

Interest Operator Lectures

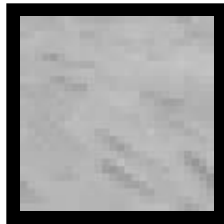
0. Introduction to Interest Operators

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. **Use of multiple interest operators in insect recognition**

0. Introduction to Interest Operators

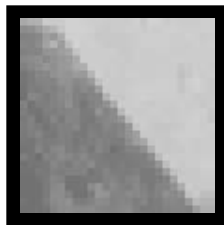
- Find “interesting” pieces of the image
 - e.g. corners, salient regions
 - Focus attention of algorithms
 - Speed up computation
- Many possible uses in matching/recognition
 - Search
 - Object recognition
 - Image alignment & stitching
 - Stereo
 - Tracking
 - ...

Interest points



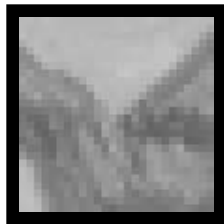
0D structure

➡ not useful for matching



1D structure

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

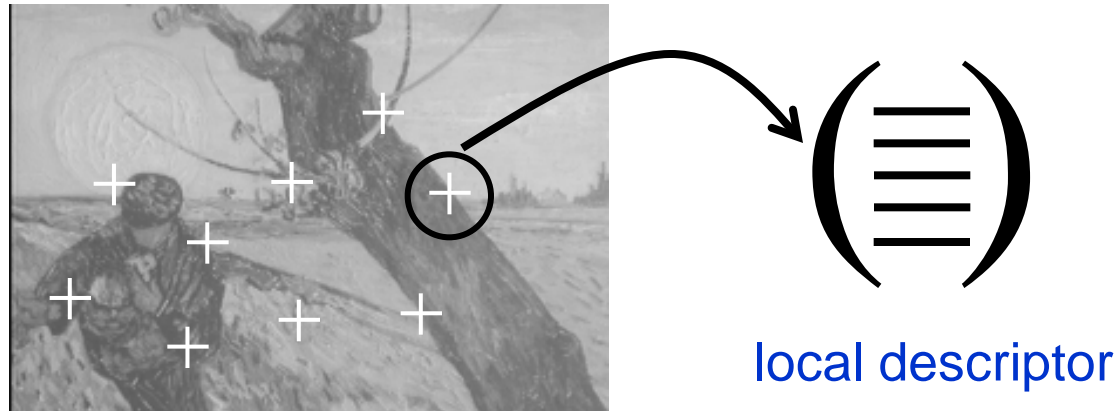


2D structure

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

Interest Points have **2D** structure.

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

⇒ Not very discriminating (why?)

⇒ Solution : matching with interest points & correlation

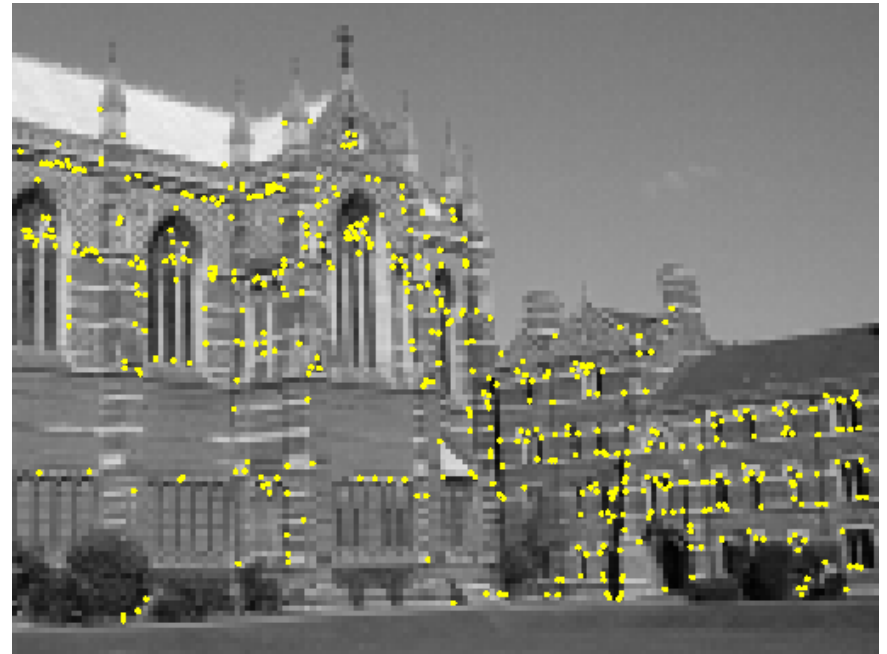
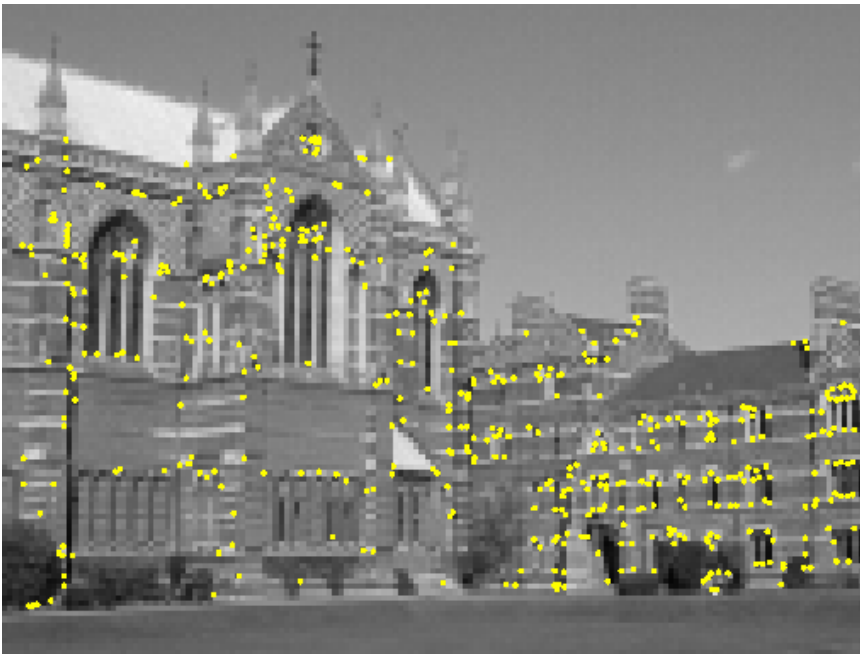
[A robust technique for matching two uncalibrated images through the recovery of the unknown epipolar geometry,
Z. Zhang, R. Deriche, O. Faugeras and Q. Luong,
Artificial Intelligence 1995]

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. CH 12-13⁶

Preview: Harris detector

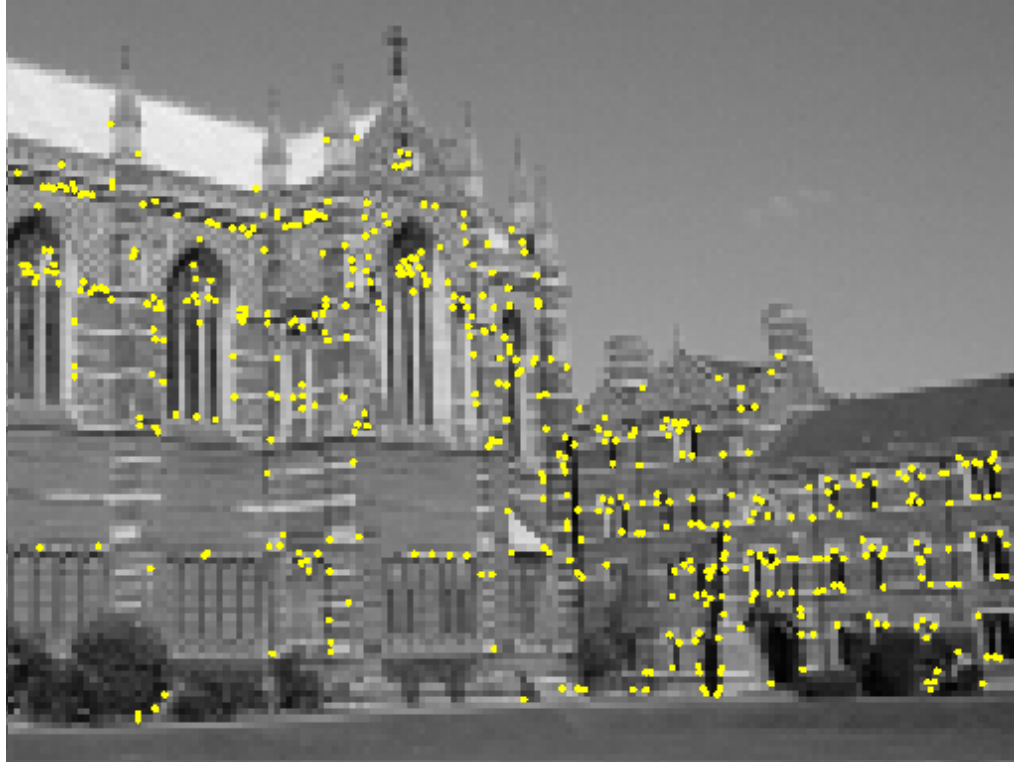


Interest points extracted with Harris (~ 500 points)

Harris detector



Harris detector



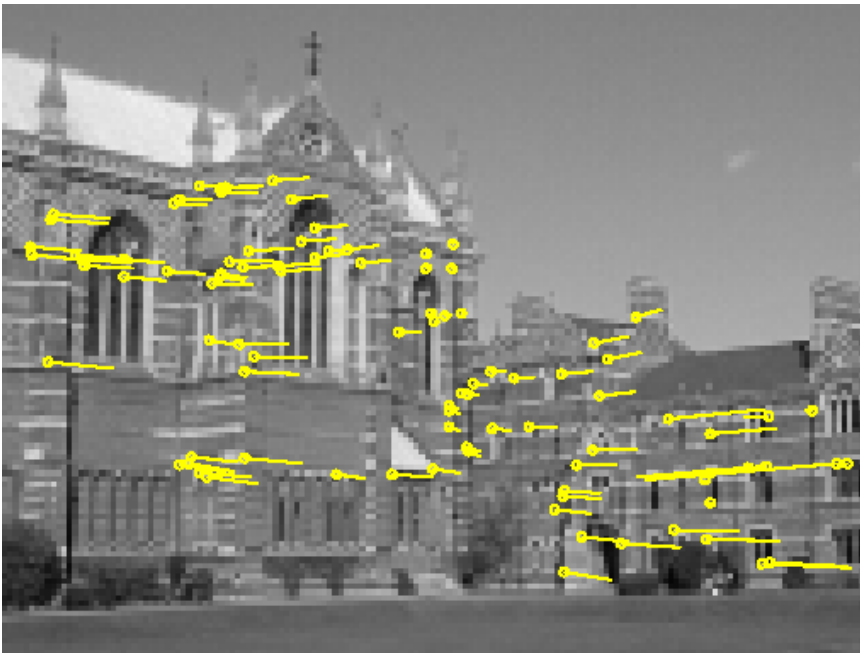
Cross-correlation matching



Initial matches – motion vectors (188 pairs)

Global constraints

Robust estimation of the fundamental matrix (RANSAC)



99 inliers



89 outliers

General Interest Detector/Descriptor Approach

interest points



- 1) Extraction of interest points (characteristic locations)
- 2) Computation of local descriptors (**rotational invariants**)
- 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

what is this?

$$\text{with } I(x_k + \Delta x, y_k + \Delta y) = I(x_k, y_k) + \begin{pmatrix} I_x(x_k, y_k) & I_y(x_k, y_k) \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

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

Harris detector

Rewrite as inner (dot) product

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

The center portion is a 2x2 matrix

Have we seen
this matrix before?

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

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

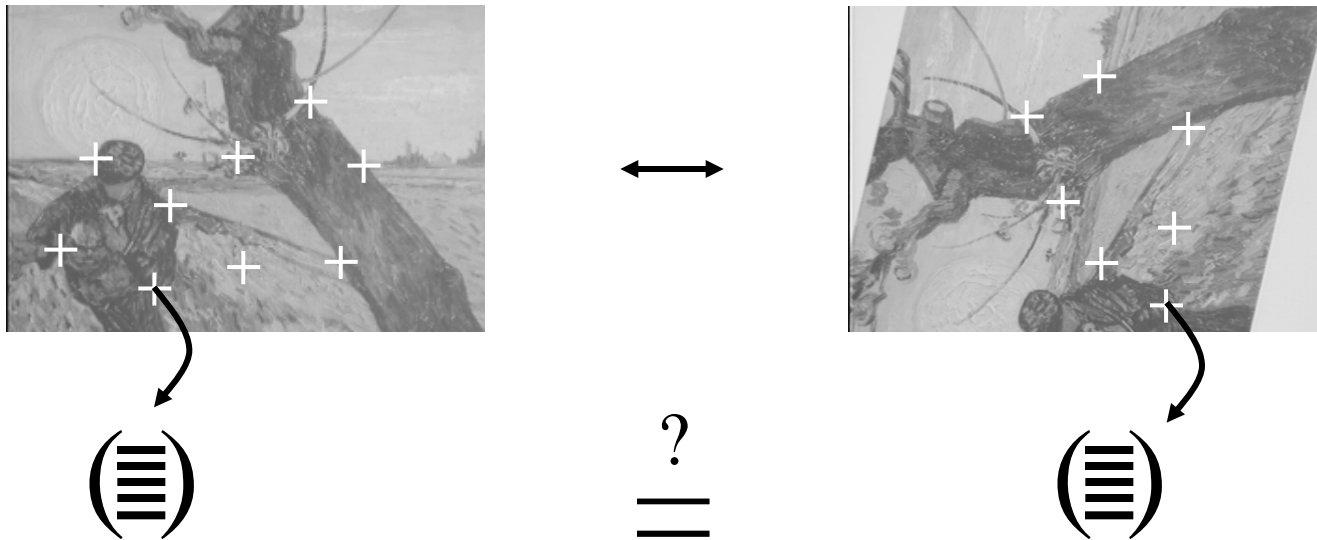
Some Details from the Harris Paper

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

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

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

Determining correspondences

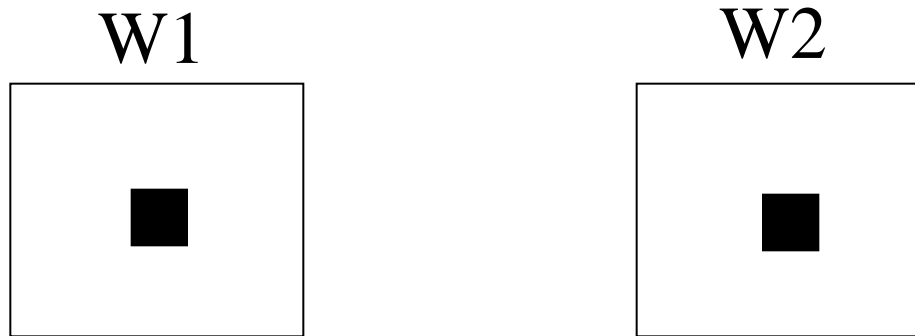


Vector comparison using a distance measure

What are some suitable distance measures?

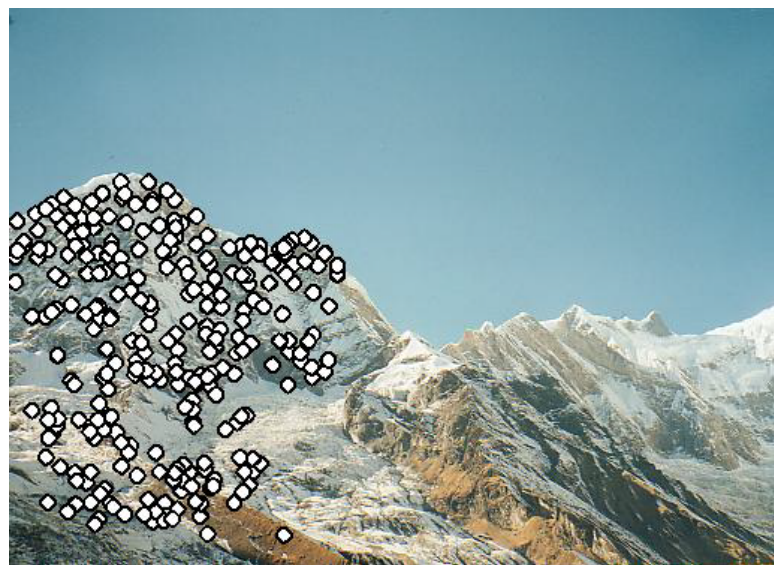
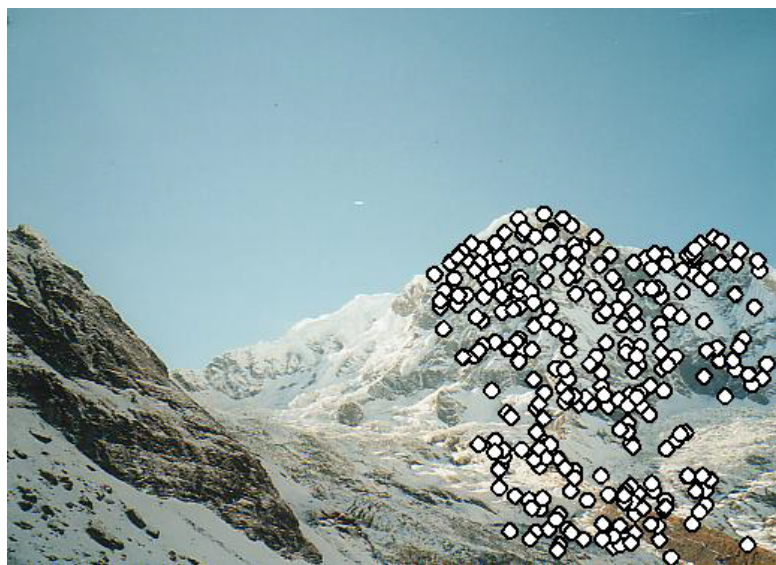
Distance Measures

- 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 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

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scaled

	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	?
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Rotation/Scale Invariance



original

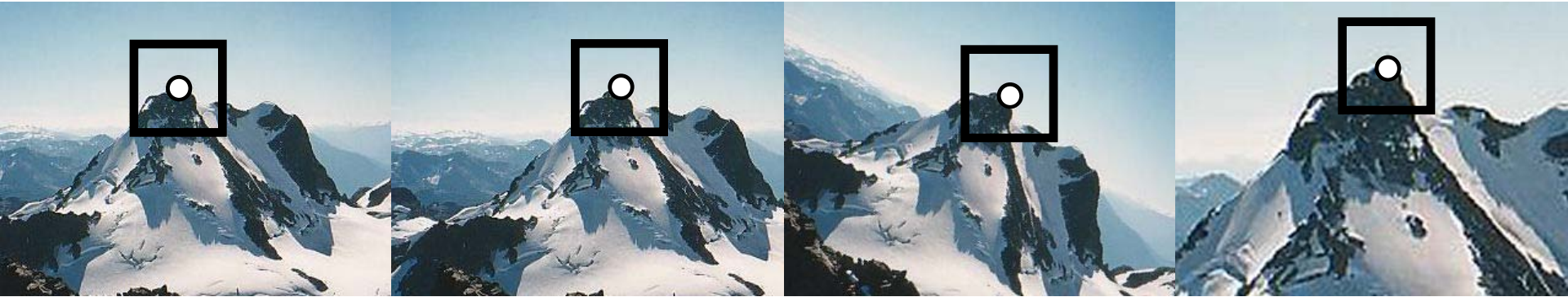
translated

rotated

scaled

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

Rotation/Scale Invariance



original

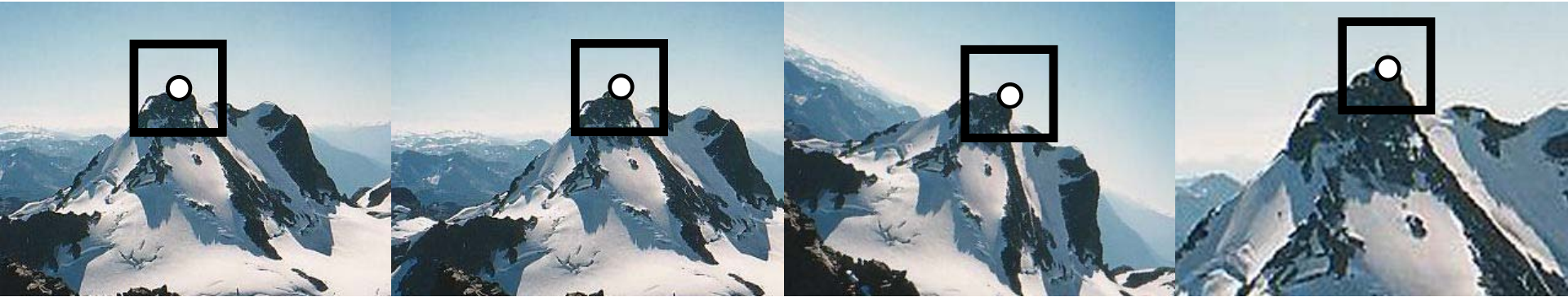
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rotated

scaled

	Translation	Rotation	Scale
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Rotation/Scale Invariance



original

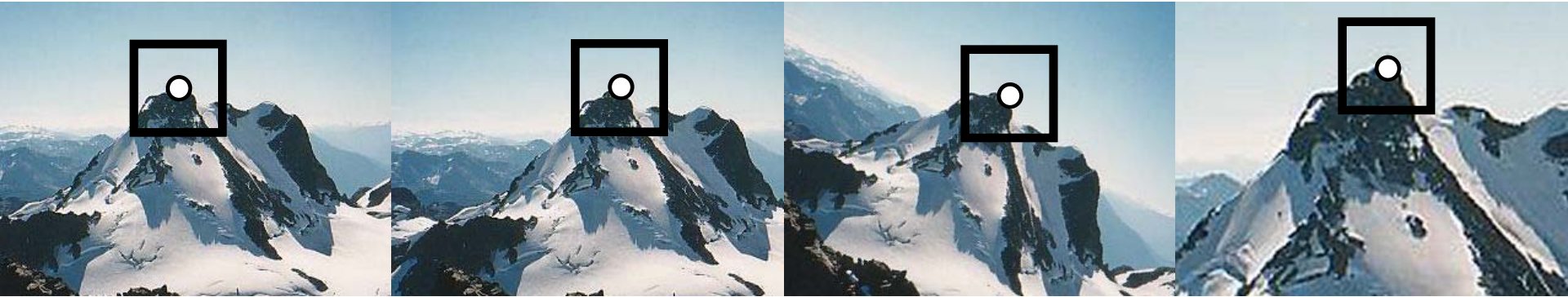
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Rotation/Scale Invariance



original

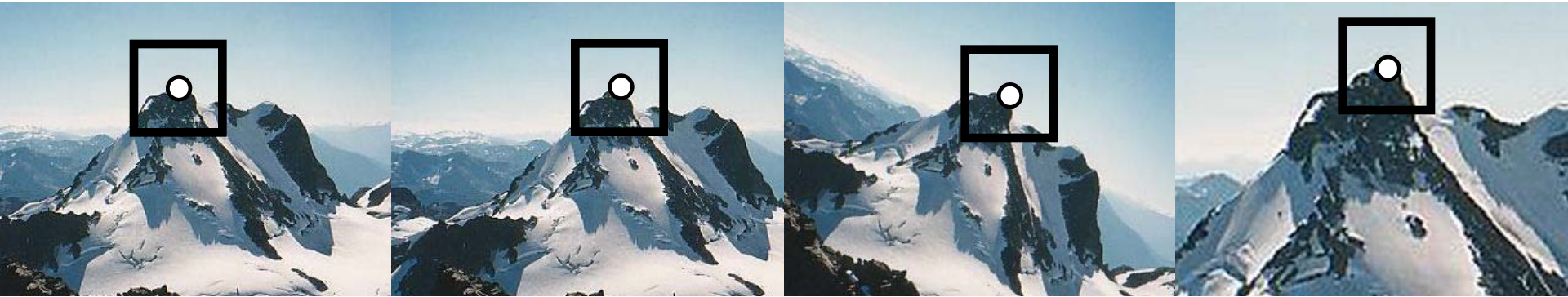
translated

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scaled

	Translation	Rotation	Scale
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Rotation/Scale Invariance



original

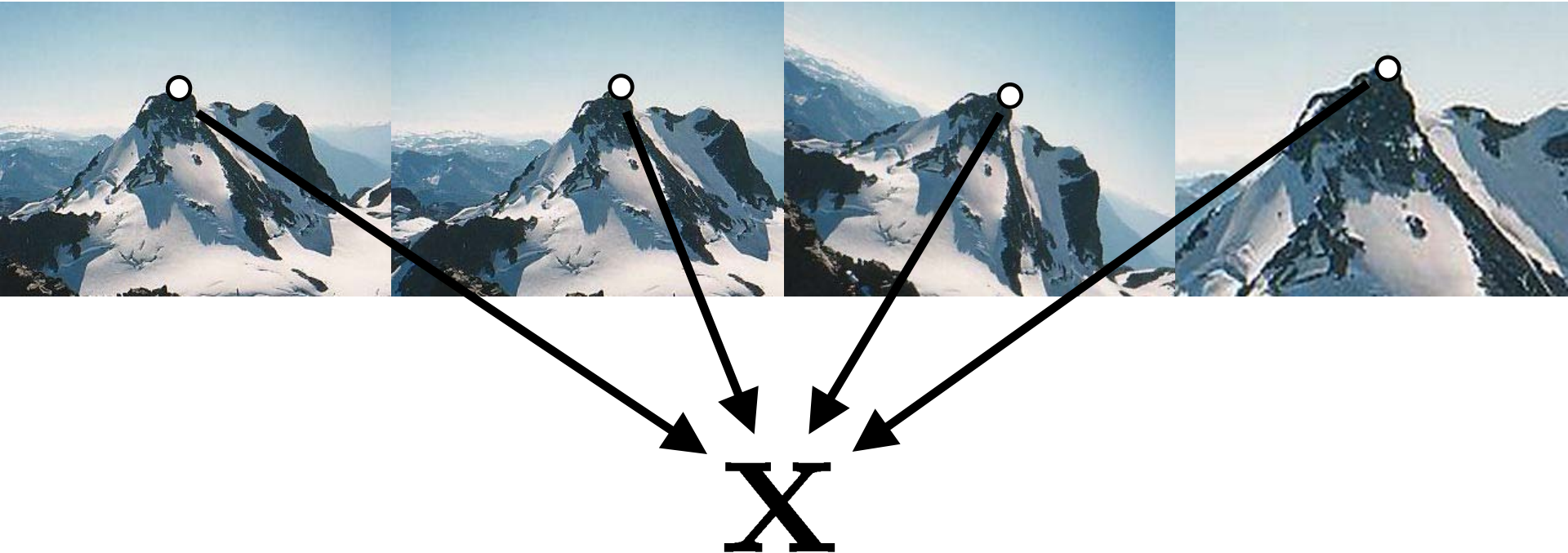
translated

rotated

scaled

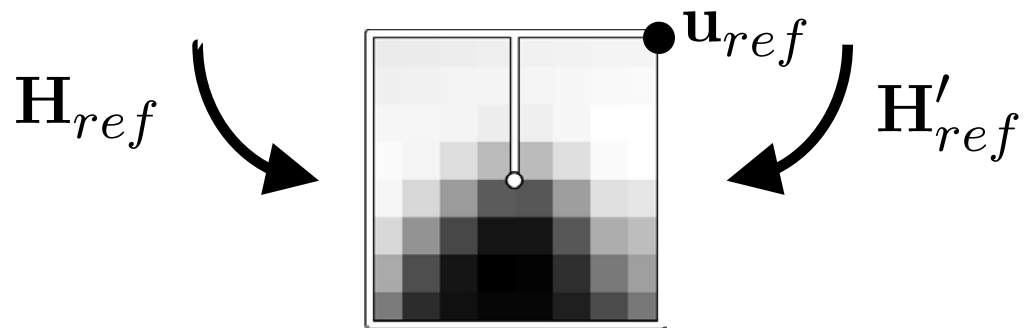
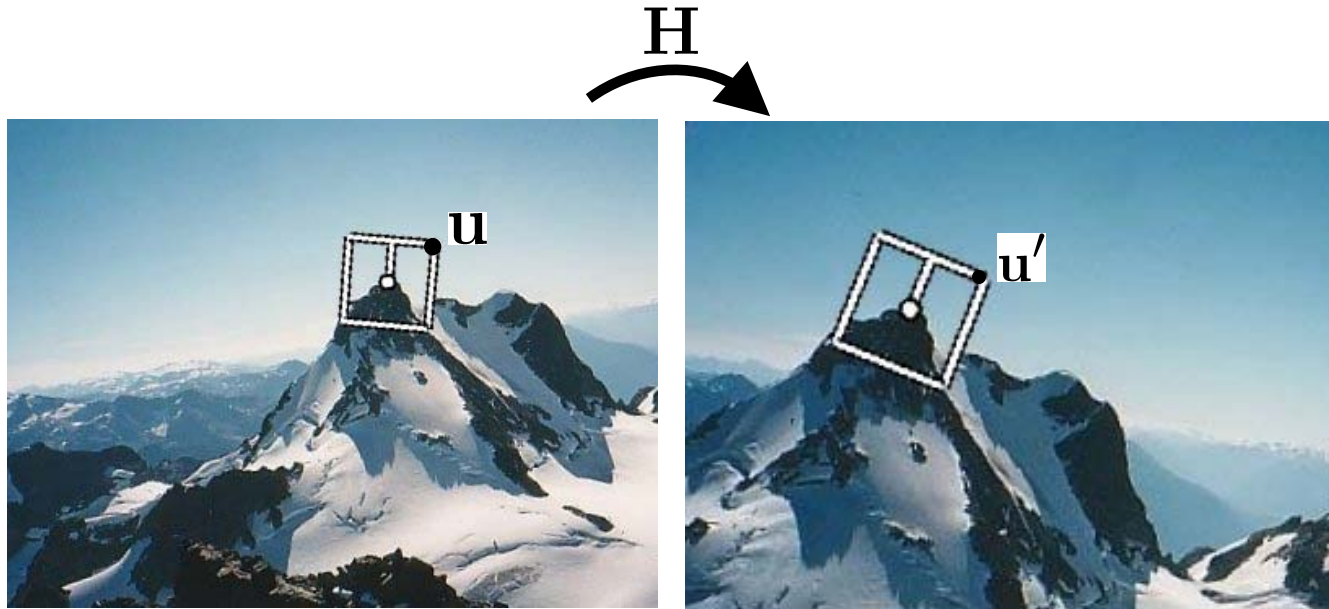
	Translation	Rotation	Scale
Is Harris invariant?	YES	YES	NO
Is correlation invariant?	YES	NO	NO

Matt Brown's Invariant Features



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

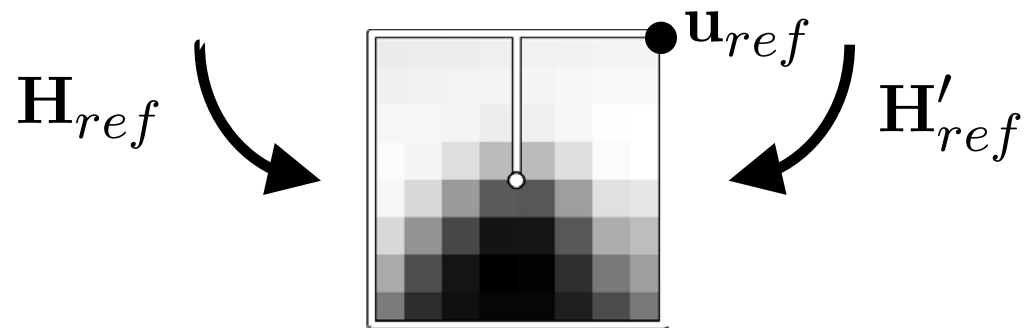
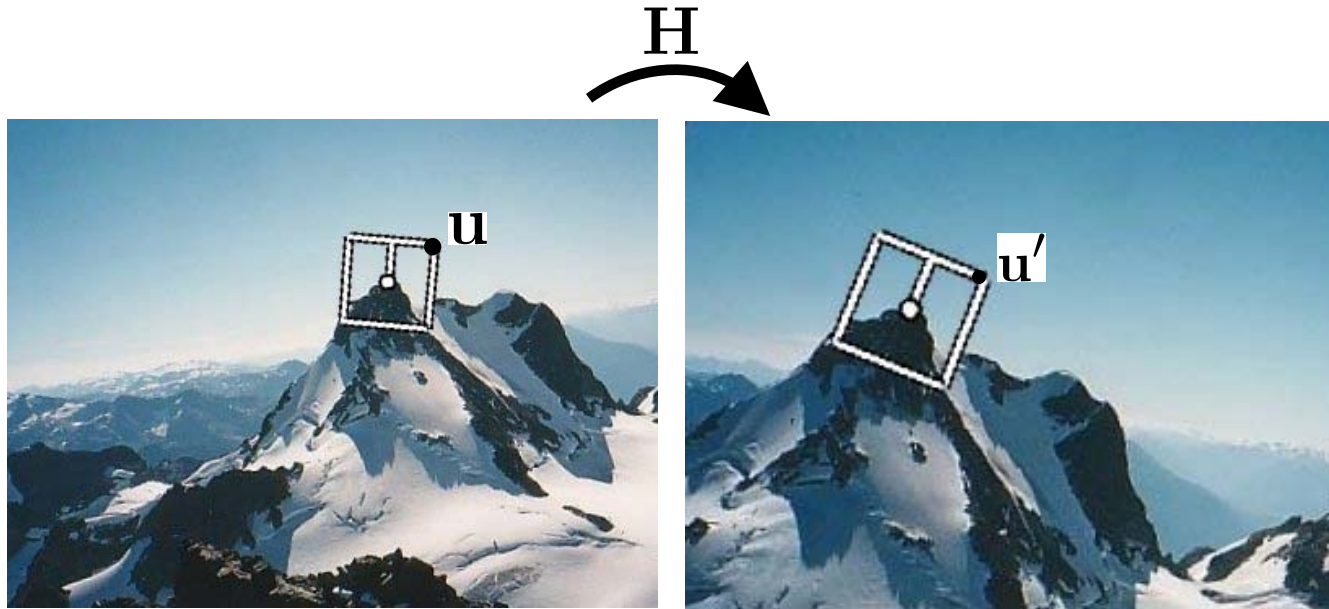
Canonical Frames



$$u' = Hu$$

$$H'_{ref} = H_{ref}H^{-1}$$

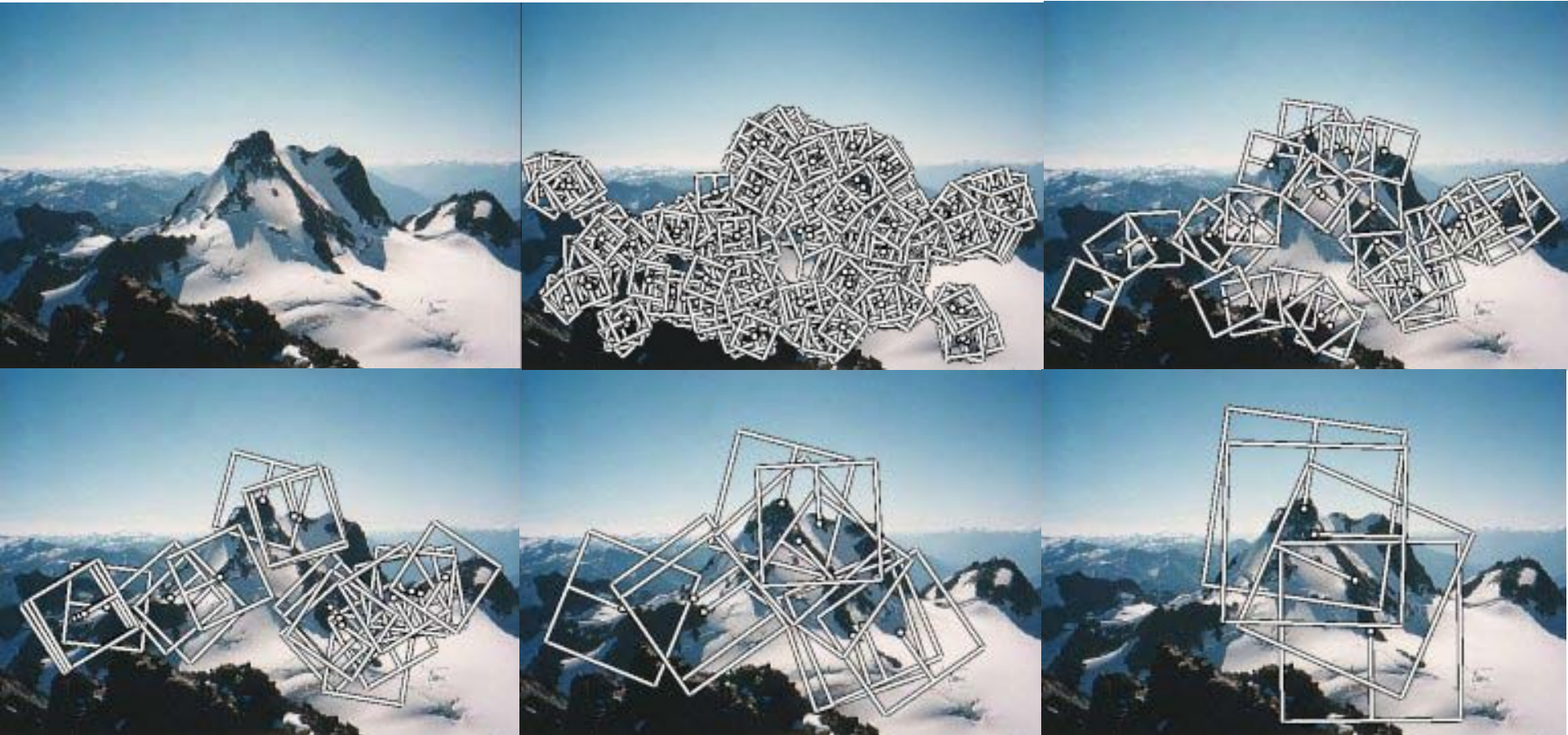
Canonical Frames



$$u' = Hu$$

$$H'_{ref} = H_{ref}H^{-1}$$

Multi-Scale Oriented Patches



- Extract oriented patches at multiple scales using dominant orientation

Multi-Scale Oriented Patches

- Sample scaled, oriented patch



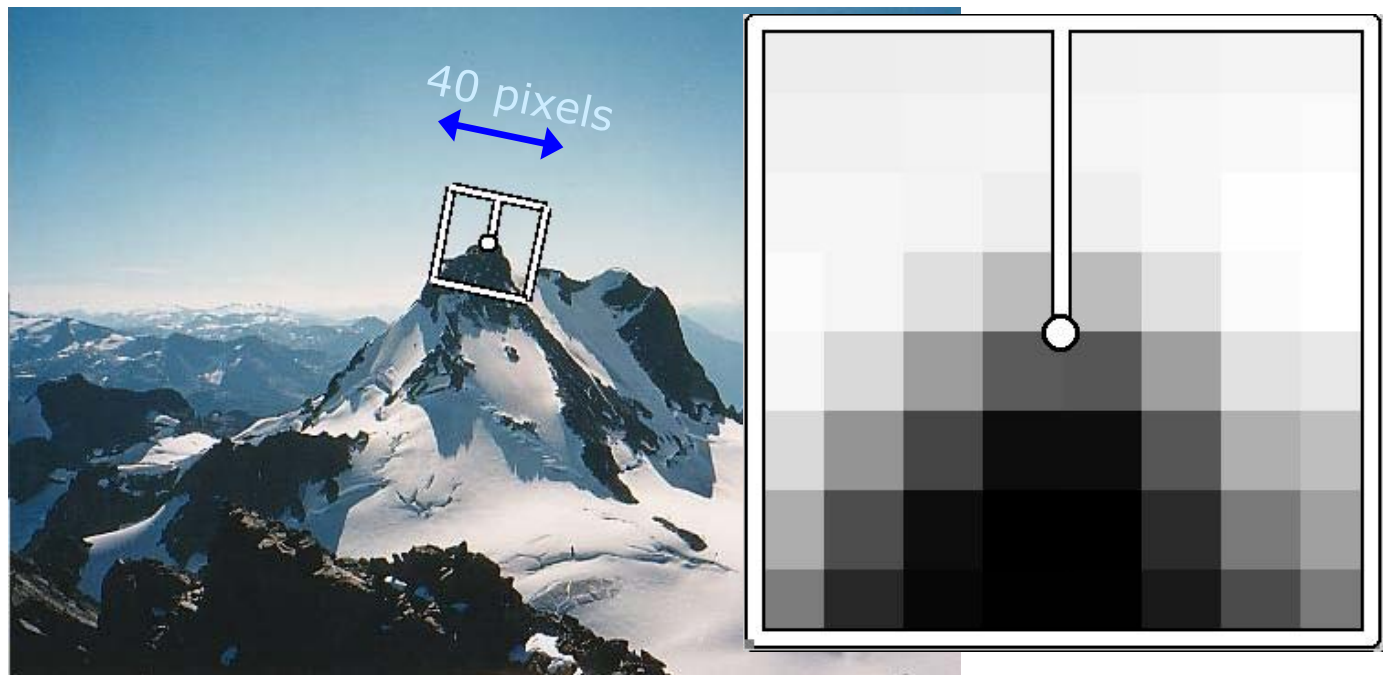
Multi-Scale Oriented Patches

- 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