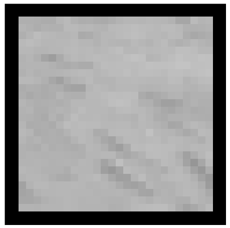
Interest Operators

- Find “interesting” pieces of the image
  - e.g. corners, salient regions
  - Focus attention of algorithms
  - Speed up computation

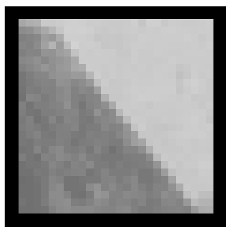
- Many possible uses in matching/recognition
  - Search
  - Object recognition
  - Image alignment & stitching
  - Stereo
  - Tracking
  - …

Interest points



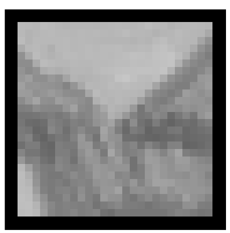
0D structure

➡ not useful for matching



1D structure

➡ edge, can be localised in 1D, subject to the aperture problem

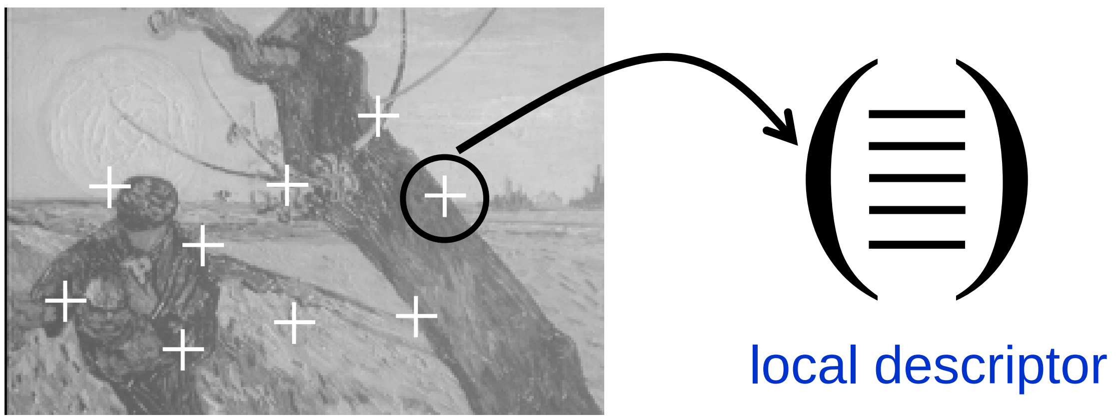


2D structure

➡ corner, or **interest point**, can be localised in 2D, good for matching

Interest Points have **2D** structure. Edge Detectors e.g. Canny [Canny86] exist, but **descriptors** are more difficult.

Local invariant photometric descriptors



Local : robust to occlusion/clutter + no segmentation

Photometric : (use pixel values) distinctive descriptions

Invariant : to image transformations + illumination changes

History - Matching

1. Matching based on correlation alone
2. Matching based on geometric primitives

   e.g. line segments

$\Rightarrow$ Not very discriminating (why?)

$\Rightarrow$ Solution : matching with interest points & correlation

[A robust technique for matching two uncalibrated images through the recovery of the unknown epipolar geometry,

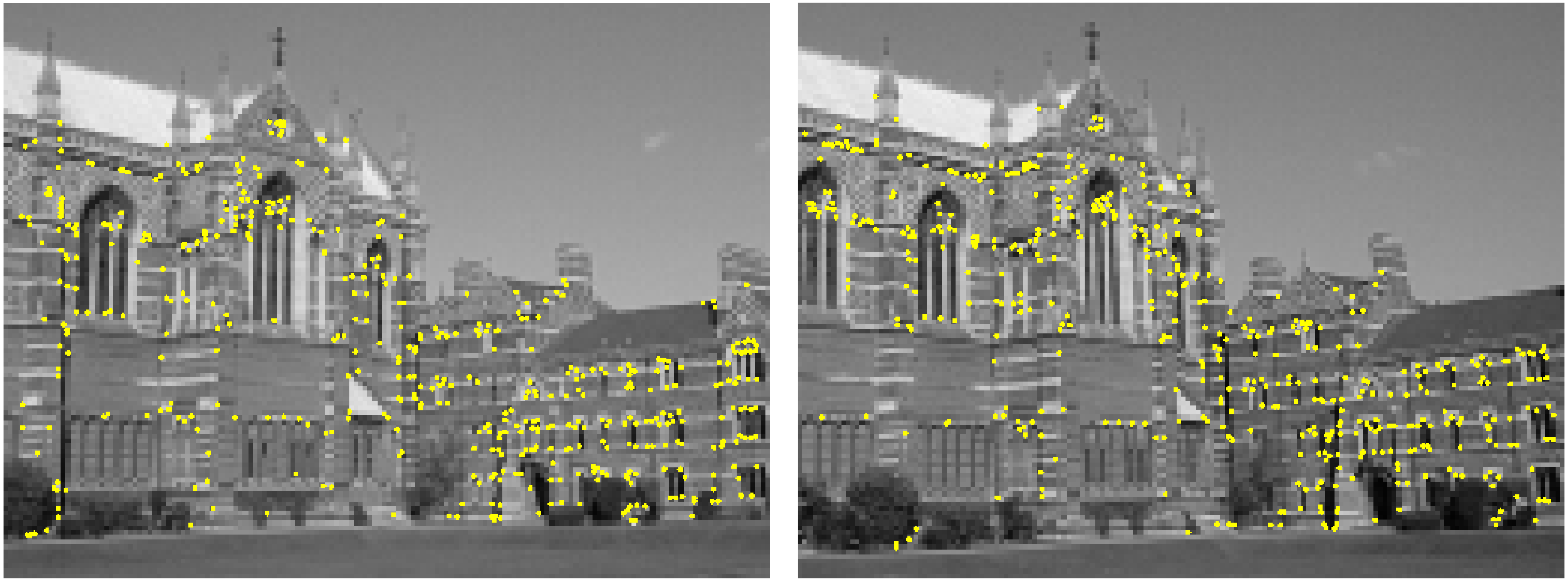
Z. Zhang, R. Deriche, O. Faugeras and Q. Luong,

Artificial Intelligence 1995]

Approach

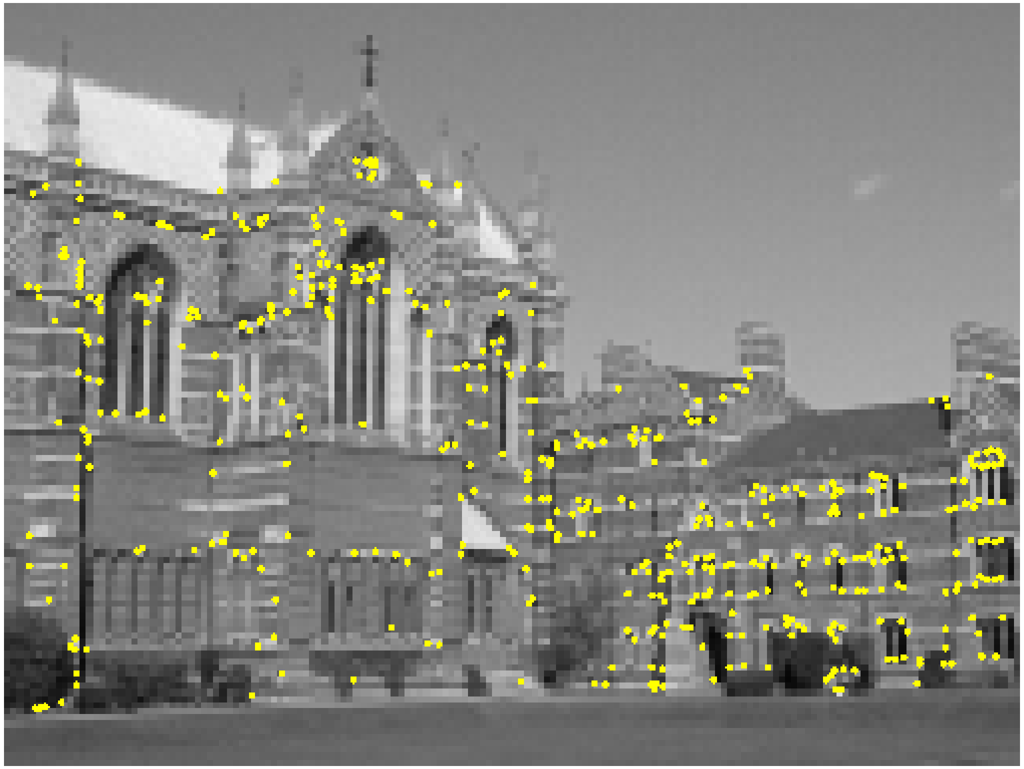
- Extraction of interest points with the Harris detector
- Comparison of points with cross-correlation
- Verification with the fundamental matrix

Harris detector

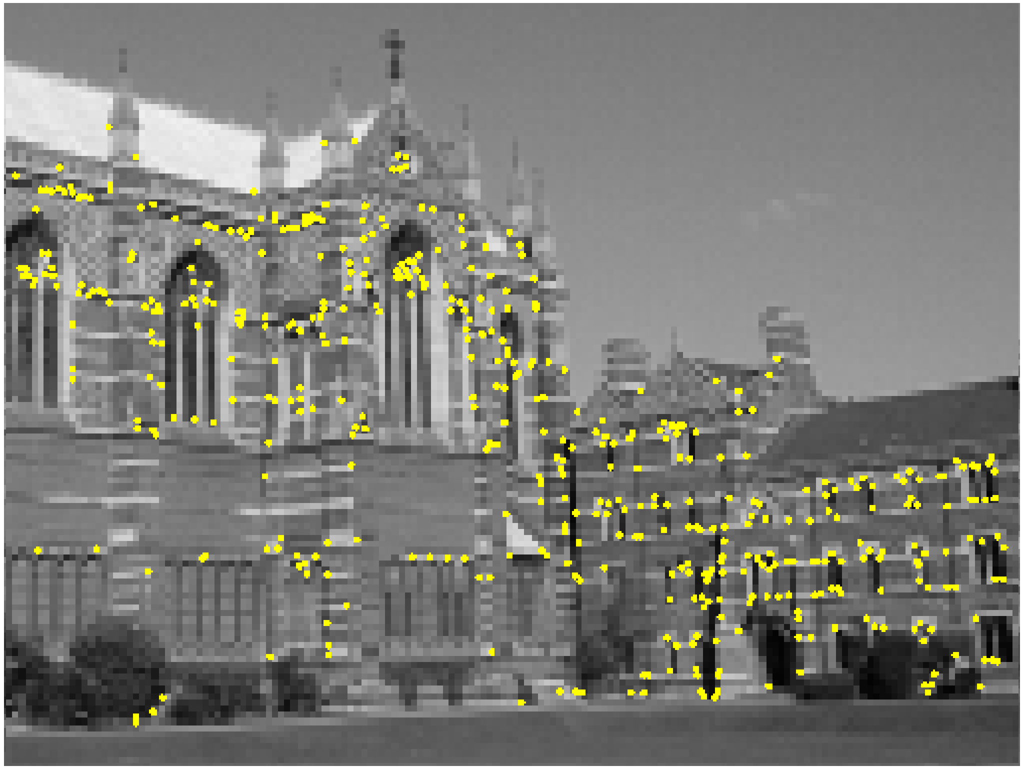


Interest points extracted with Harris (~ 500 points)

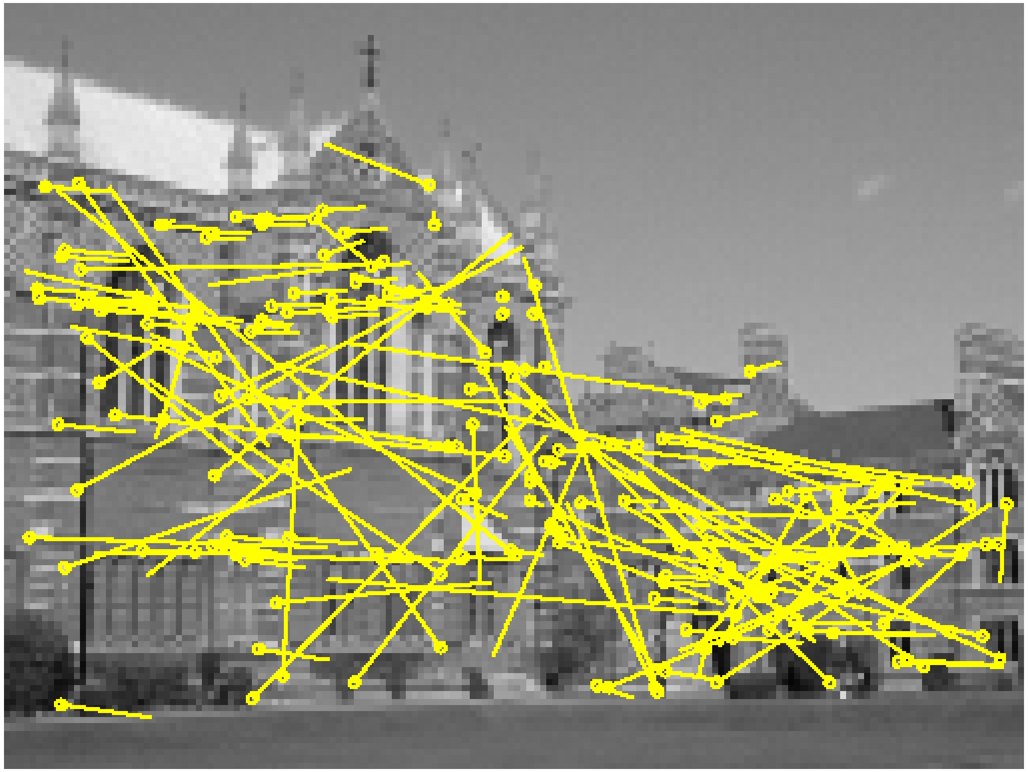
Harris detector



Harris detector



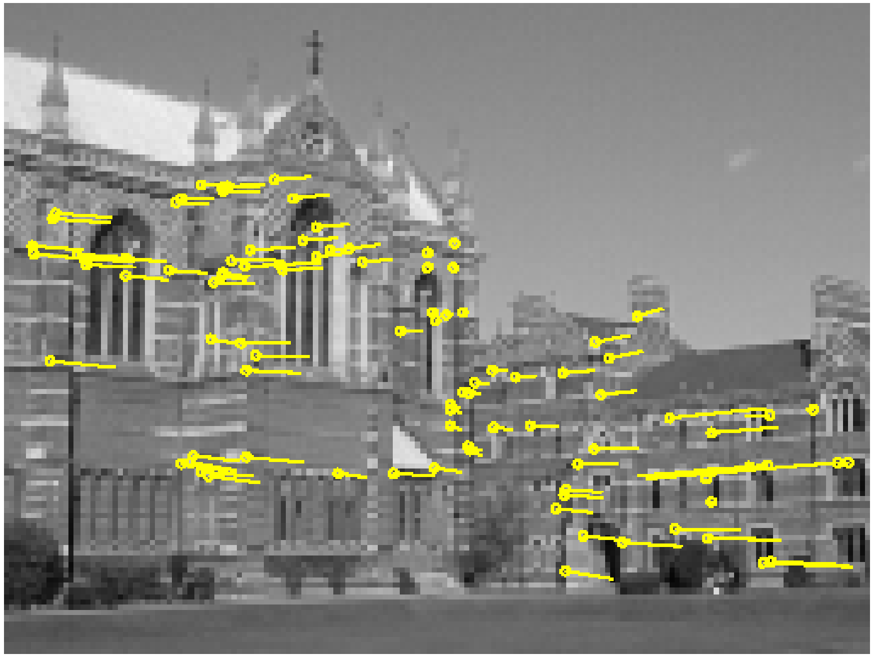
Cross-correlation matching



Initial matches – motion vectors (188 pairs)

Global constraints

Robust estimation of the fundamental matrix (RANSAC)



99 inliers

89 outliers

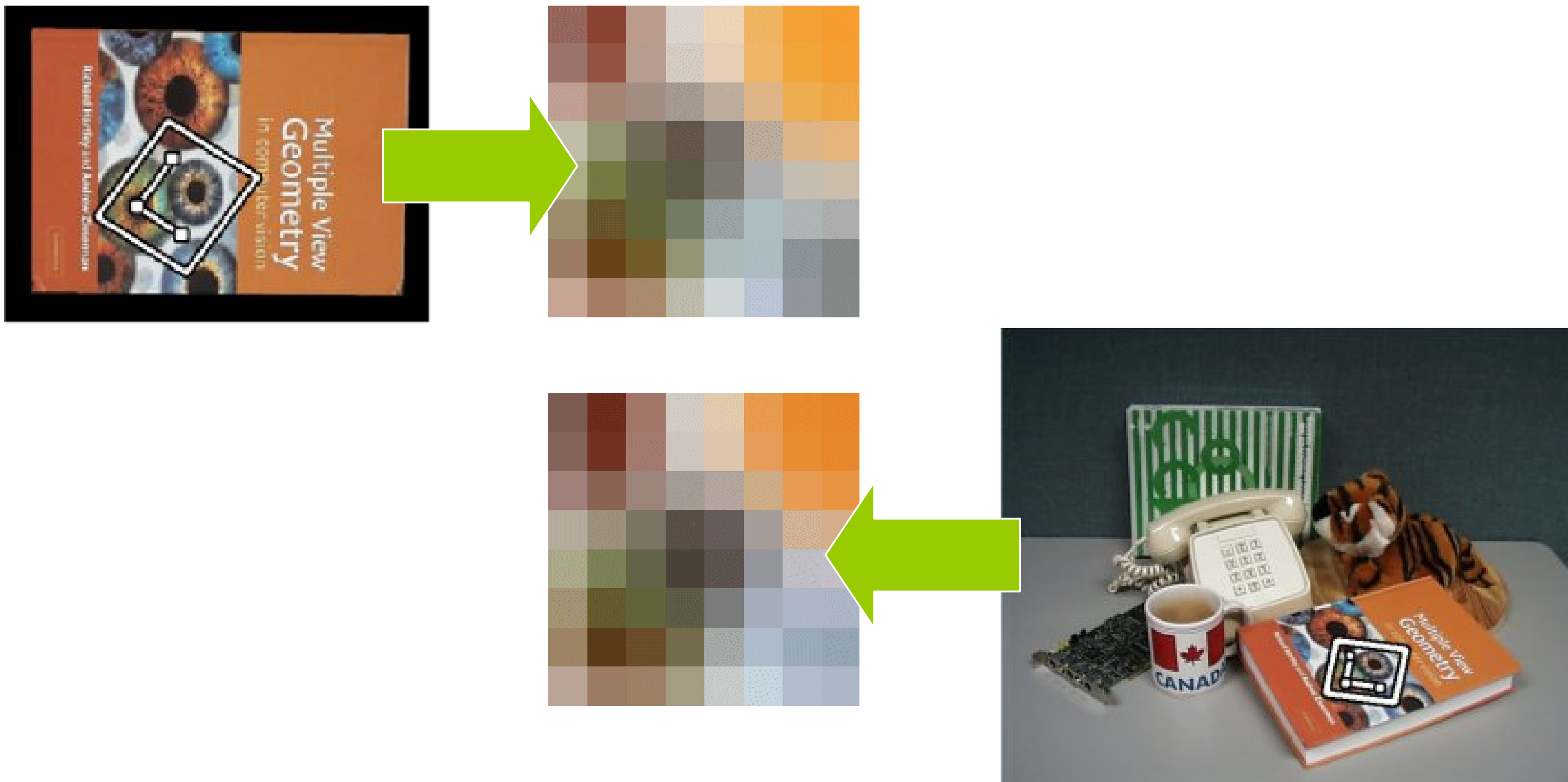
Summary of the approach

- Very good results in the presence of occlusion and clutter
  - local information
  - discriminant greyvalue information
  - robust estimation of the global relation between images
  - works well for **limited view point changes**

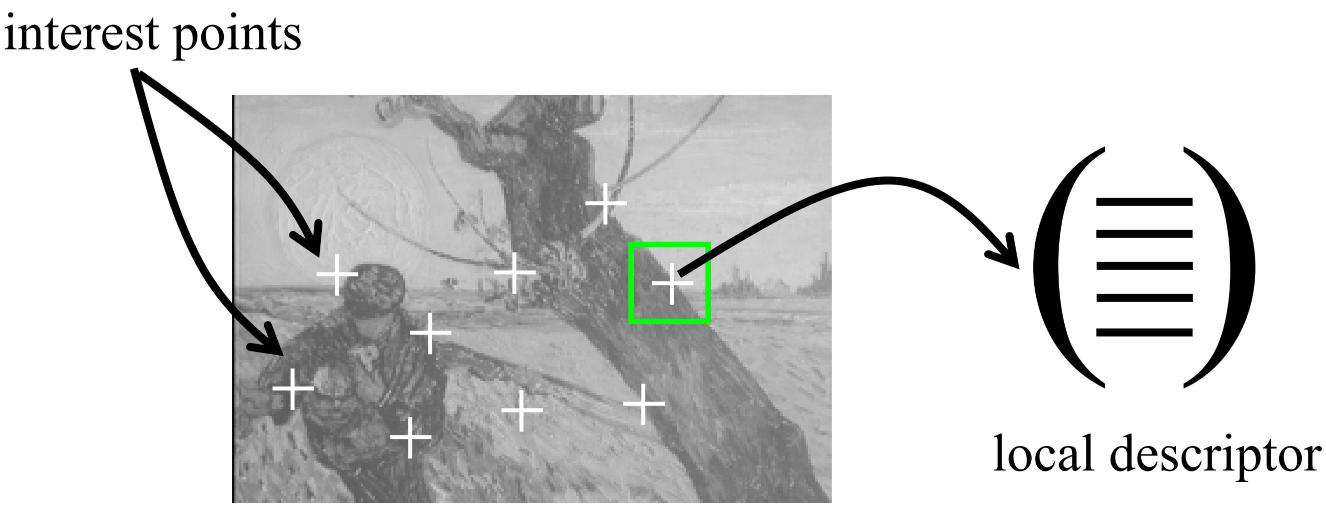
- Solution for more general view point changes
  - wide baseline matching (different viewpoint, scale and rotation)
  - local **invariant descriptors** based on greyvalue information

Invariant Features

- **Schmid & Mohr 1997**, Lowe 1999, Baumberg 2000, Tuytelaars & Van Gool 2000, Mikolajczyk & Schmid 2001, Brown & Lowe 2002, Matas et. al. 2002, Schaffalitzky & Zisserman 2002



Approach



1) Extraction of interest points (characteristic locations)

2) Computation of local descriptors (**rotational invariants**)

3) Determining correspondences

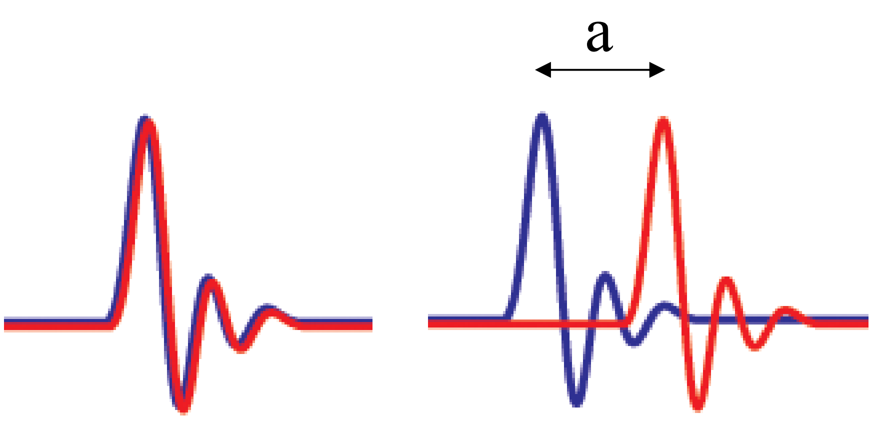
4) Selection of similar images

Harris detector

Based on the idea of auto-correlation

Important difference in all directions => interest point

Autocorrelation

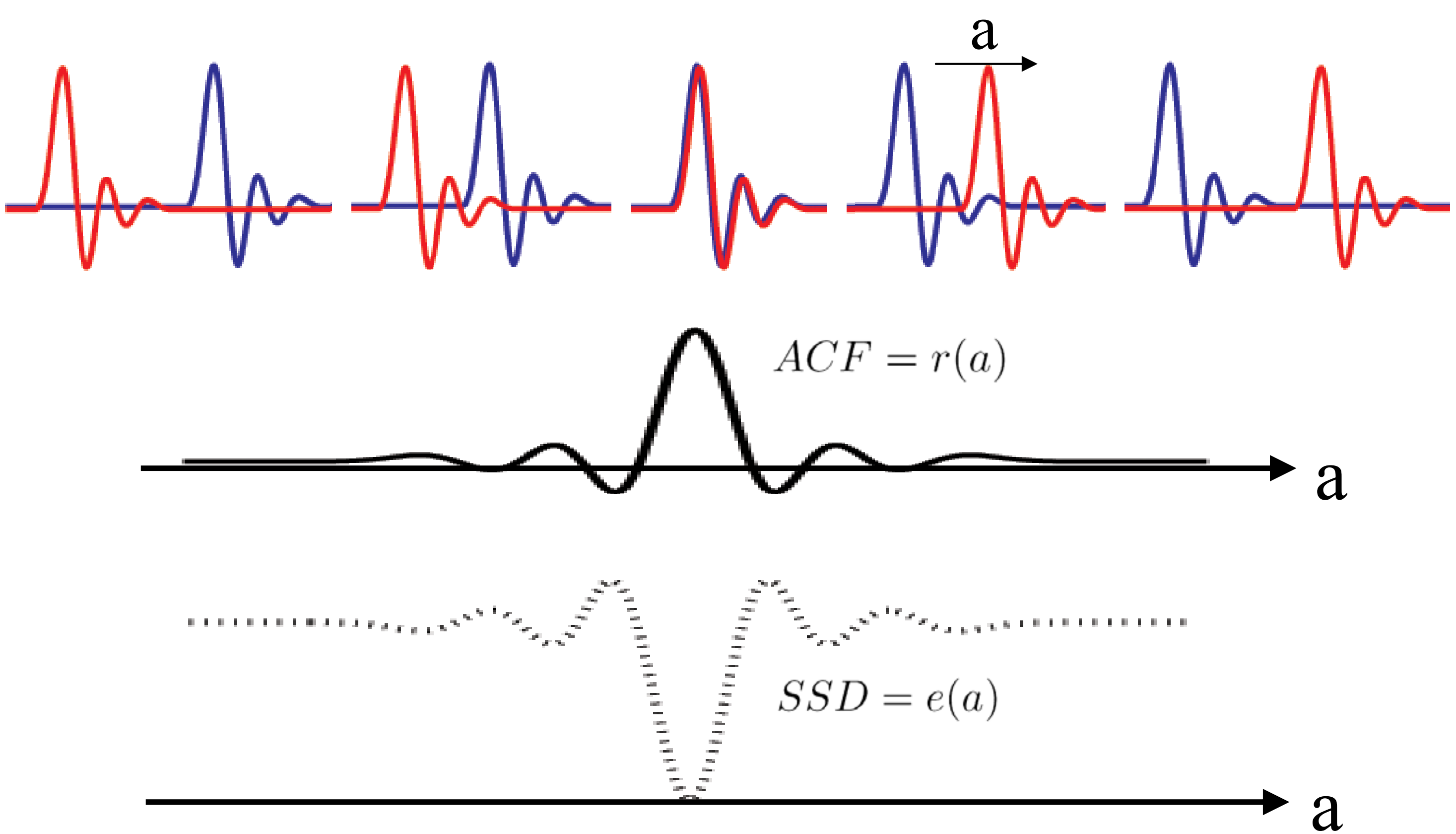


$$ACF = r(a) = \int_{-\infty}^{\infty} f(x) f(x-a) dx$$

$$SSD = e(a) = \int_{-\infty}^{\infty} (f(x) - f(x-a))^2 dx$$

Autocorrelation function (ACF) measures the **self similarity** of a signal

Autocorrelation



- Autocorrelation related to sum-square difference:

$$SSD = 2(1 - ACF)$$

(if $\int f(x)^2 dx = 1$)

Background: Moravec Corner Detector

- take a window w in the image
- shift it in four directions (1,0), (0,1), (1,1), (-1,1)
- compute a difference for each
- compute the min difference at each pixel
- local maxima in the min image are the corners

$$E(x,y) = \sum_{u,v \text{ in } w} w(u,v)\,|I(x+u,y+v) - I(u,v)|^2$$

Shortcomings of Moravec Operator

- Only tries 4 shifts. We'd like to consider "all" shifts.
- Uses a discrete rectangular window. We'd like to use a smooth circular (or later elliptical) window.
- Uses a simple min function. We'd like to characterize variation with respect to direction.

Result: Harris Operator

Harris detector

Auto-correlation fn (SSD) for a point (x, y) and a shift $(\Delta x, \Delta y)$

$$f(x, y) = \sum_{(x_k, y_k) \in W} (I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y))^2$$

Discrete shifts can be avoided with the auto-correlation matrix

$$\text{with} \quad I(x_k + \Delta x, y_k + \Delta y) = \underbrace{I(x_k, y_k) + (I_x(x_k, y_k) \quad I_y(x_k, y_k))}^{\textcolor{red}{\text{what is this?}}} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

$$f(x, y) = \sum_{(x_k, y_k) \in W} \left(\begin{pmatrix} I_x(x_k, y_k) & I_y(x_k, y_k) \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \right)^2$$

Harris detector

Rewrite as inner (dot) product

$$f(x,y) = \sum_{(x_k,y_k)\epsilon W} \left(\begin{bmatrix} I_x(x_k,y_k) & I_y(x_k,y_k) \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \right)^2$$

$$= \sum_{(x_k,y_k)\epsilon W} \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} I_x(x_k,y_k) \\ I_y(x_k,y_k) \end{bmatrix} \begin{bmatrix} I_x(x_k,y_k) & I_y(x_k,y_k) \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

The center portion is a 2x2 matrix

$$= \sum_W \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \sum_W \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

Harris detector

$$
= \begin{pmatrix} \Delta x & \Delta y \end{pmatrix} \begin{bmatrix} \sum_{(x_k, y_k) \in W} (I_x(x_k, y_k))^2 & \sum_{(x_k, y_k) \in W} I_x(x_k, y_k) I_y(x_k, y_k) \\ \sum_{(x_k, y_k) \in W} I_x(x_k, y_k) I_y(x_k, y_k) & \sum_{(x_k, y_k) \in W} (I_y(x_k, y_k))^2 \end{bmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}
$$

Auto-correlation matrix M

Harris detection

- Auto-correlation matrix
  - captures the structure of the local neighborhood
  - measure based on **eigenvalues** of M
    - 2 strong eigenvalues => interest point
    - 1 strong eigenvalue => contour
    - 0 eigenvalue => uniform region
- Interest point detection
  - threshold on the eigenvalues
  - local maximum for localization

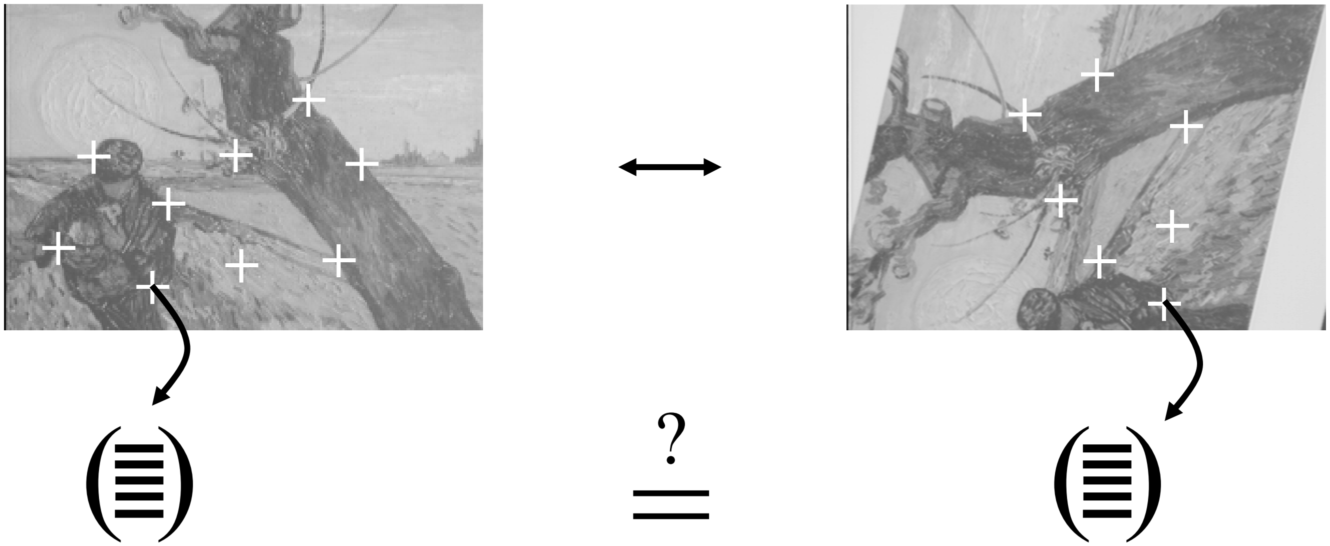
Some Details from the Harris Paper

- Corner strength $R = \mathrm{Det}(M) - k\,\mathrm{Tr}(M)^2$
- Let α and β be the two eigenvalues
- $\mathrm{Tr}(M) = \alpha + \beta$
- $\mathrm{Det}(M) = \alpha\beta$

- R is positive for corners, - for edges, and small for flat regions
- Select corner pixels that are 8-way local maxima

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \qquad \begin{aligned} \det(\mathbf{A}) &= a_{11}a_{22} - a_{12}a_{21} \\ \mathrm{tr}(\mathbf{A}) &= a_{11} + a_{22} \end{aligned}$$

Determining correspondences

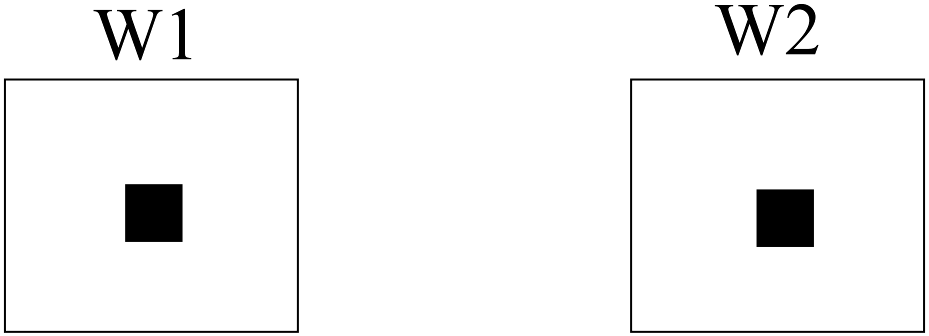


Vector comparison using a distance measure

What are some suitable distance measures?

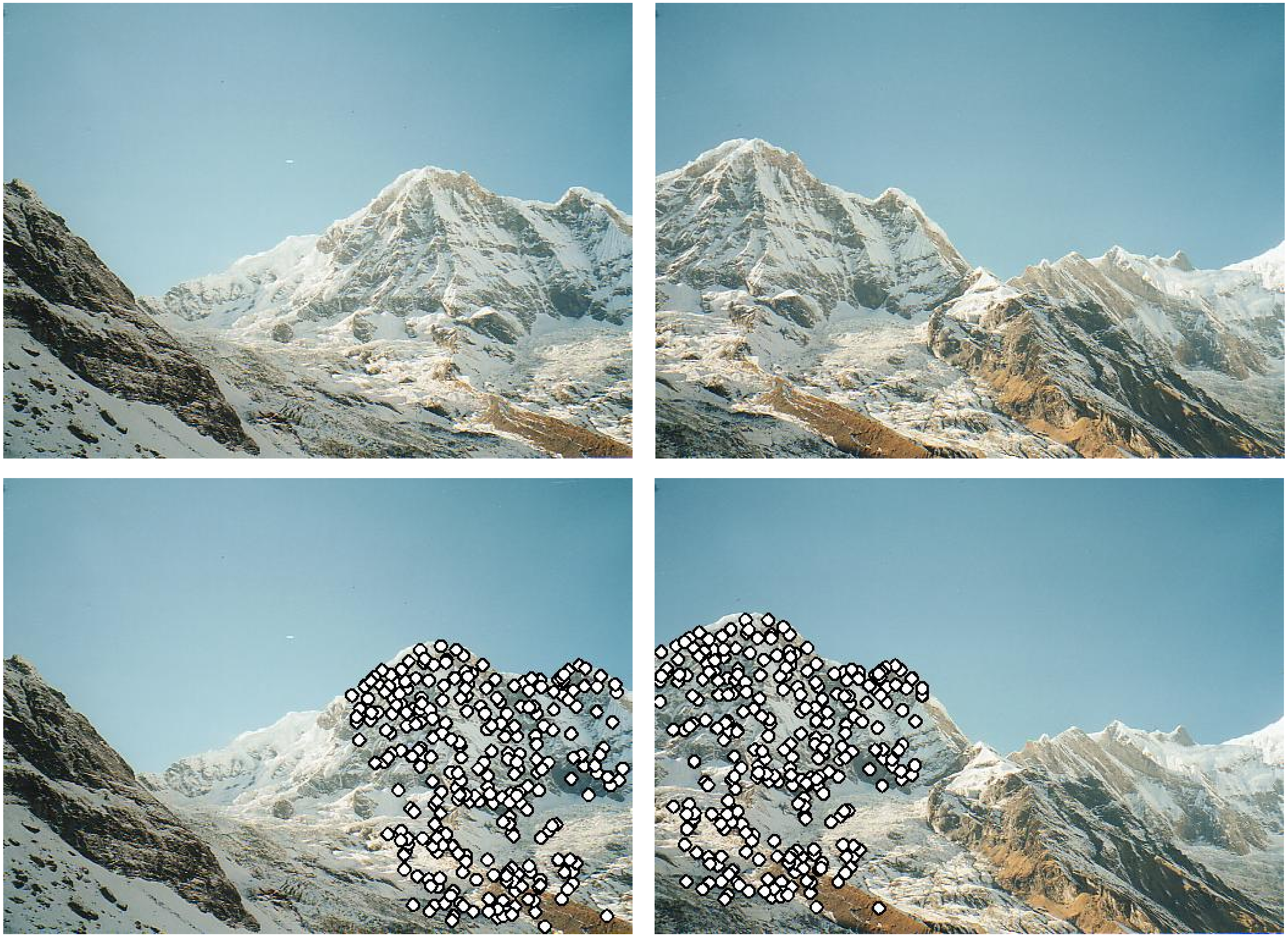
Distance Measures

- We can use the sum-square difference of the values of the pixels in a square neighborhood about the points being compared.

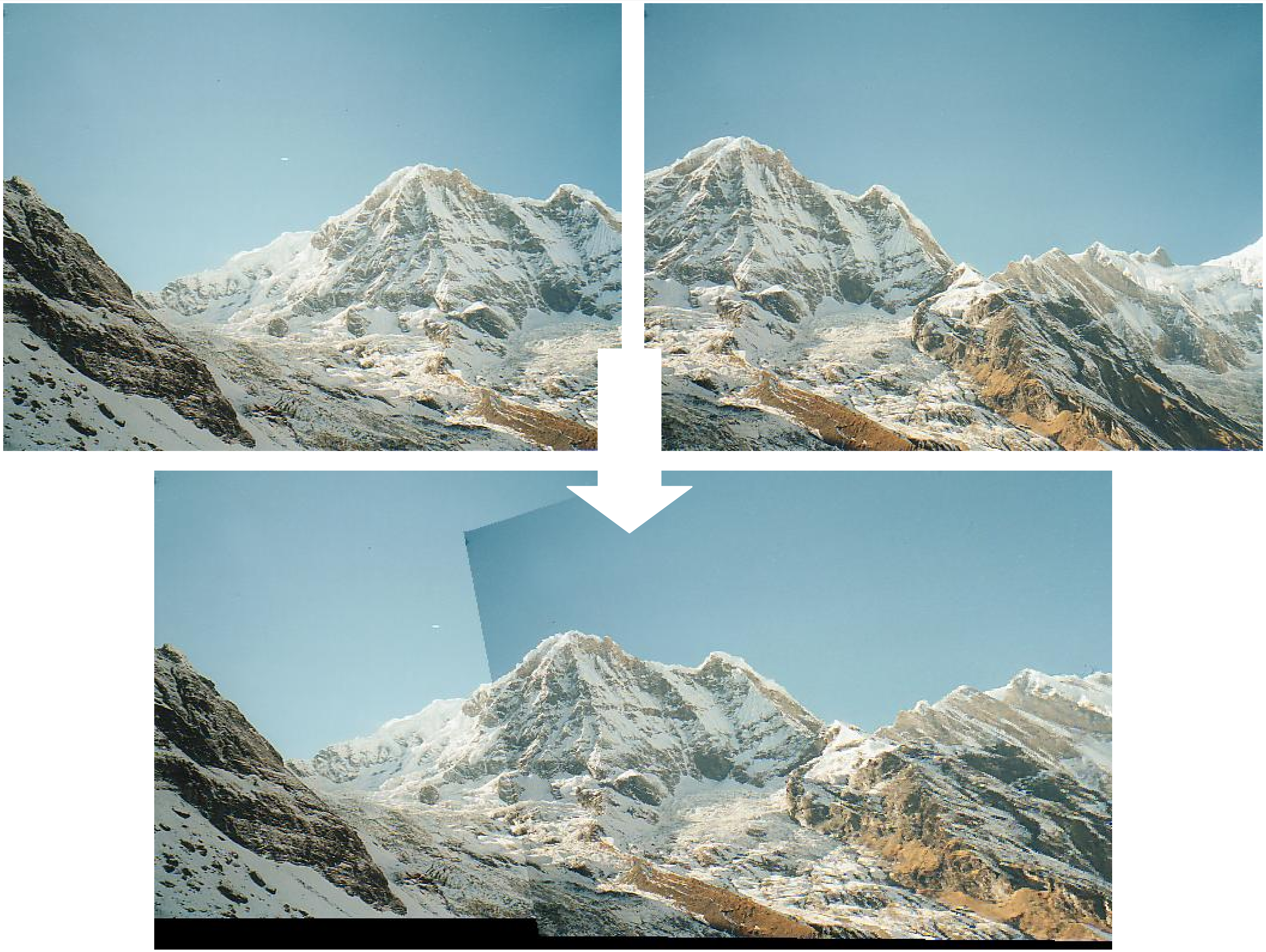


$$SSD = \sum\sum(W1(i,j) - (W2(i,j))^2$$

Some Matching Results



Some Matching Results



Summary of the approach

- Basic feature matching = **Harris Corners & Correlation**
- Very good results in the presence of occlusion and clutter
  - local information
  - discriminant greyvalue information
  - invariance to image rotation and illumination

- Not invariance to scale and affine changes

- Solution for more general view point changes
  - local invariant descriptors to scale and rotation
  - extraction of invariant points and regions

Rotation/Scale Invariance

original

translated

rotated

scaled

	Translation	Rotation	Scale
Is Harris invariant?	?	?	?
Is correlation invariant?	?	?	?

Rotation/Scale Invariance

original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	?	?	?
Is correlation invariant?	?	?	?

Rotation/Scale Invariance

original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	?	?
Is correlation invariant?	?	?	?

Rotation/Scale Invariance

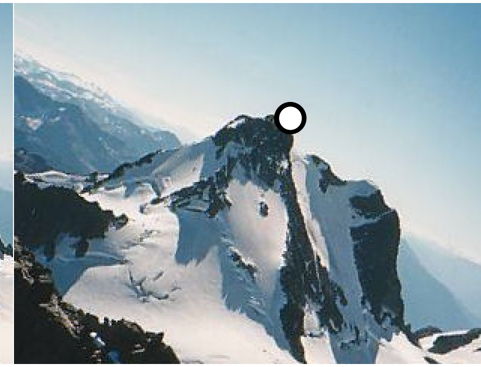
original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	?
Is correlation invariant?	?	?	?

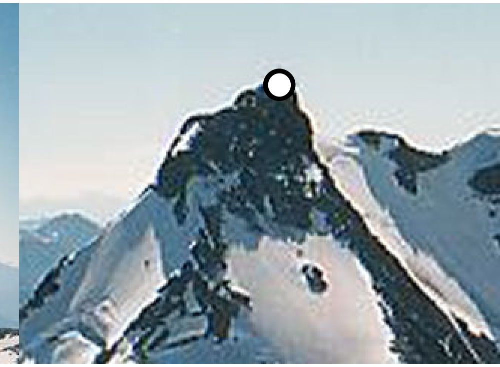
Rotation/Scale Invariance

original

translated



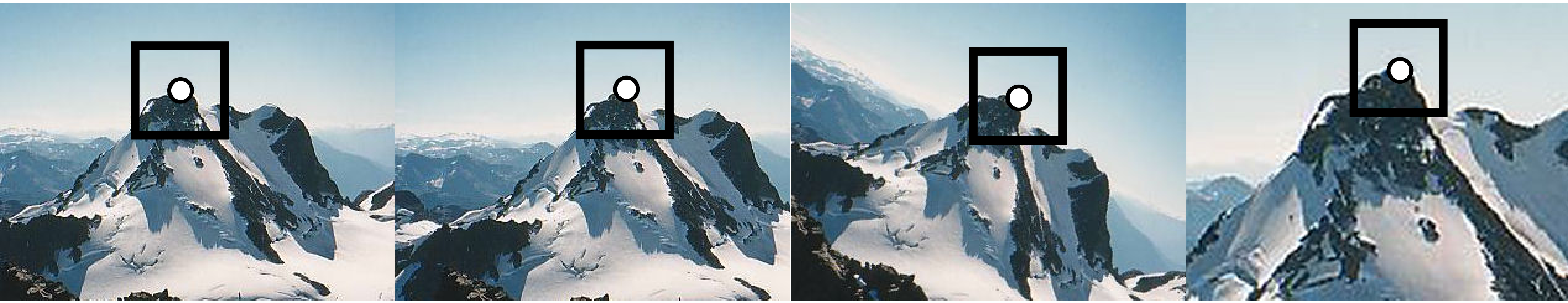
rotated



scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	?	?	?

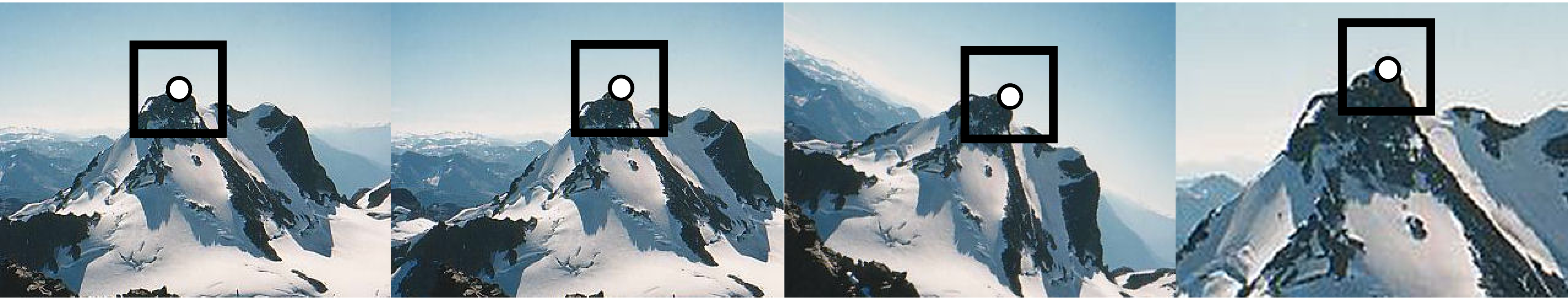
Rotation/Scale Invariance



original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	?	?	?

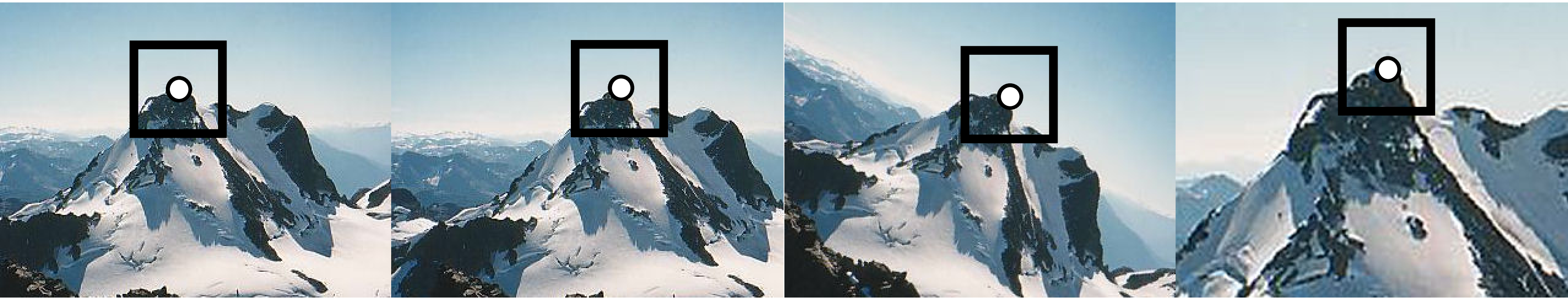
Rotation/Scale Invariance



original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	?	?

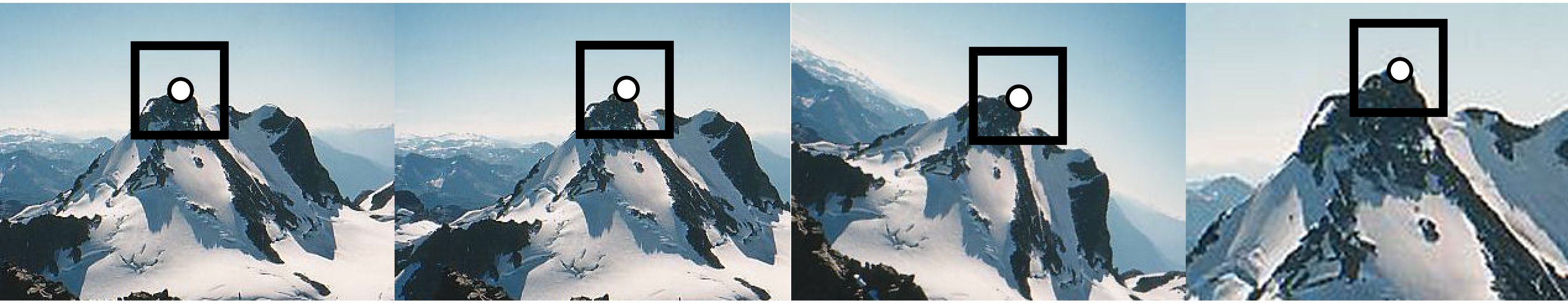
Rotation/Scale Invariance



original translated rotated scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	?

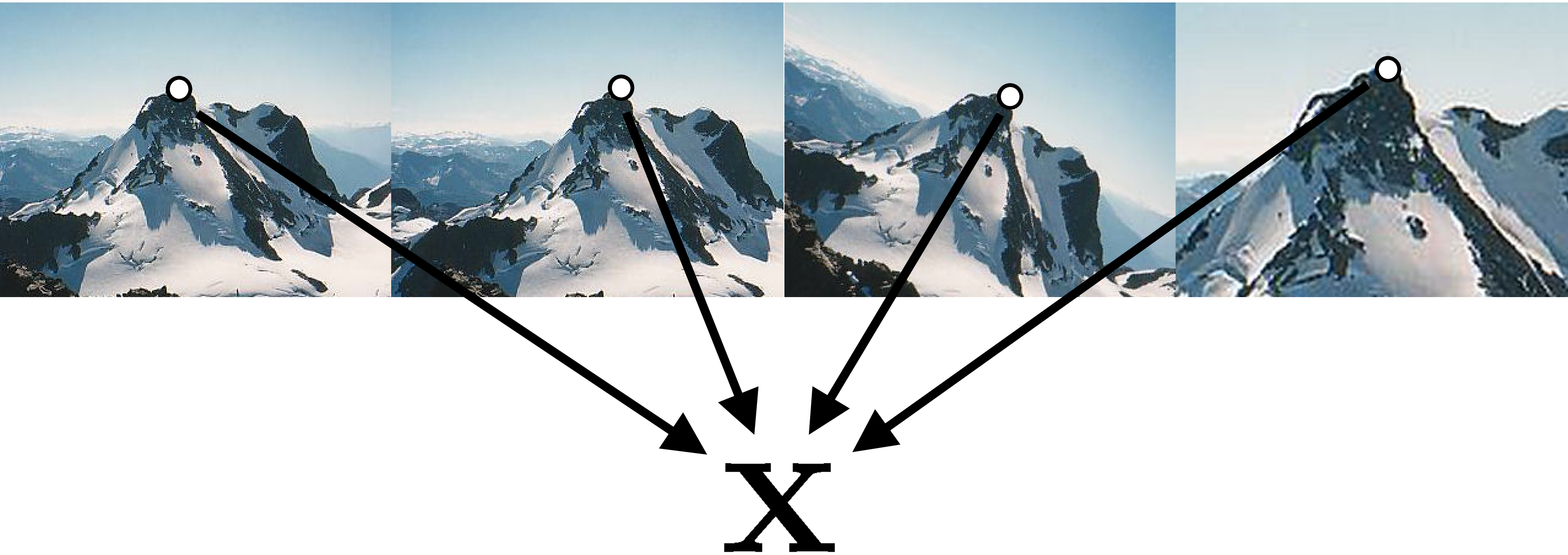
Rotation/Scale Invariance



original translated rotated scaled

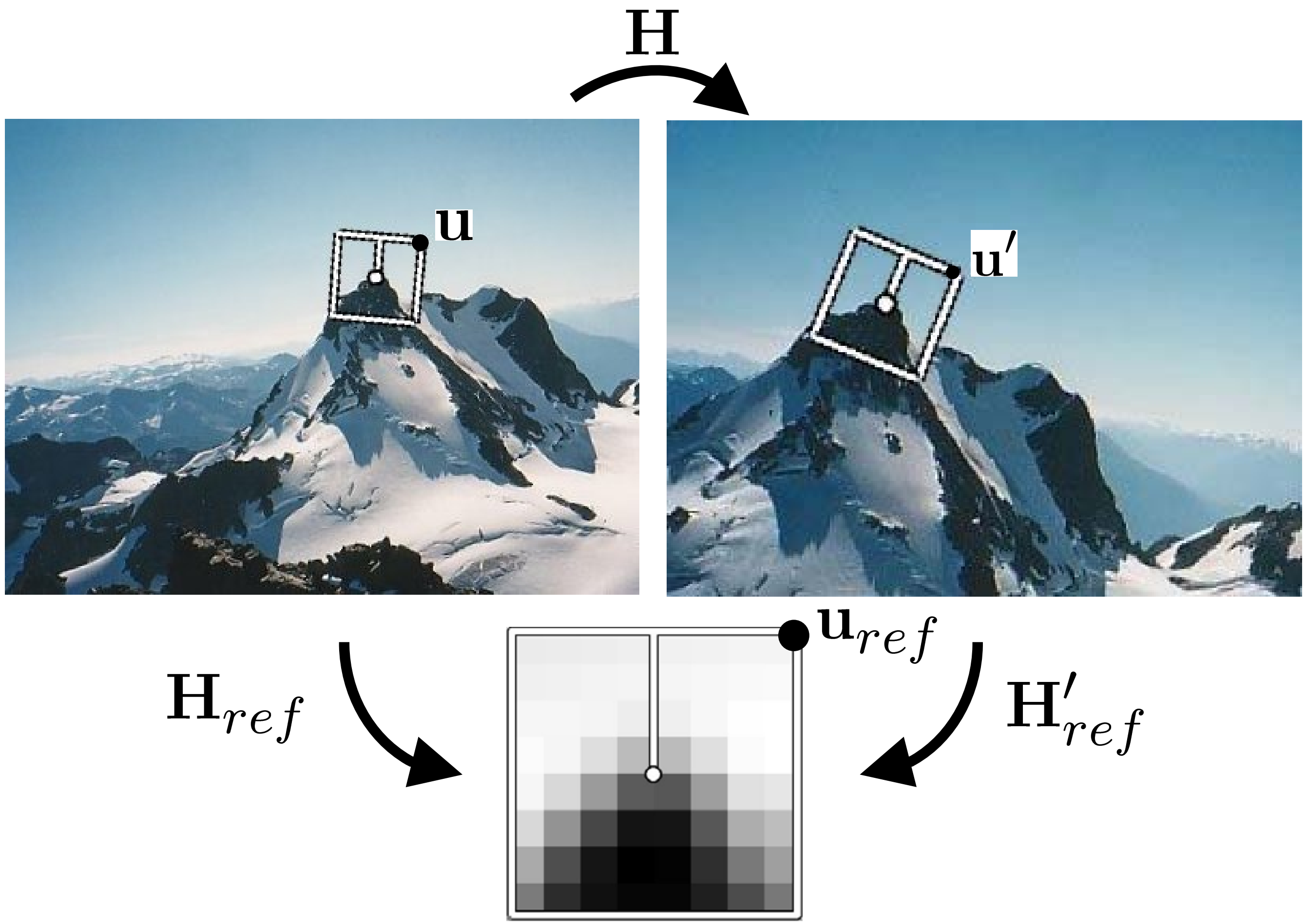
	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	NO

Invariant Features



- Local image descriptors that are *invariant* (unchanged) under image transformations

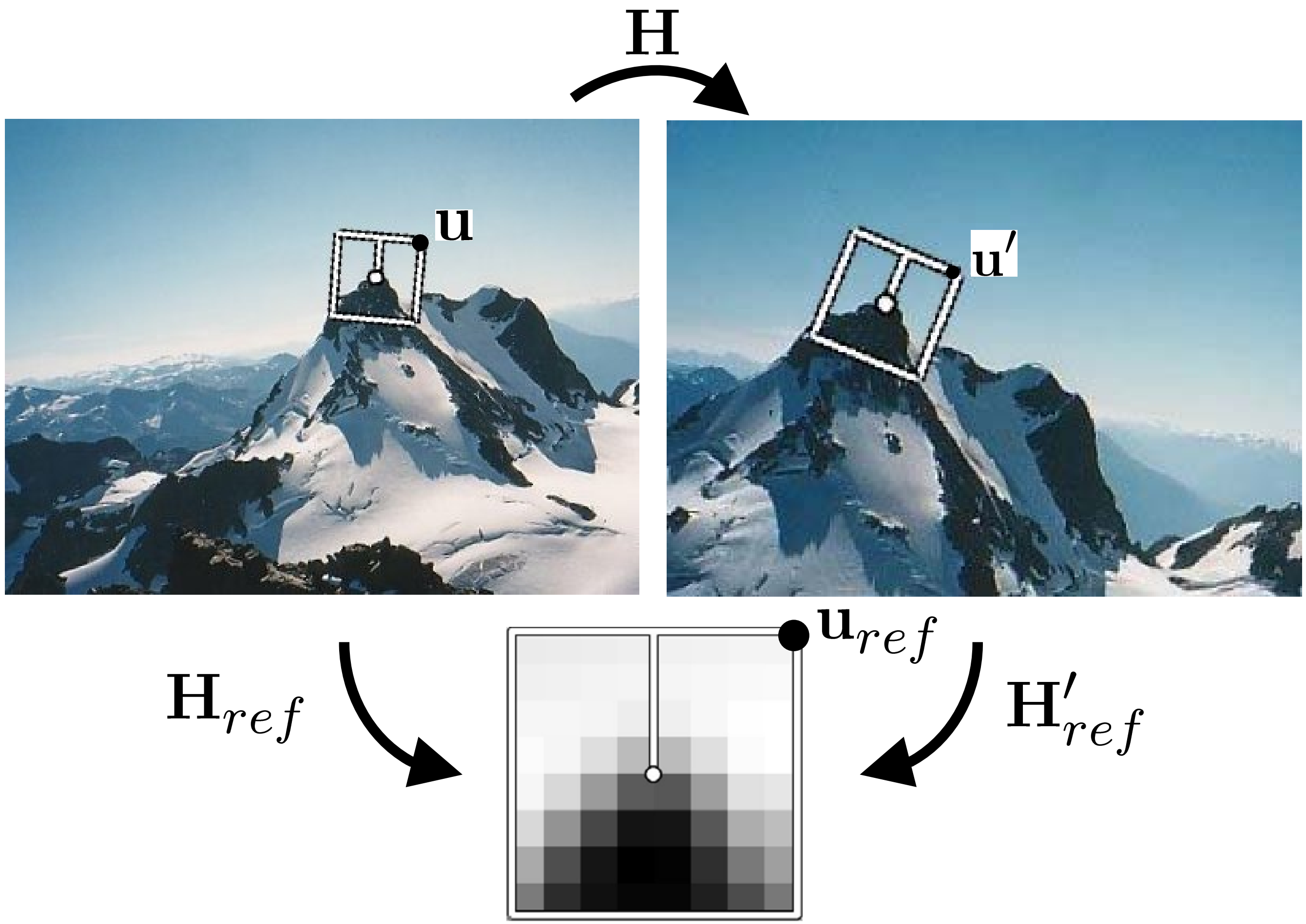
Canonical Frames



$$\mathbf{u}' = \mathbf{H}\mathbf{u}$$

$$\mathbf{H}'_{ref} = \mathbf{H}_{ref}\mathbf{H}^{-1}$$

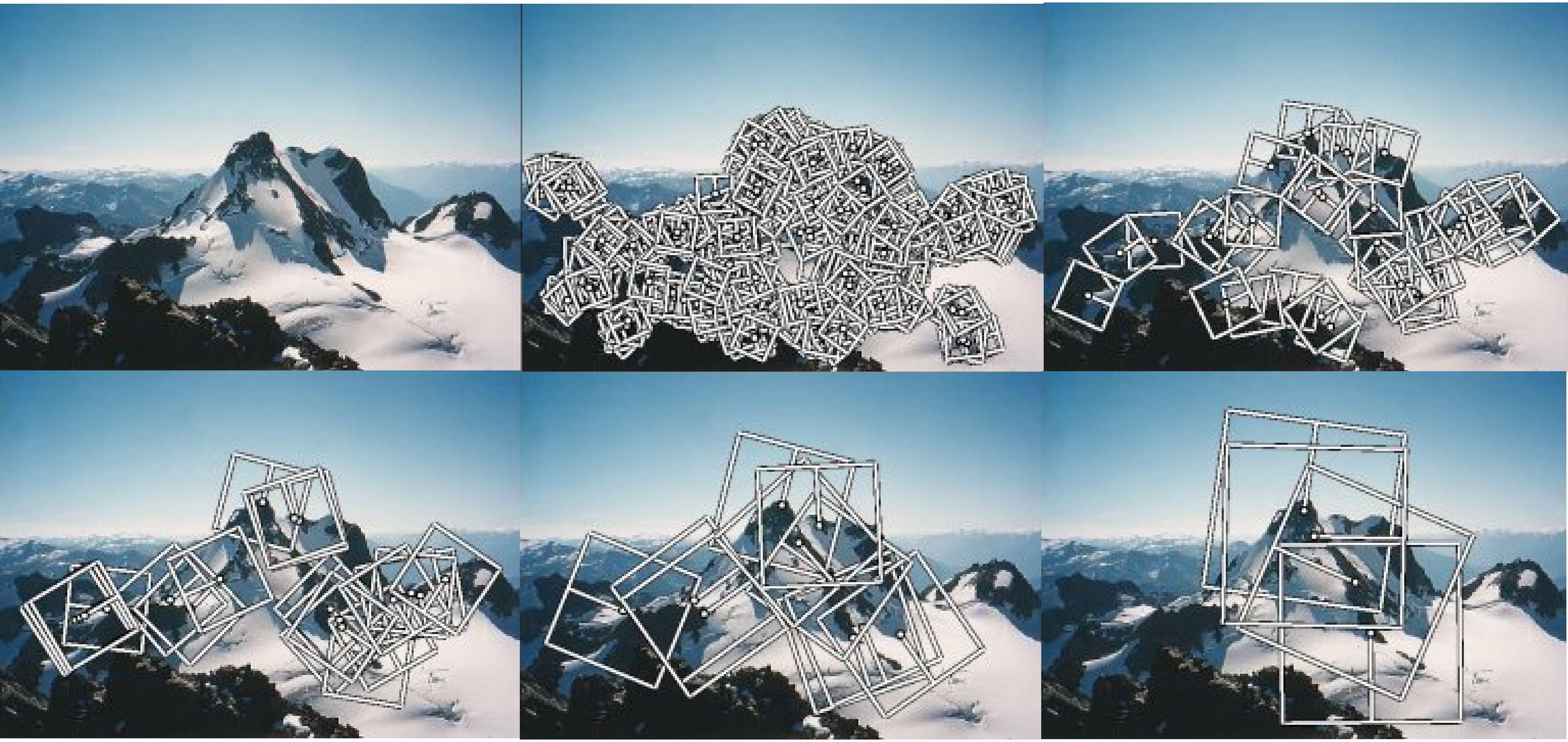
Canonical Frames



$$\mathbf{u}' = \mathbf{H}\mathbf{u}$$

$$\mathbf{H}'_{ref} = \mathbf{H}_{ref}\mathbf{H}^{-1}$$

Multi-Scale Oriented Patches



- Extract oriented patches at multiple scales

Multi-Scale Oriented Patches

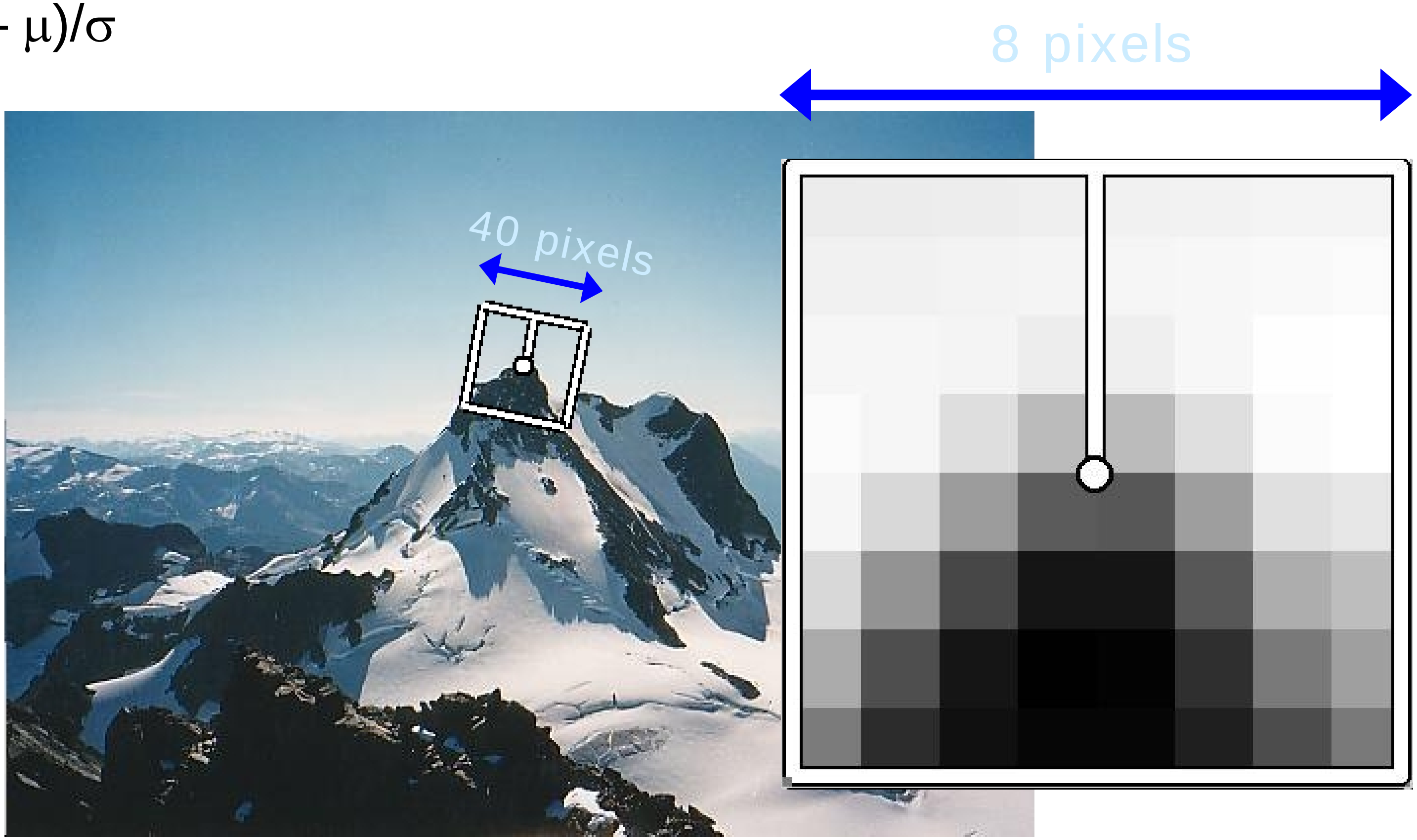
- Sample scaled, oriented patch

Multi-Scale Oriented Patches

- Sample scaled, oriented patch
  - 8x8 patch, sampled at 5 x scale

Multi-Scale Oriented Patches

- Sample scaled, oriented patch
  - 8x8 patch, sampled at 5 x scale
- Bias/gain normalised
  - $I' = (I - \mu)/\sigma$



Matching Interest Points: Summary

- Harris corners / correlation
  - Extract and match repeatable image features
  - Robust to clutter and occlusion
  - BUT not invariant to scale and rotation
- Multi-Scale Oriented Patches
  - Corners detected at multiple scales
  - Descriptors oriented using local gradient
    - Also, sample a blurred image patch
  - Invariant to scale and rotation

Leads to: **SIFT** – state of the art image features