Interest Operator Lectures

0. Introduction to Interest Operators

1. Harris Corner Detector: the first and most basic interest operator

2. Kadir Entropy Detector and its use in object recognition

3. SIFT interest point detector and region descriptor

4. MSER region detector and Harris Affine in region matching

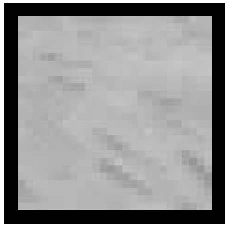
5. Additional applications.

0. Introduction to Interest Operators

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

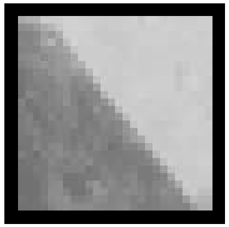
- Many possible uses in matching/recognition
  - Search
  - Object recognition
  - Image alignment & stitching
  - Stereo
  - Tracking
  - …

Interest points



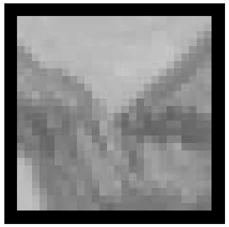
0D structure: single points

➡ not useful for matching



1D structure: lines

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

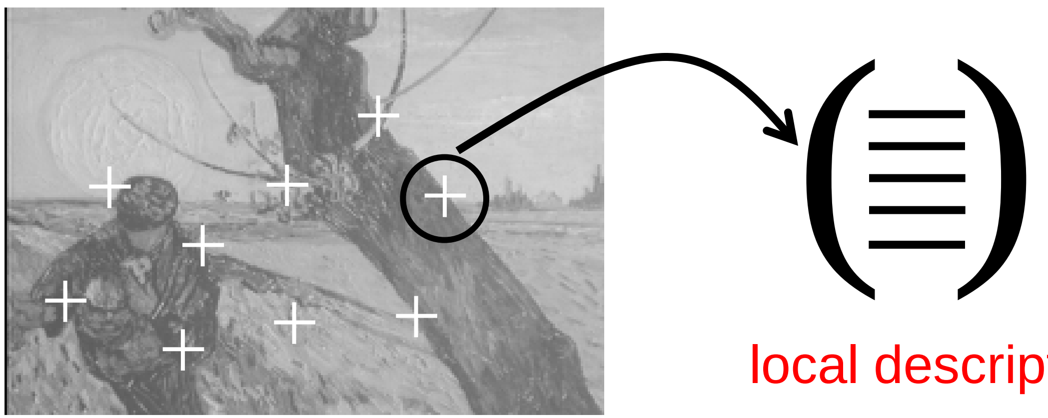


2D structure: corners

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

Interest Points have **2D** structure.

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,

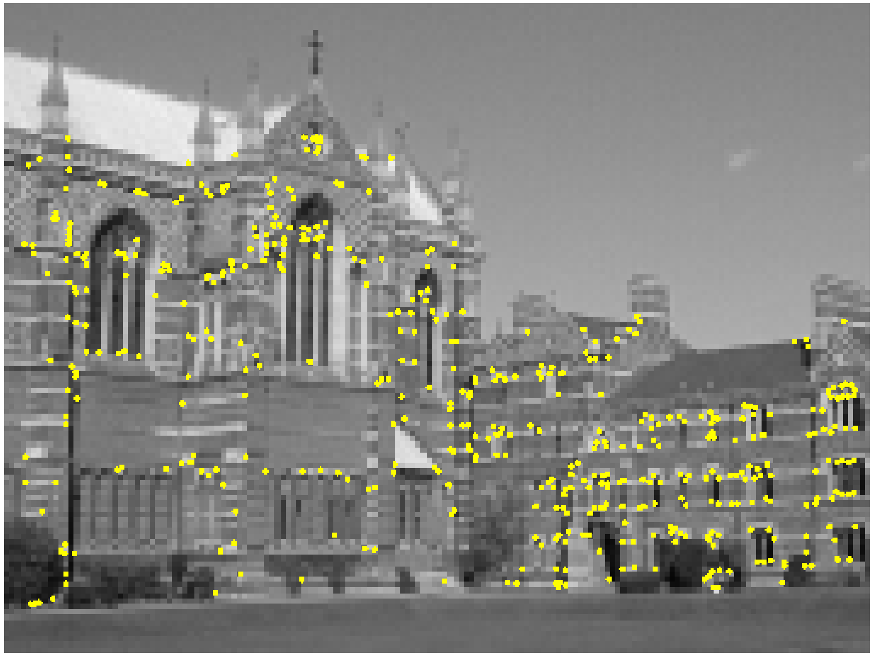
Artificial Intelligence 1995]

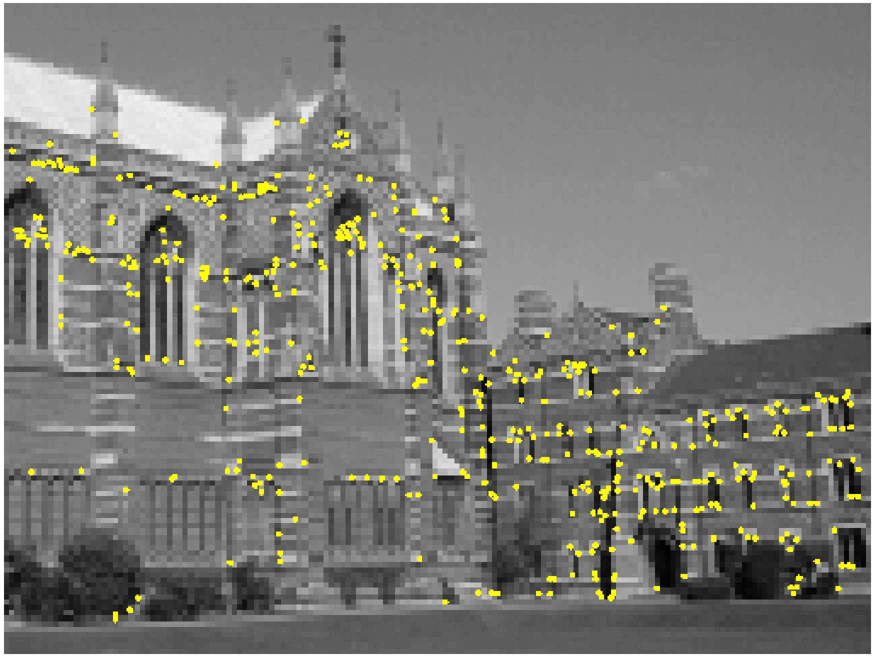
Zhang Approach

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

The fundamental matrix maps points from the first image to corresponding points in the second matrix using a homography that is determined through the solution of a set of equations that usually minimizes a least square error.

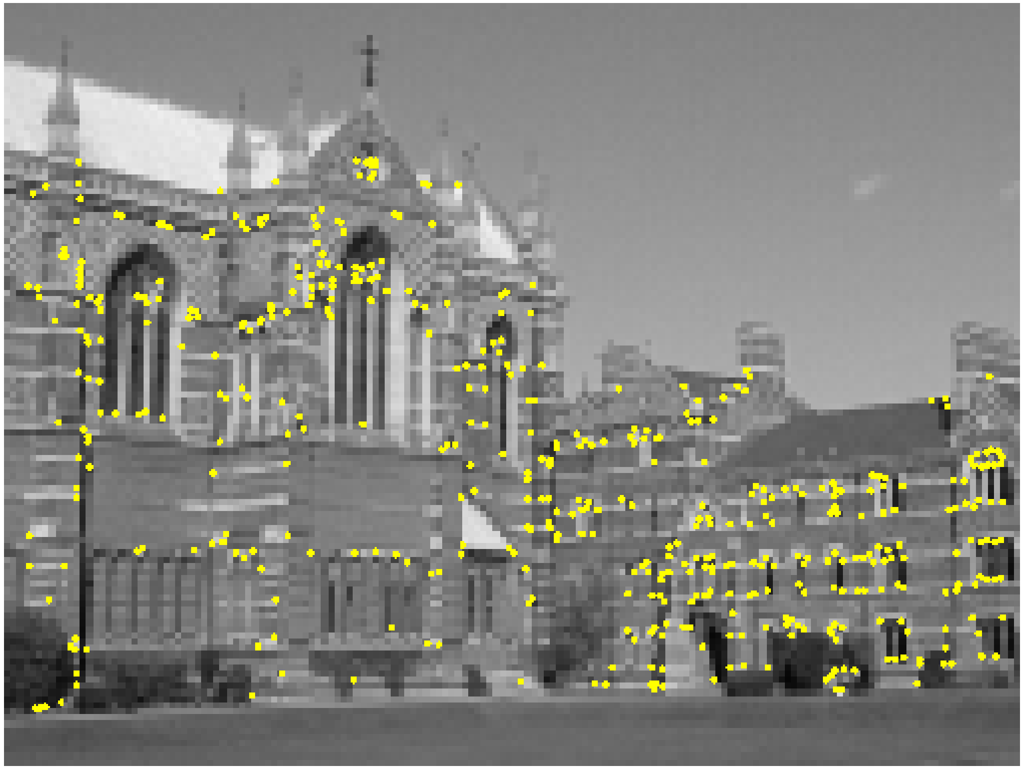
Preview: Harris detector



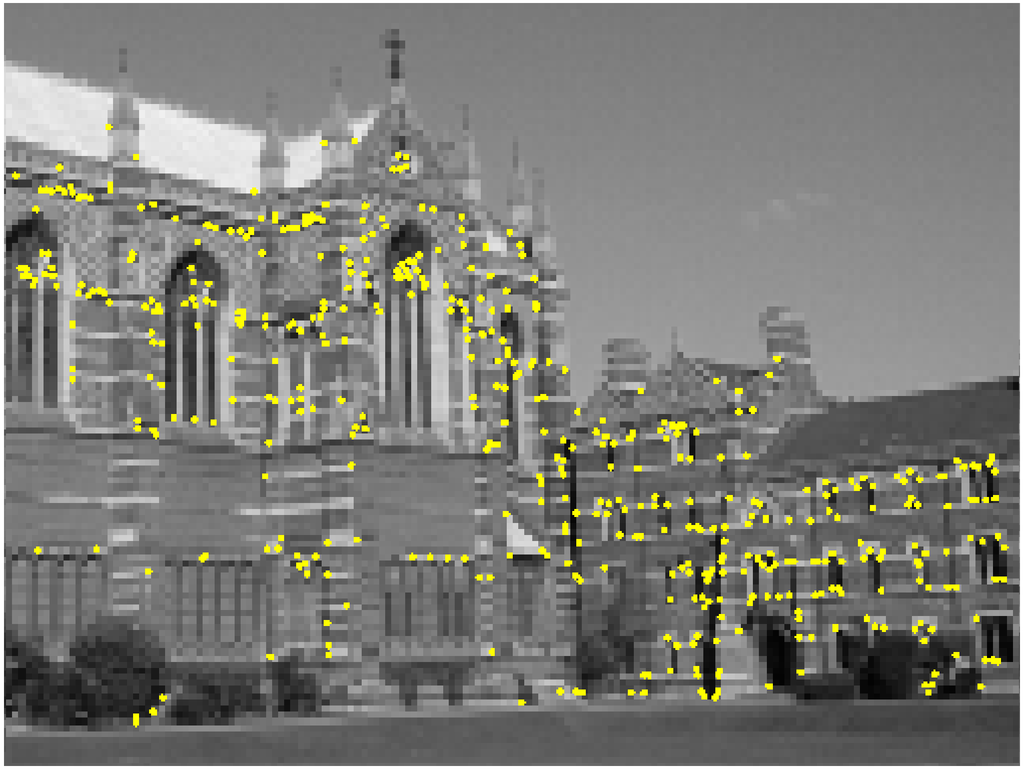


Interest points extracted with Harris (~ 500 points)

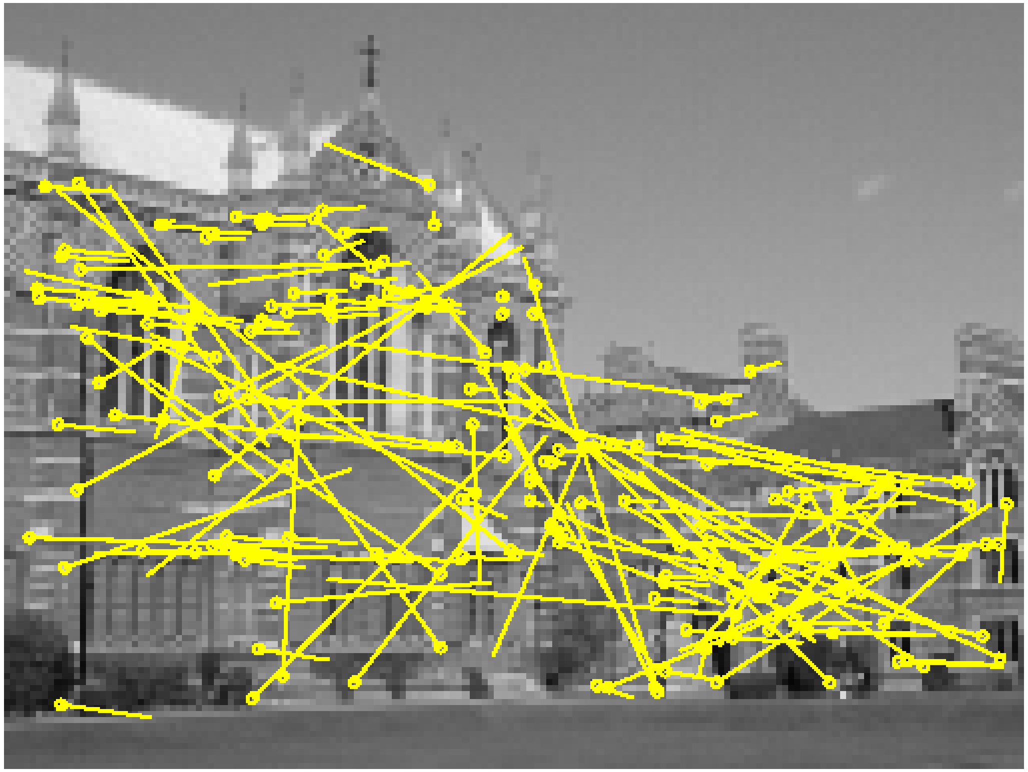
Harris detector



Harris detector



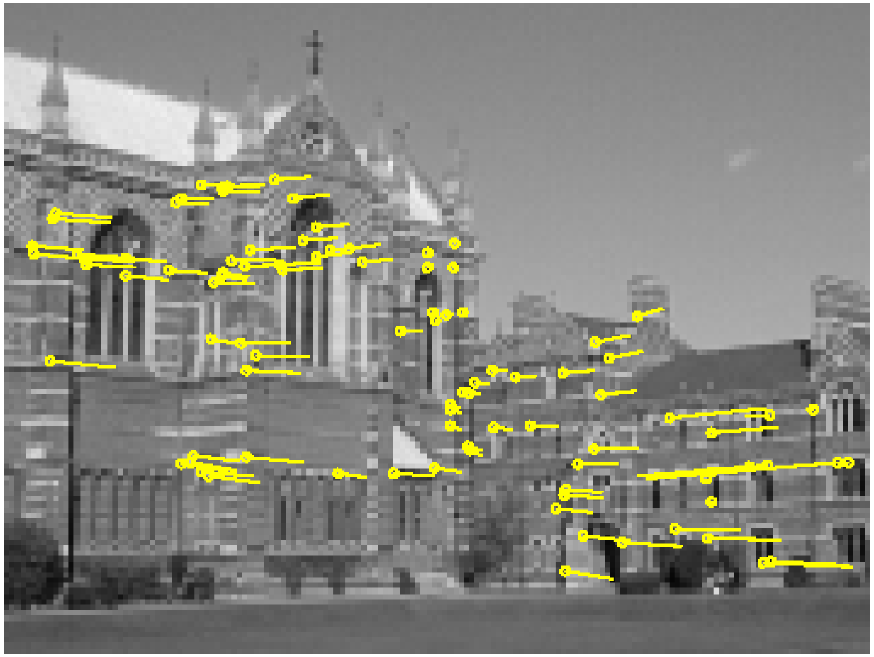
Cross-correlation matching



Initial matches – motion vectors (188 pairs)

Global constraints

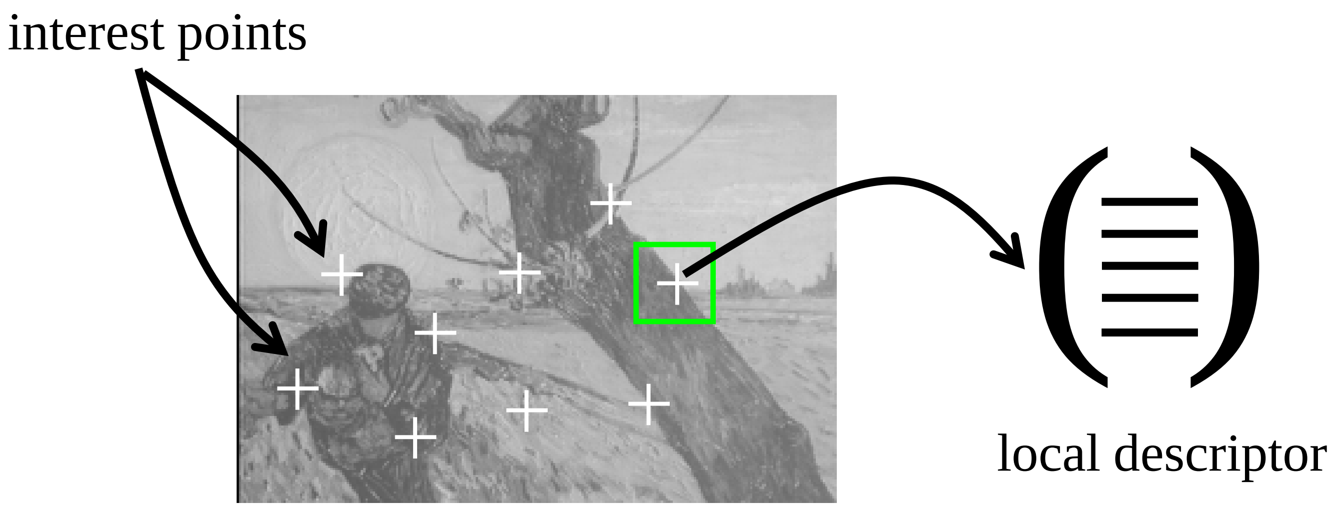
Robust estimation of the fundamental matrix (RANSAC)



99 inliers

89 outliers

General Interest Detector/Descriptor Approach



1) Extraction of interest points

2) Computation of local descriptors

3) Determining correspondences

4) Selection of similar images

1. Harris detector

Based on the idea of auto-correlation

Important difference in all directions => interest point

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

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

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 $(\Delta x, \Delta y)$

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

SSD means summed square difference

Discrete shifts can be avoided with the auto-correlation matrix

what is this?

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

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

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

Have we seen this matrix before?

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

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

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 $R = Det(M) – k\ Tr(M)^2$
- Let α and β be the two eigenvalues. We don't have to calculate them! Instead, use trace and determinant:
- $Tr(M) = \alpha + \beta$
- $Det(M) = \alpha\beta$

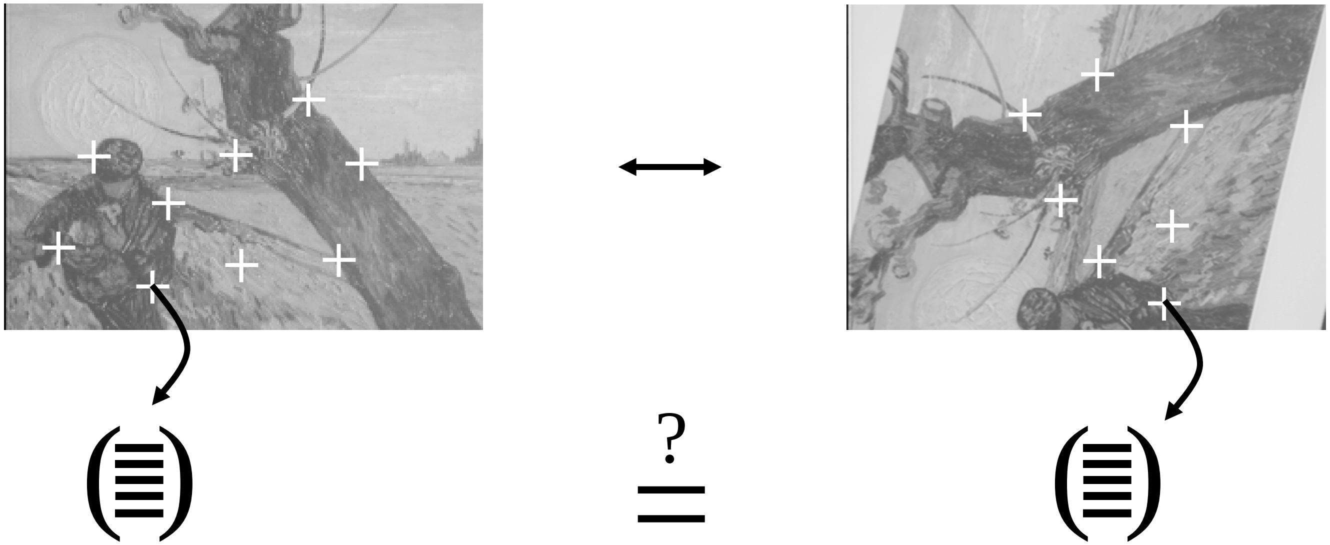
- R is positive for corners, - for edges, and small for flat regions
- Select corner pixels that are 8-way local maxima

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

$$\operatorname{tr}(\mathbf{A}) = a_{11} + a_{22}$$

)

Determining correspondences



Vector comparison using a distance measure

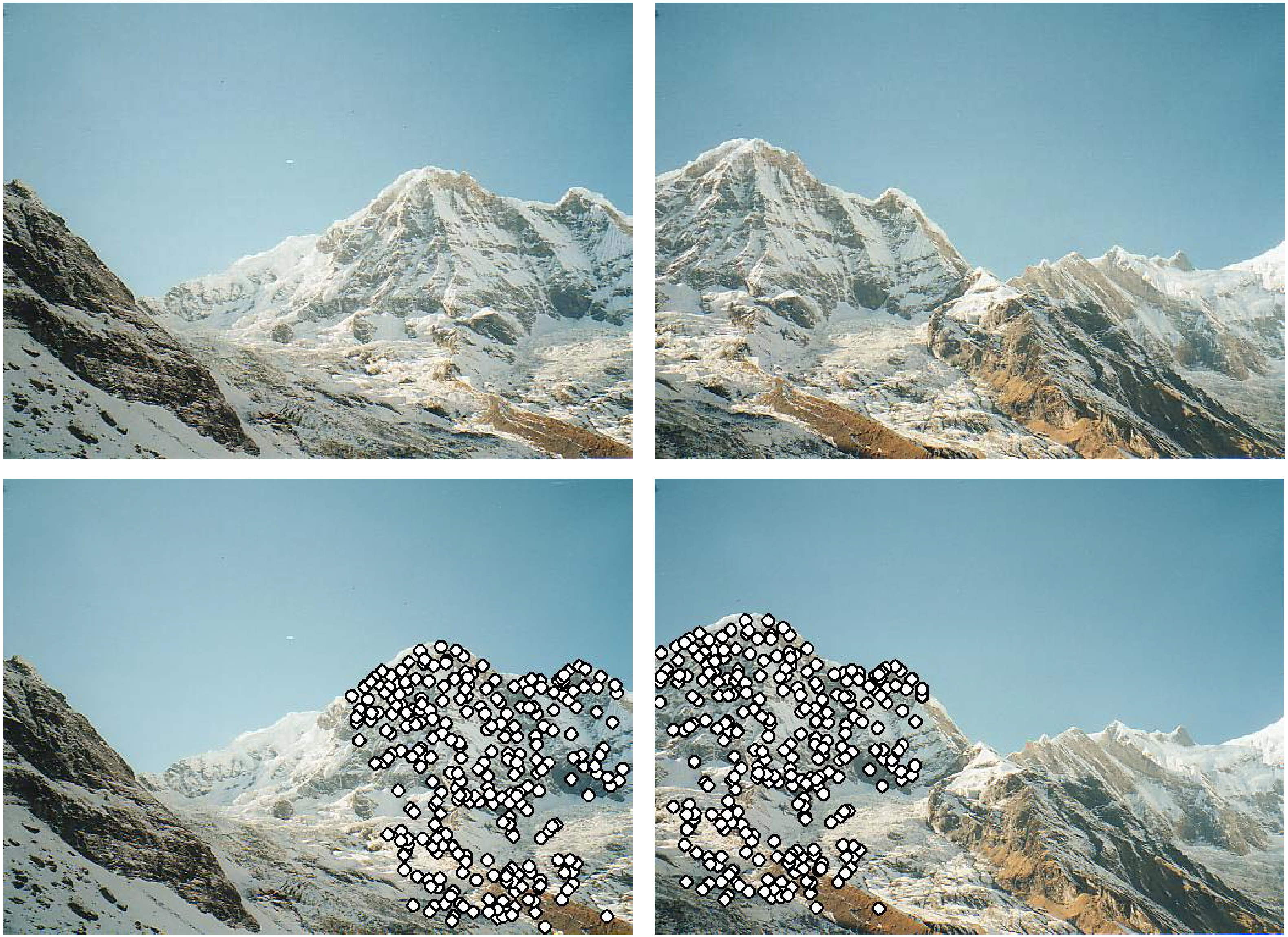
What are some suitable distance measures?

Distance Measures

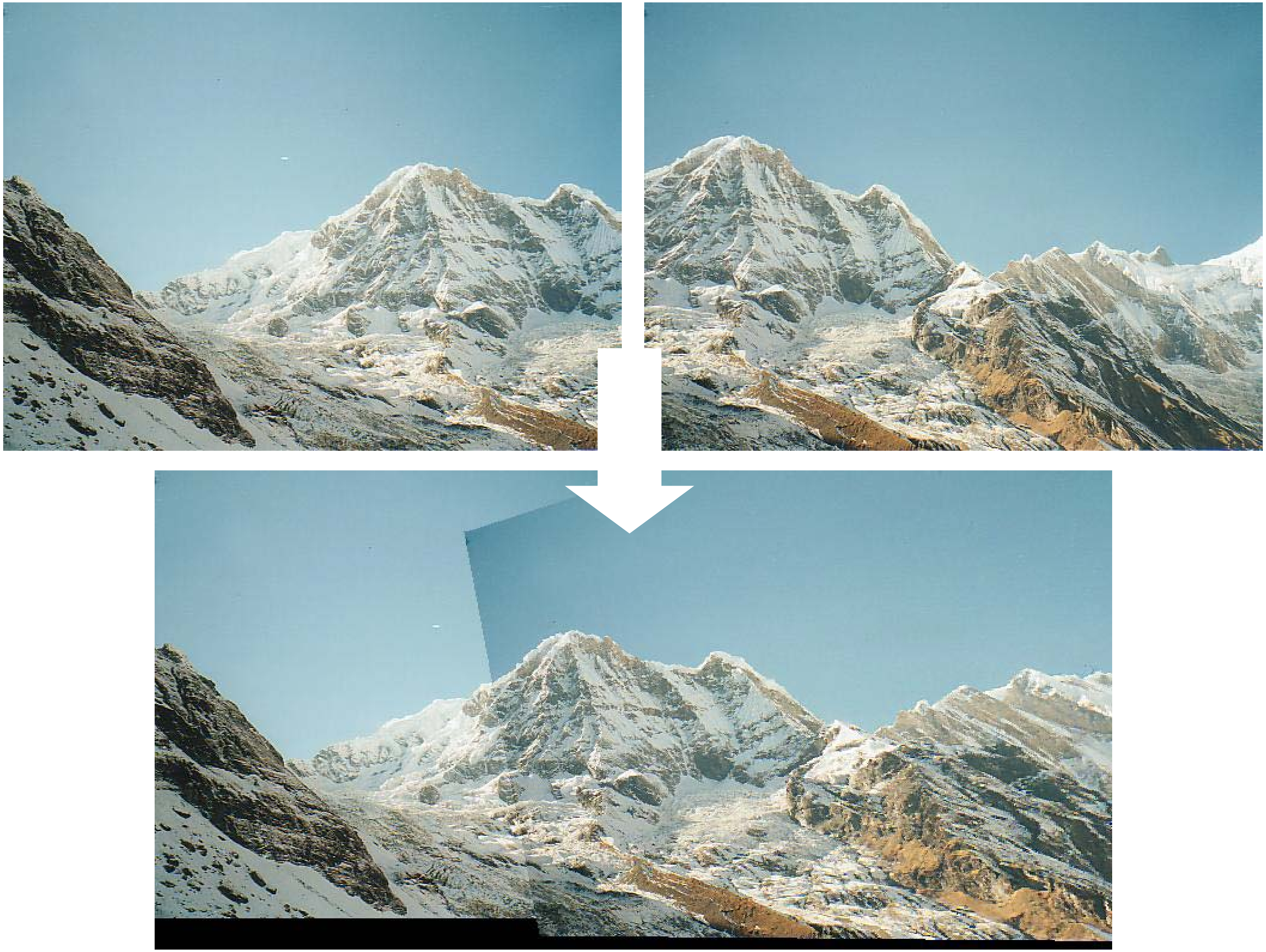
- We can use the sum-square difference of the values of the pixels in a square neighborhood about the points being compared. This is the simplest measure.

$$SSD = \sum\sum(W1_{i,j} - W2_{i,j})^2$$

Some Matching Results from Matt Brown



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

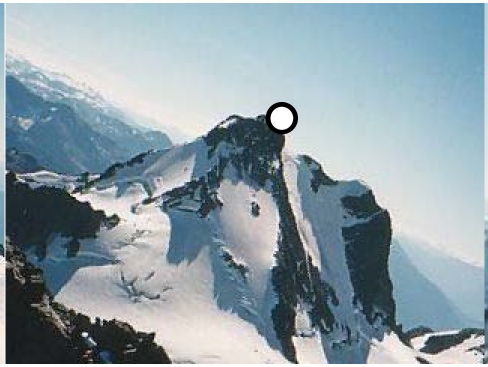
original translated rotated scaled

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

Rotation/Scale Invariance

original

translated

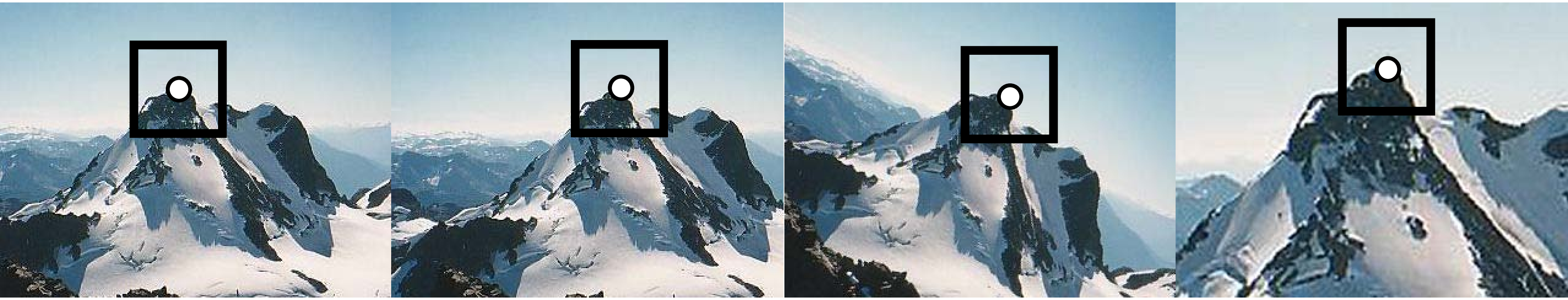


rotated

scaled

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

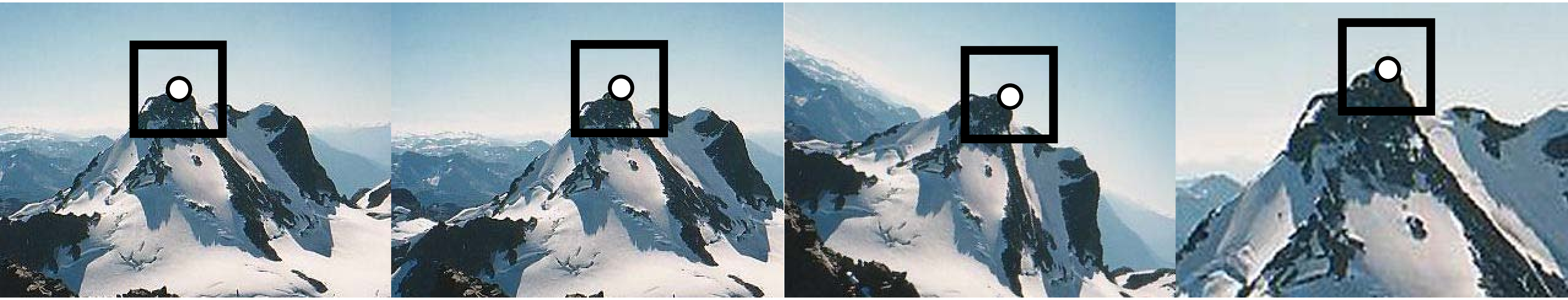
Rotation/Scale Invariance



original translated rotated scaled

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

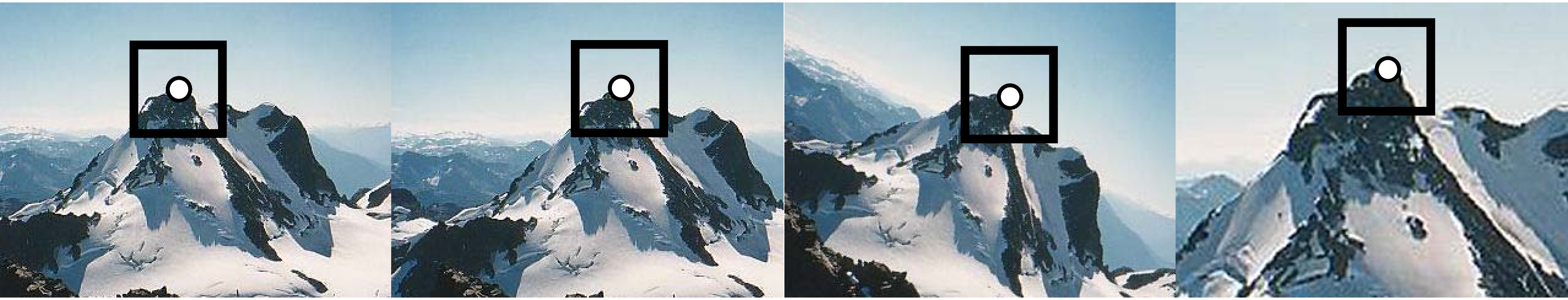
Rotation/Scale Invariance



original translated rotated scaled

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

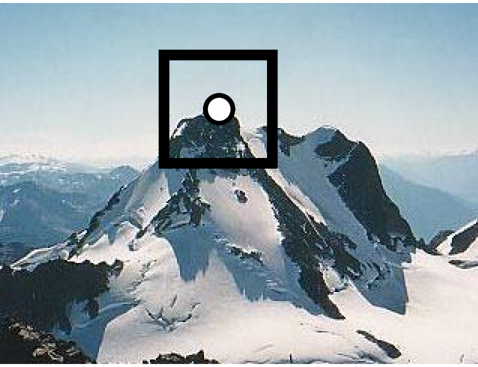
Rotation/Scale Invariance



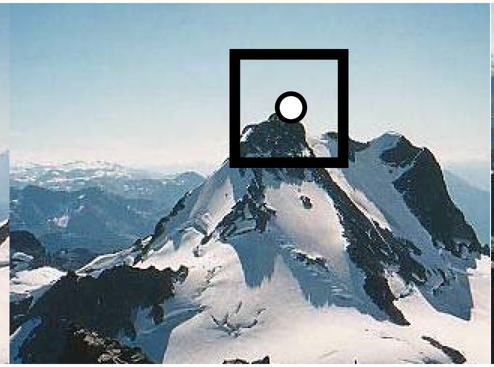
original translated rotated scaled

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

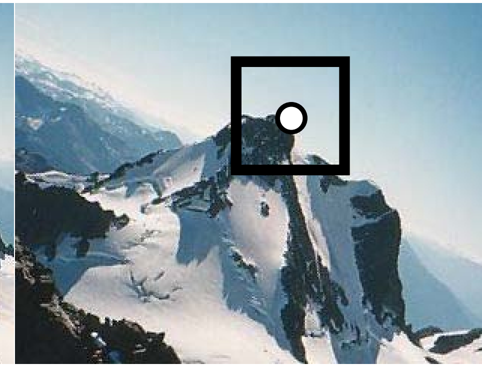
Rotation/Scale Invariance



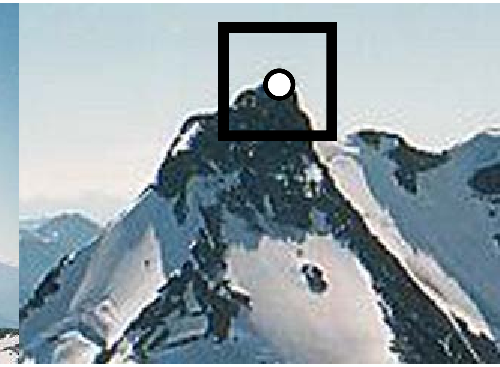
original



translated



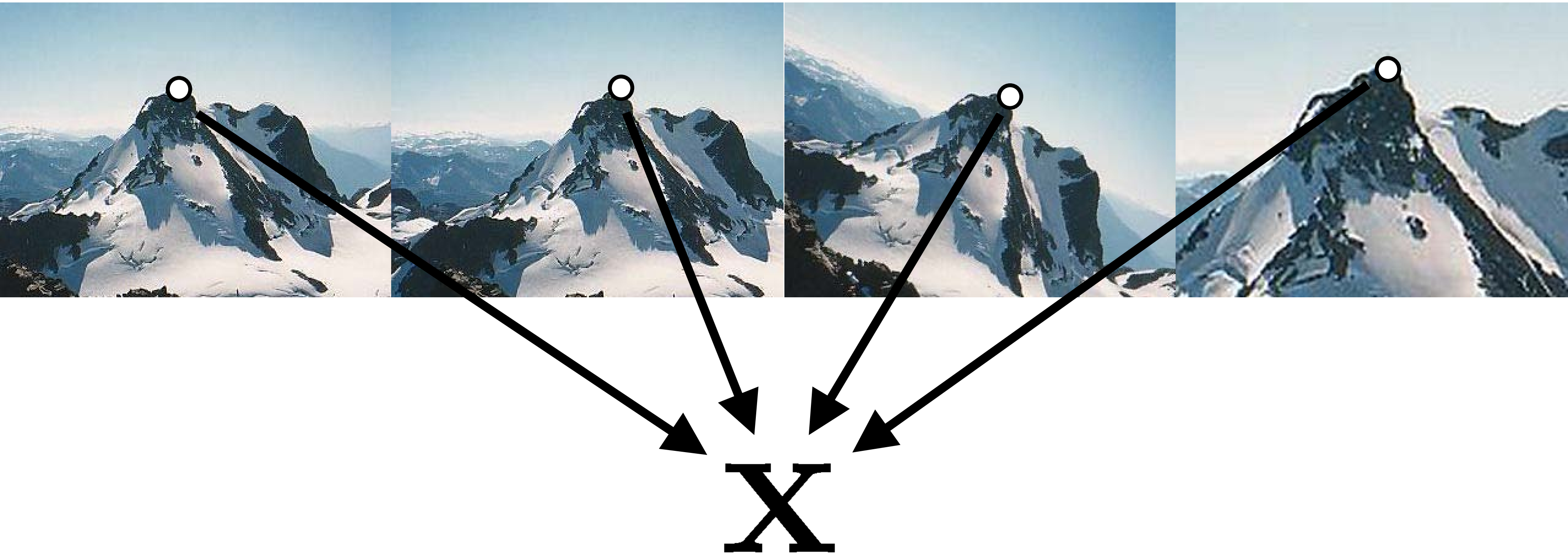
rotated



scaled

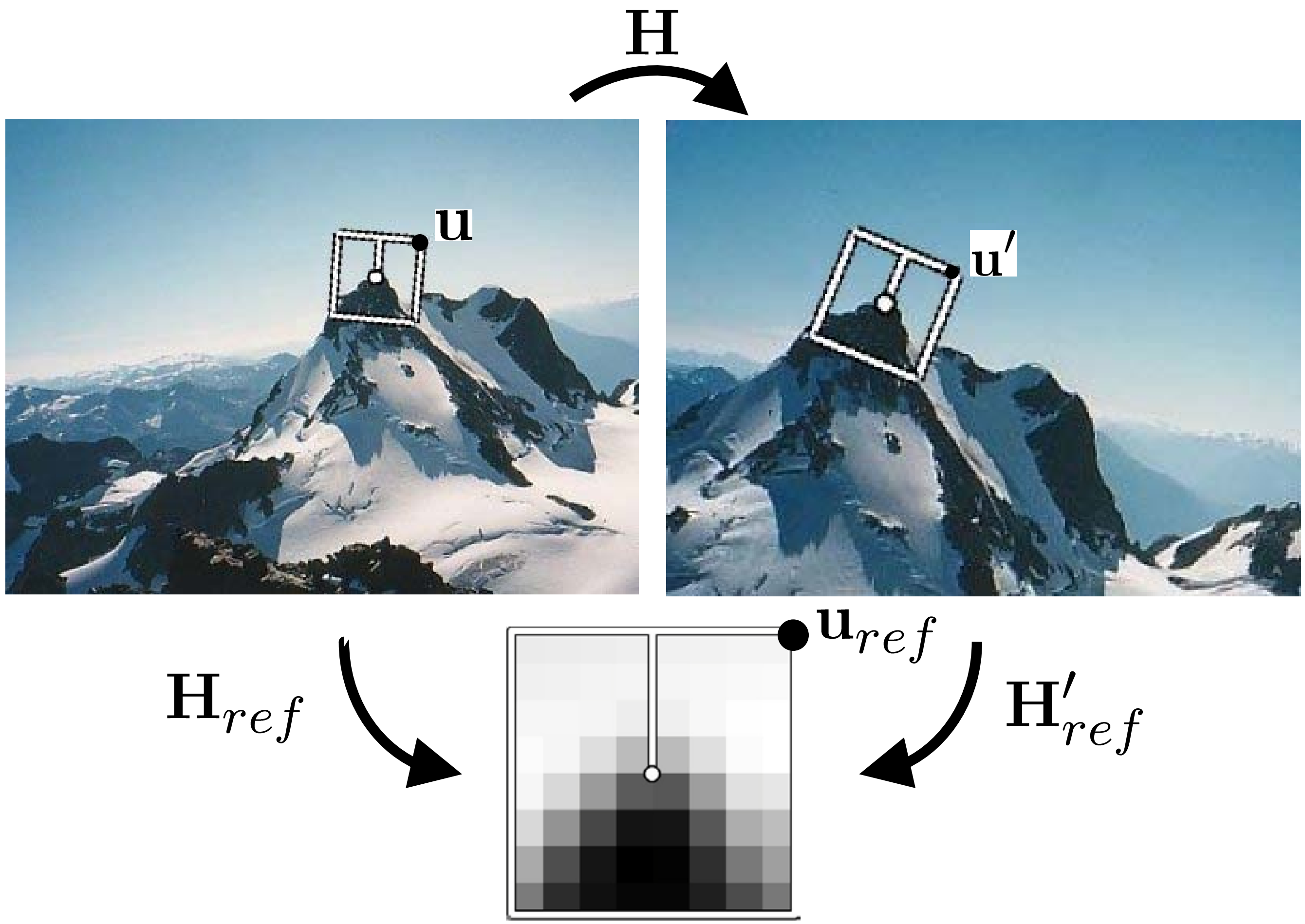
	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	NO

Matt Brown's Invariant Features



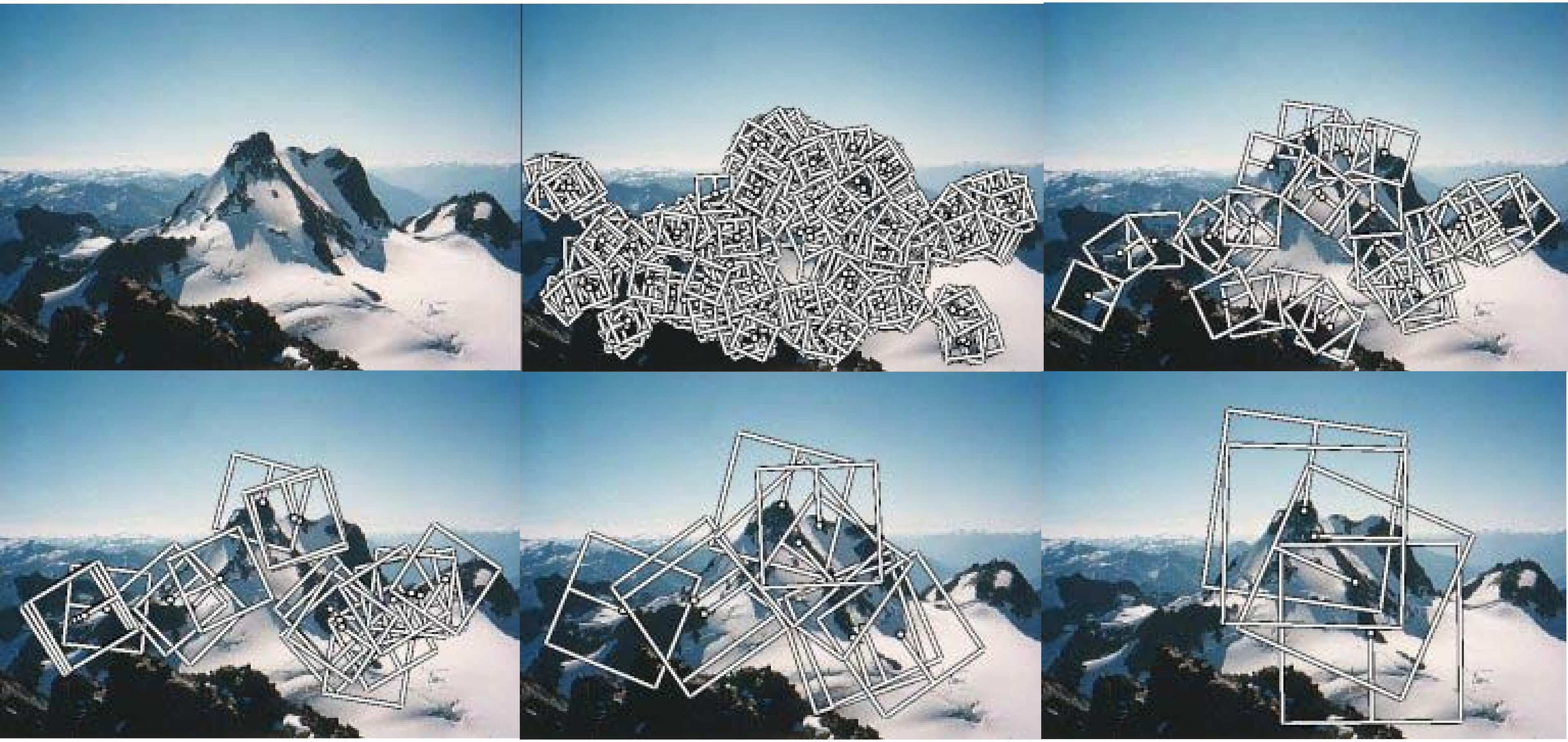
- Local image descriptors that are *invariant* (unchanged) under image transformations

Canonical Frames



Rotation-invariant descriptor.

Multi-Scale Oriented Patches



- Extract oriented patches at multiple scales using dominant orientation

Multi-Scale Oriented Patches

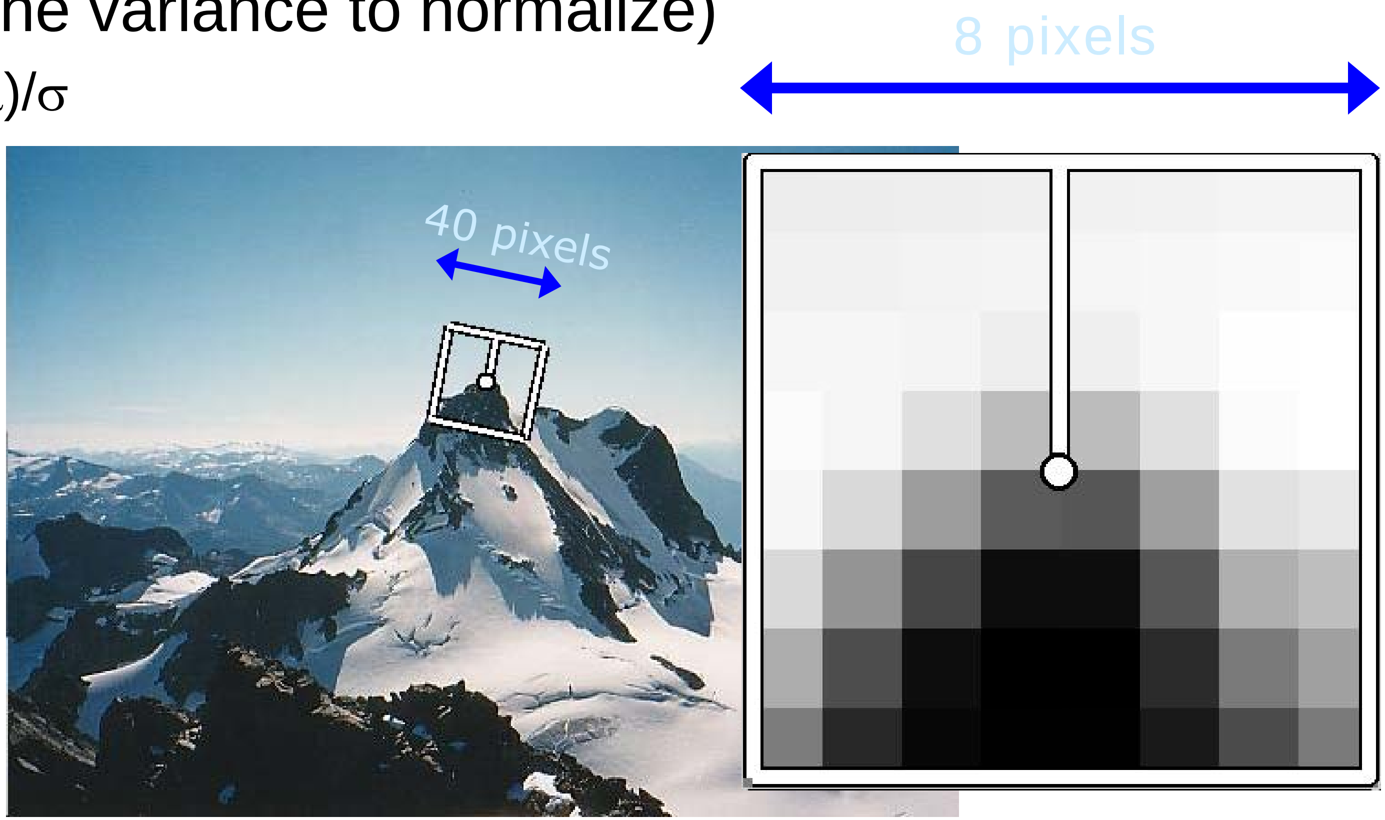
- Sample scaled, oriented patch

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 normalized (subtract the mean of a patch and divide by the variance to normalize)
  - $I' = (I - \mu)/\sigma$



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