Interest Operator Lectures

0. Introduction to Interest Operators

1. Harris Corner Detector: the first and most basic interest operator; Matt Brown's invariant features

2. Kadir Entropy Detector and its use in object recognition

3. SIFT interest point detector and region descriptor; HOG descriptor

4. MSER region detector and Harris Affine in region matching

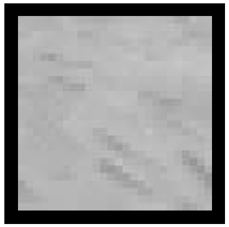
5. Additional applications

0. Introduction to Interest Operators

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

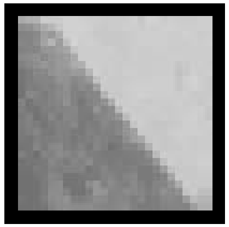
- Many possible uses in matching/recognition
  - Search
  - Object recognition
  - Image alignment & stitching
  - Stereo
  - Tracking
  - …

Interest points



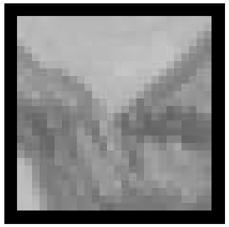
0D structure: single points

➡ not useful for matching



1D structure: lines

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

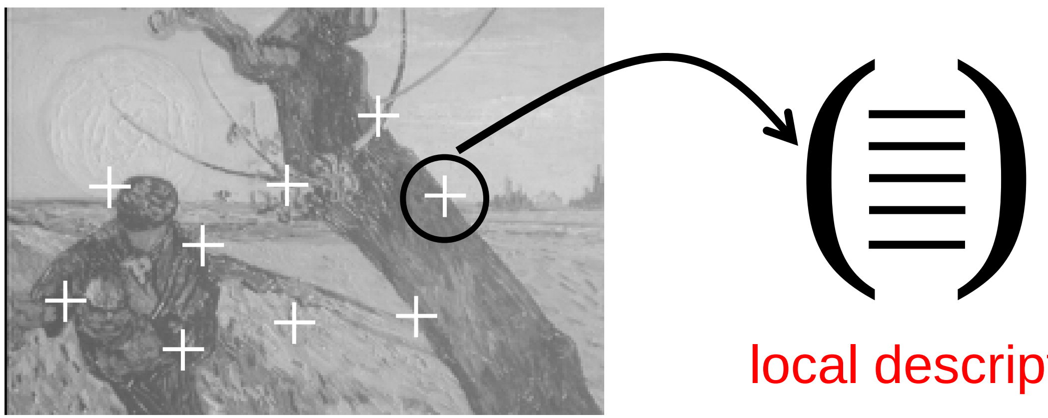


2D structure: corners

➡ 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,

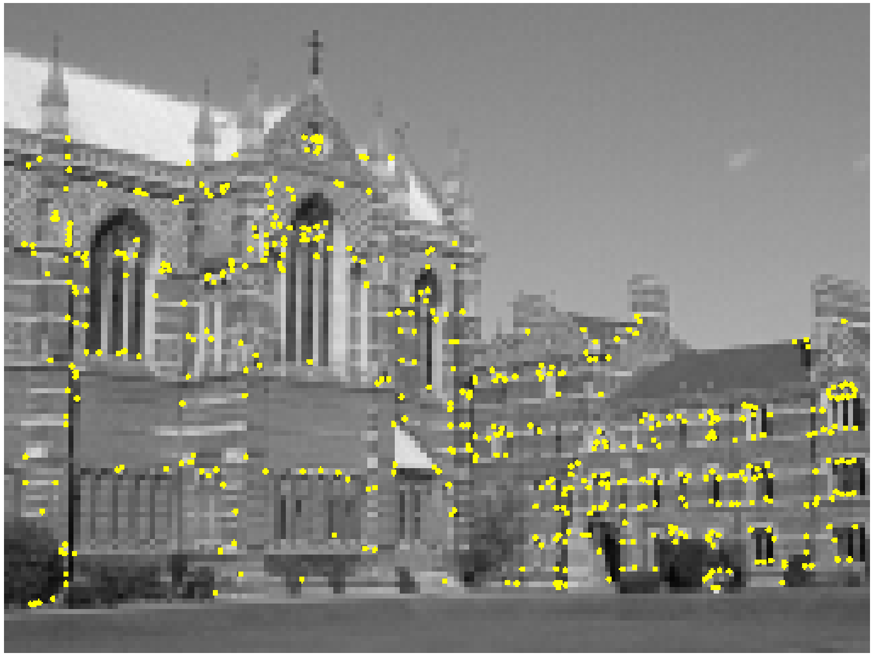
Artificial Intelligence 1995]

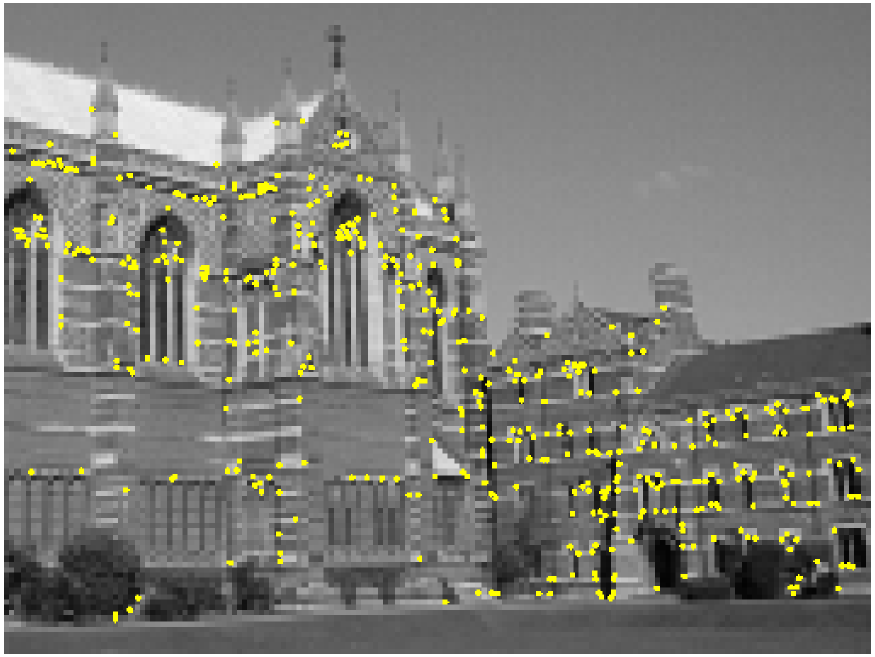
Zhang Approach

- 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.

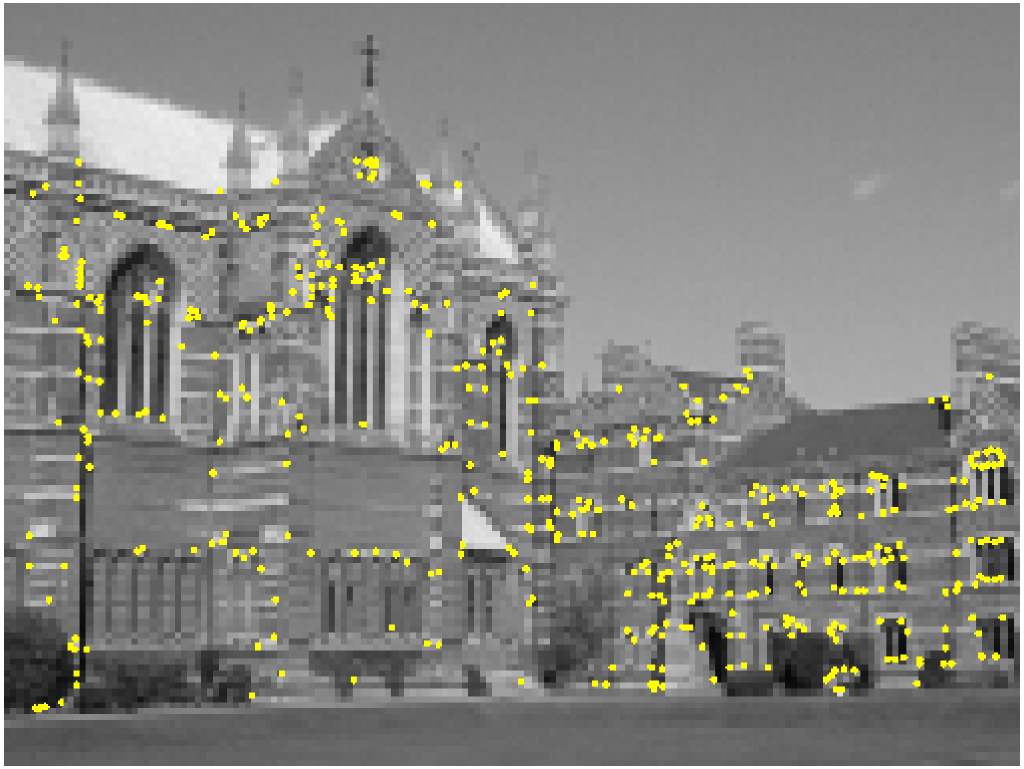
Preview: Harris detector



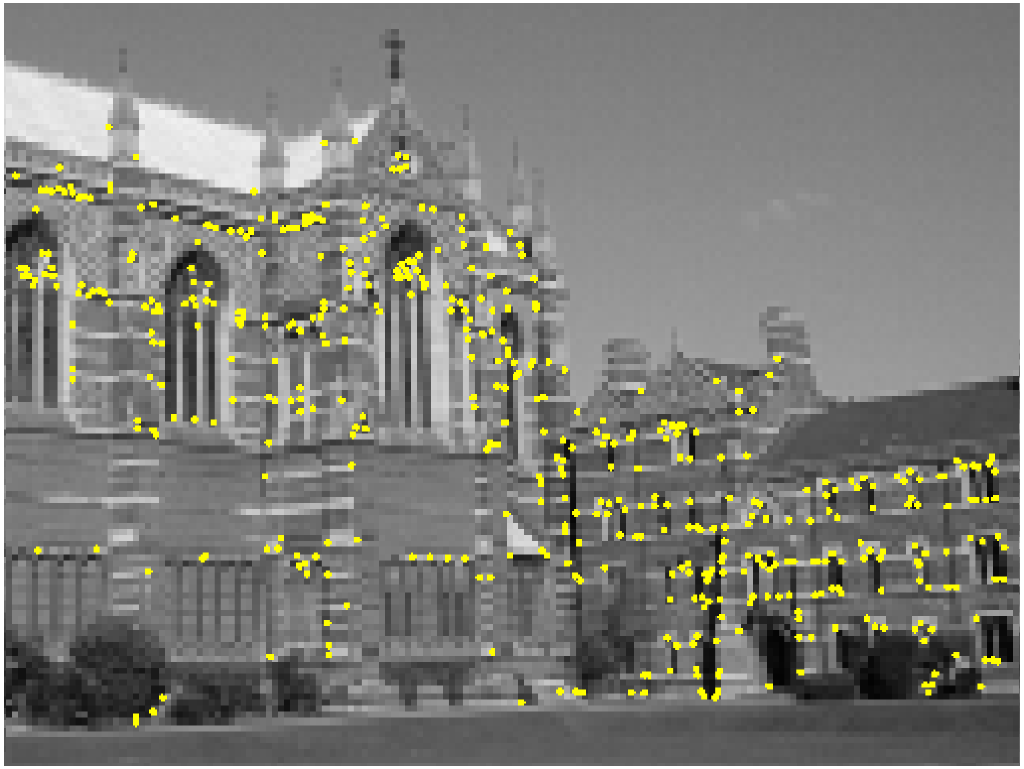


Interest points extracted with Harris (~ 500 points)

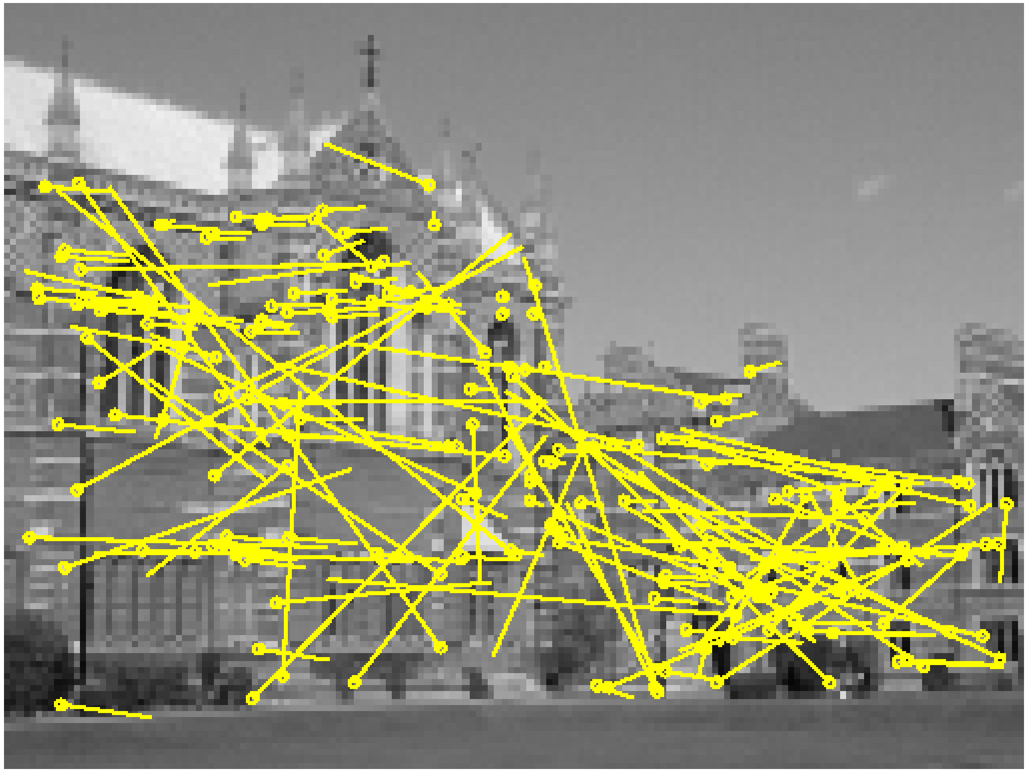
Harris detector



Harris detector



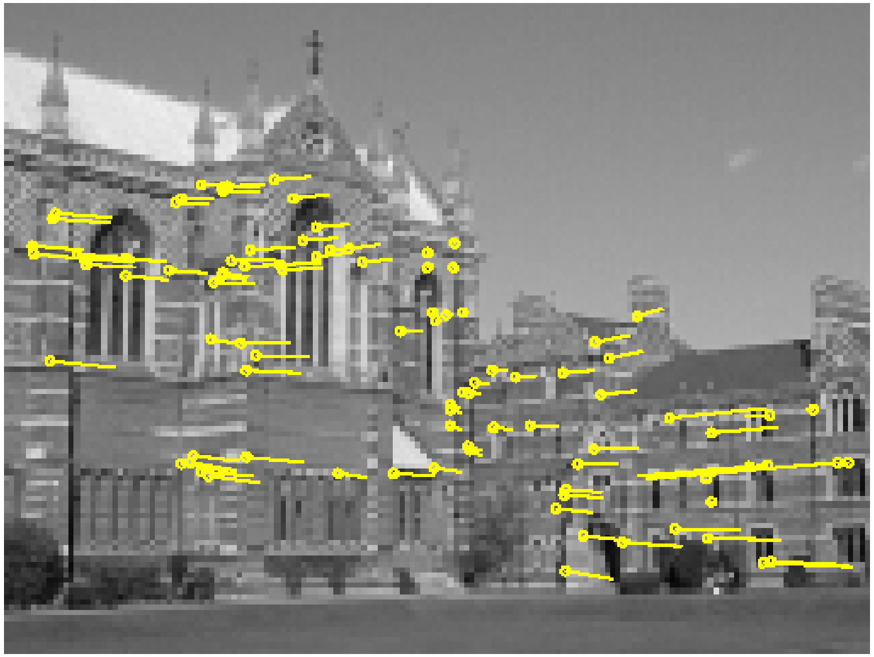
Cross-correlation matching



Initial matches – motion vectors (188 pairs)

Global constraints

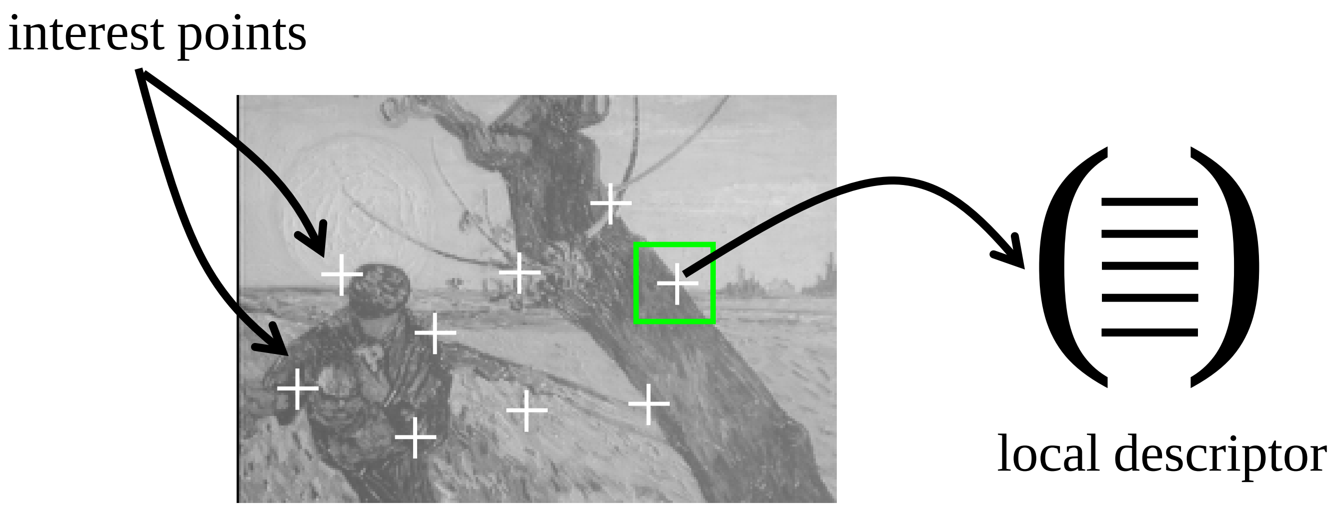
Robust estimation of the fundamental matrix (RANSAC)



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

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

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

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

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

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

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

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

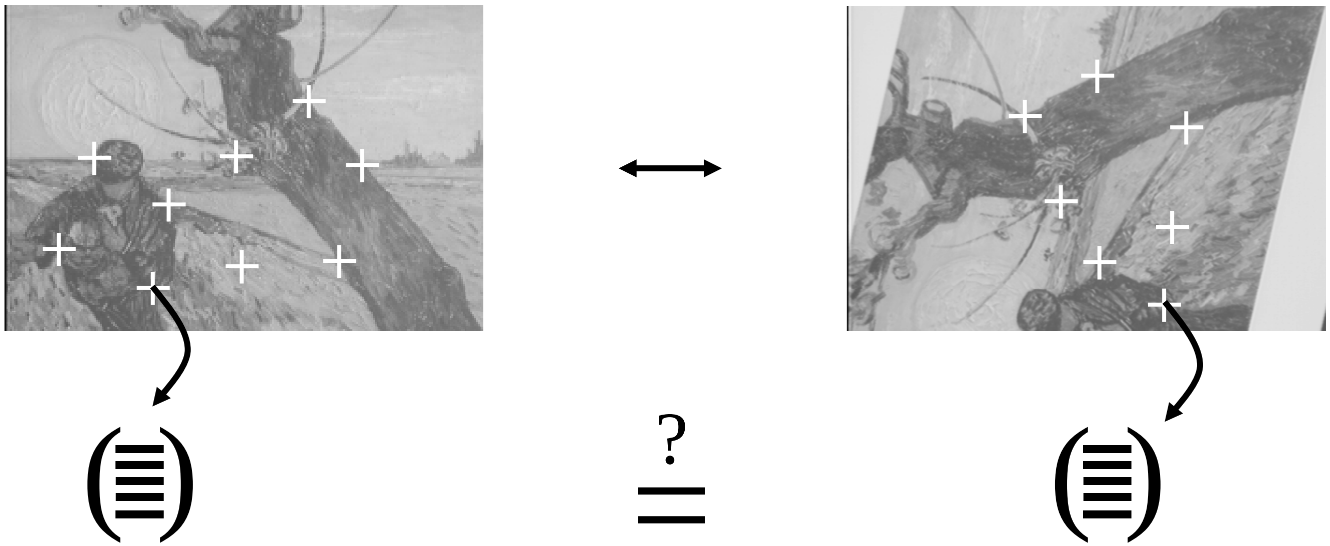
- Corner strength $R = Det(M) – k\ Tr(M)^2$
- Let α and β be the two eigenvalues. We don't have to calculate them! Instead, use trace and determinant:
- $Tr(M) = \alpha + \beta$
- $Det(M) = \alpha\beta$

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

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

)

Determining correspondences



Vector comparison using a distance measure

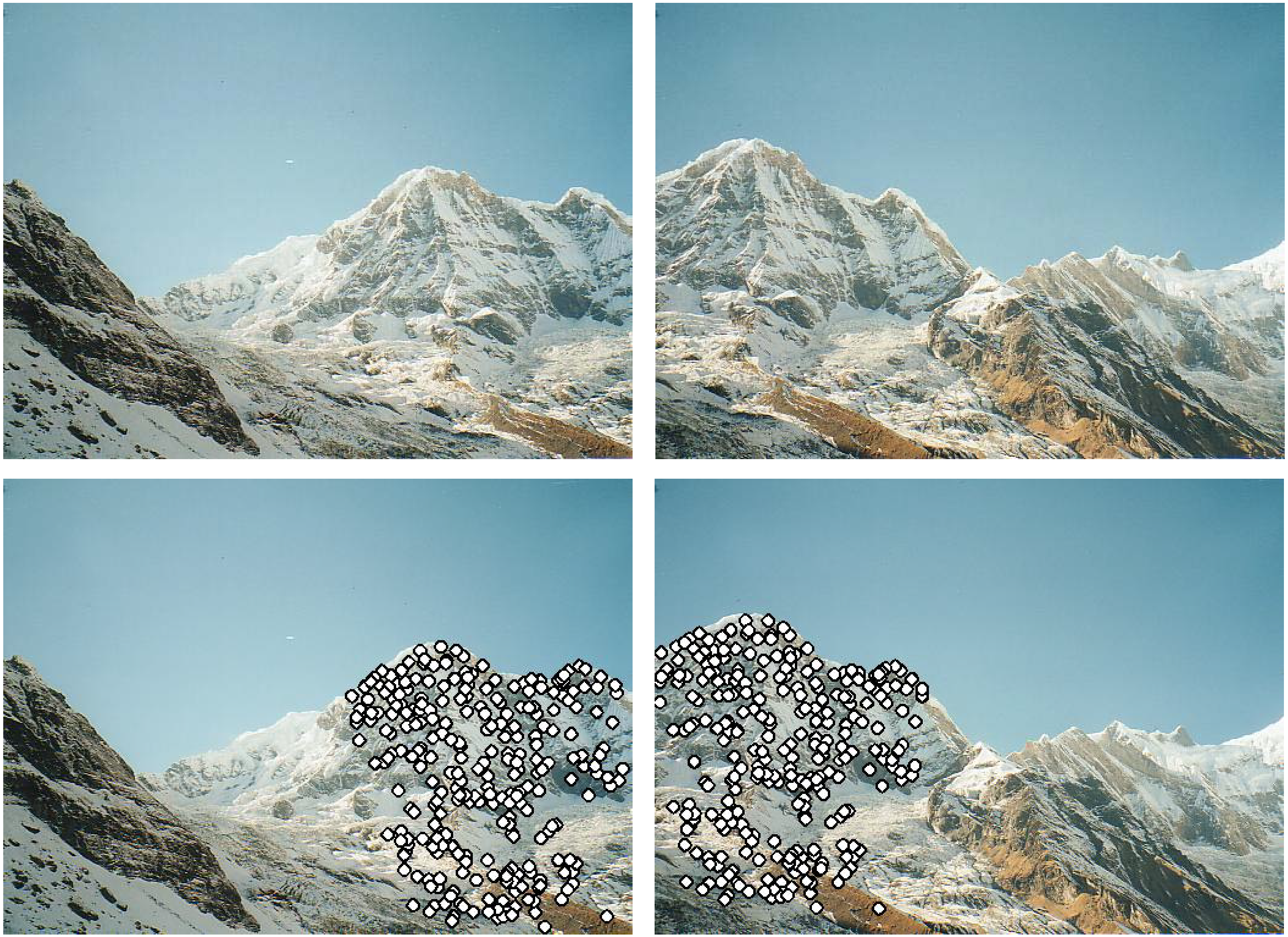
What are some suitable distance measures?

Distance Measures

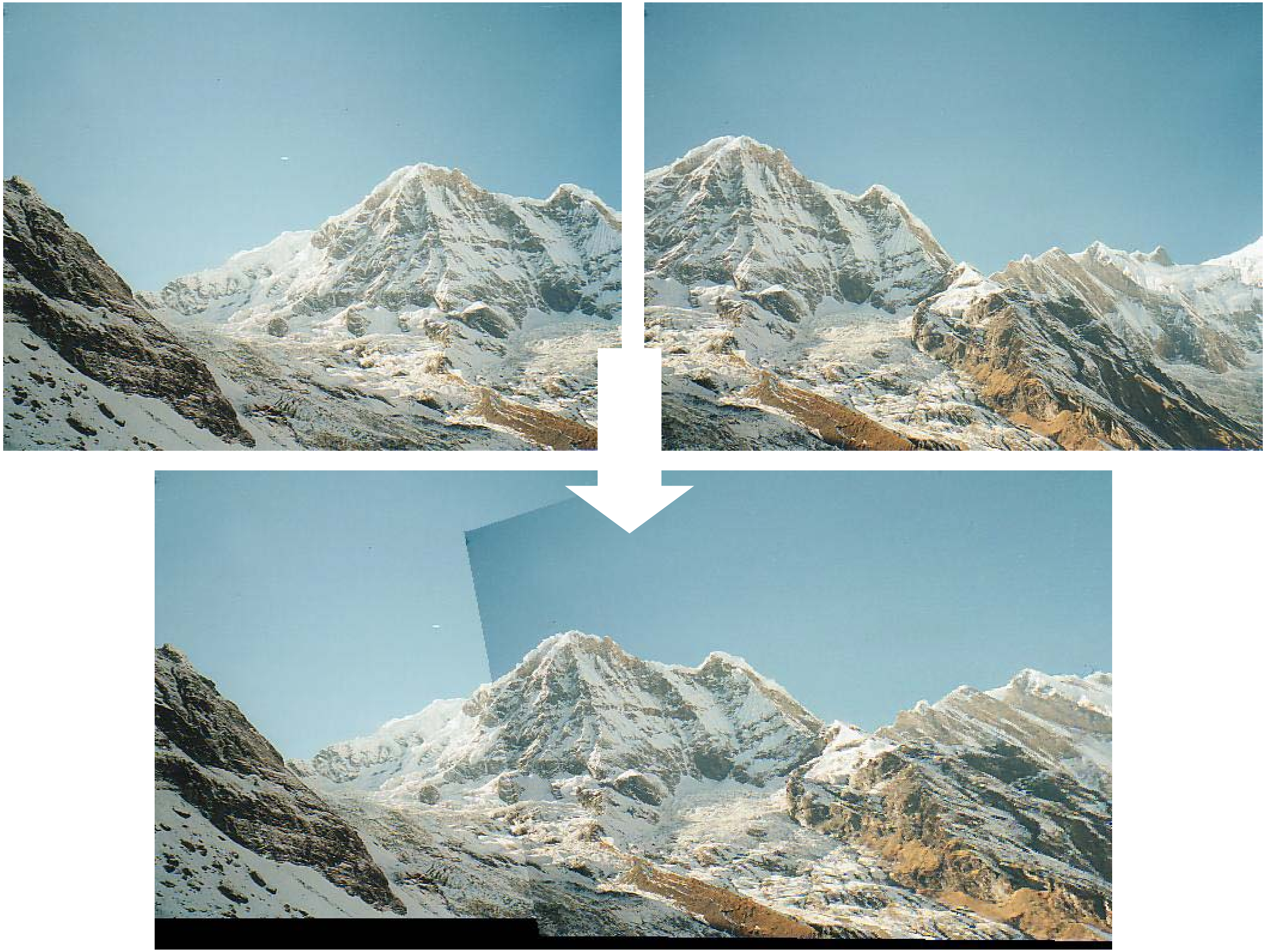
- We can use the sum-square difference of the values of the pixels in a square neighborhood about the points being compared. This is the simplest measure.

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

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

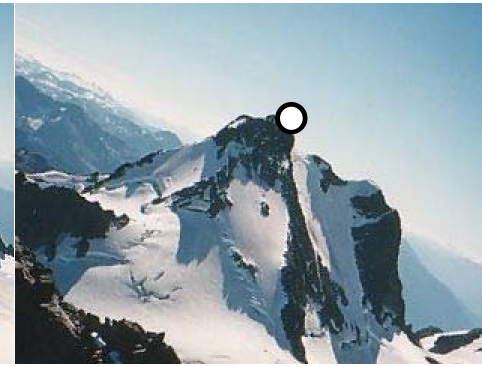
original translated rotated scaled

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

Rotation/Scale Invariance


original

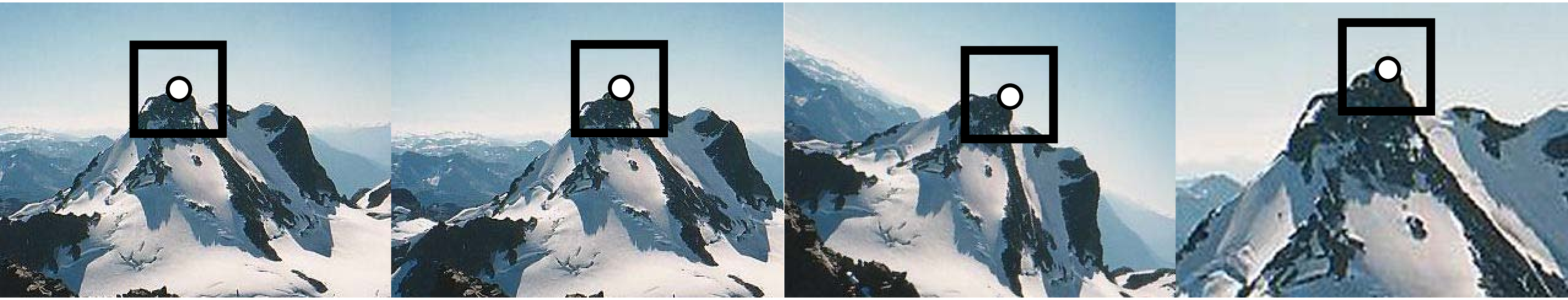

translated


rotated


scaled

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

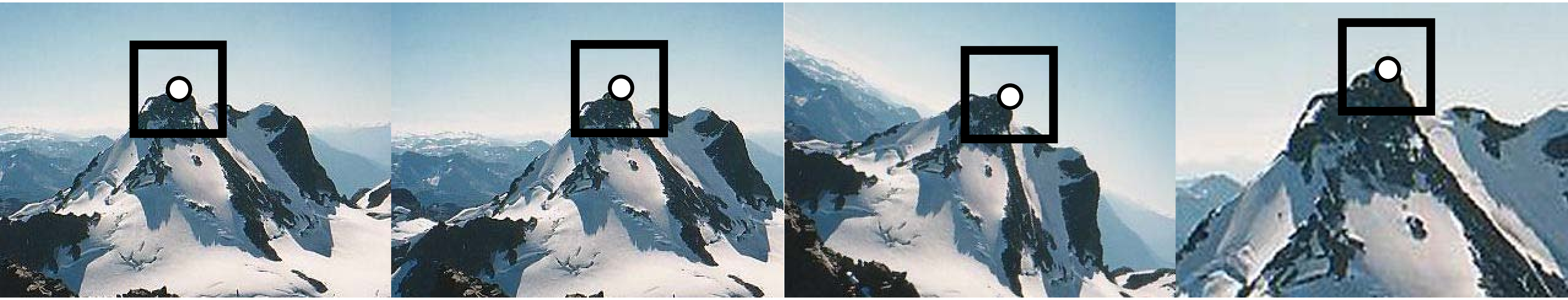
Rotation/Scale Invariance



original translated rotated scaled

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

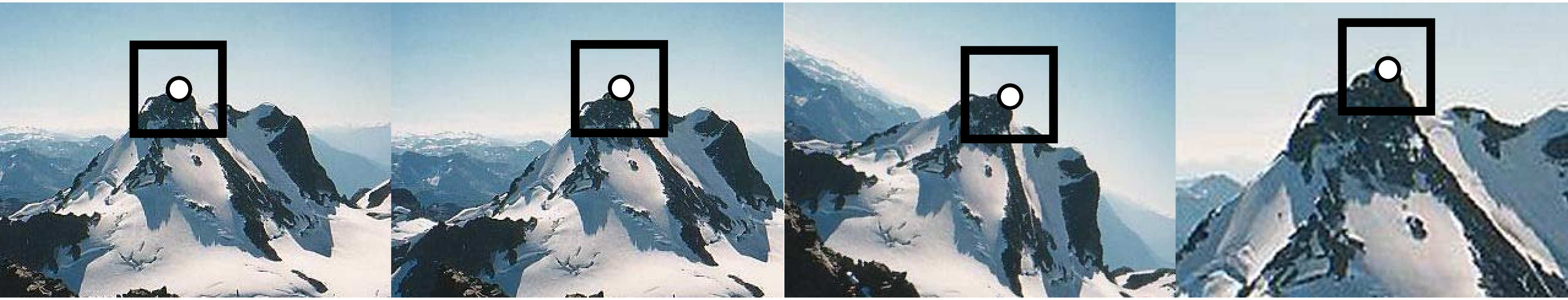
Rotation/Scale Invariance



original translated rotated scaled

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

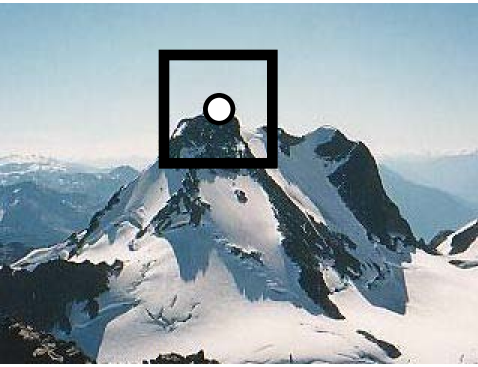
Rotation/Scale Invariance

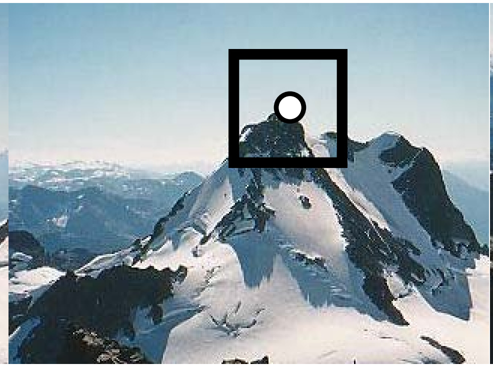


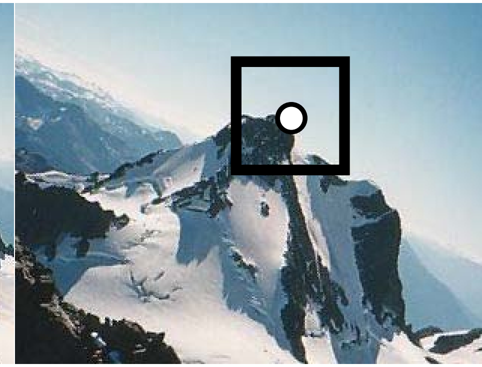
original translated rotated scaled

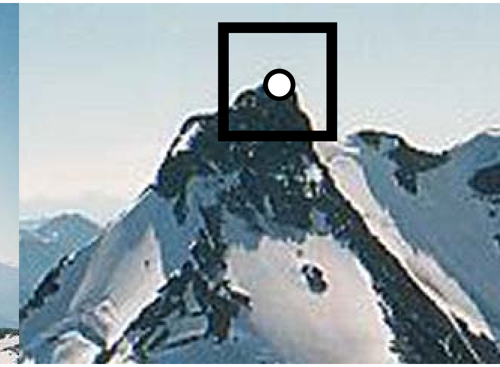
	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	?

Rotation/Scale Invariance


original

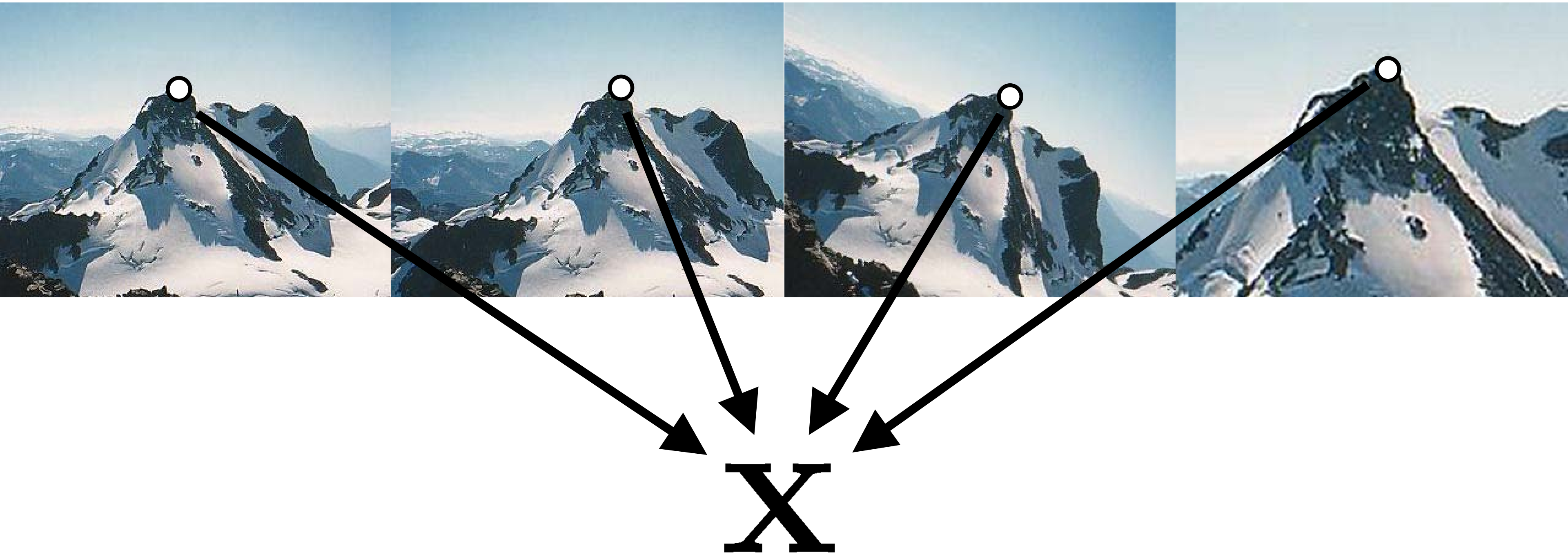

translated


rotated


scaled

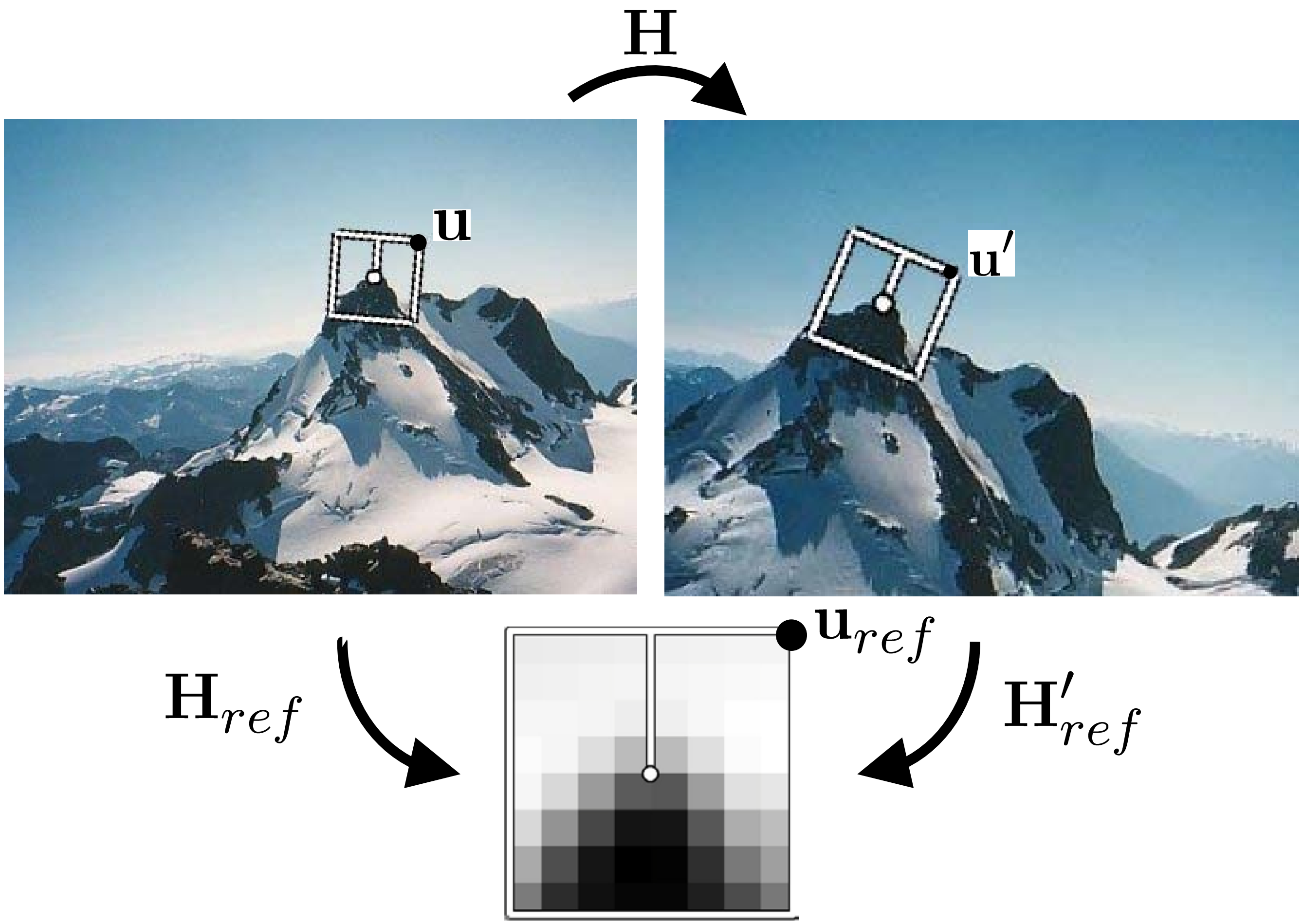
	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	NO

Matt Brown's Invariant Features



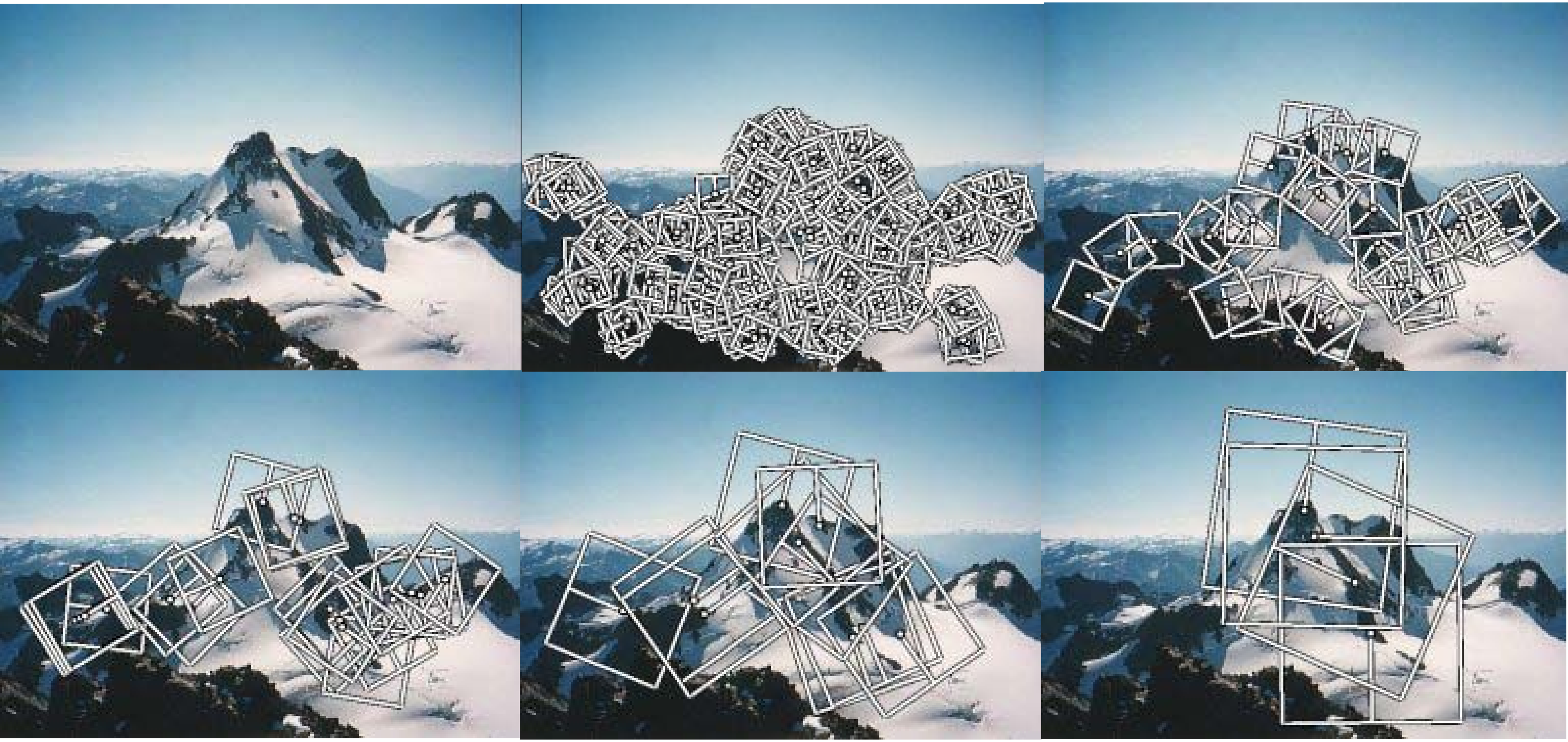
- Local image descriptors that are *invariant* (unchanged) under image transformations

Canonical Frames



Rotation-invariant descriptor.

Multi-Scale Oriented Patches



- Extract oriented patches at multiple scales using dominant orientation

Multi-Scale Oriented Patches

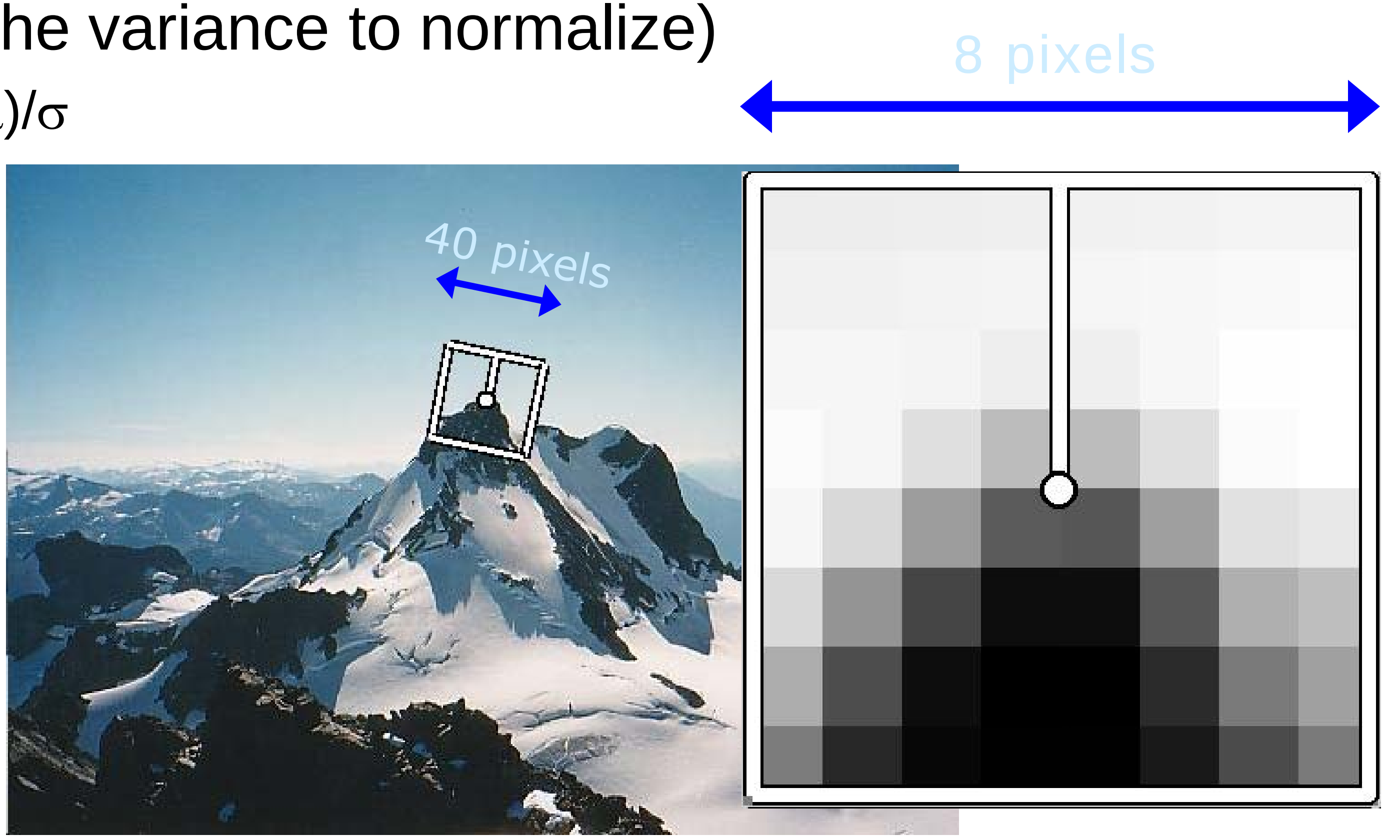
- Sample scaled, oriented patch

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