# SIFT: Scale Invariant Feature Transform

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## SIFT Features

SIFT: Scale Invariant Feature Transform

Image points + local description
(128 vector)

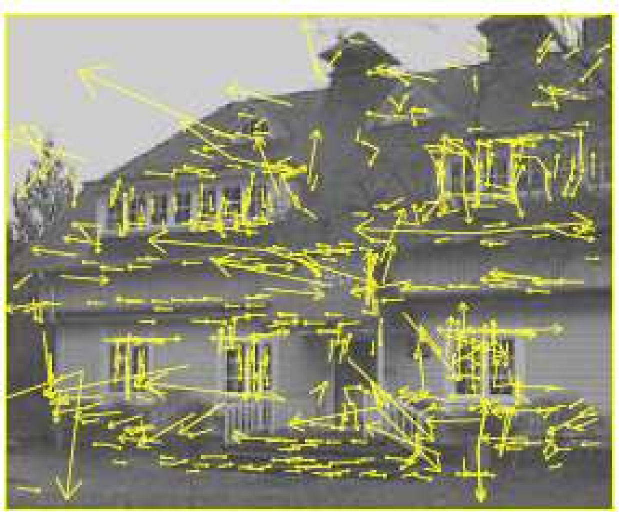
Sparse, reasonably distinguishable points

[ ? ] to translation, rotation, scale, some 3D





## Example feature locations







## Matching Applications

[ ? ] features for:

- Object recognition
- Model-data alignment
- Image registration
- Stereo matching

## Four Step Algorithm

1. Detect extremal points in scale space
2. Accurate ? subpixel localization
3. Feature orientation estimation
4. Keypoint descriptor calculation





## Scale Space Smoothing

Gaussian ? via convolution

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

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

Difference of Gaussians:

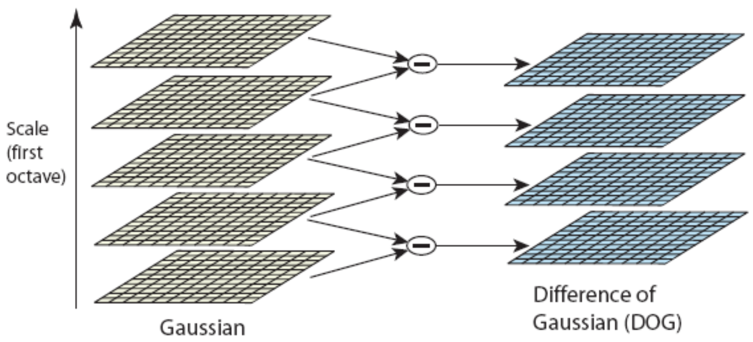
$$D(x, y, n) = L(x, y, 2^{\frac{n}{S}}) - L(x, y, 2^{\frac{n-1}{S}})$$

where $n = 1 \dots N$
$S = 3$ best





?

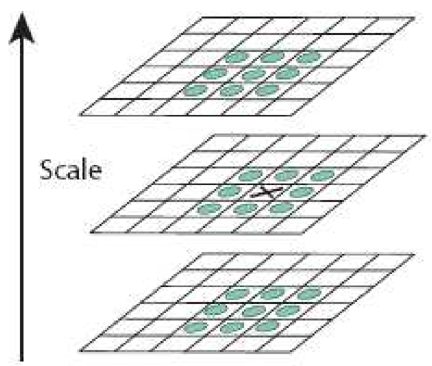







## Point Extrema

Pick ? points larger/smaller than their 26 neighbours:



**Subpixel Extrema** ?

Hessian:

$$\mathrm{H}_3 = \begin{bmatrix} \partial^2 D/\partial x^2 & \partial^2 D/\partial x \partial y & \partial^2 D/\partial x \partial \sigma \\ \partial^2 D/\partial x \partial y & \partial^2 D/\partial y^2 & \partial^2 D/\partial y \partial \sigma \\ \partial^2 D/\partial x \partial \sigma & \partial^2 D/\partial y \partial \sigma & \partial^2 D/\partial \sigma^2 \end{bmatrix}$$





Optimal position is $(x, y, \sigma) + \hat{x}$, where

$$\hat{x} = -\mathrm{H}_3^{-1} \begin{bmatrix} \partial D/\partial x \\ \partial D/\partial y \\ \partial D/\partial \sigma \end{bmatrix}$$





**Low** ? **Extrema Pruning**

Predict DoG value at subpixel extrema:

$$p = \mid D(x, y, \sigma) + \frac{1}{2} \left[ \frac{\partial D}{\partial x}, \frac{\partial D}{\partial y}, \frac{\partial D}{\partial \sigma} \right] \hat{x} \mid$$

Reject if $p < 0.03$





? **Point Extrema Pruning**

Let

$$\mathrm{H}_2 = \begin{bmatrix} \partial^2 D/\partial x^2 & \partial^2 D/\partial x \partial y \\ \partial^2 D/\partial x \partial y & \partial^2 D/\partial y^2 \end{bmatrix}$$

Reject if $det(H_2) < 0$ or

$$\frac{trace(\mathrm{H}_2)^2}{det(\mathrm{H}_2)} > \tau \; (e.g. 12)$$

Rejects points that can slide along an edge

## Getting Rotation Invariance

? orientation $\hat{\theta}$ estimation

Use keypoint scale $\sigma$

Let $\vec{v} = \nabla L(r,s,\sigma)$ for $(r,s) \in neigh(x,y)$
Compute strength $m = \mid \vec{v} \mid$ and
$\theta = direction(\vec{v})$
Compute histogram of $\theta$ values weighted by $m$

Pick top peak direction $\hat{\theta}$ in histogram for feature orientation





## Local ? Computation

Use $16 \times 16$ neighbourhood about feature point subdivided into 16 $4 \times 4$ pixel blocks
Create an 8 orientation histogram for each block
$\rightarrow$ 128 vector
Compute gradient orientation at each point
Rotate all orientations by $\hat{\theta}$ (for invariance)
Add to histogram weighted (details in paper)

Normalize 128 vector to unit length for illumination invariance

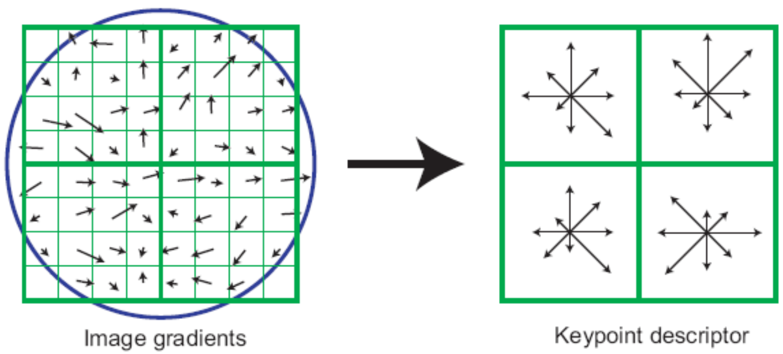
Descriptor similarity using Euclidean distance





## Descriptor Example

4 histograms from $8 \times 8$ neighbourhood about ?:








## SIFT Summary

- Sparse, distinctive ? features
- Translation independent by using local histogram
- Rotation independent by orientation adjustment
- Scale independent by extremal scale estimation
- Illumination independent by descriptor normalisation
- Widely used
- Real-time implementation possible

## SIFT References

www.cs.ubc.ca/~lowe/papers/ijcv04.pdf

en.wikipedia.org/wiki/Scale-invariant_feature_transform