#### The heat equation for ever

(The SIFT method and its extensions)

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D. G. Lowe, Object recognition from local scale-invariant features, IJCV 2, 1999



# The new state of art: It is by now possible to recognize a solid object in a digital image, no matter what the angle and the distance, up to limits that only depend on resolution.

In this pair: A very large transition tilt (extreme angle);  $\simeq 36$ . The transition tilt will be defined later.



#### 120 correct matches (not all shown), 4 outliers. Each match is indicated by a white segment

Recognition in spite of a very large view point change. The matches were obtained by the Affine SIFT method (A-SIFT), a variant of the SIFT method. Both methods will be explained.



Figure 1: Recognition with extreme scale difference. 26 matches, 6 outliers. Exp. : Rabin, Gousseau, Delon, SIFT method

#### Camera Model



Figure 2: Dürer 1525 "Le Portillon". Illustration of perspective deformation of solid objects

#### Camera Model



#### Affine simplification



Figure 3: Uccello's miracle (1465): "Oh che dolce cosa è questa prospettiva!" Projective transforms are differentiable and therefore locally equivalent to affine transforms. The room is a trapezoid, but it is paved with parallelograms. This means that affine invariance is enough for shape recognition.

#### **Conclusion:** the local camera model

All digital images obtained from a locally smooth object whose local frontal view is  $\mathbf{u}_0$  satisfy, locally,

 $u =: \mathbf{S}_1 \mathbf{G}_1 \mathbf{A} \mathbf{u}_0$ 

for some planar affine map  $\mathbf{A}$  (six parameters)!.

$$\begin{pmatrix} x \\ y \end{pmatrix} \rightarrow \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} e \\ f \end{pmatrix}$$
$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \mathbf{H}_{\lambda} \mathbf{R}_{1}(\psi) \mathbf{T}_{t} \mathbf{R}_{2}(\phi) = \lambda \begin{bmatrix} \cos \psi & -\sin \psi \\ \sin \psi & \cos \psi \end{bmatrix} \begin{bmatrix} t & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \cos \phi & -\sin \phi \\ \sin \phi & \cos \phi \end{bmatrix}$$



- $\phi$ : *longitude* angle between optical axis and a fixed vertical plane.
- θ = arccos(1/t): *latitude* angle between optical axis and the normal to the image plane.
  Tilt t > 1 ↔ θ ∈ [0°, 90°].
- $\psi$ : rotation angle of camera around optical axis.
- $\lambda$ : *zoom* parameter.
- $\mathcal{T} = (e, f)^T$ : translation, not presented here.

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For recognition, shapes must be described by local image features that are invariant to 8 parameters! This leads to 4 Image comparison requirements and to

our PLAN

- 1. independence from sampling (interpolation required);
- 2. invariance from illuminance changes (at least 2 parameters);
- 3. independence from: scale (that means independence of blur!), rotation, translation: 4 parameters, SIFT method
- 4. independence from tilts: (slanted view angle): 2 parameters, A-SIFT method

If each one of the 8 parameters has 10 values (which is an underestimate) a single comparison of two images would require the simulation of  $10^8$  different possible views for a single image, followed by  $10^8$  comparisons.

Problem 1: Independence from sampling: From a digital image back to a continuous image by Shannon interpolation

- $\mathbf{S}_1$ : the sampling operator at rate 1. The sampled digital image  $u = \mathbf{S}_1 \mathbf{u}$  is defined on  $\mathbb{Z}^2$  by  $u(n_1, n_2) = \mathbf{u}(n_1, n_2)$ ;
- If  $u \in l^2 \cap l^1(\mathbb{Z}^2)$ , the Shannon interpolate of u is the only  $L^2(\mathbb{R}^2)$  function  $\mathbf{u} = Iu$  having u as samples and with spectrum support contained in  $(-\pi, \pi)^2$ . Then  $\mathbf{S}_1 Iu = u$ .
- Conversely, if **u** is  $L^2$  and band-limited in  $(-\pi, \pi)^2$ , then  $I\mathbf{S}_1\mathbf{u} = \mathbf{u}$ .

## 2 Solution of the second problem : Invariance to illumination conditions

- Contrast change: g(s) increasing, smooth,  $\mathbf{u} \to g(\mathbf{u})$
- Level lines of  $\mathbf{u}$  and  $g(\mathbf{u})$  are identical, (used in Mathematical Morphology, Matheron, Serra, and recently by the MSER and LLD methods shape recognition methods)
- The direction of the gradient  $\frac{\nabla \mathbf{u}}{||\nabla u||}$  also invariant (SIFT method).

3 Solution of the third problem : independence from scale (BLUR !), rotation, and translation: The SIFT method



Figure 4: Shapes change with distance: The level lines not stable by down-sampling This is the main problem with level lines methods (MSER) Why the heat equation ?

• 
$$G_{\sigma}(x_1, x_2) = \frac{1}{2\pi\sigma^2} e^{-\frac{x_1^2 + x_2^2}{2\sigma^2}},$$

$$\frac{\partial G_{\sigma}}{\partial \sigma} = \sigma \Delta G_{\sigma}, \quad G_{\delta} G_{\beta} = G_{\sqrt{\delta^2 + \beta^2}}.$$

• Main assumption: the blur is gaussian

$$u = \mathbf{S}_1 G_s \mathbf{u}_0, \quad (\mathbf{G}_s * \mathbf{u}_0)(\mathbf{x}) =: \int_{\mathbb{R}^2} \mathbf{G}(\mathbf{y}) \mathbf{u}_0(\mathbf{x} - \mathbf{y}) d\mathbf{y}.$$

- If  $s \ge 0.6$ , Shannon's interpolation conditions are experimentally satisfied:  $\mathbf{G}_1 \mathbf{u}_0 =: G_s * \mathbf{u}_0$  is "band-limited";  $I\mathbf{S}_1 \mathbf{G}_1 \mathbf{u}_0 = \mathbf{G}_1 \mathbf{u}_0$ .
- Key property : if  $u_1 = \mathbf{S}_s \mathbf{G}_s \mathbf{u}_0$  and  $u_2 = \mathbf{S}_t \mathbf{G}_t \mathbf{u}_0$ ,  $t^2 = s^2 + \sigma^2$ then

$$\mathbf{u}_1 = \mathbf{G}_{\sigma} \mathbf{u}_2; \ u_1 = \mathbf{S}_s \mathbf{G}_{\sigma} I \mathbf{u}_2.$$

### Why the heat equation and not other smart nonlinear PDE's ?

- Scale space (Witkin, Koenderink):  $\frac{\partial u}{\partial t} = \Delta u$
- Anisotropic diffusion (Perona-Malik):  $\frac{\partial u}{\partial t} = div \left( \frac{\nabla u}{1 + |\nabla u|^2} \right)$
- Mean curvature motion (Osher, Sethian), commutes with contrast changes!  $\frac{\partial u}{\partial t} = |\nabla u| div \left(\frac{\nabla u}{|\nabla u|}\right)$
- Affine scale space (Sapiro, Tannenbaum, Alvarez, Guichard, Lions, M.): commutes with contrast changes and affine maps :  $\frac{\partial u}{\partial t} = |\nabla u| div \left(\frac{\nabla u}{|\nabla u|}\right)^{\frac{1}{3}}$

But the reality is: images at different scales obey the heat equation.

#### SIFT scale invariant features transform

- 1. the initial digital image is  $\mathbf{S}_1 \mathbf{G}_1 \mathbf{A} \mathbf{u}_0$ ,  $\mathbf{A}$  is any SIMILARITY,  $\mathbf{u}_0$  is the underlying infinite resolution planar image;
- 2. at all scales  $\sigma > 0$ , the SIFT method computes  $\mathbf{u}(\sigma, \cdot) = \mathbf{G}_{\sigma}\mathbf{G}_{1}\mathbf{A}\mathbf{u}_{0}$  and 'key points"  $(\sigma, \mathbf{x})$ , namely scale and space extrema of  $\Delta \mathbf{u}(\sigma, \cdot)$ ;
- 3. the blurred  $\mathbf{u}(\sigma, \cdot)$  image is sampled around each key point at a pace proportional to  $\sqrt{1 + \sigma^2}$ ;
- 4. directions of the sampling axes are fixed by a dominant direction of  $\nabla \mathbf{u}(\sigma, \cdot)$  in a  $\sigma$ -neighborhood of the key point;
- 5. this yields rotation, translation and scale invariant samples: the 4 parameters of **A** have been eliminated!;
- 6. the final SIFT descriptor keeps only orientations of the gradient to gain invariance w.r. light conditions.



Figure 5: Each key-point is associated a square image patch whose size is proportional to the scale and whose side direction is given by the assigned direction. Example of a  $2 \times 2$  descriptor array of orientation histograms (right) computed from an  $8 \times 8$  set of samples (left). The orientation histograms are quantized into 8 directions and the length of each arrow corresponds to the magnitude of the histogram entry.



Figure 6: SIFT key points (scale and orientation). Each one is covariant or invariant with respect to: translation, rotation, scale, and contrast changes (6 parameters out of 8)



Figure 7: left : the Pisa tower, SIFT method Outliers elimination method: Rabin, Gousseau, Delon

#### High Transition Tilts



 $\mathbf{u} = \mathbf{G}_1 \mathbf{H}_{\lambda} \mathbf{R}_1(\psi) \mathbf{T}_t \mathbf{R}_2(\phi) \mathbf{u}_0, \quad \mathbf{v} = \mathbf{G}_1 \mathbf{H}_{\lambda'} \mathbf{R}_1(\psi') \mathbf{T}_{t'} \mathbf{R}_2(\phi') \mathbf{u}_0$  $\mathbf{v} = \mathbf{G}_1 \mathbf{H}_{\mu} \mathbf{R}_1(\psi_1) \mathbf{T}_{\tau} \mathbf{R}_2(\phi_1) \mathbf{u}$ 

- Absolute tilts t: from  $\mathbf{u}$  to  $\mathbf{u}_0$ .
- Transition tilts  $\tau(t, t', \phi \phi')$ : the absolute tilt from **u** to **v** under the assumption that **u** is frontal.
- In contrast with absolute tilts, most transition tilts are **LARGE**.

#### High Transition Tilts



 $\tau = 36 \Rightarrow \theta = \mathbf{88.41}^\circ$ 

#### High Transition Tilts: 79 matches (A-SIFT)





#### High Transition Tilts: 50 matches (A-SIFT)





#### State-of-the-art

- SIFT (Scale-Invariant Feature Transform) [Lowe 99, 04]:
  - Rotation and translation are *normalized*.
  - Zoom is *simulated* in the scale space.
  - Modest robustness to tilt:  $\tau_{\rm max} < 2.5$ .
- MSER (Maximally Stable Extremal Region) [Matas et al. 02]
  - Zoom and tilt are inverted by *normalization* (but only an approximation: normalization does not commute with blur).
  - Rotation invariance is used (rotation is normalizable).
  - Weakness: few features, limited affine invariance  $\tau_{\rm max} < 5$ .

#### Transition tilts attainable with each method



#### Affine-SIFT (A-SIFT) Overview

- Simulate the tilts (two parameters).
- Simulated images are compared by a rotation-, translationand zoom-invariant algorithm, e.g., SIFT. (SIFT normalizes translation and rotation and simulates zoom.)



#### Sampling the observation sphere



Figure 8: It is enough to simulate five tilts  $\sqrt{2}$ , 2,  $2\sqrt{2}$ , 4,  $4\sqrt{2}$  and a growing but moderate number of longitudes per tilt. The overall simulated image area is five times the original.



t = 3 ( $\theta$  = 70.5°), 107 A-SIFT matches (3 false).



t = 5.2 ( $\theta$  = 78.9°), 25 A-SIFT matches (7 false).



t = 3.8 ( $\theta$  = 74.7°), 71 A-SIFT matches (4 false).



t = 5.6 ( $\theta$  = 79.7°), 33 A-SIFT matches (4 false).



Absolute tilts t = t' =2.1. transition tilt:  $\tau =$ 3.0.

Top: A-SIFT finds 1667 correspondences, all correct.

Middle: SIFT finds 3 correspondences.

Bottom: MSER finds 46 correspondences, out of which 35 are correct.









Absolute tilts t = 2.1(left), t' = 6.0 (right). transition tilt:  $\tau = 2.9$ .

Top: A-SIFT finds 338 correspondences, out of which 2 are false.

Middle: SIFT finds 5 correspondences.

Bottom: MSER finds 3 false correspondences in total that have been rejected.





Transition tilt:  $\tau \approx 3.2$ .

Top: A-SIFT finds 724 correspondences, out of which 3 are false.

Middle: SIFT finds 6 correspondences.

Bottom: MSER finds 127 correspondences, out of which 50 are correct.



Top: A-SIFT finds 255 matches out of which 1 is false.

Middle: SIFT finds 16 matches out of which 6 are false.

Bottom: MSER finds 70 tentative correspondences out of which there are 51 inliers.

#### Symmetry Detection in Perspective

- Symmetry detection = image comparison with the flipped version.
- Symmetric object not in frontal view
   ⇒ a viewpoint change between the flipped images.





- SIFT fails: big viewpoint change.
- MSER fails: two wings confused.

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