776 Computer Vision

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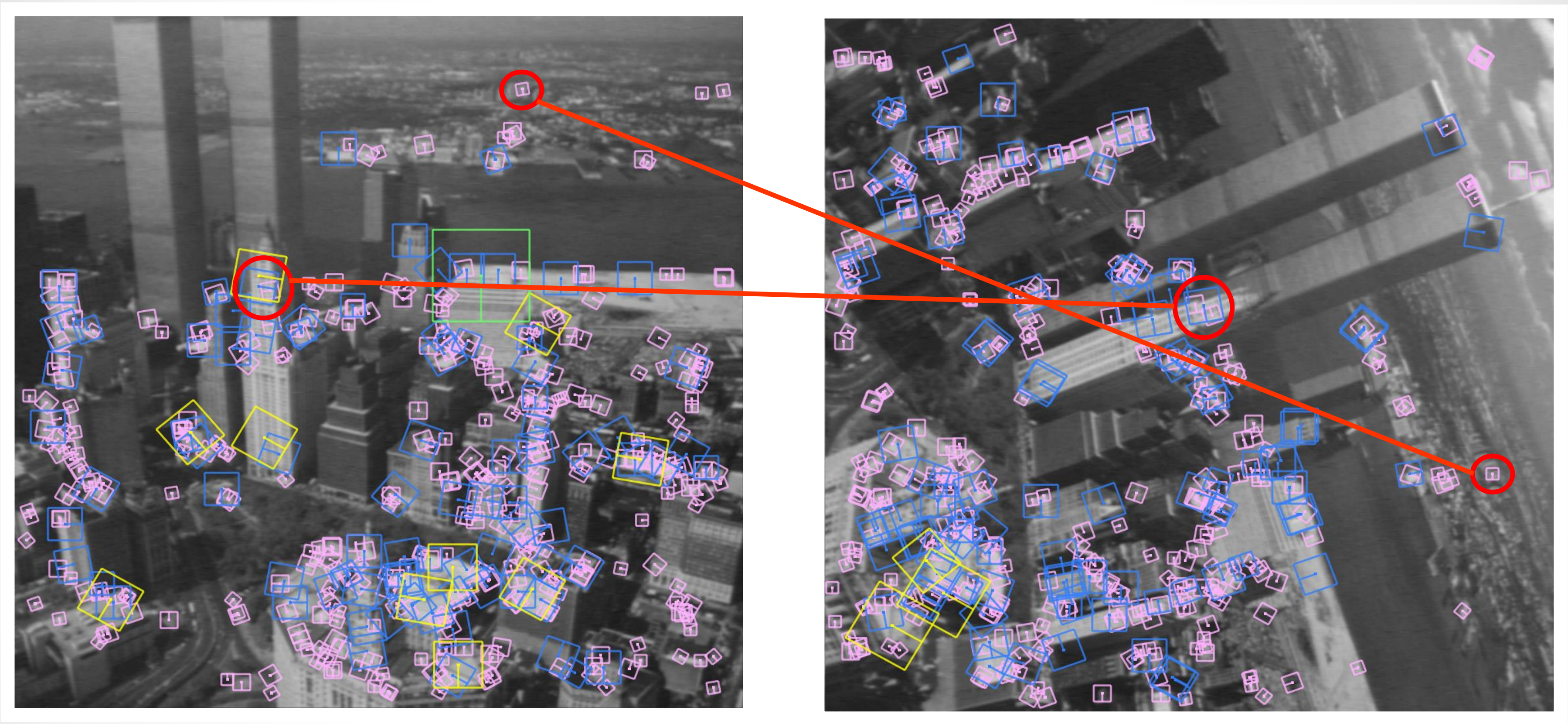
Spring 2013

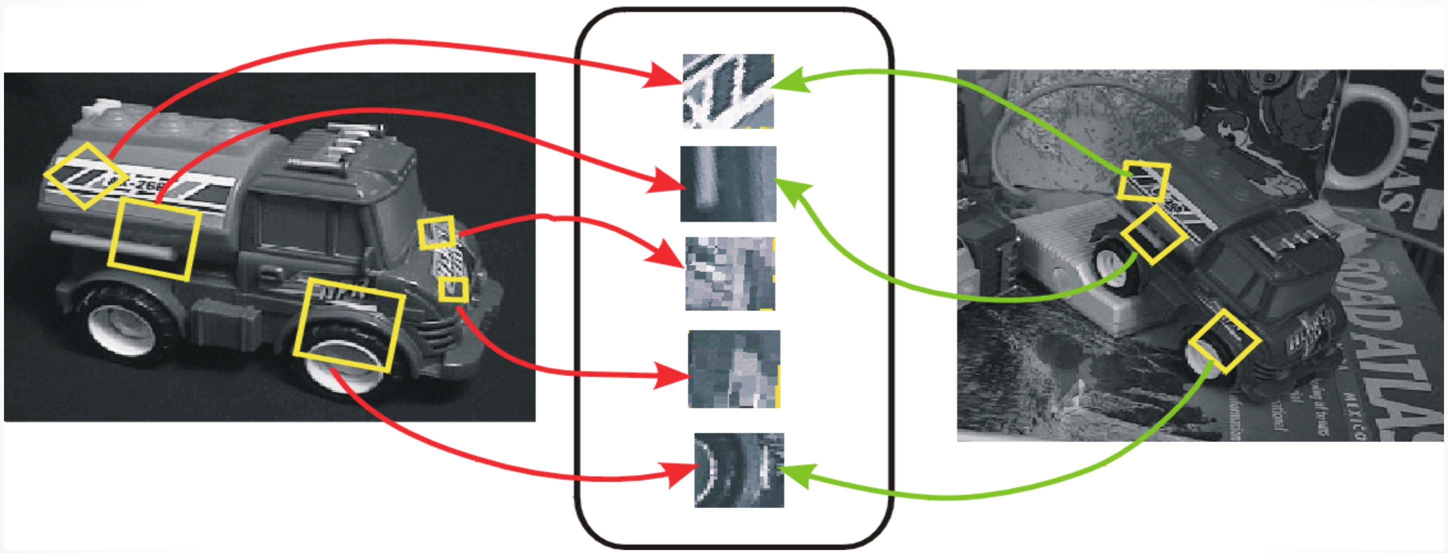
SIFT-detector



Problem: want to detect features at different scales (sizes) and with different orientations!

SIFT-detector

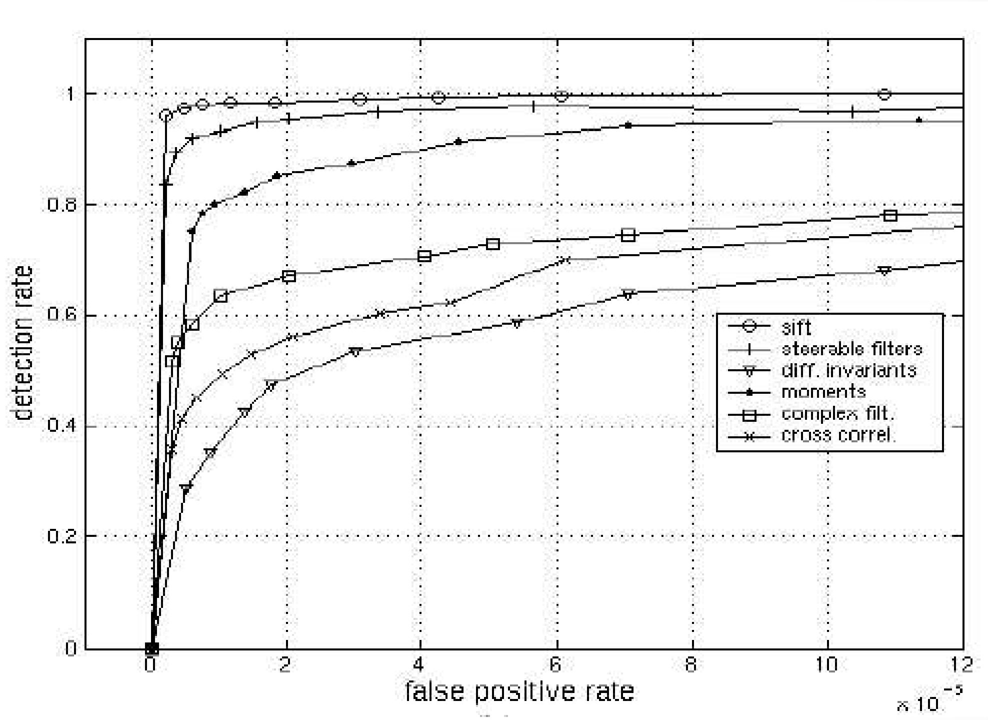
- Scale and image-plane-rotation invariant feature descriptor [Lowe 2004]
    - -Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



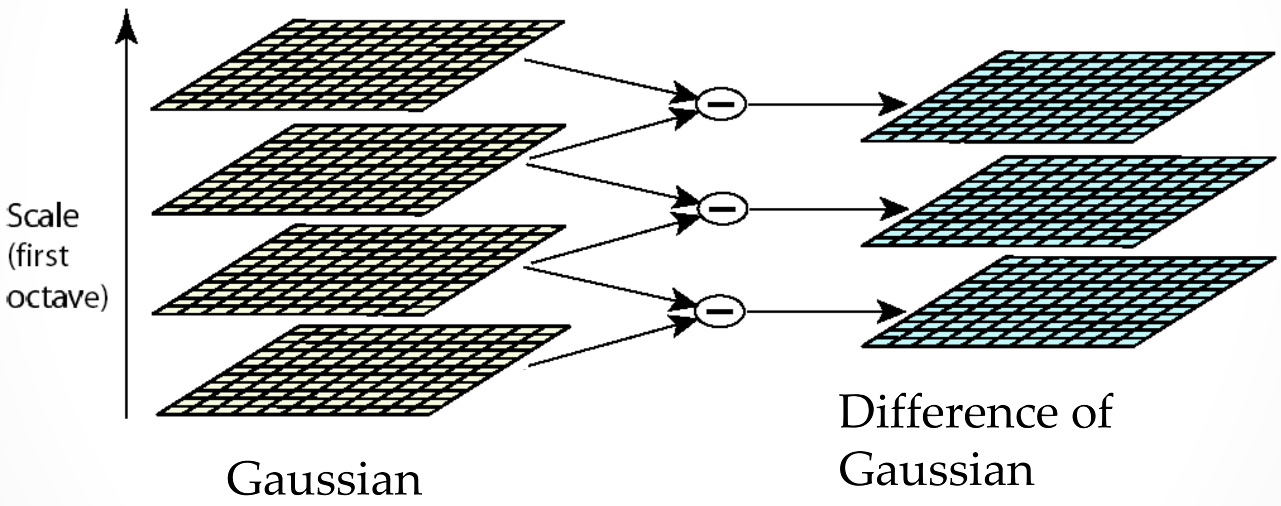
SIFT-detector

- Empirically found to perform very good **[Mikolajczyk 2003]**

Scale = 2.5
Rotation = 45^0

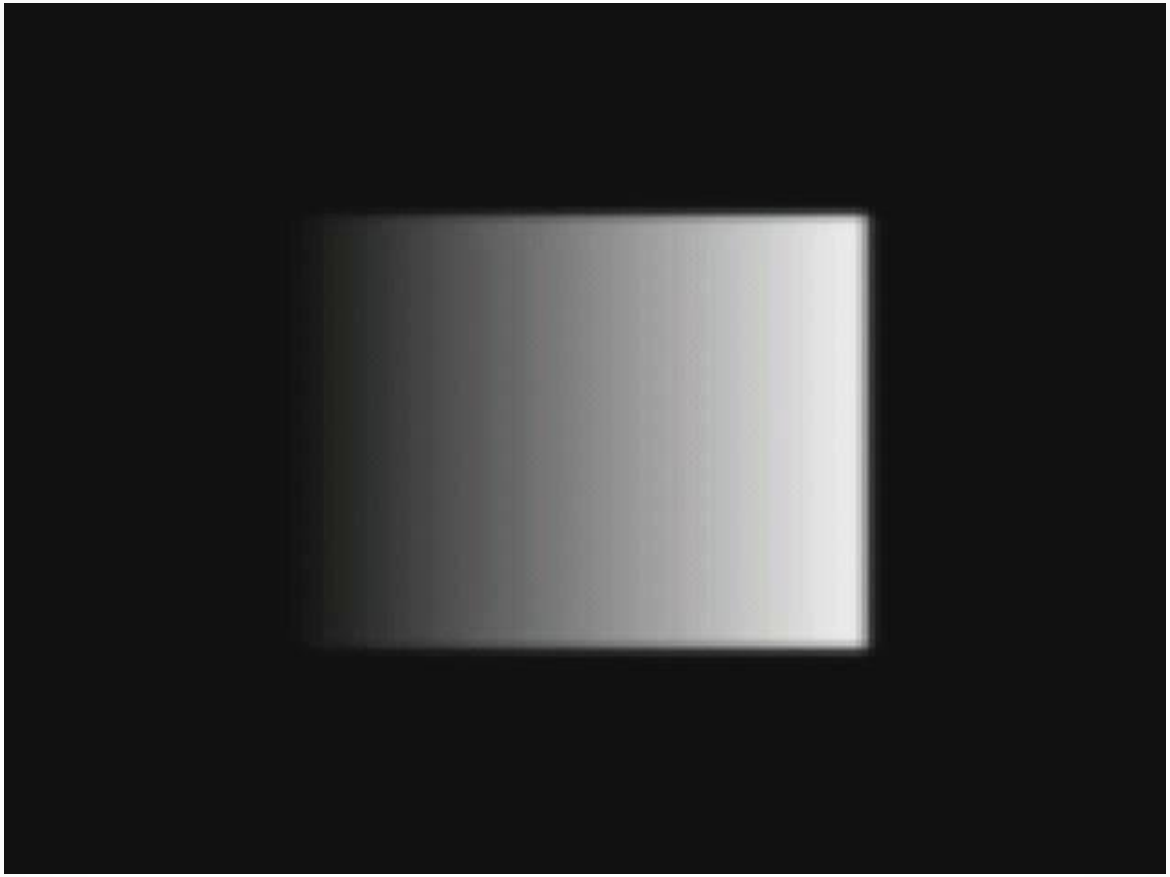


Scale invariance



- Difference-of-Gaussian with constant ratio of scales is a close approximation to Lindeberg's scale-normalized Laplacian [Lindeberg 1998]

Scale invariance



- Difference-of-Gaussian with constant ratio of scales is a close approximation to Lindeberg's scale-normalized Laplacian [Lindeberg 1998]

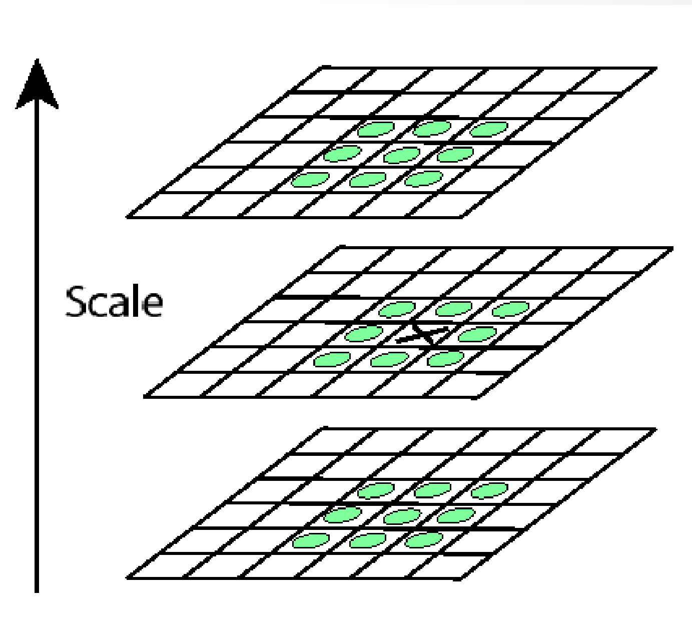
Key point localization

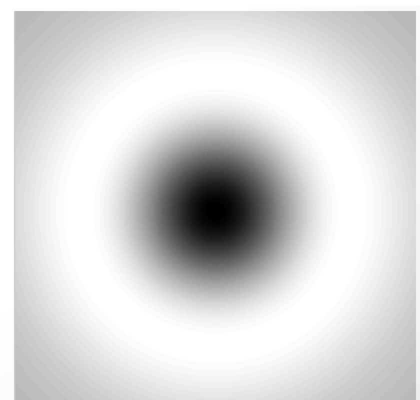
- Detect maxima and minima of difference-of-Gaussian in scale space
- Fit a quadratic to surrounding values for sub-pixel and sub-scale interpolation (Brown & Lowe, 2002)
- Ta

$$D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^{\mathbf{T}} \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$

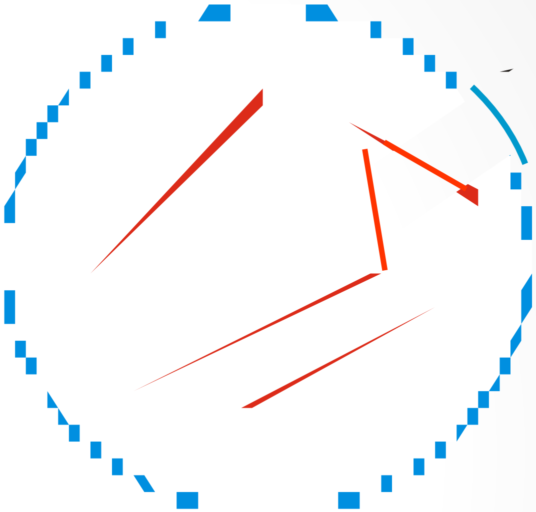
- Offset of extremum (use finite differenc ves):

$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}$$





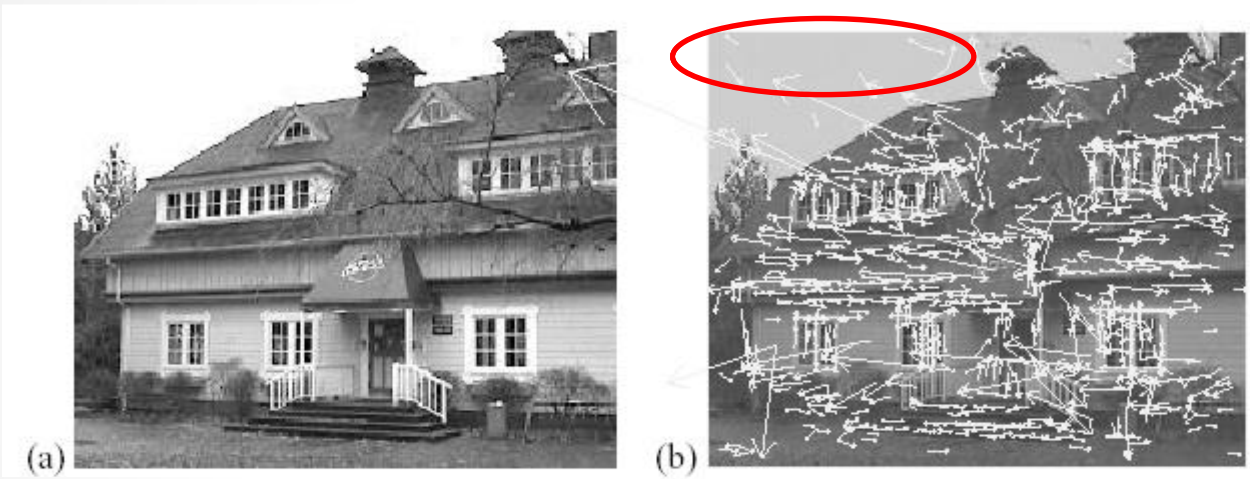
Orientation normalization



- Histogram of local gradient directions computed at selected scale
- Assign principal orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientatio

Example of keypoint detection

Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)

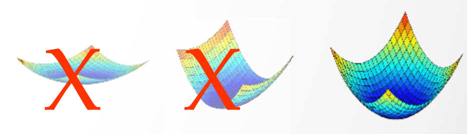


(a) 233x189 image
(b) 832 DOG extrema

k

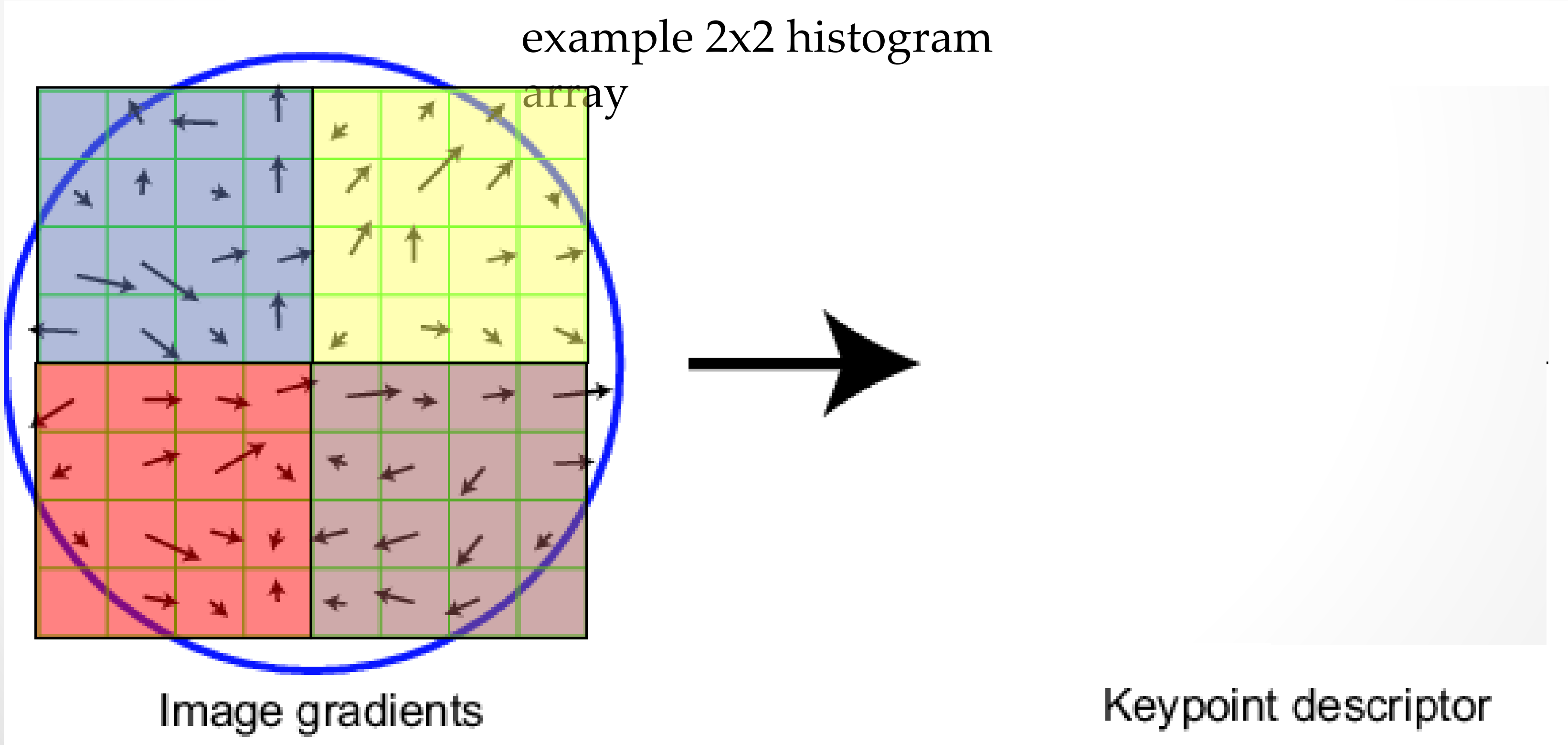
ng

curvatures



SIFT vector formation

- Thresholded image gradients are sampled over 16x16 array of locations in scale space
- Create array of orientation histograms
- 8 orientations x 4x4 histogram array = 128 dimensions



© Lowe

Sift feature detector

Goal

Image Patch

[0, 0, 1, 0, 1, 1, 0, 1, …]

Binary Descriptor

slide: J. Heinly

BRIEF

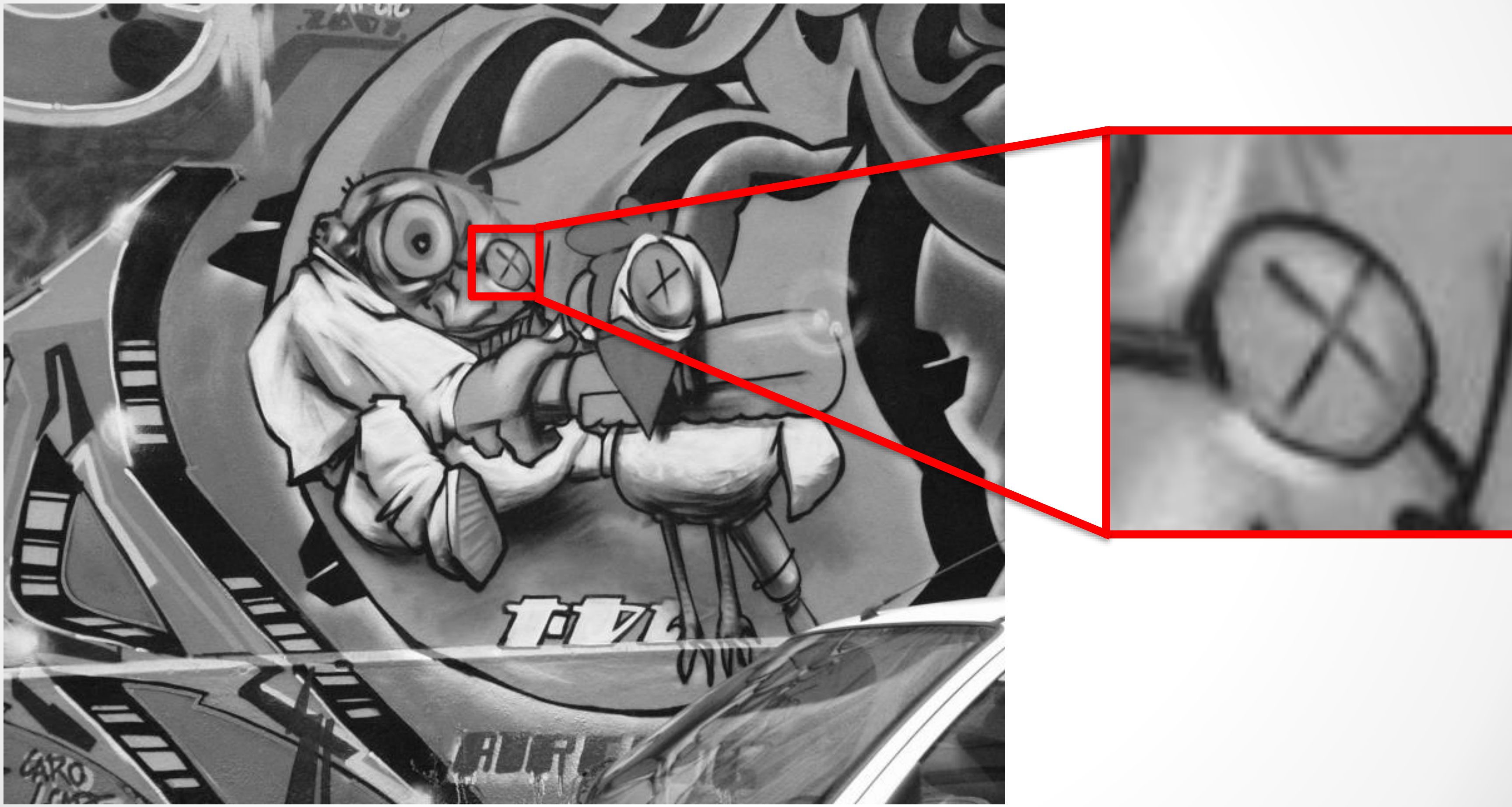
Binary Robust Independent Elementary Features

Calonder et al.

ECCV 2010

slide: J. Heinly

Feature Description



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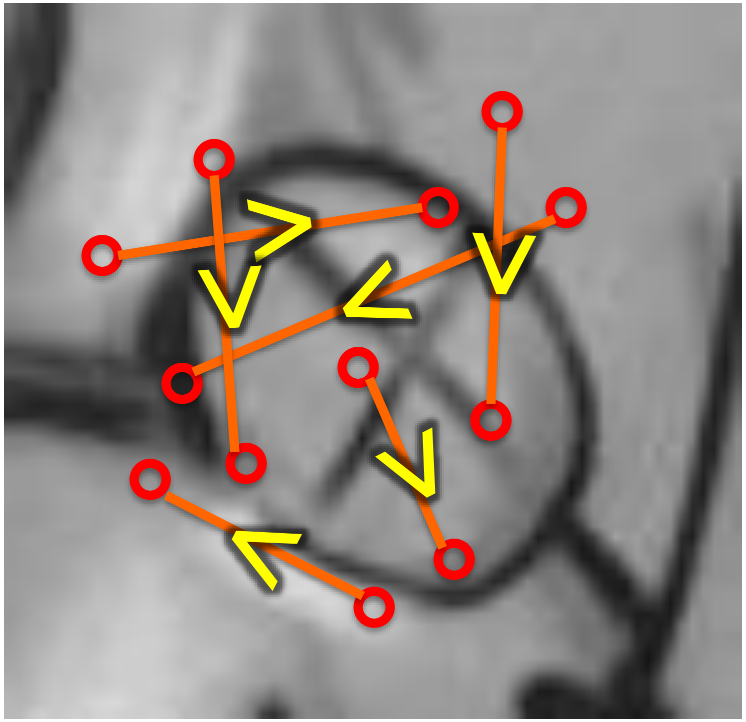
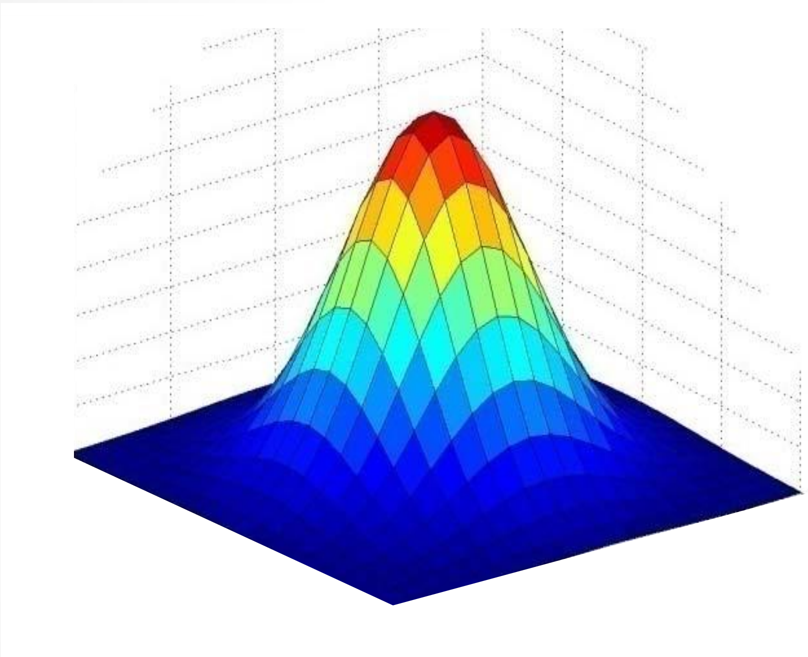
BRIEF: Method



Descriptor: **0 1 1 0 1 0 …**

slide: J. Heinly

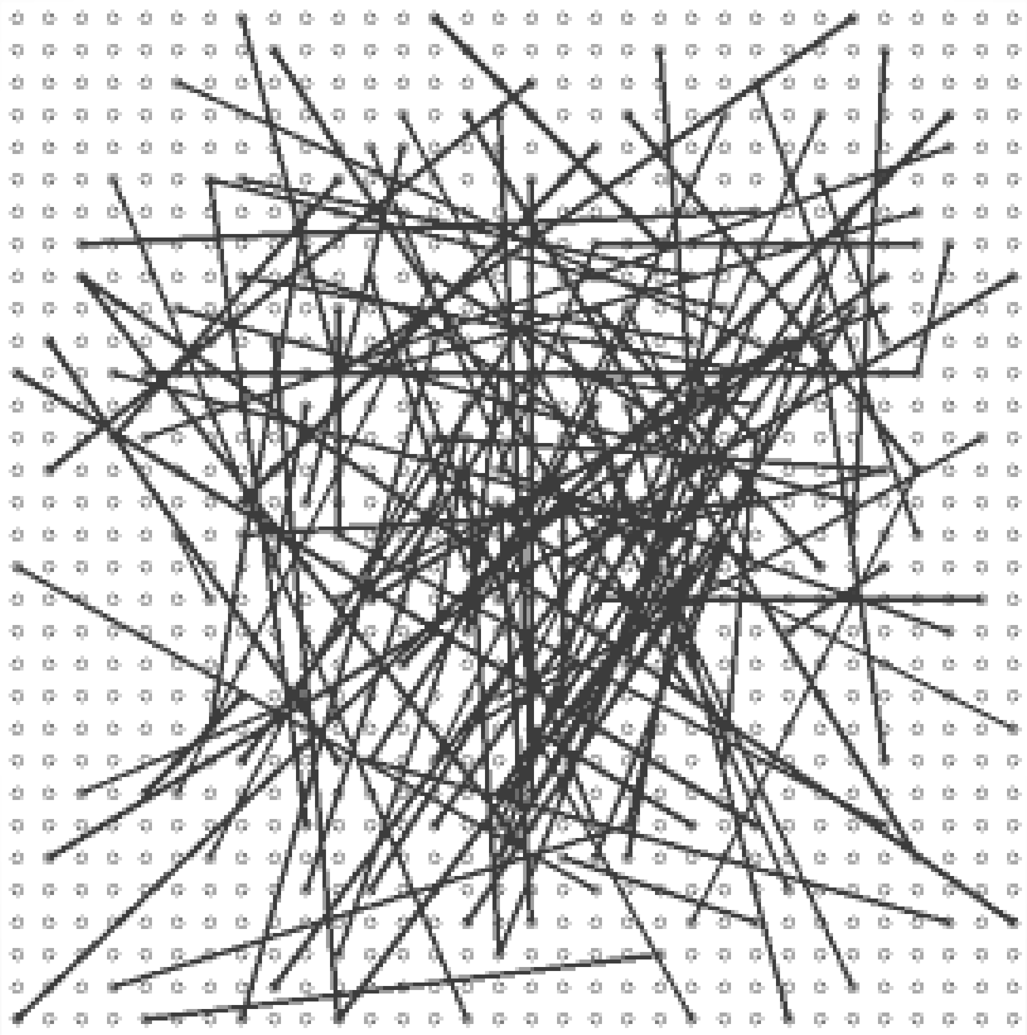
BRIEF: Sampling



Endpoints from 2D Gaussian

slide: J. Heinly

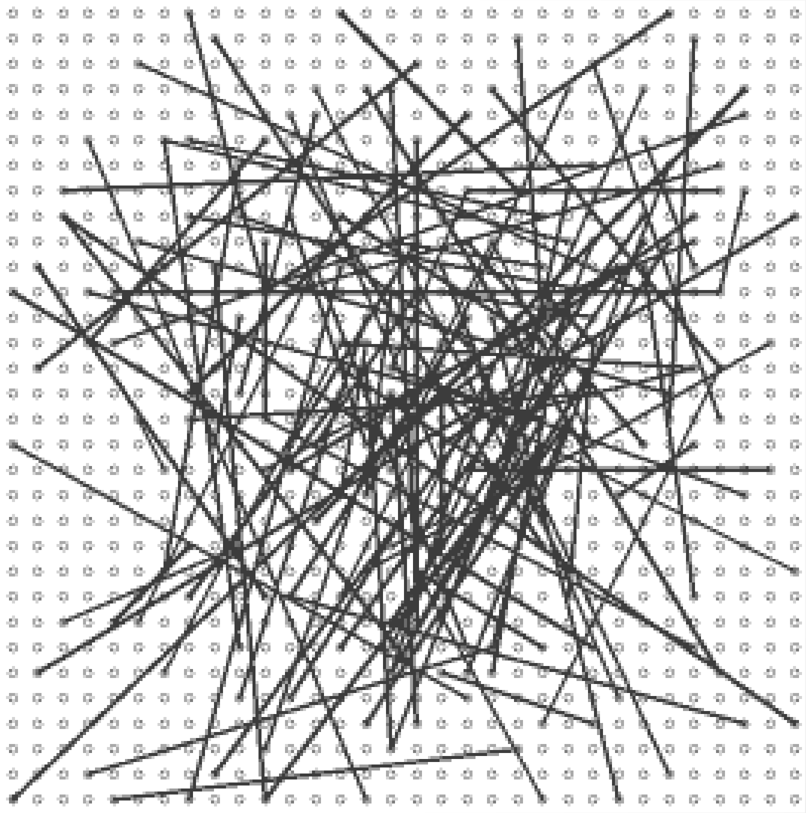
BRIEF: Descriptor



slide: J. Heinly

BRIEF: Descriptor

- 128, 256, or 512 bits
  - 16, 32, or 64 bytes
- Hamming distance matching



slide: J. Heinly

BRIEF: Summary

- Pros
  - Highly efficient
- Cons
  - No scale invariance
  - No rotation invariance
  - Sensitive to noise

slide: J. Heinly

ORB
An Efficient Alternative to SIFT or SURF

Rublee et at.

ICCV 2011

slide: J. Heinly

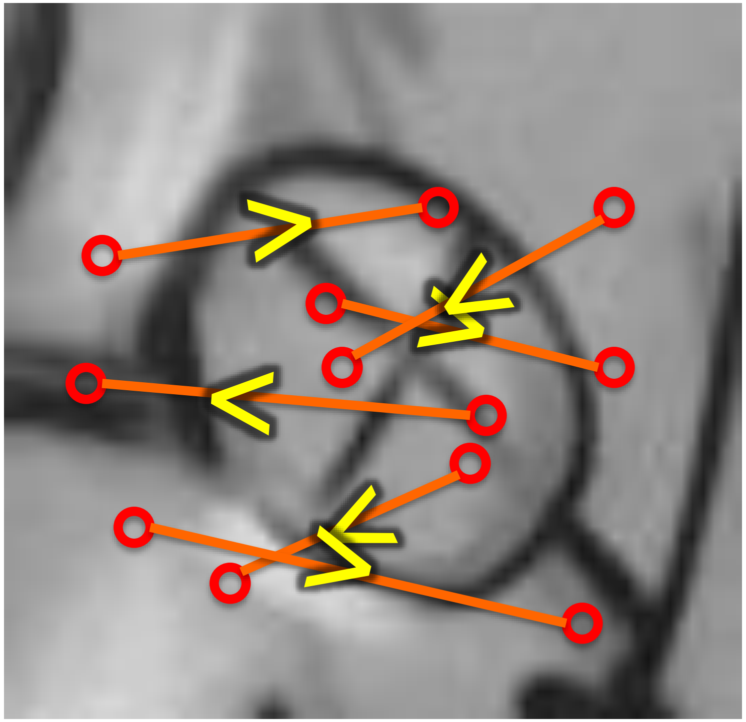
Limitations of BRIEF

- No rotation invariance

slide: J. Heinly

ORB: Method

Feature
Directio
n

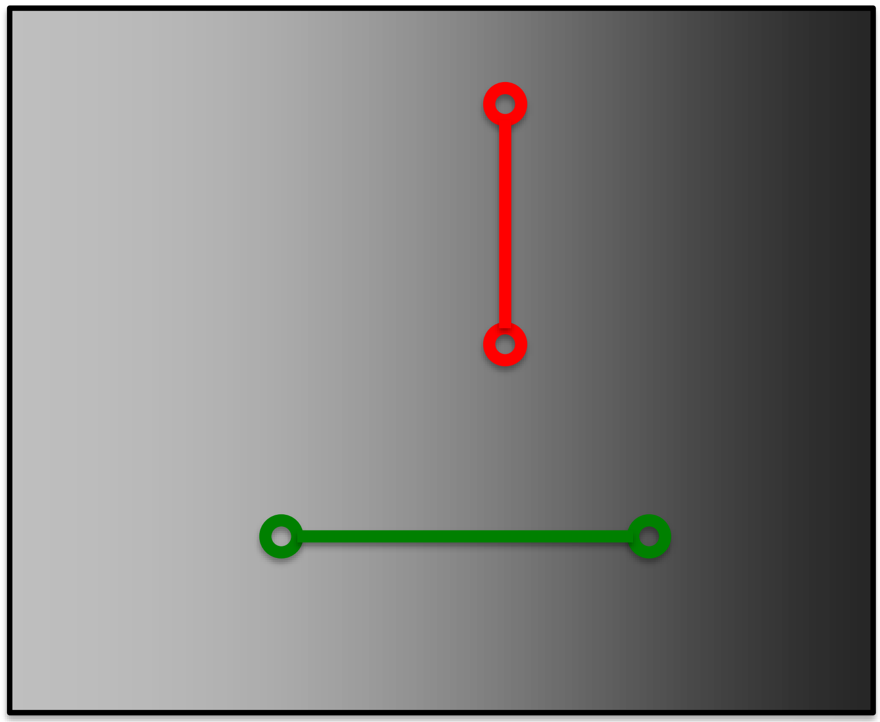


Descriptor: 0 1 1 0 1 0 …

slide: J. Heinly

ORB: Gradient Alignment

Gradient Direction



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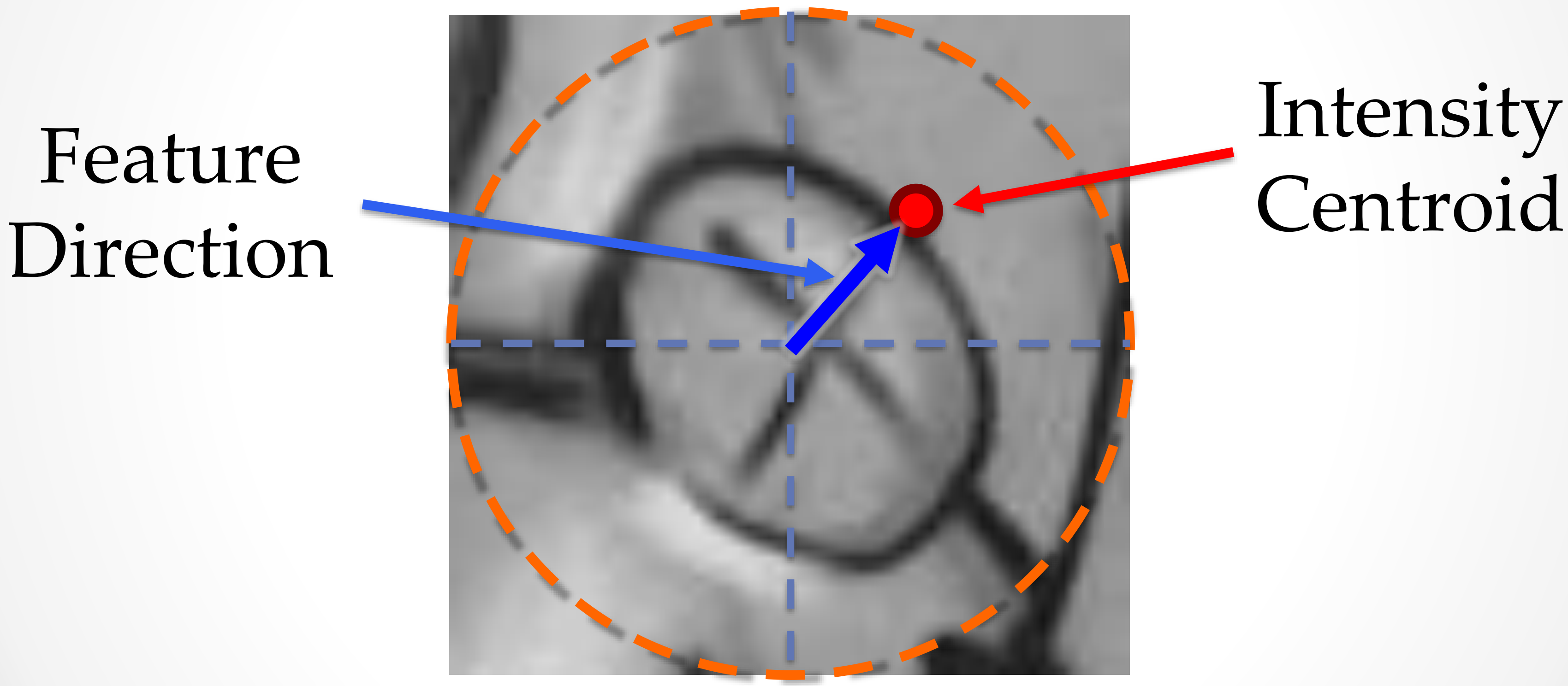
ORB: Rotation Invariance



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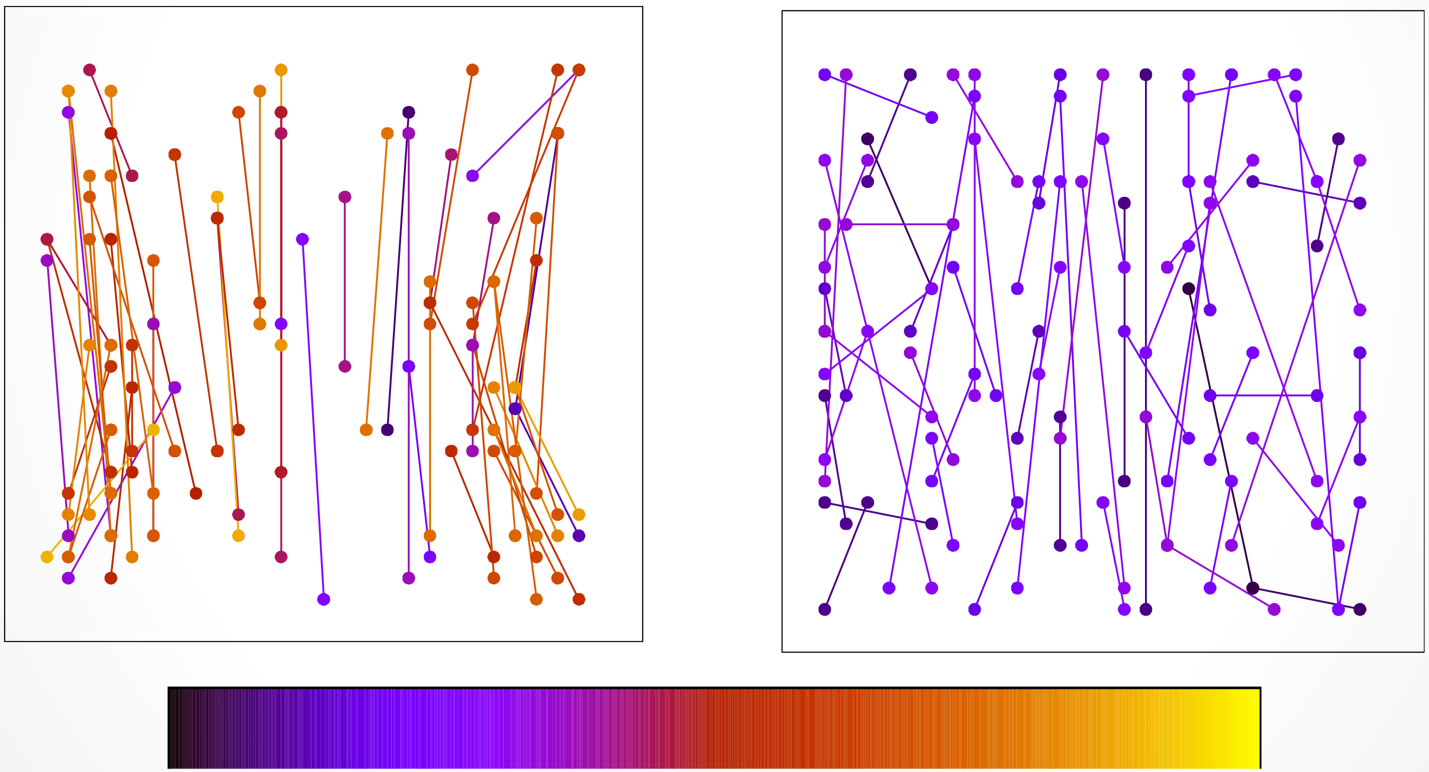
ORB: Descriptor

Candidate Arrangement Learned Arrangement



Low Endpoint Correlation **High**

slide: J. Heinly

ORB: Summary

- Pros
  - Efficient
  - Rotation invariance
- Cons
  - No scale invariance
  - Sensitive to noise

slide: J. Heinly

BRISK

Binary Robust Invariant Scalable Keypoints

Leutenegger et al.

ICCV 2011

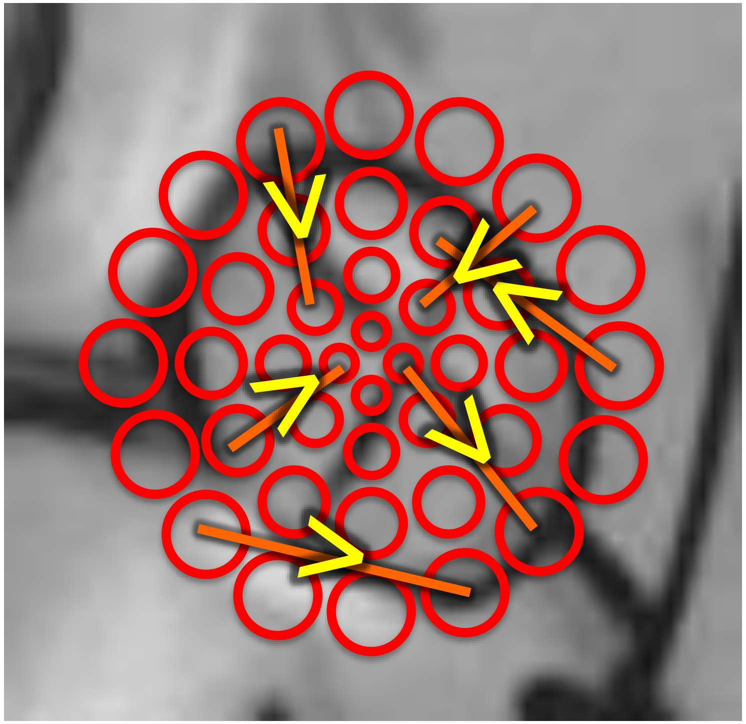
slide: J. Heinly

Limitations of BRIEF

- No rotation invariance
- No scale invariance
- Sensitive to noise

slide: J. Heinly

BRISK: Method

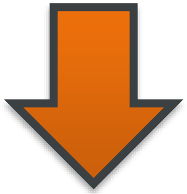


Descriptor: **0 1 1 0 1 0 …**

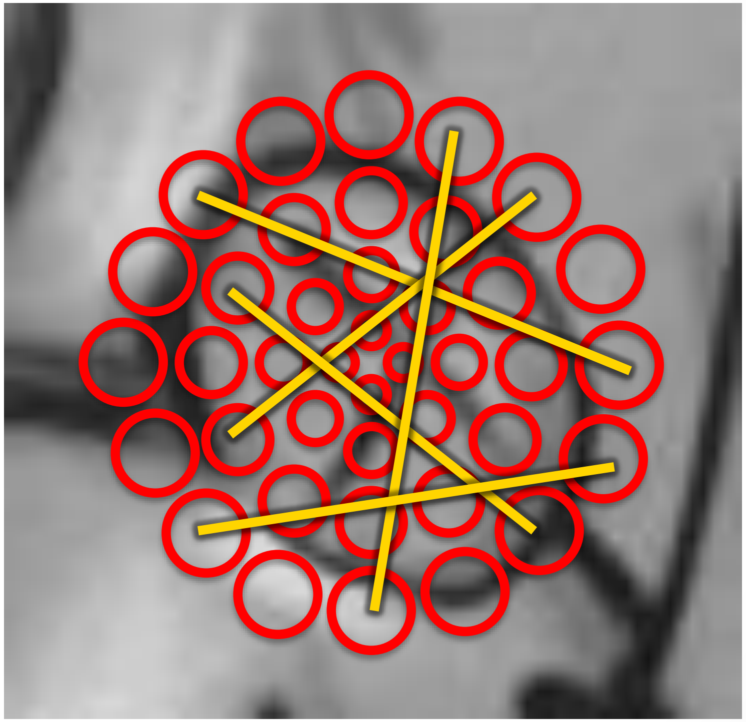
slide: J. Heinly

BRISK: Rotation Invariance

Long-distance comparisons

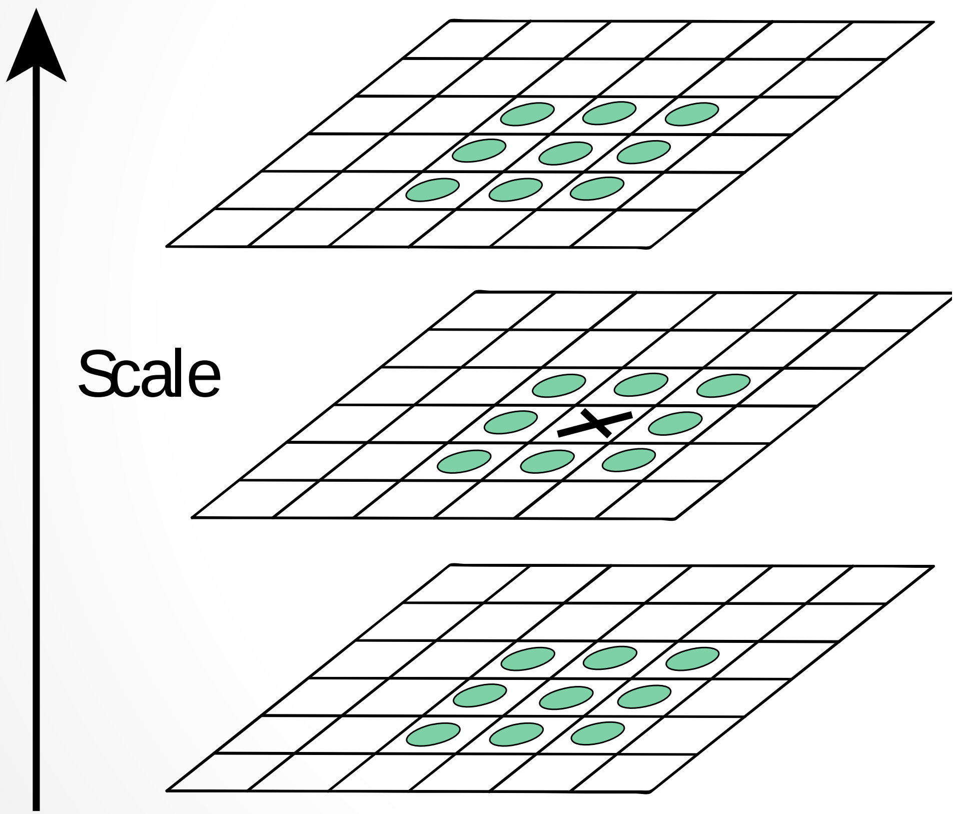


Gradient direction



slide: J. Heinly

BRISK: Scale Invariance



Find maximum response

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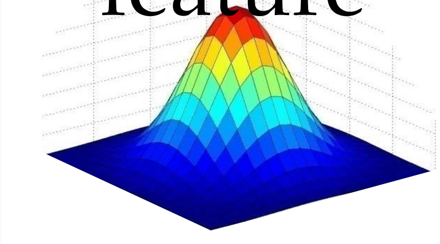
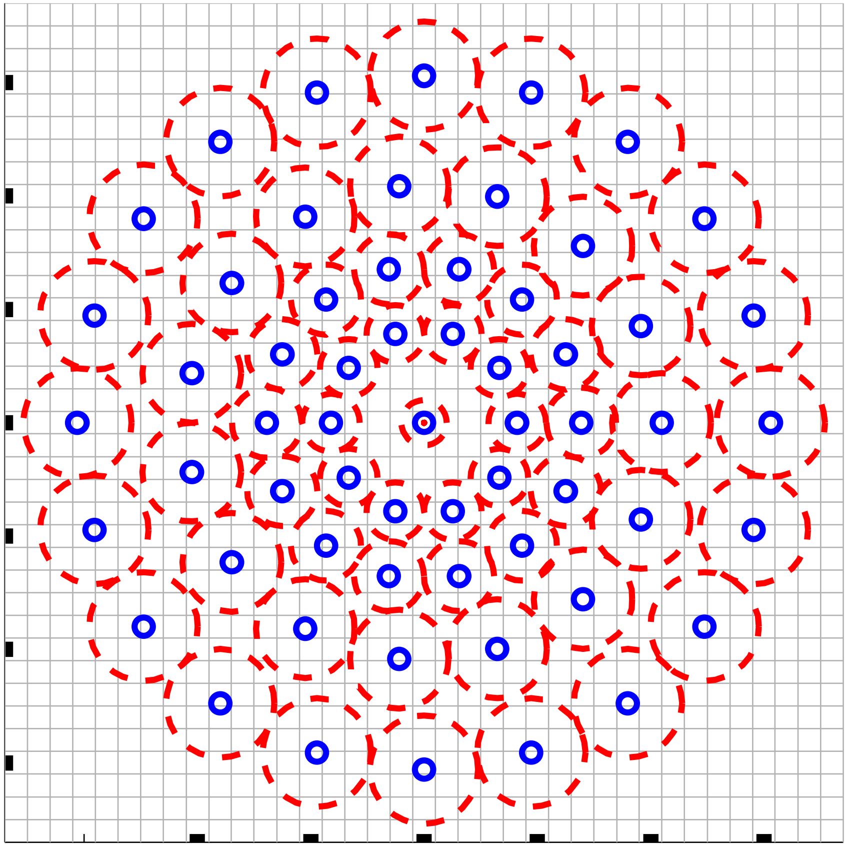
BRISK: Descriptor

2D Gaussian around each feature



Robust to noise



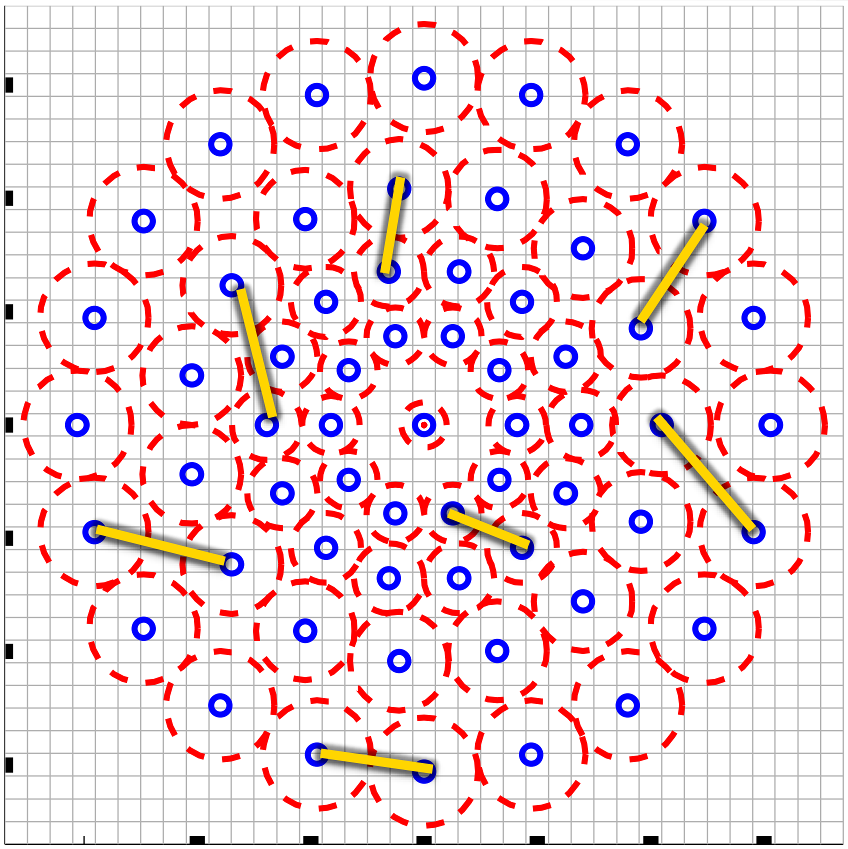
Centers: **BLUE** Gaussian: **RED**

slide: J. Heinly

BRISK: Descriptor

512 Comparisons
64 bytes

Avoid short-distance comparisons



Centers: **BLUE** Gaussian: **RED**

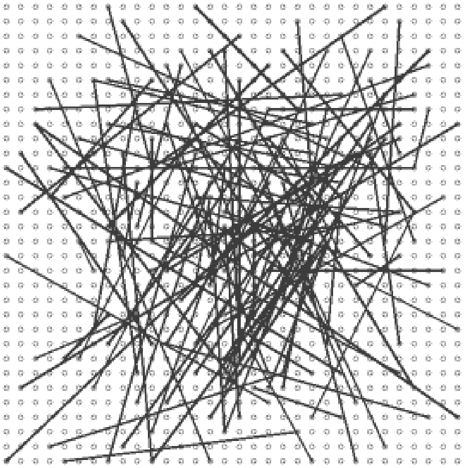
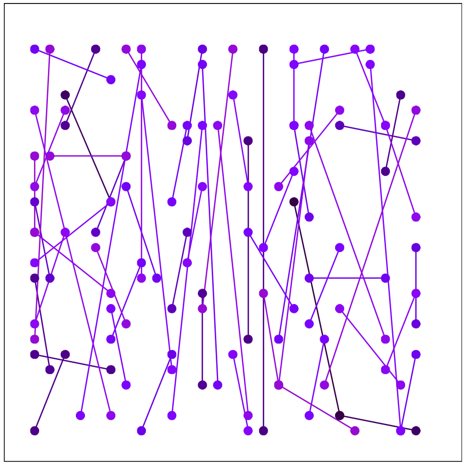
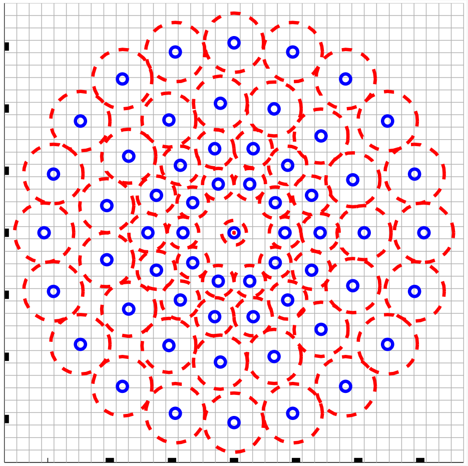
slide: J. Heinly

BRISK: Summary

- Pros
  - Efficient
  - Rotation invariance
  - Scale invariance
  - Robust to noise

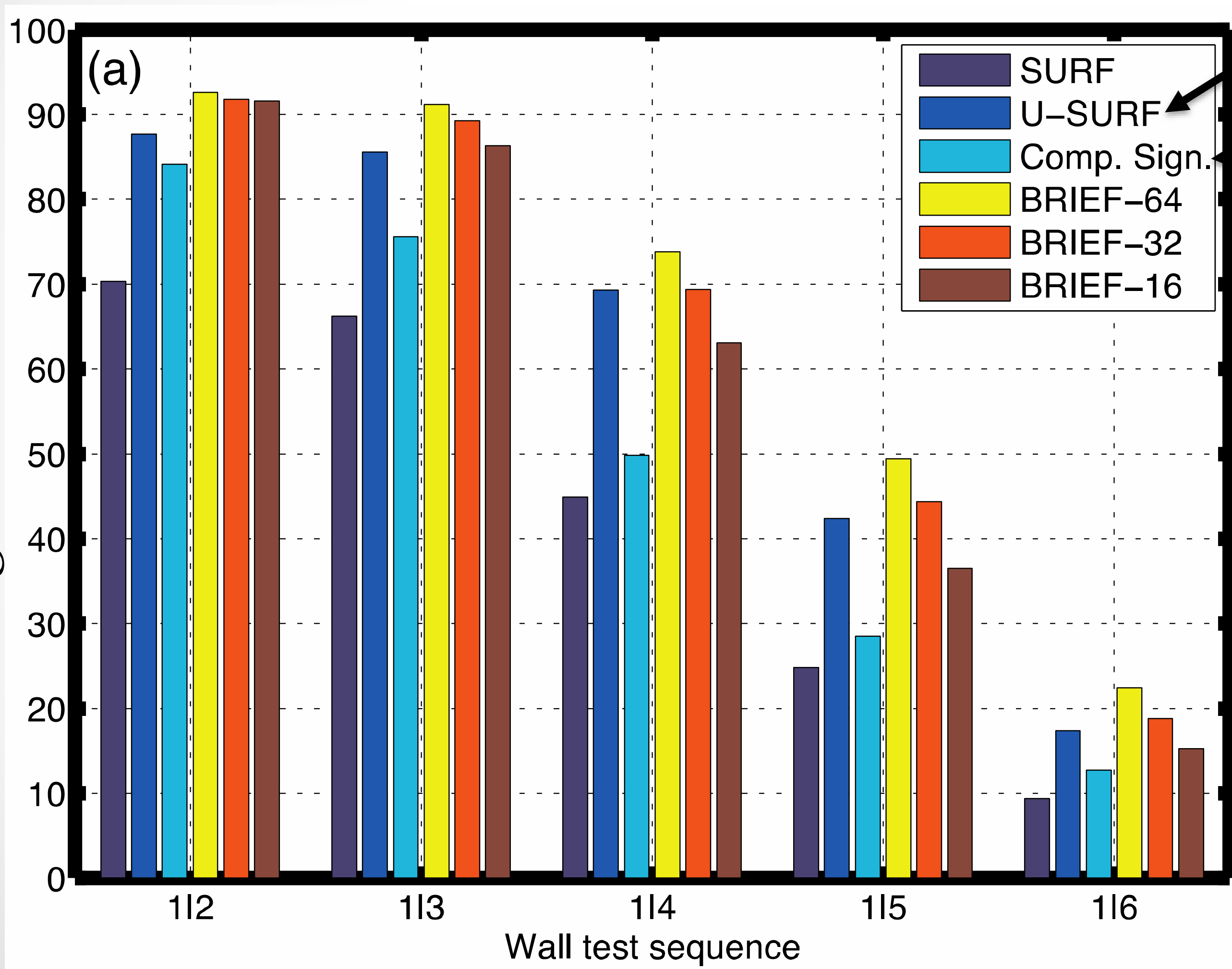
slide: J. Heinly

Summary

BRIEF	ORB	BRISK
		
• Efficient	• Efficient • Rotation	• Efficient • Rotation • Scale • Noise

slide: J. Heinly

Results: BRIEF



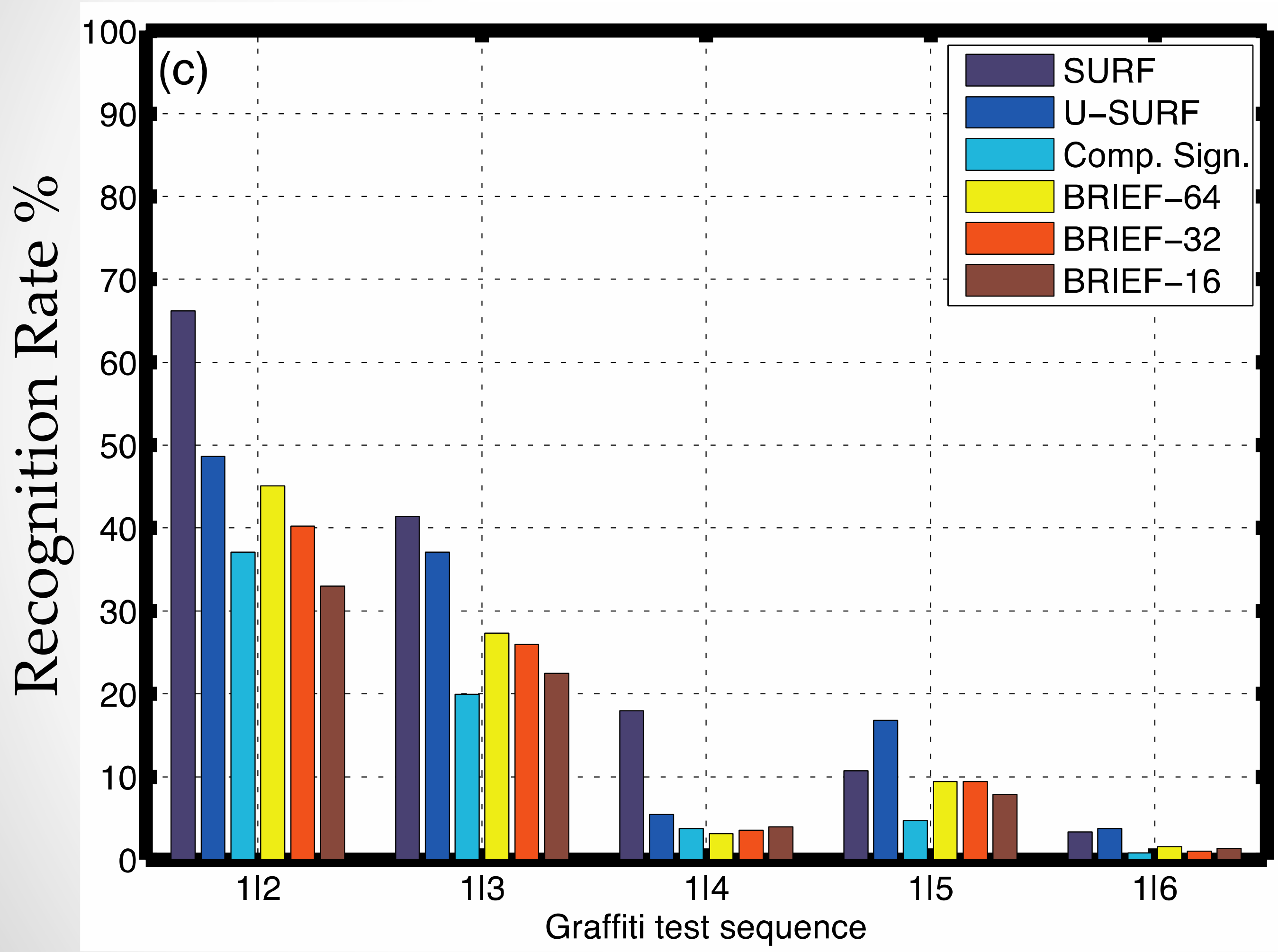
No Rotation

Dimensionali
ty Reduction

Increased Difficulty

slide: J. Heinly

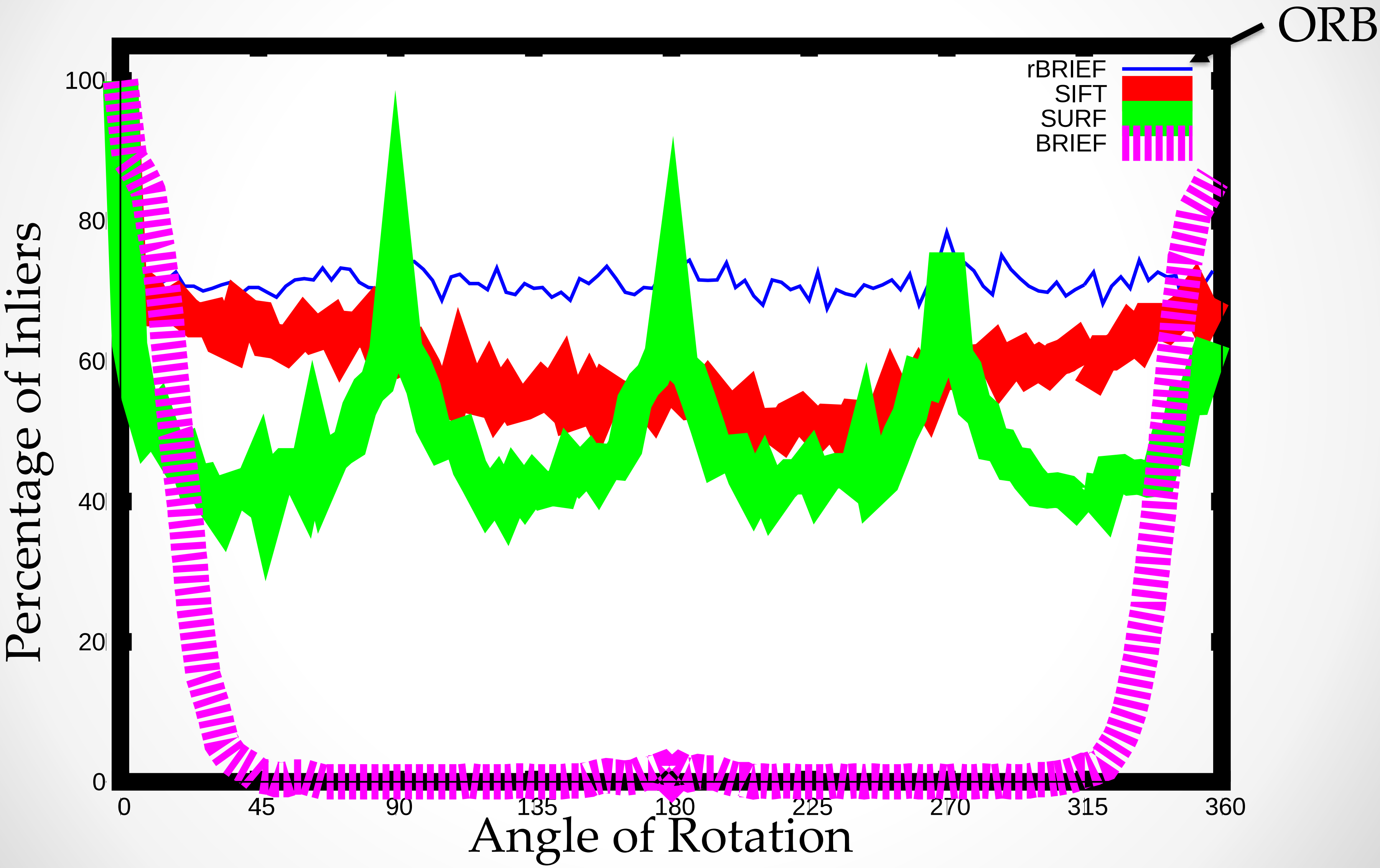
Results: BRIEF



Increased Difficulty

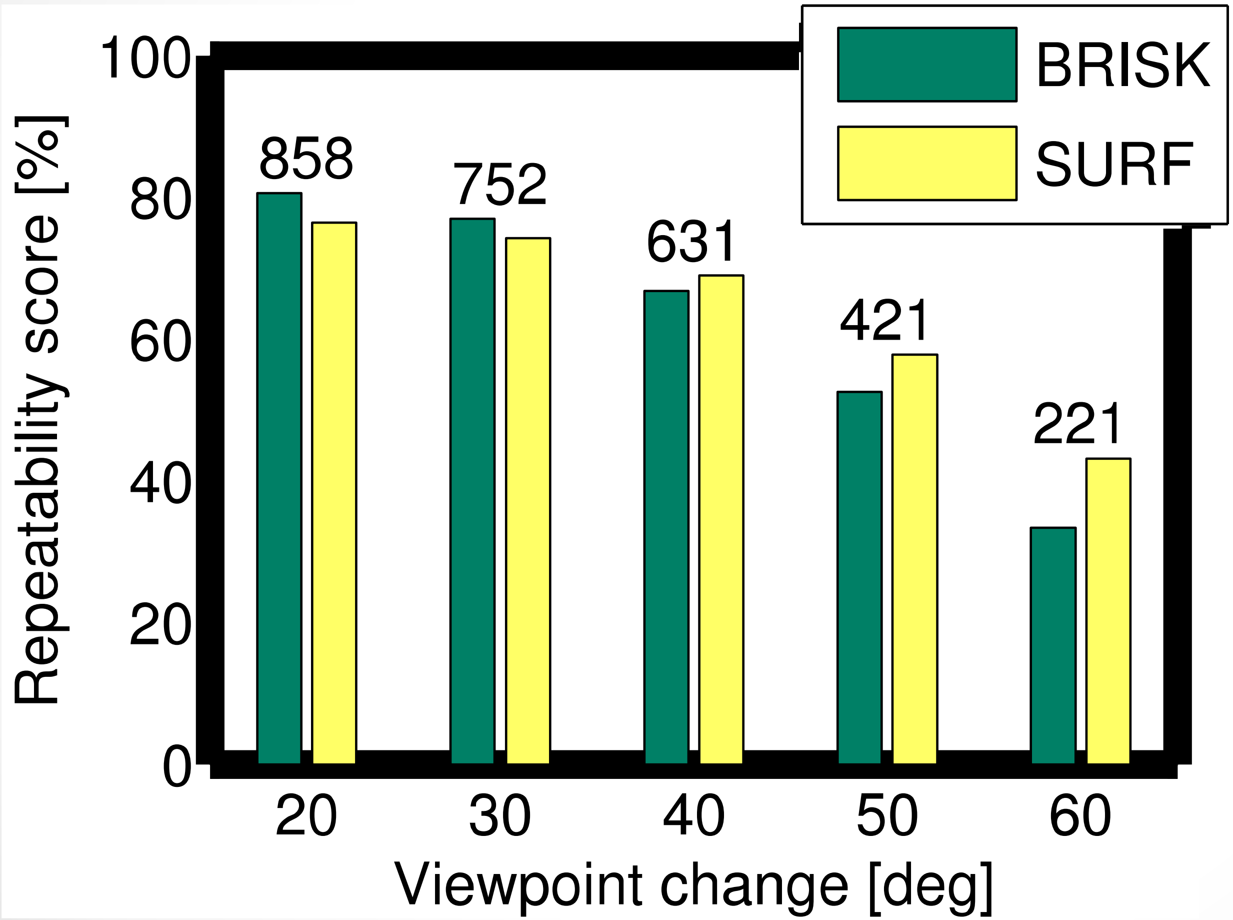
slide: J. Heinly

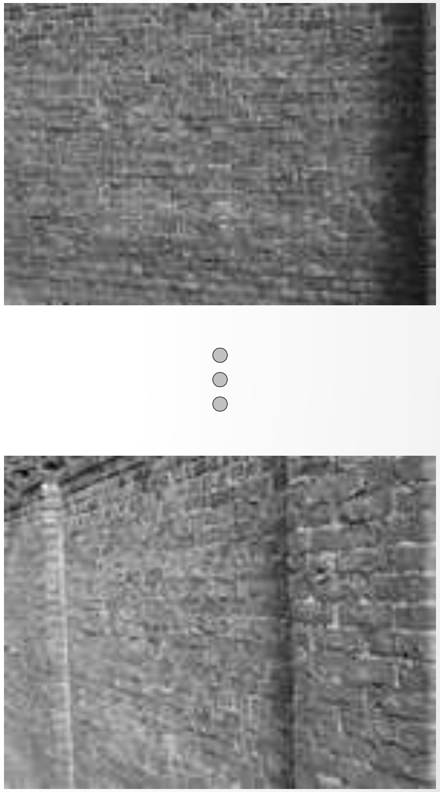
Results: ORB



slide: J. Heinly

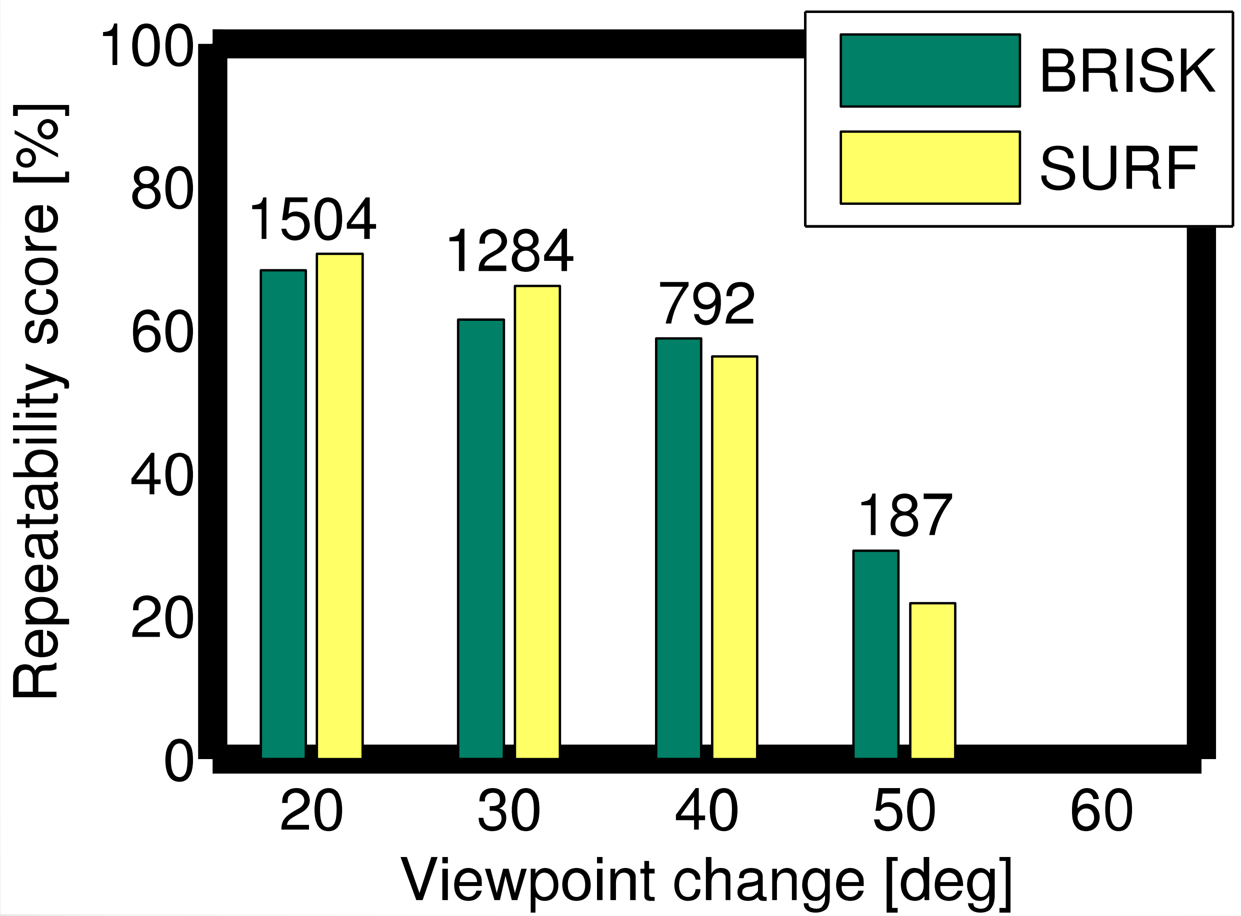
Results: BRISK





slide: J. Heinly

Results: BRISK



slide: J. Heinly

Results

- Many more tests…

Key Observation: **Results are comparable to traditional feature descriptors.**

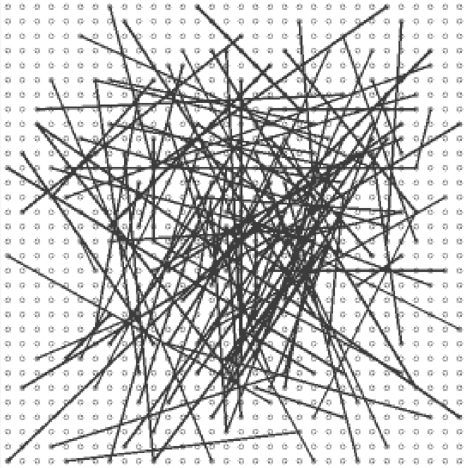
Efficiency

	SURF	SIFT	BRIEF	ORB	BRISK
Normalized Time	1.0	19.0	0.027	0.070	0.087
Speedup			**37.2**	**14.2**	**11.5**

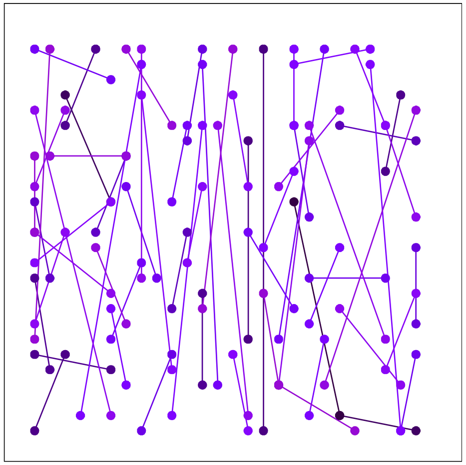
slide: J. Heinly

Summary

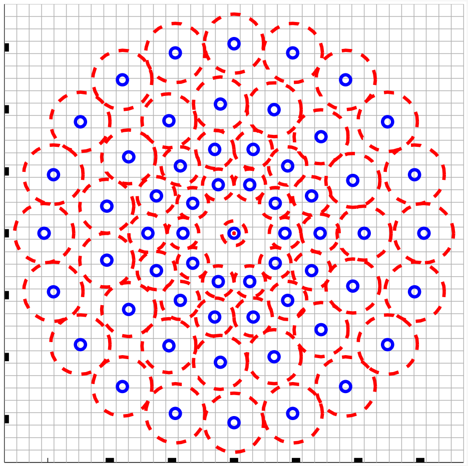
BRIEF



ORB



BRISK



Efficient Binary Descriptors

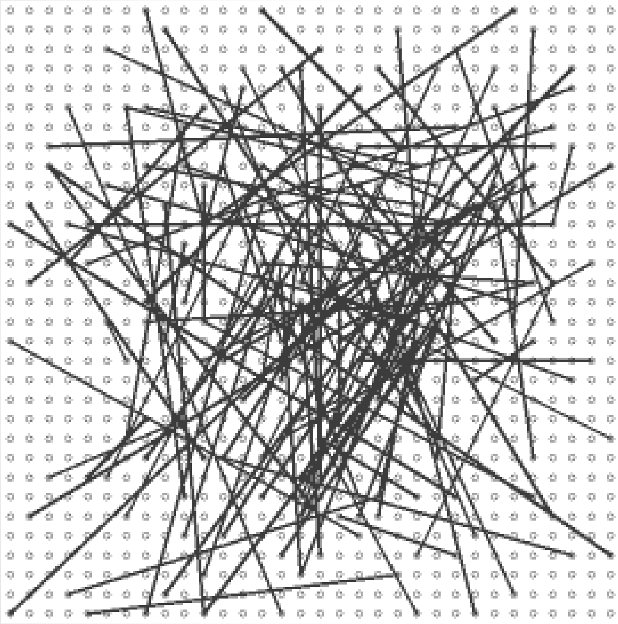
slide: J. Heinly

Future Work

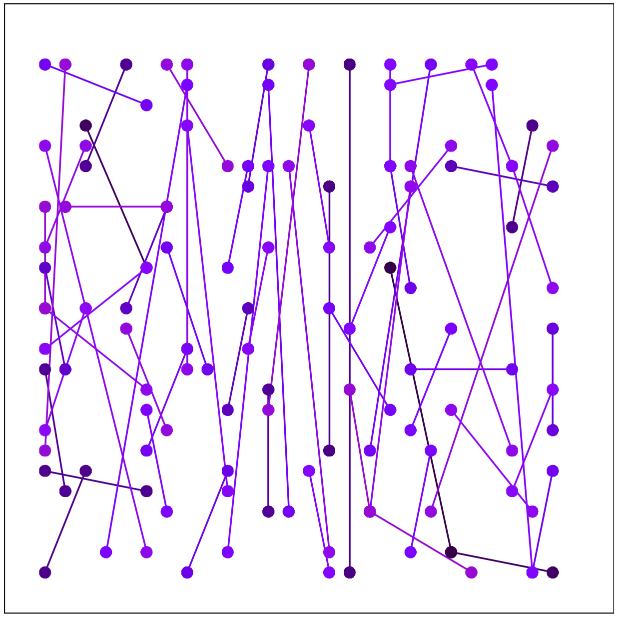
- Improved robustness
  - Rotation
  - Scale
  - Noise
- Coupling with detector

slide: J. Heinly

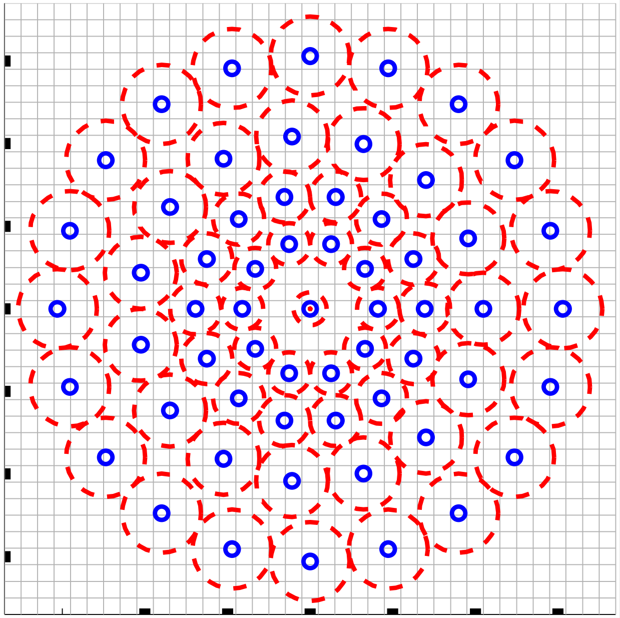
BRIEF



ORB



BRISK



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