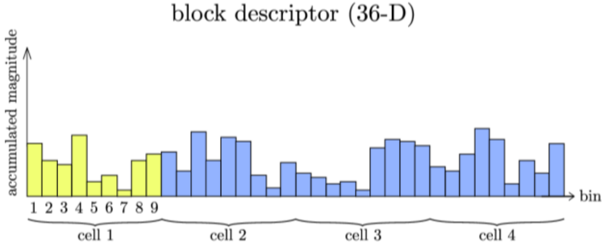
Block Normalization (cf. Dalal and Triggs, 2005)



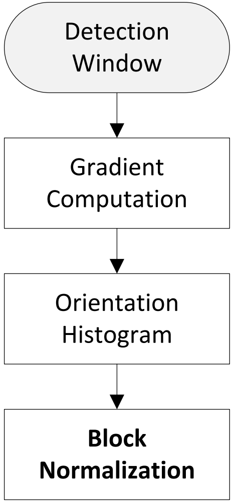


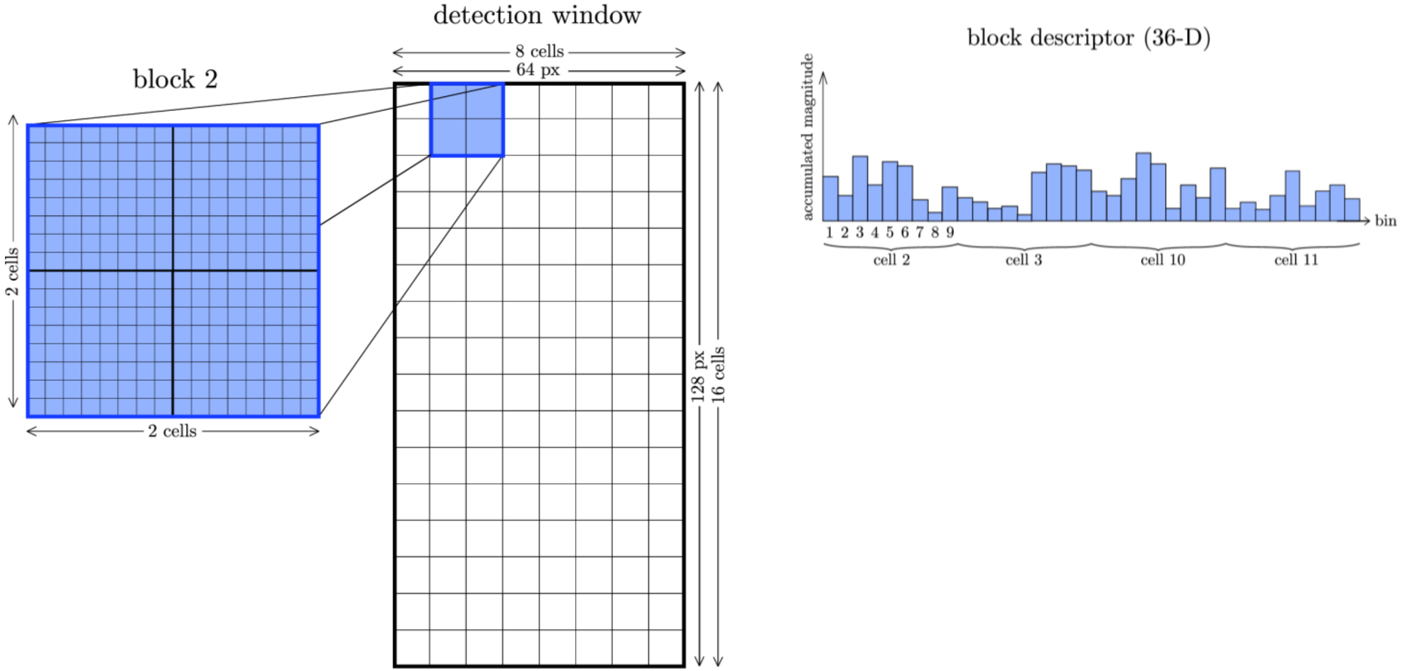


$$f \rightarrow \frac{f}{\sqrt{\|f\|_2^2 + \epsilon^2}}$$

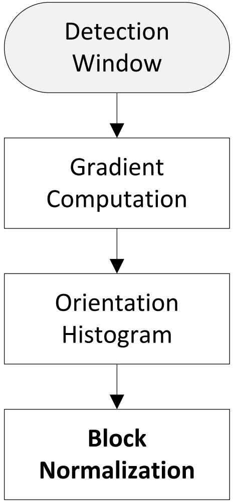


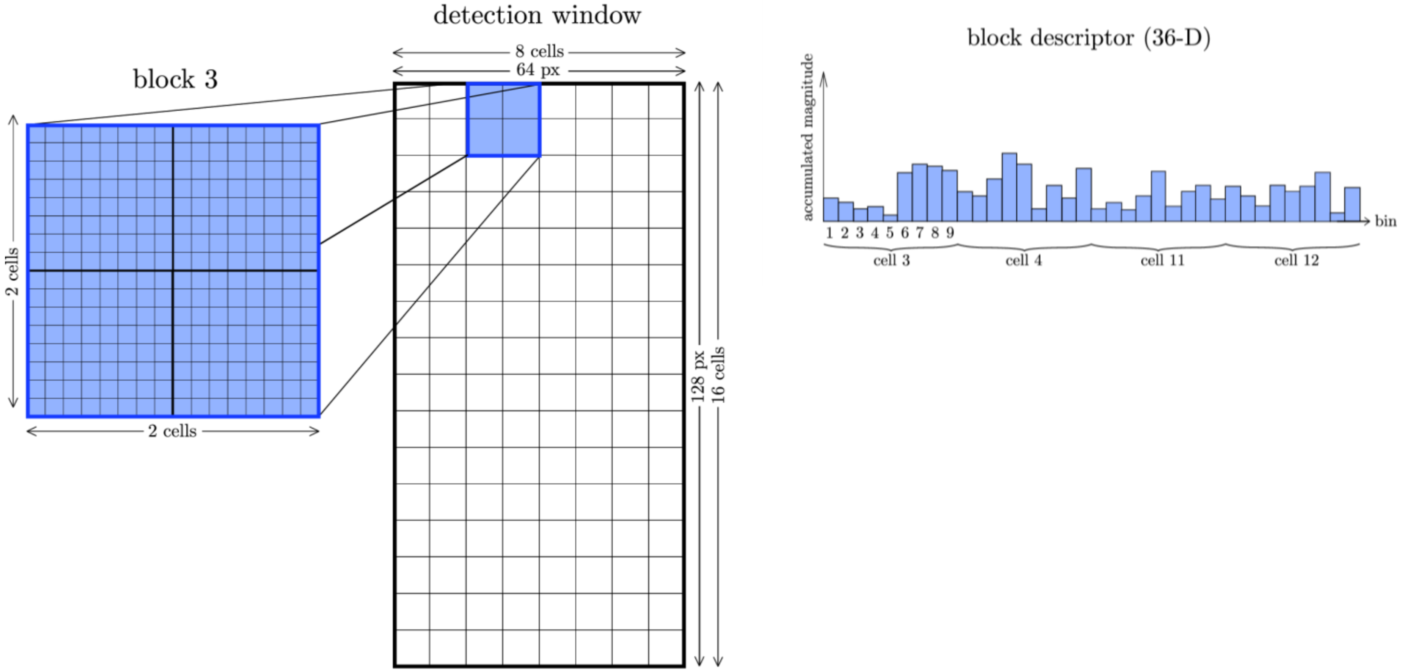
Block Normalization (cf. Dalal and Triggs, 2005)



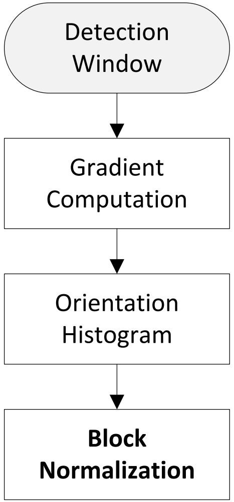


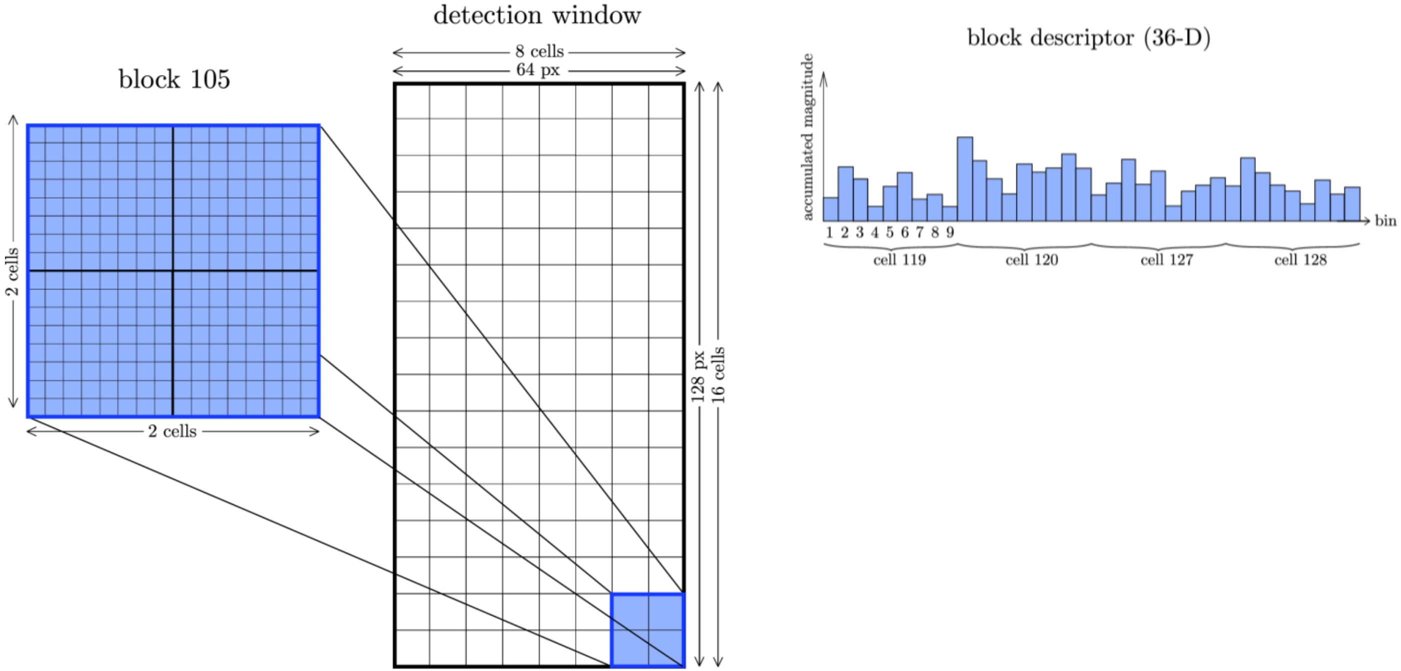
Block Normalization (cf. Dalal and Triggs, 2005)





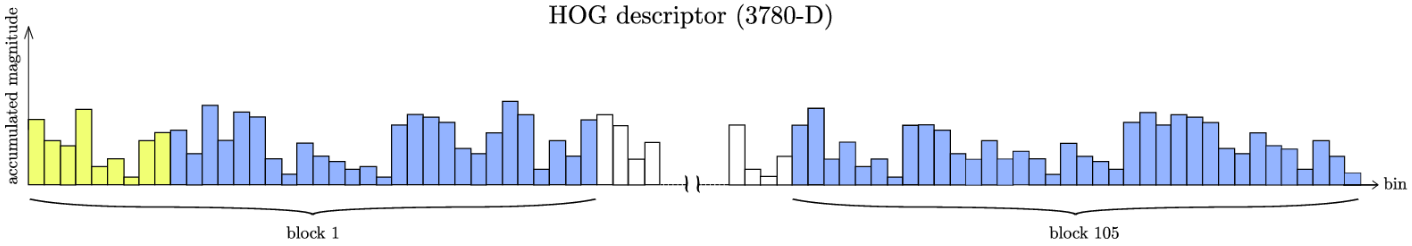
Block Normalization (cf. Dalal and Triggs, 2005)





HOG Descriptor (cf. Dalal and Triggs, 2005)

Detection Window
↓
Gradient Computation
↓
Orientation Histogram
↓
Block Normalization
↓
HOG Descriptor



Topics

SIFT – Key Point Localization

SIFT – Orientation Assignment

SIFT – Key Point Descriptor

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- 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

Medical Image Processing for Interventional Applications

Feature Matching

Online Course – Unit 13

Andreas Maier, Sebastian Bauer, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern
FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Feature Matching

Correspondence search

Acceleration

Summary

Take Home Messages

Further Readings

Feature Matching

- We know how to detect points.
- We know how to compute feature descriptors.

→ **How to match them?**

Correspondence Search

- Nearest neighbor matching of feature vectors:

→ Distance metrics: L_1-Norm, Euclidean, KL divergence

Correspondence Search

- Nearest neighbor matching of feature vectors:

→ Distance metrics: L_1-Norm, Euclidean, KL divergence

- Removal of outliers (erroneous correspondences):
  - filter the set of correct matches from the full set
  - compare distance of nearest neighbor to second nearest neighbor
  - clustering strategies
  - …

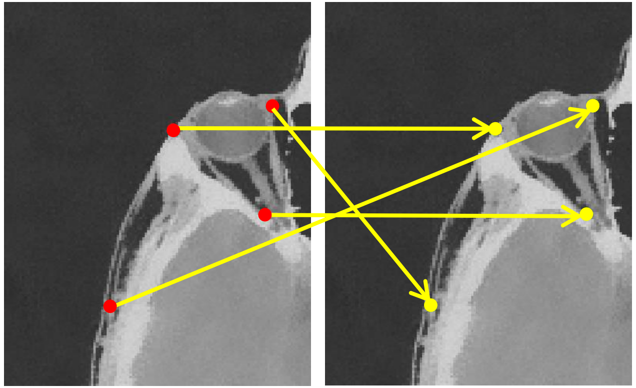


Figure 1: Unfiltered set of correspondences

Correspondence Search

- Nearest neighbor matching of feature vectors:

→ Distance metrics: L_1-Norm, Euclidean, KL divergence

- Removal of outliers (erroneous correspondences):
  - filter the set of correct matches from the full set
  - compare distance of nearest neighbor to second nearest neighbor
  - clustering strategies
  - …

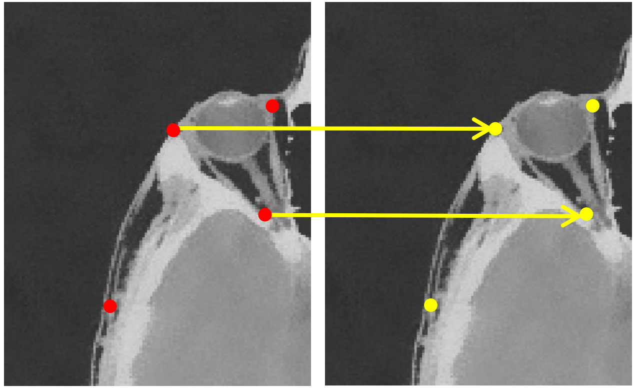


Figure 2: Outliers are removed

Implementation

- Naive approach:
  - Exhaustive brute force search
  - Curse of dimensionality

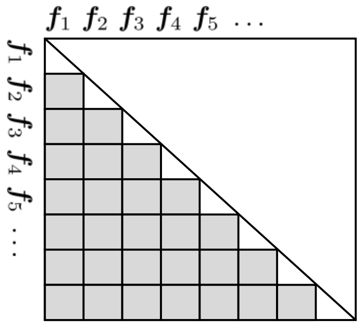


Figure 3: Checking all possible correspondences is usually not reasonable.

Implementation

- Naive approach:
  - Exhaustive brute force search
  - Curse of dimensionality
- Acceleration structures
  - Nearest neighbor techniques (kd-tree, …)
  - Hashing
  - …

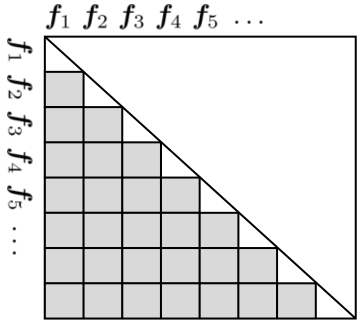


Figure 3: Checking all possible correspondences is usually not reasonable.

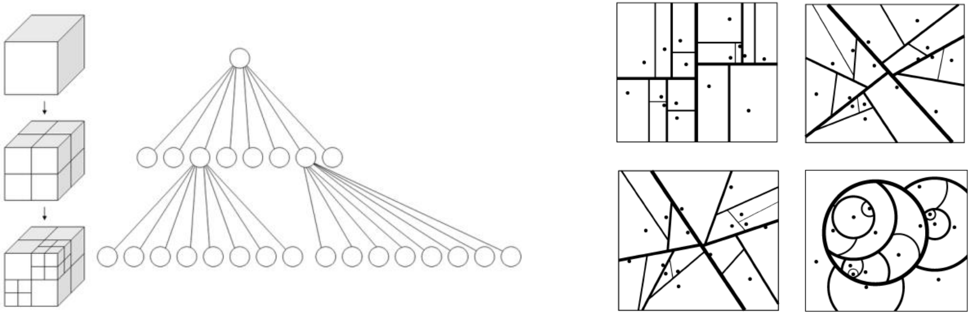


Figure 4: Schemes for faster matching strategies based on tree structures

Hardware Acceleration Techniques

Random **b**all **c**over (RBC, Cayton, 2011):

- Acceleration structure for efficient NN search
- Exploits parallel architecture of modern GPUs
- Both construction of data structure and queries based on brute force primitive

Hardware Acceleration Techniques

Random **b**all **c**over (RBC, Cayton, 2011):

- Data Point
- Representative
- Nearest Representative
- NN List

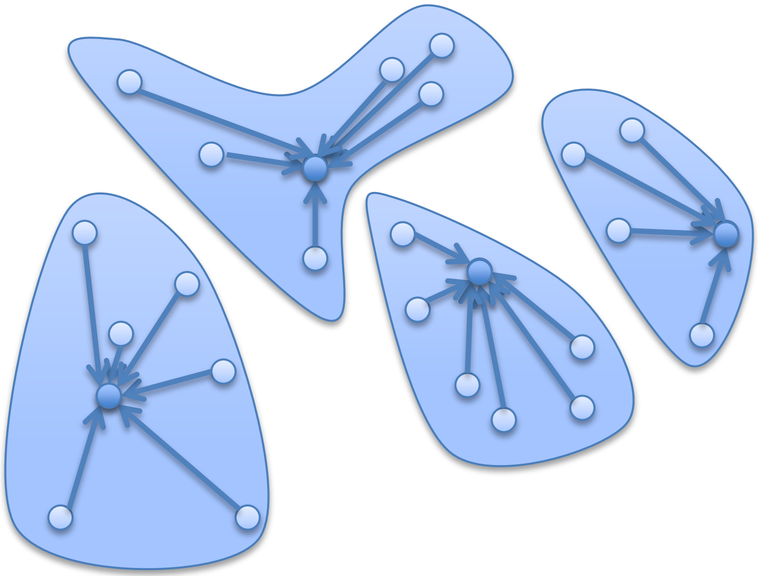


Figure 4: Construction

Hardware Acceleration Techniques

Random **b**all **c**over (RBC, Cayton, 2011):

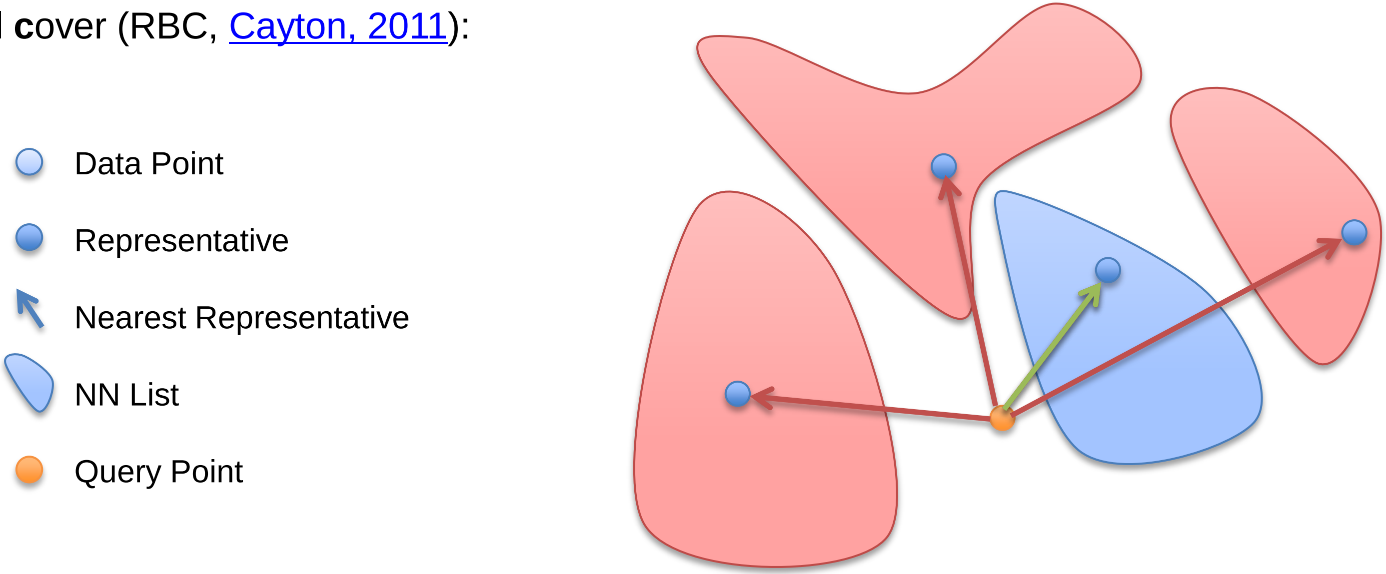


Figure 5: Query

Hardware Acceleration Techniques

Random **b**all **c**over (RBC, Cayton, 2011):

- Data Point
- Representative
- Nearest Representative
- NN List
- Query Point
- Nearest Neighbor (approximative)

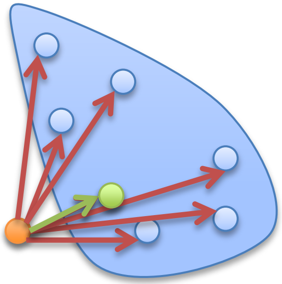


Figure 6: Possible query result

Topics

Feature Matching

- Correspondence search
- Acceleration

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- Feature matching is the process of finding valid correspondences of feature vectors between images.
- Brute force search might work with a small set of key points, but is naturally not recommended.
- Several acceleration techniques exist of which we have introduced Cayton’s RBC approach.

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
- L. Cayton. "Accelerating Nearest Neighbor Search on Manycore Systems". In: *2012 IEEE 26th International Parallel and Distributed Processing Symposium*. IEEE, May 2012, pp. 402–413. DOI: 10.1109/IPDPS.2012.45
- A. E. Johnson and M. Hebert. "Using Spin Images for Efficient Object Recognition in Cluttered 3D Scenes". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 21.5 (May 1999), pp. 433–449. DOI: 10.1109/34.765655

Medical Image Processing for Interventional Applications

Feature Matching – Applications in Medical Image Processing

Online Course – Unit 14
Andreas Maier, Sebastian Bauer, Frank Schebesch
Pattern Recognition Lab (CS 5)

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Topics

Applications in Medical Image Processing

Summary

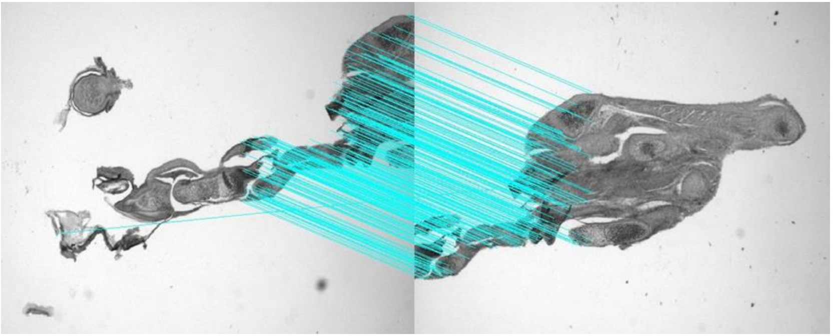
- Take Home Message
- Further Readings

Examples

- Microscopic imaging: image alignment, stitching
- Augmented reality in open liver surgery: registration of intra-operative with pre-operative data
- Patient positioning in radiation therapy: pose/transformation estimation

Microscopic Imaging

- Image registration
- Stitching



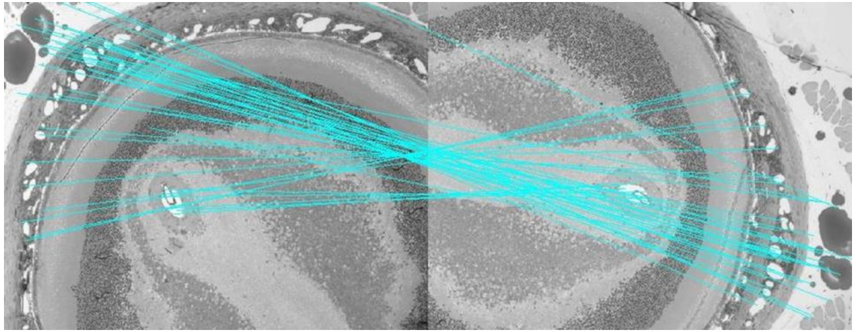


Figure 1: Images by S. Gaffling, Pattern Recognition Lab, FAU

Augmented Reality in Open Liver Surgery (cf. Beller et al., 2007)

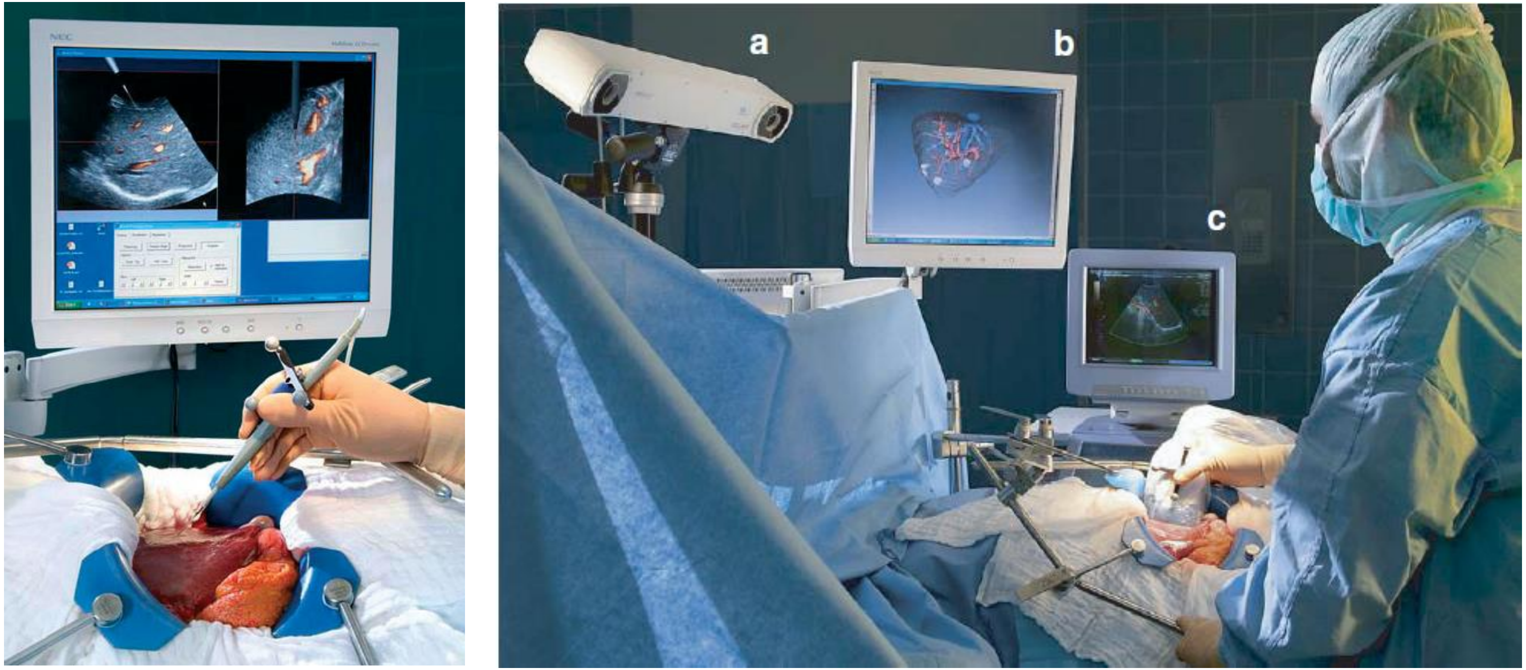


Figure 2: Organ registration – range imaging / CT

Augmented Reality

Liver registration: range imaging / CT

- From 2-D to 3-D surface features
- Same matching pipeline

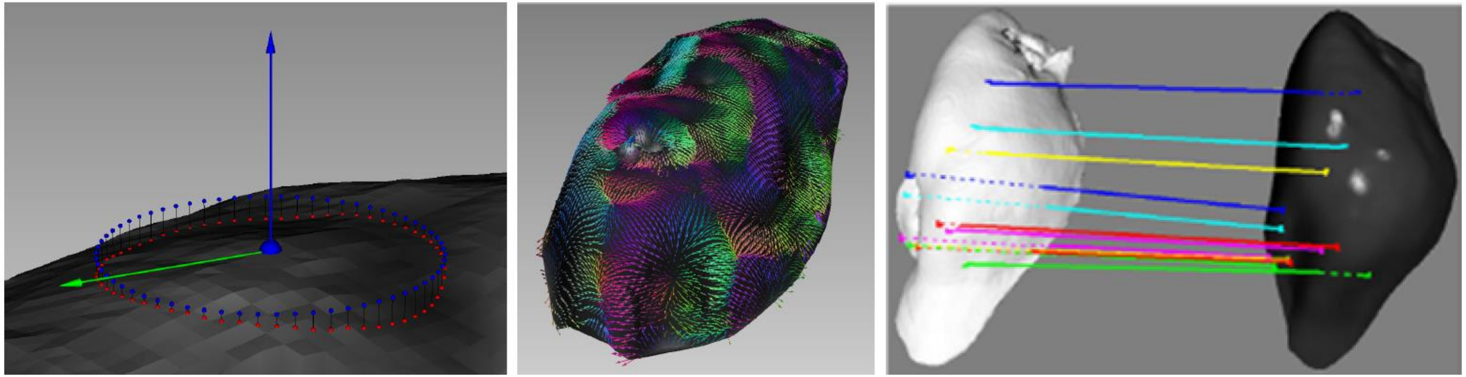


Figure 3-1: Images by S. Bauer and J. Wasza, Pattern Recognition Lab, FAU

Augmented Reality

Liver registration: range imaging / CT

- From 2-D to 3-D surface features
- Same matching pipeline

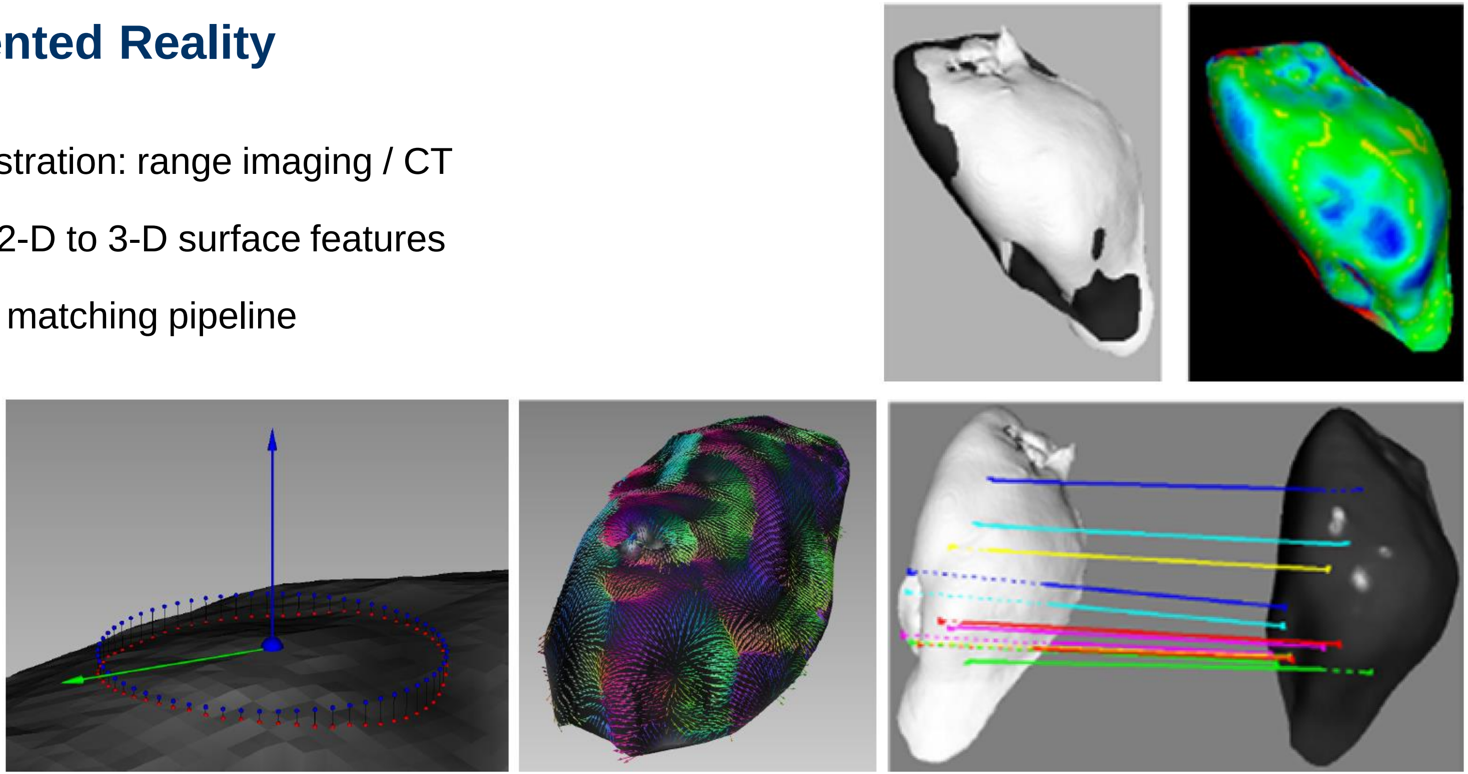


Figure 3-2: Images by S. Bauer and J. Wasza, Pattern Recognition Lab, FAU

3-D Local Invariant Feature Descriptors

- Spin images
- MeshHOG
- RIFF
- …

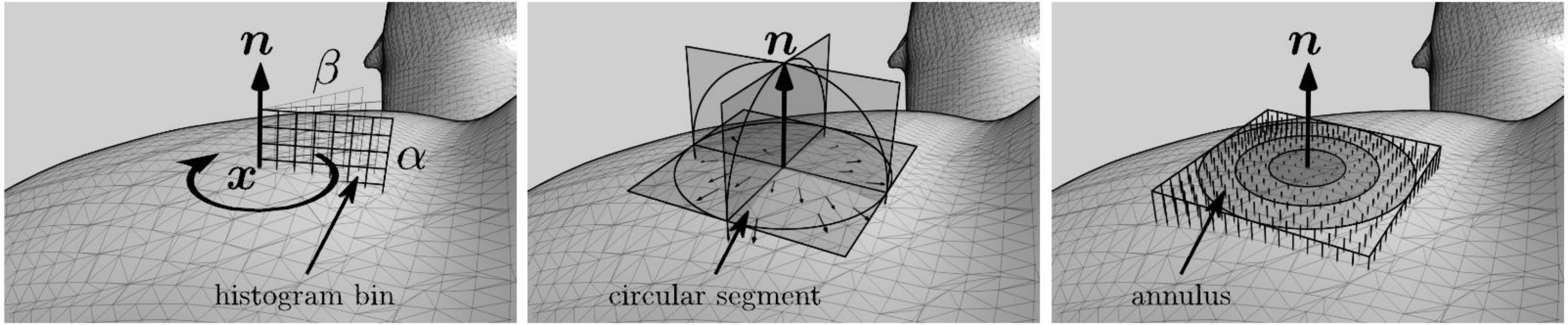


Figure 4: Images by S. Bauer, J. Wasza, and S. Haase, Pattern Recognition Lab, FAU

Spin Images (cf. Johnson and Hebert, 1999)

- Express neighborhood in 2-D cylindrical coordinates:

$$\alpha = \boldsymbol{n}^T(\boldsymbol{v} - \boldsymbol{x})$$

$$\beta = \sqrt{\|\boldsymbol{v} - \boldsymbol{x}\|_2^2 - \alpha^2}$$

  - α signed elevation component
  - β perpendicular radial distance

- Descriptor: 2-D histogram over the (α, β) space

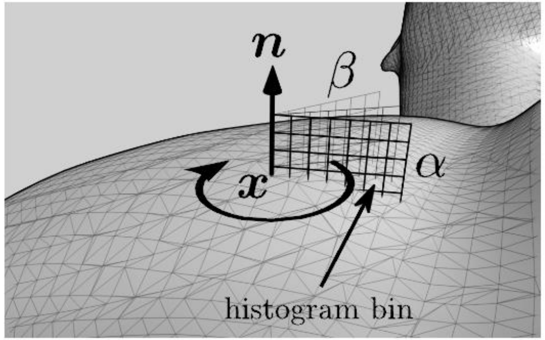


Figure 5: Image by S. Bauer, J. Wasza, and S. Haase, Pattern Recognition Lab, FAU

3-D Range Imaging in Radiation Therapy

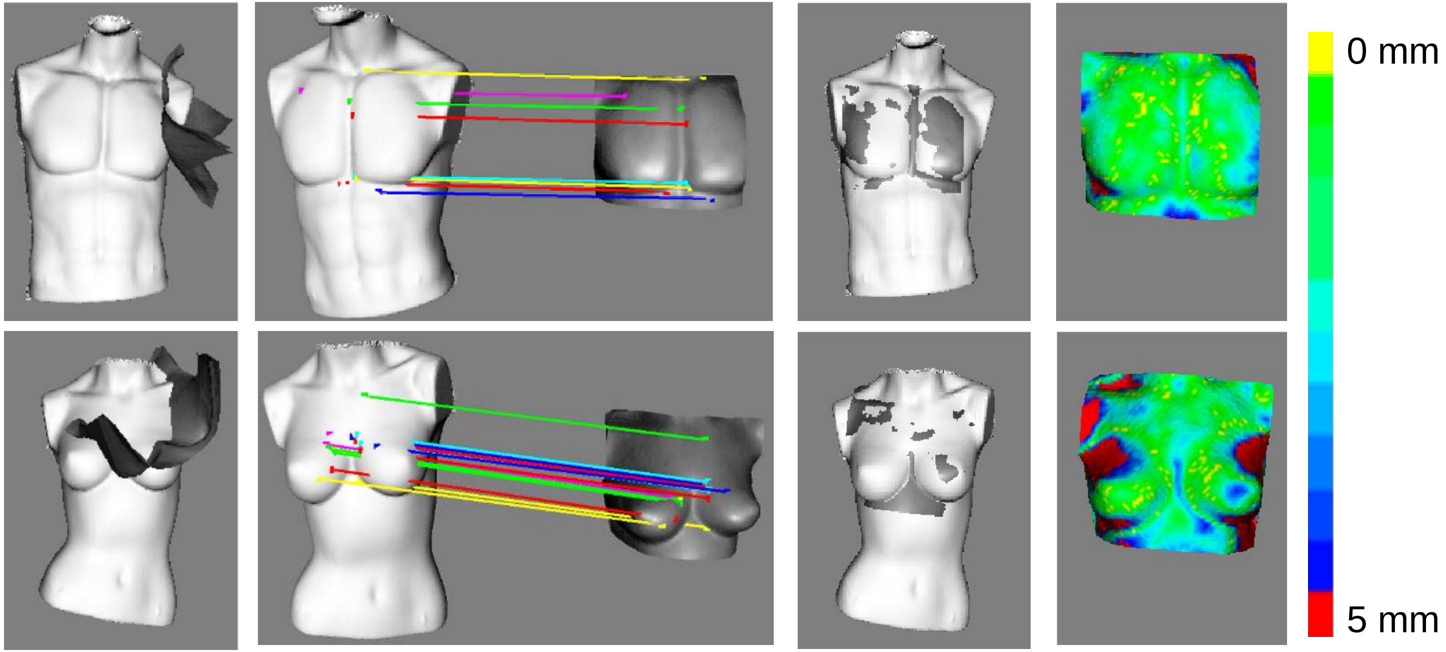


Figure 6: Both rows from left to right: original position, correspondences, registration, refinement (S. Bauer and J. Wasza, Pattern Recognition Lab, FAU)

Stereo Vision in Image-guided Radiation Therapy

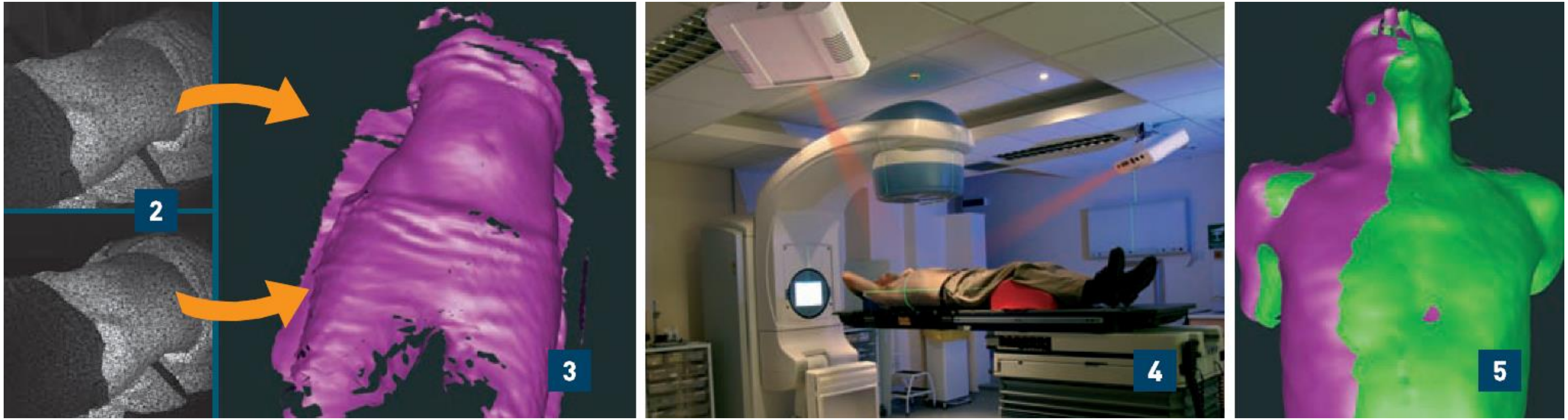


Figure 7: Overview of the workflow in image-guided radiation therapy (AlignRT system, VisionRT)

Topics

Applications in Medical Image Processing

Summary

Take Home Message

Further Readings

Take Home Message

In conclusion of the units on feature detectors and descriptors we have seen several applications:

- image stitching in microscopic imaging,
- augmented reality in open liver surgery,
- and 3-D range imaging in radiation therapy.

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

- A. E. Johnson and M. Hebert. “Using Spin Images for Efficient Object Recognition in Cluttered 3D Scenes”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 21.5 (May 1999), pp. 433–449. DOI: 10.1109/34.765655
- S. Beller et al. “Image-guided Surgery of Liver Metastases by Three-dimensional Ultrasound-based Optoelectronic Navigation”. In: *British Journal of Surgery* 94.7 (Mar. 2007), pp. 866–875. DOI: 10.1002/bjs.5712