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CENTRE FOR AUTONOMOUS SYSTEMS

41014 Sensors and Control for Mechatronic Systems

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1. Lecture 1-3

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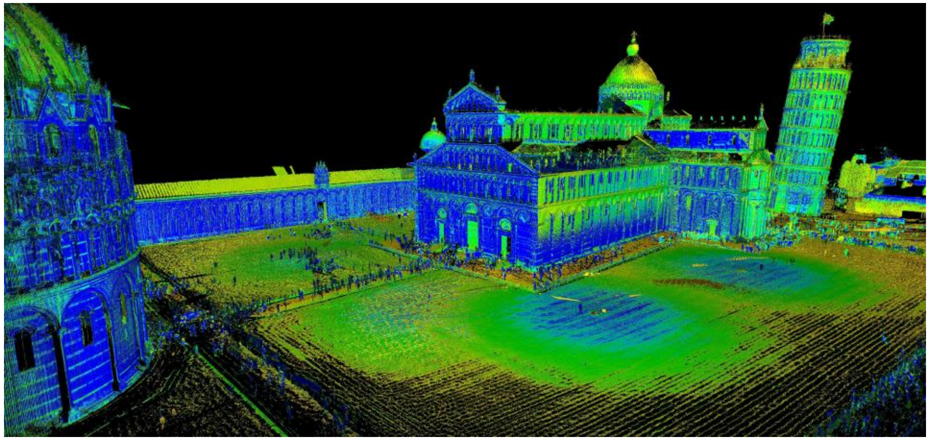
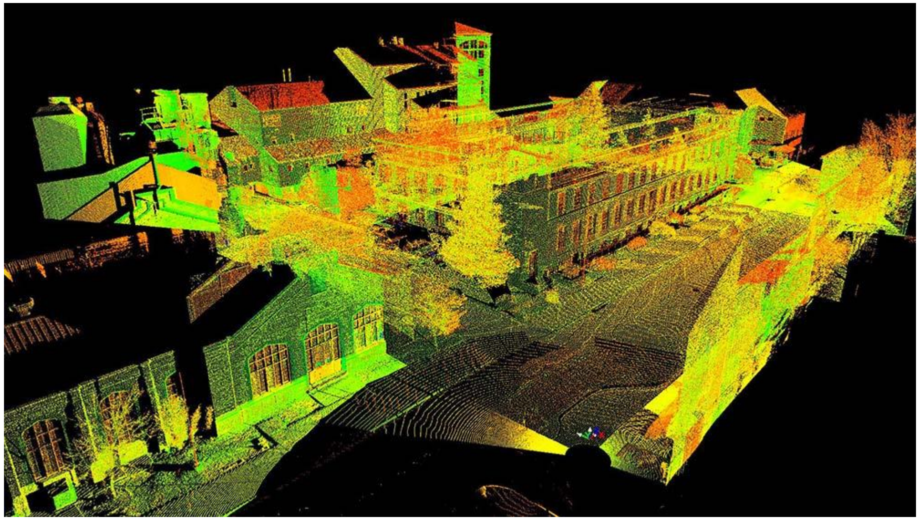
- **Sensors:**
  - Cameras
  - RGB-D Cameras
  - ToF sensors

- **In details of**
  - Fundamental
  - Data and Processing





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41014 Sensors and Control for Mechatronic Systems

Lecture-5: Feature Extraction and Tracking

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1. Lecture-5

❖ Lecture:

- Feature Extraction and Tracking
- Harris Corner Detection
- SIFT Feature Extraction and Matching
- SURF Feature Extraction and Matching
- RANSAC Outlier Removal

❖ Active hands on:

1. Lecture-5

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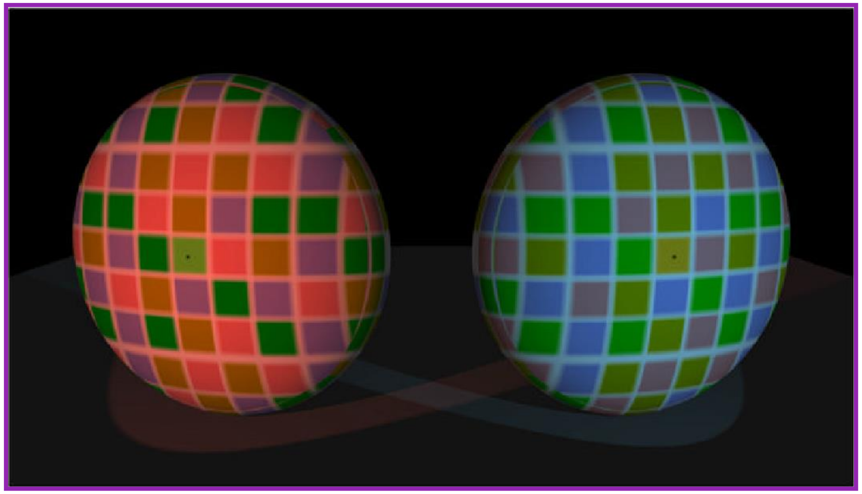
- **Lecture:**
  - Feature Extraction and Tracking
- **Active hands on: Run codes of**
  - Harris Corner detection;
  - SIFT feature extraction and matching;
  - SURF feature extraction and matching.
  - RANSAC outlier removal;

3.1 Features

What is a feature?

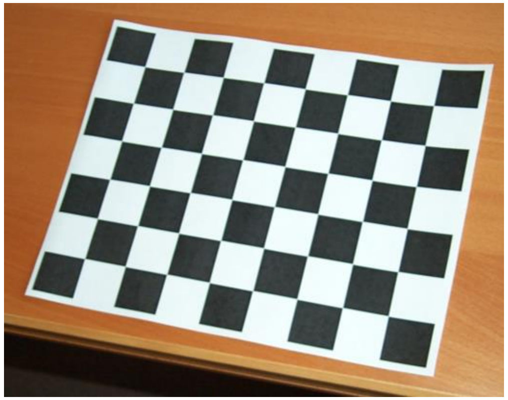
- Local, meaningful, detectable part in an image
  - Corners
  - Lines
  - Square, etc…



Why use features?

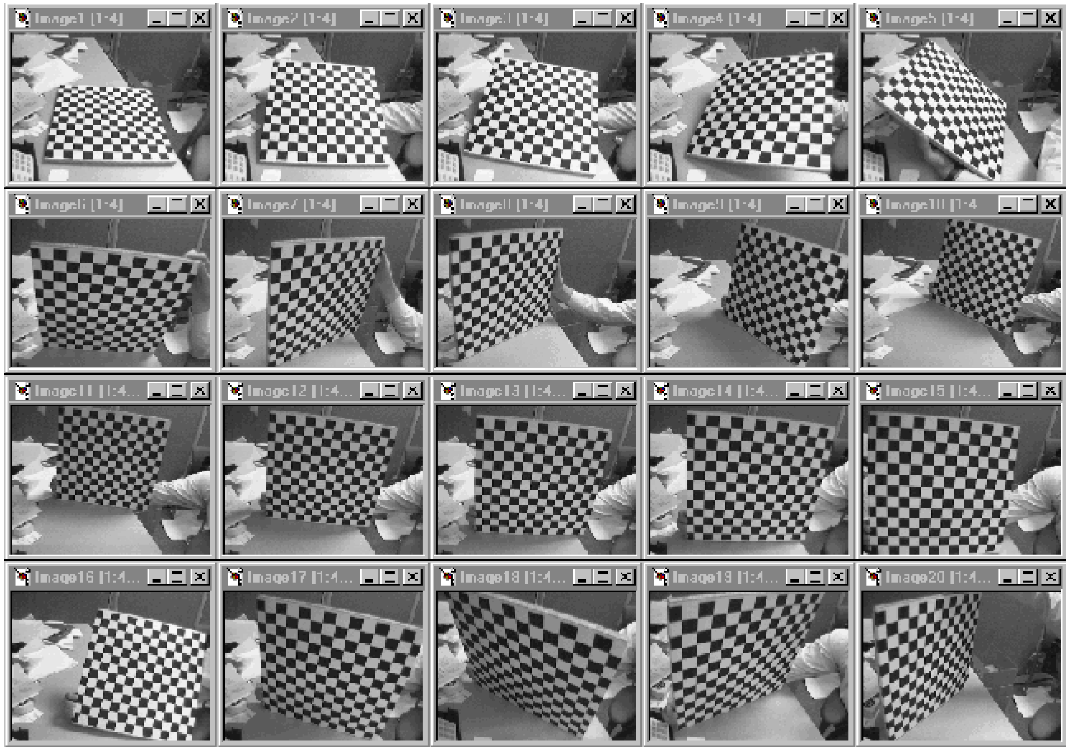
- Information content is high
- Invariant to change of view point, illumination
- Reduces computational burden

3.1 Features



❖ What is a good feature?

- Invariance
  - View point (scale, orientation, translation)
  - Lighting condition
  - Object deformations
  - Partial occlusion

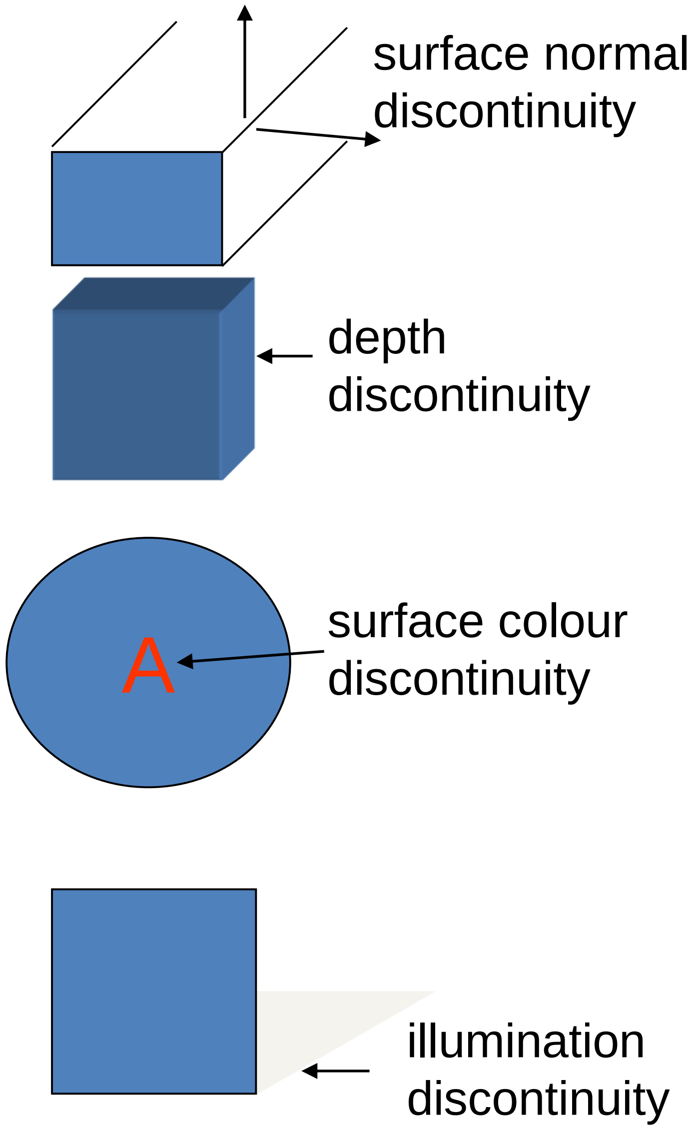


❖ Other Characteristics

- Uniqueness
- Sufficiently many
- Tuned to the task

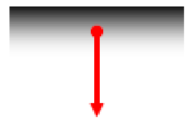
3.2 Edges

- Edge in an image can be due to many causes
- Edge can be considered as a compact representation of part of the image
- Biological plausibility
- Initial stages of mammalian vision systems involve detection of edges and local features

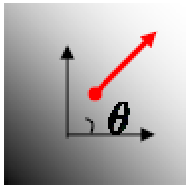


- The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x} \quad \frac{\partial f}{\partial y} \right]$

$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$



$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$



$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

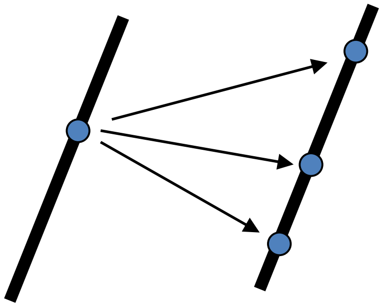
- The gradient direction is given by: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} \Big/ \frac{\partial f}{\partial x} \right)$

- The gradient magnitude is given by:

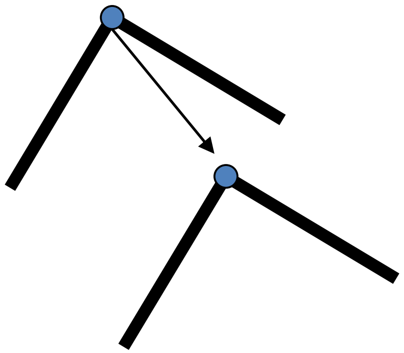
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

3.3 Corners

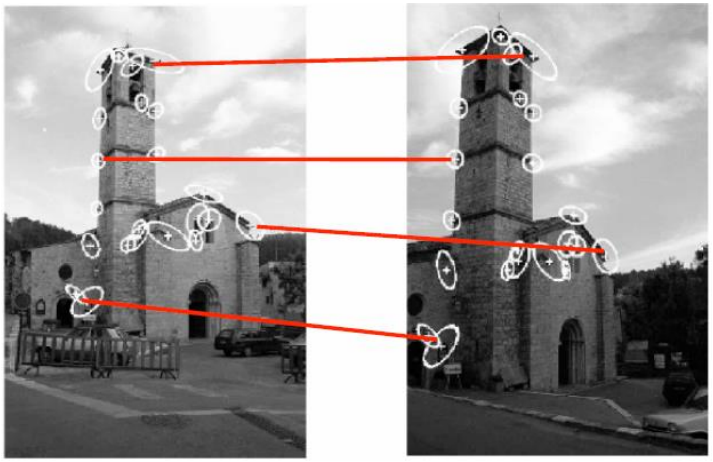
- Intensity gradient exactly at a corner is ambiguous
- However, in the region around a corner, gradient has two or more different values.
- Corners are spatially better distinguishable features than edges



Point on a line is ambiguous



Corner is non ambiguous



3.3 Harris Corner Detector

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- Harris corner detector
- Second order moment matrix

$$C = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

- Consider the following example

- Symmetric matrix
- Sum over a small region around the interested point

$$C = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

- All the values are gradients in x (I_X) or y (I_Y) directions
- If either λ is close to 0, then this is not a corner, so look for locations where both are large

4.1 SIFT

- The Harris operator is not invariant to scale and correlation is not invariant to rotation.

- **Scale-invariant feature transform**
  - SIFT: to detect and describe local features in an images.
  - Proposed by David Lowe in ICCV1999.
  - Refined in IJCV 2004.
  - Cited more than 12000 times till now.
  - Wildly used in image search, object recognition, video tracking, gesture recognition, etc.

David Lowe
Professor in UBC

Why SIFT is so popular?

An instance of object matching

4.1 SIFT

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- **Why SIFT is so popular?**

- **Desired property of SIFT**
  - Invariant to scale change
  - Invariant to rotation change
  - Invariant to illumination change
  - Robust to addition of noise
  - Robust to substantial range of affine transformation
  - Robust to 3D view point
  - Highly distinctive for discrimination

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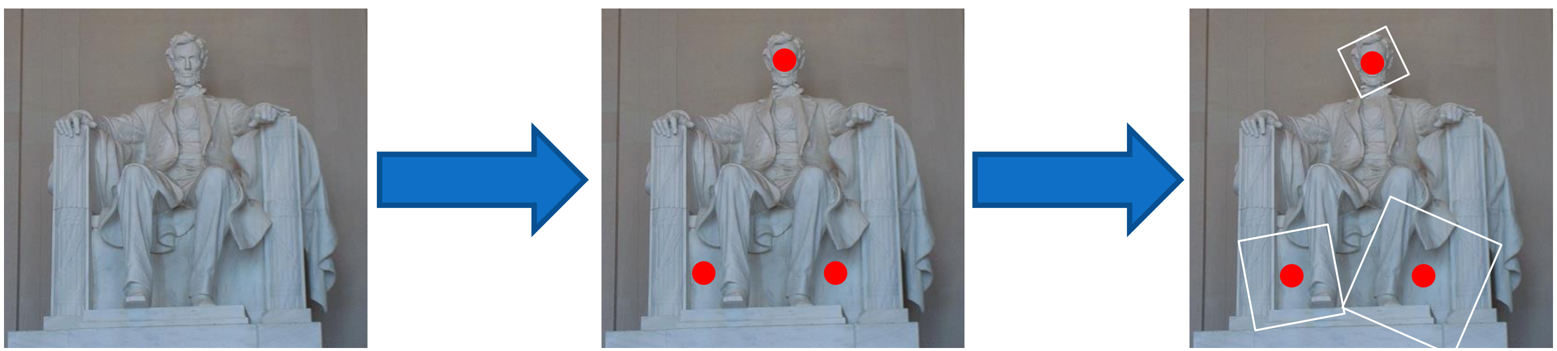
How to extract SIFT



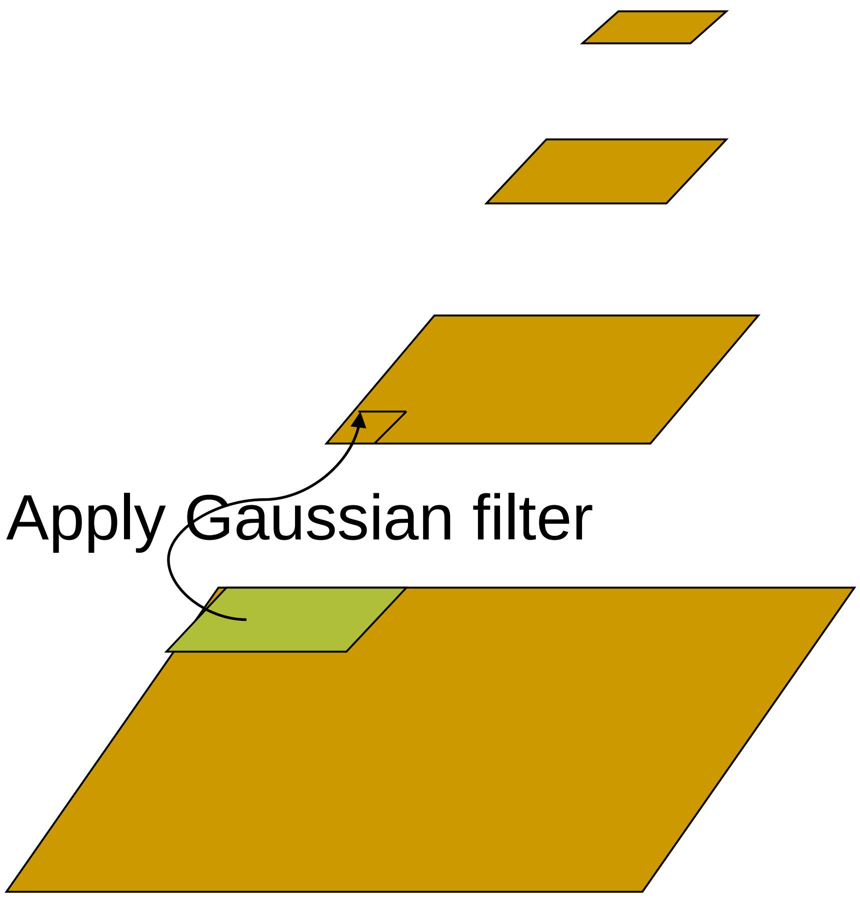
Test image

Detector: where are the local features?

Descriptor: how to describe them?

4.2 SIFT: Feature

- **Aside: Gaussian Pyramid**
  At each level, image is smoothed and reduced in size



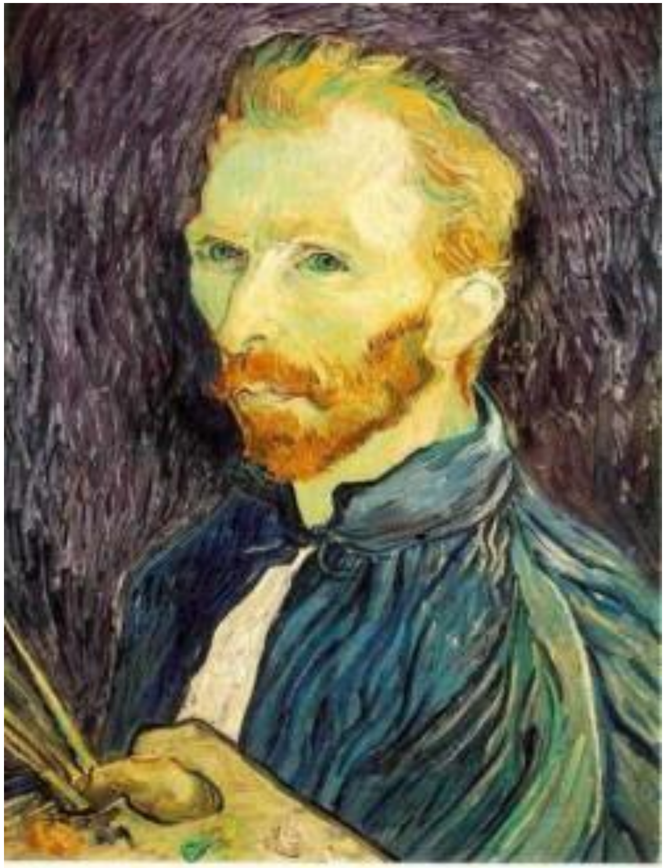
And so on

At 2nd level, each pixel is the result of applying a Gaussian mask to the first level and then subsampling to reduce the size

Bottom level is the original image

4.2 SIFT: Feature

- **Example: Subsampling with Gaussian pre-filtering**



Gaussian 1/2

G 1/4

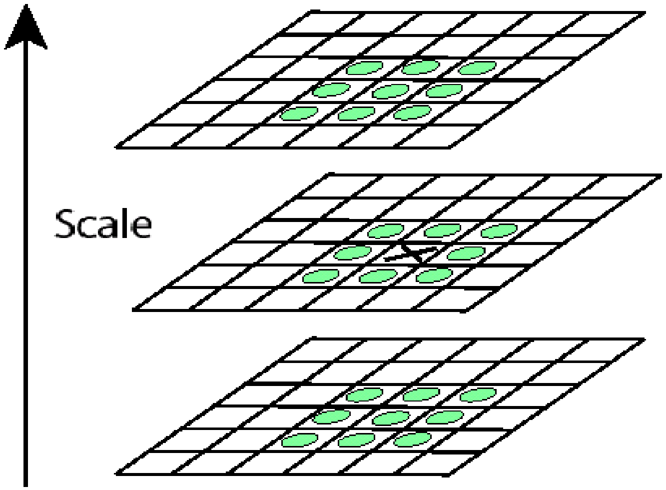
G 1/8

4.2 SIFT: Feature

- **Detect maxima and minima of difference-of-Gaussian in scale space**

s+2 difference images.
top and bottom ignored.
s planes searched.

- **Each point is compared to its 8 neighbors in the current image and 9 neighbors each in the scales above and below**

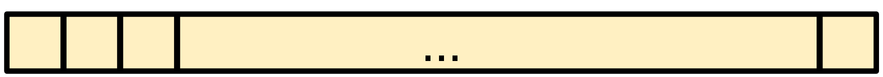


For each max or min found, output is the location and the scale.

4.3 SIFT: Descriptor

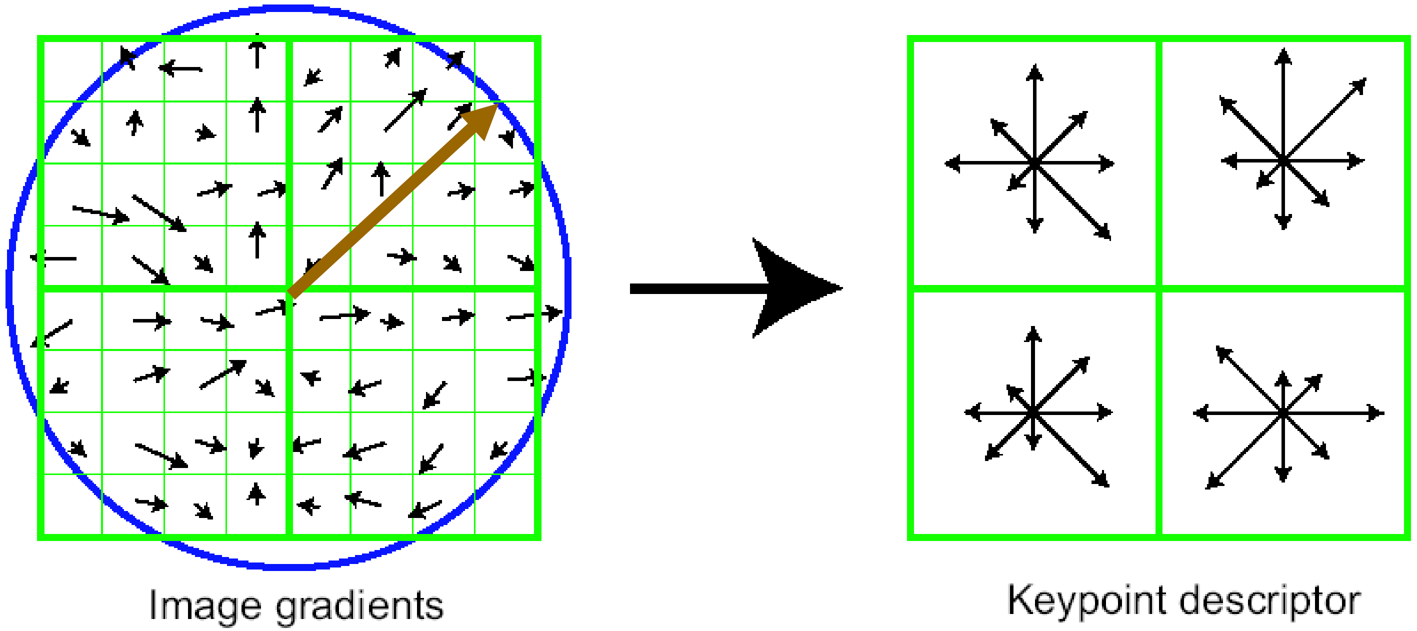
SIFT Keypoint Descriptor

- use the normalized region about the keypoint
- compute gradient magnitude and orientation at each point in the region
- weight them by a Gaussian window overlaid on the circle
- create an orientation histogram over the 4 X 4 subregions of the window
- 4 X 4 descriptors over 16 X 16 sample array were used in practice. 4 X 4 times 8 directions gives **a vector of 128 values**.



4.3 SIFT: Descriptor

- **Lowe's Keypoint Descriptor (shown with 2 X 2 descriptors over 8 X 8)**



In experiments, 4x4 arrays of 8 bin histogram is used, a total of 128 features for one keypoint

4.4 SIFT: Applications

- **Feature points are used also for:**
  - Image alignment (homography, fundamental matrix)
  - 3D reconstruction (e.g. Photo Tourism)
  - Motion tracking
  - Object recognition
  - Indexing and database retrieval
  - Robot control & navigation
  - … many others

4.5 SIFT: Example

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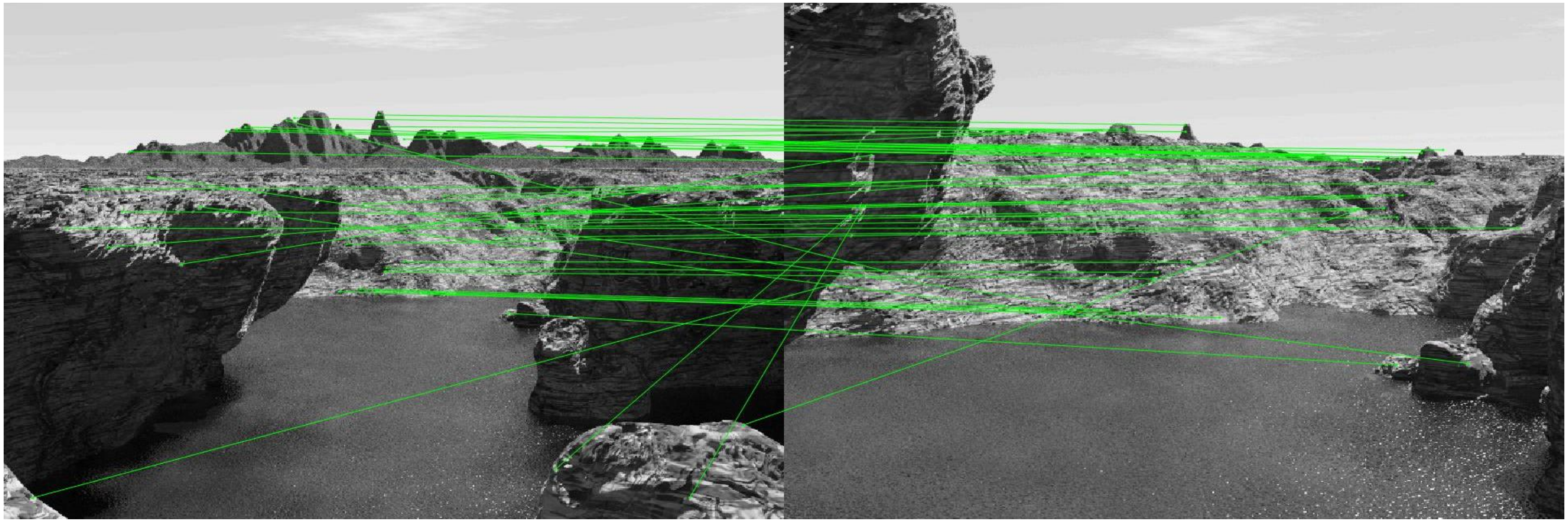
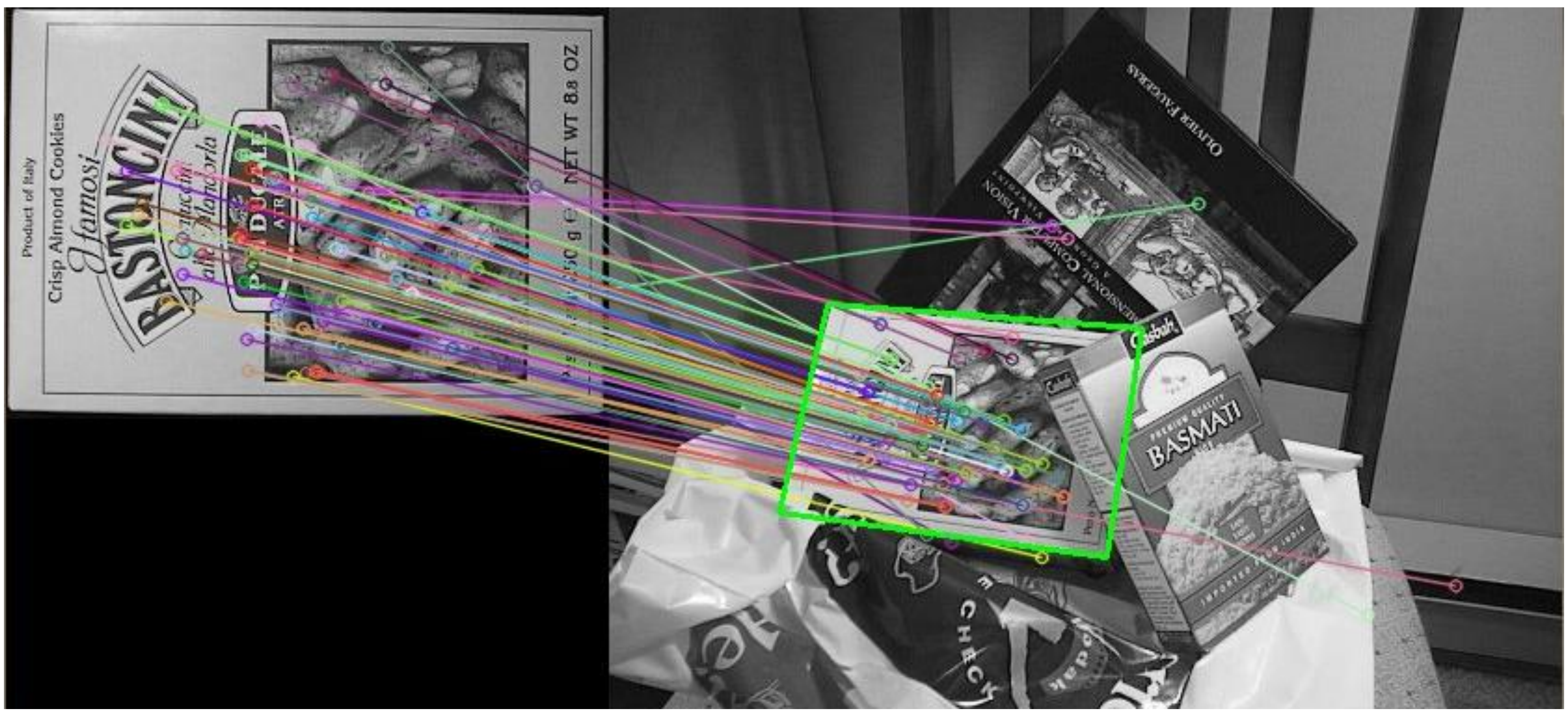
- SIFT Example



5.1 SURF

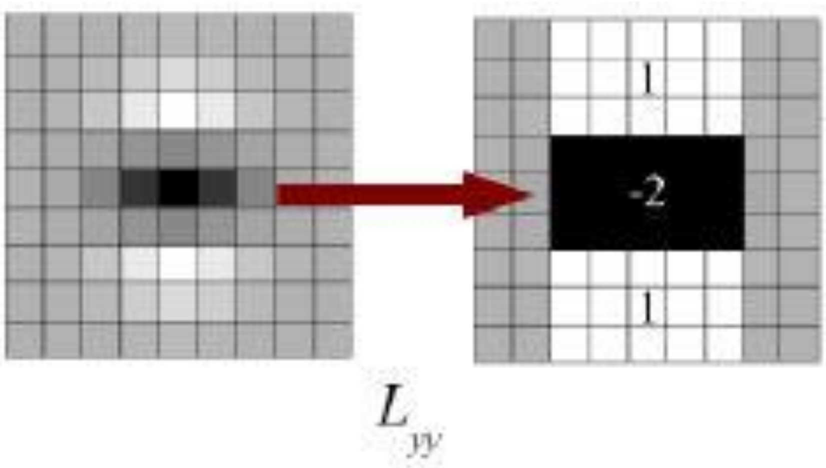
❖ SURF: Speeded Up Robust Features

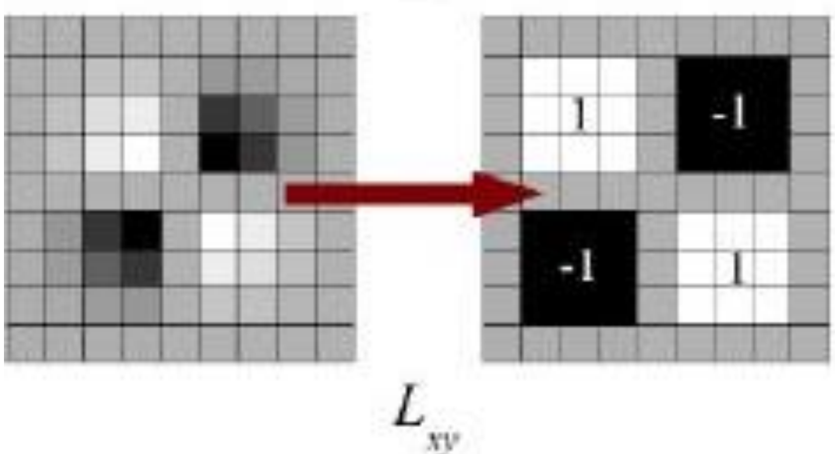
- Comparing to SIFT
- Speed up in both feature location and descriptor



❖ SURF: Speeded Up Robust Features

- Feature location
- SIFT: approximate Laplacian of Gaussian with Difference of Gaussian for finding scale-space.
- SURF: goes a little further and **approximates LoG with Box Filter**.



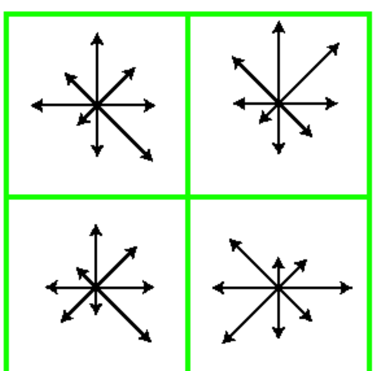


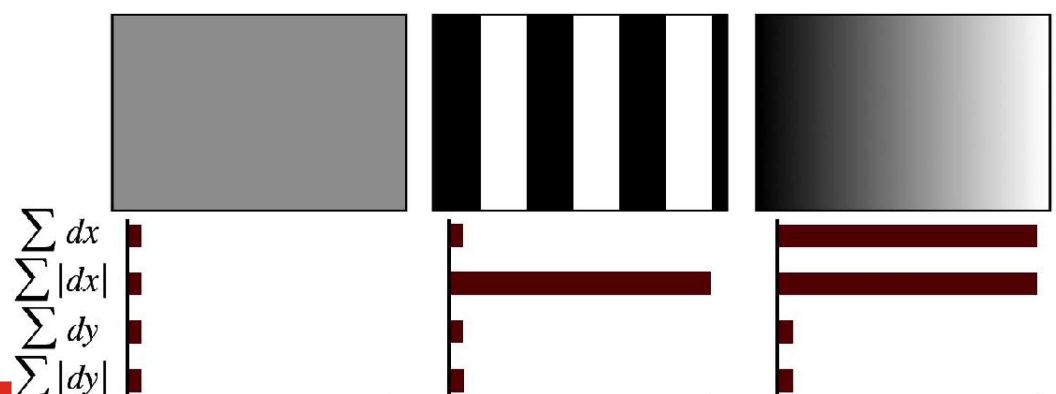
5.3 SURF: Descriptor

❖ SURF: Speeded Up Robust Features

- Feature descriptor
- SIFT: 4 X 4 descriptors over 16 X 16 sample array. 4 X 4 times 8 directions gives **a vector of 128 values**.
- SURF: uses Wavelet responses in horizontal and vertical direction: 4x4 subregions, for each subregion **horizontal and vertical** wavelet responses are taken. **4x4x4=64**

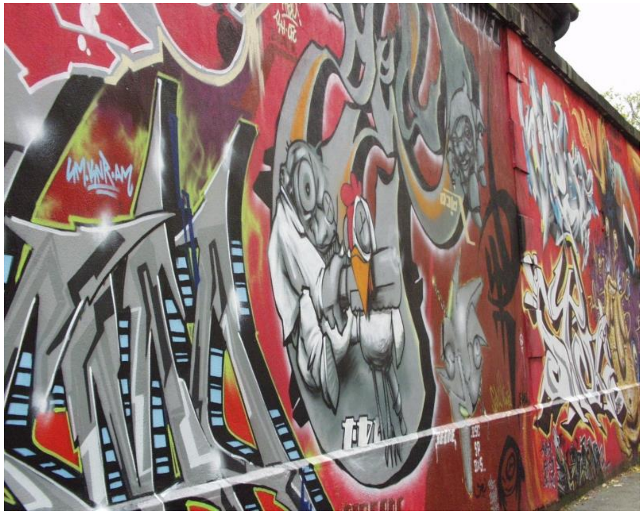
$$v = \left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right)$$

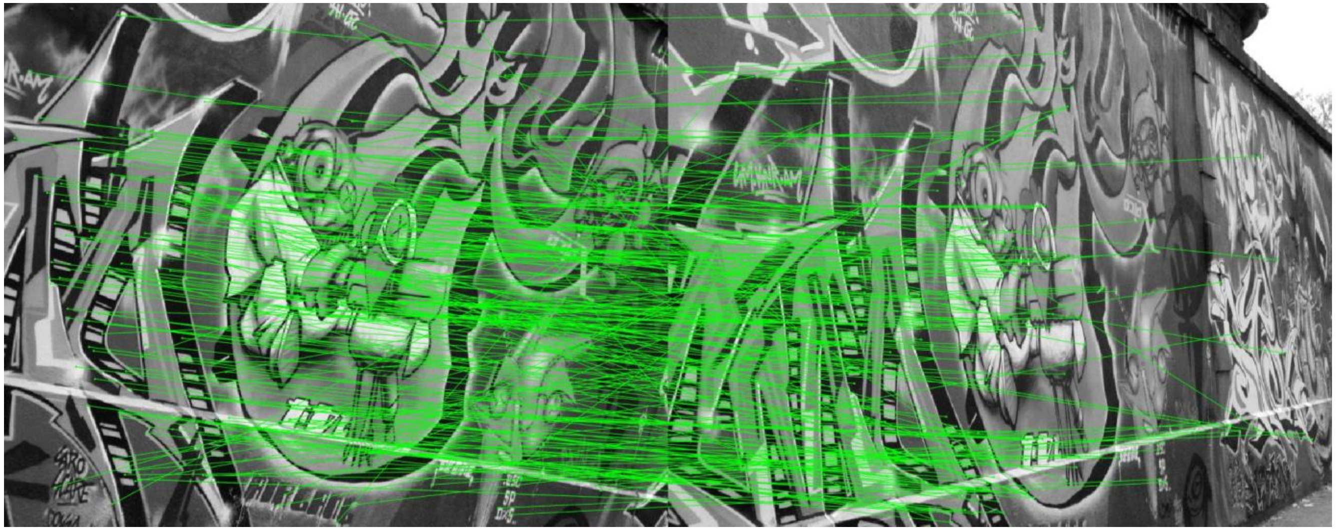




6. RANSAC

❖ Outlier Removal





6.1 RANSAC

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RANSAC: RANdom SAmple Consensus

Objective

Robust fit of model to data set S which contains outliers

Algorithm

(i) Randomly select a sample of *s* data points from S and instantiate the model from this subset.

(ii) Determine the set of data points S_i which are within a distance threshold *t* of the model. The set S_i is the consensus set of samples and defines the inliers of S.

(iii) If the subset of S_i is greater than some threshold *T*, re-estimate the model using all the points in S_i and terminate

(iv) If the size of S_i is less than *T*, select a new subset and repeat the above.

(v) After *N* trials the largest consensus set S_i is selected, and the model is re-estimated using all the points in the subset S_i

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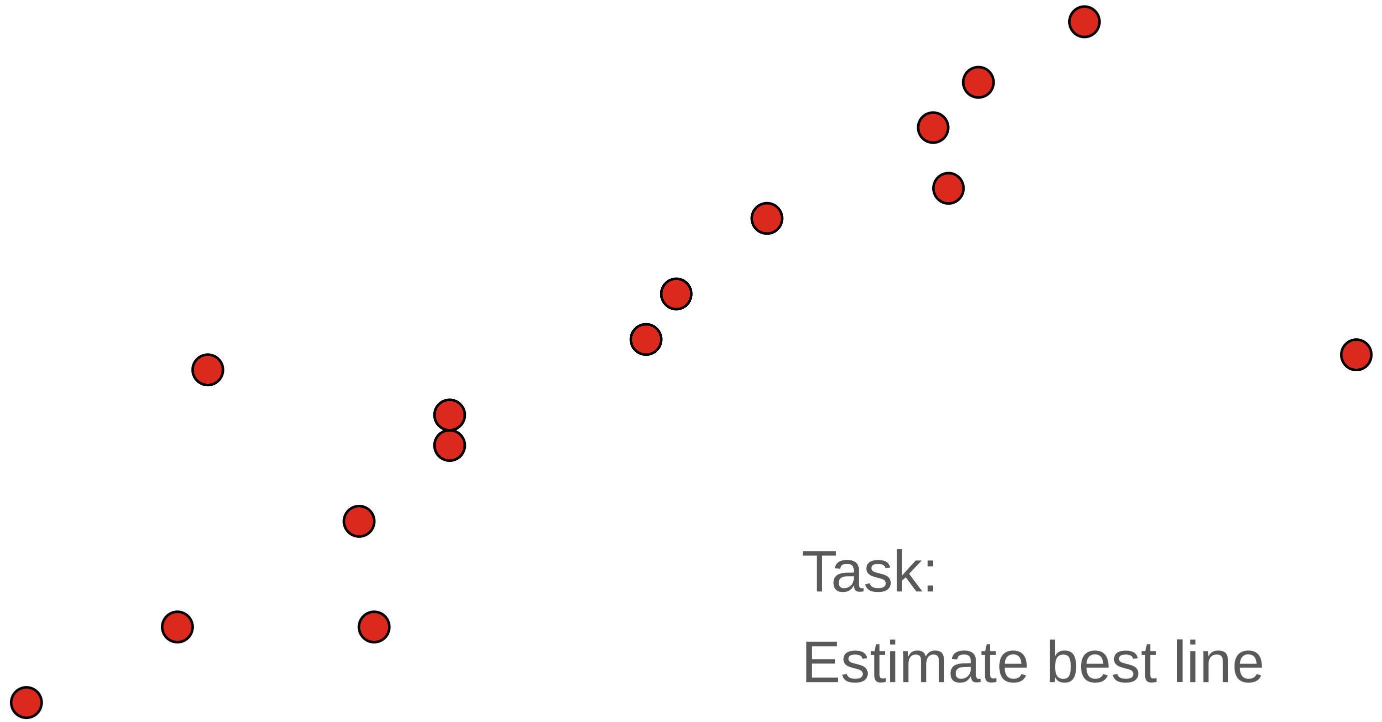
❖ RANSAC line fitting example



Task:

Estimate best line

Remove outliners

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6.1 RANSAC

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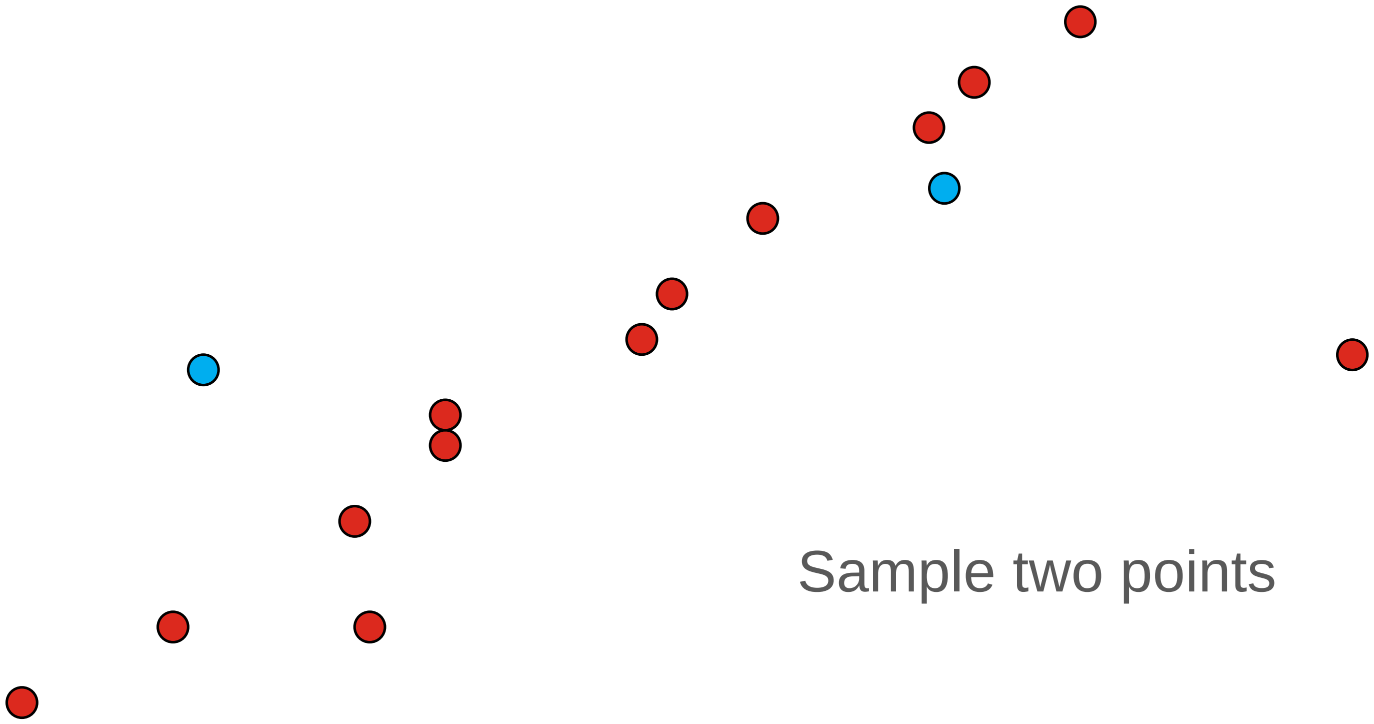
❖ **RANSAC line fitting example**



Sample two points

6.1 RANSAC

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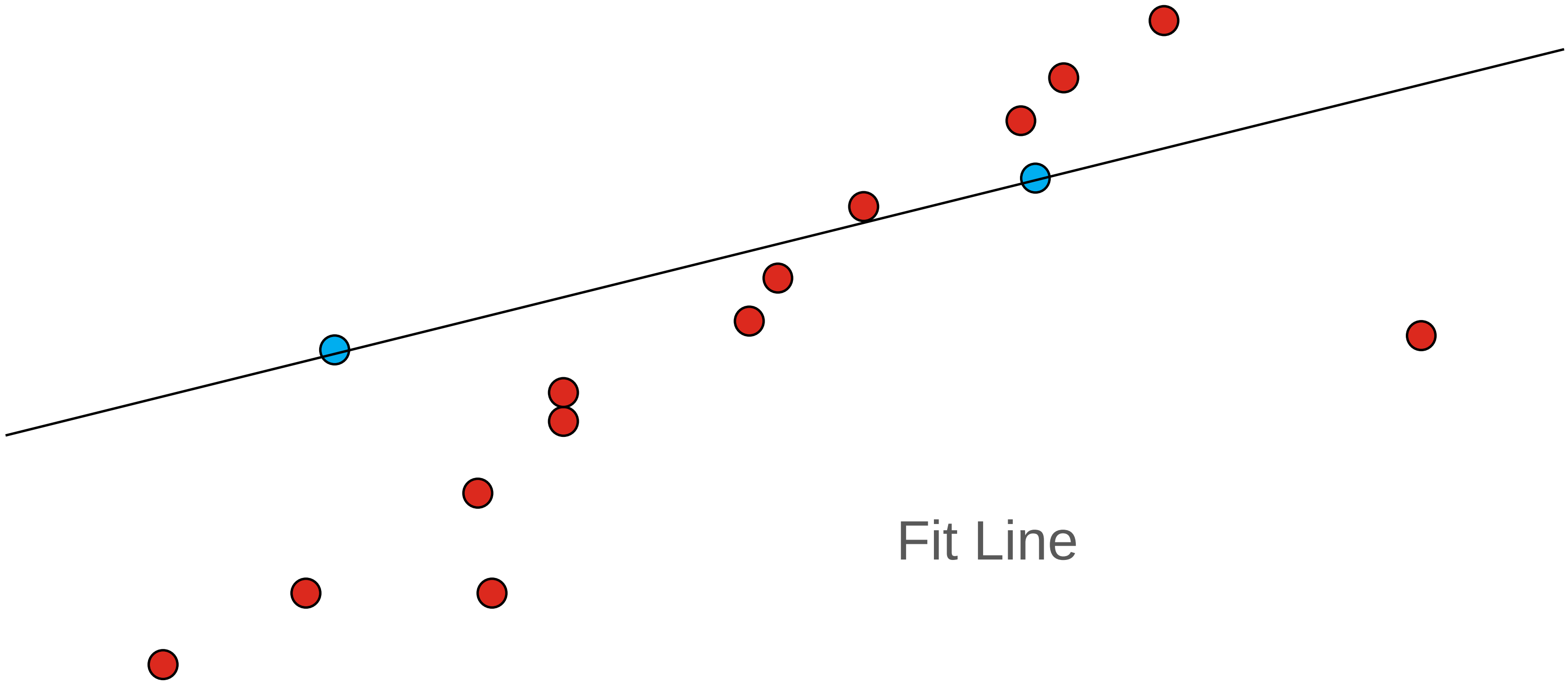
❖ **RANSAC line fitting example**



6.1 RANSAC

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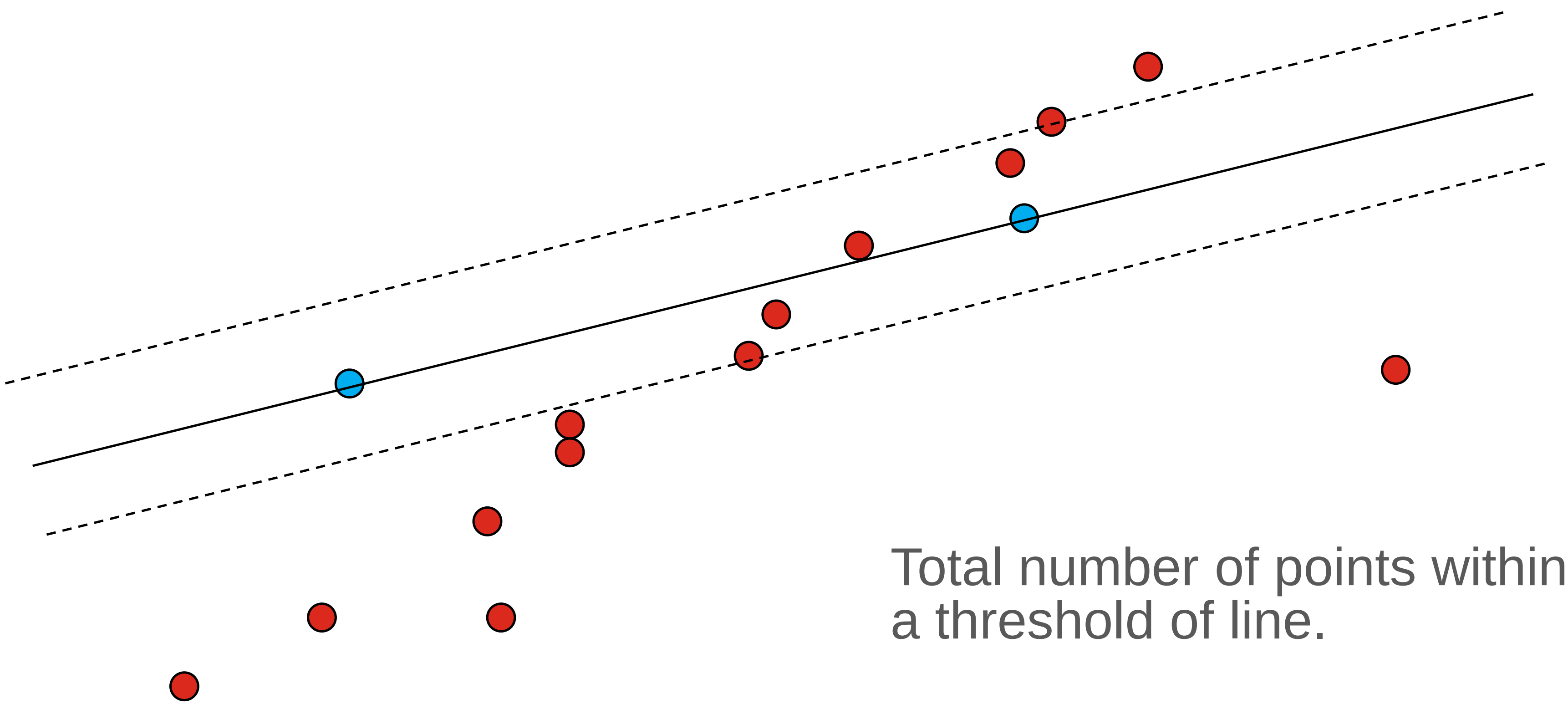
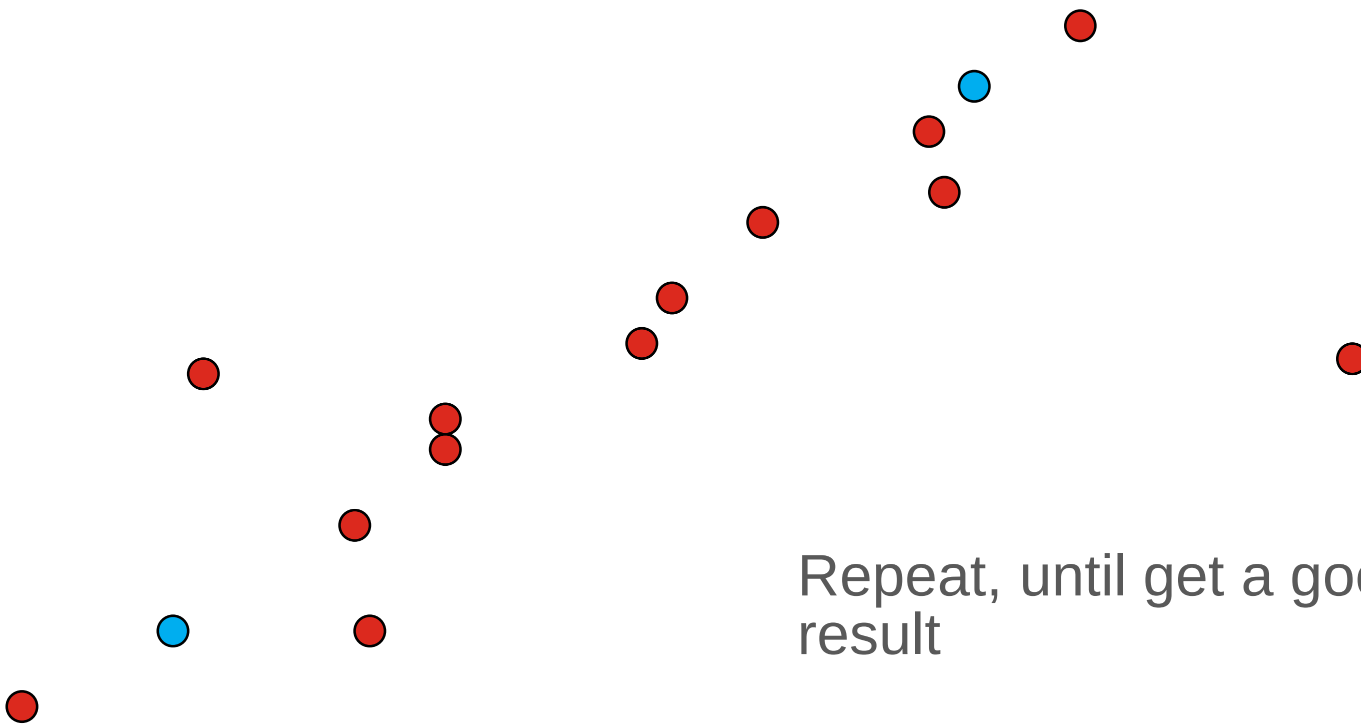
- **RANSAC line fitting example**



Total number of points within a threshold of line.

6.1 RANSAC

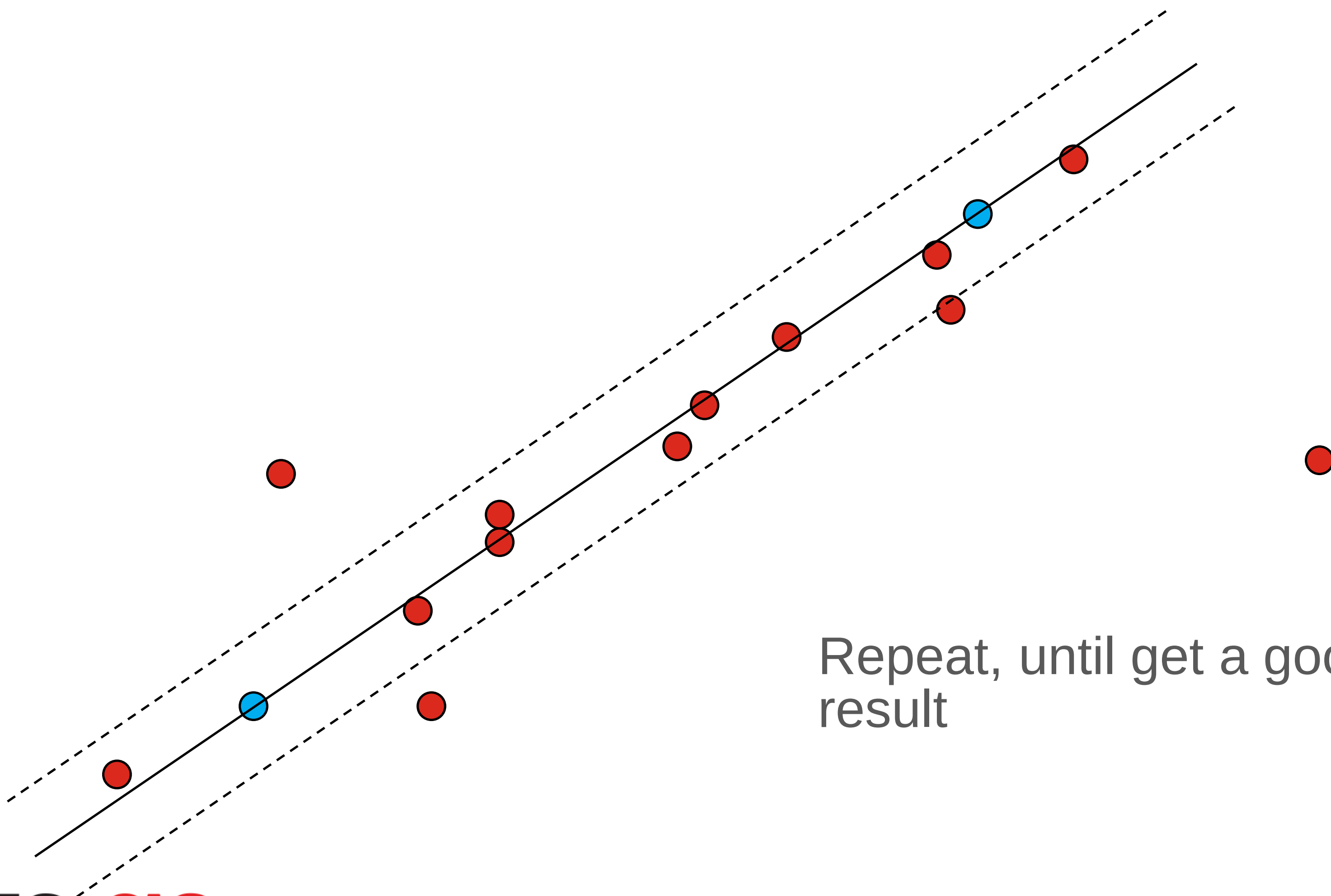
❖ RANSAC line fitting example



Repeat, until get a good result

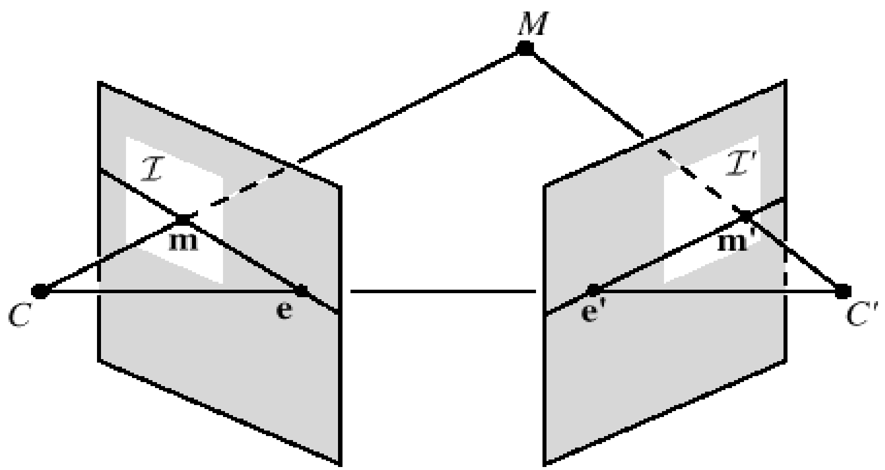
6.1 RANSAC

❖ RANSAC line fitting example



Repeat, until get a good result

RANSAC outlier removal with epipolar constraint



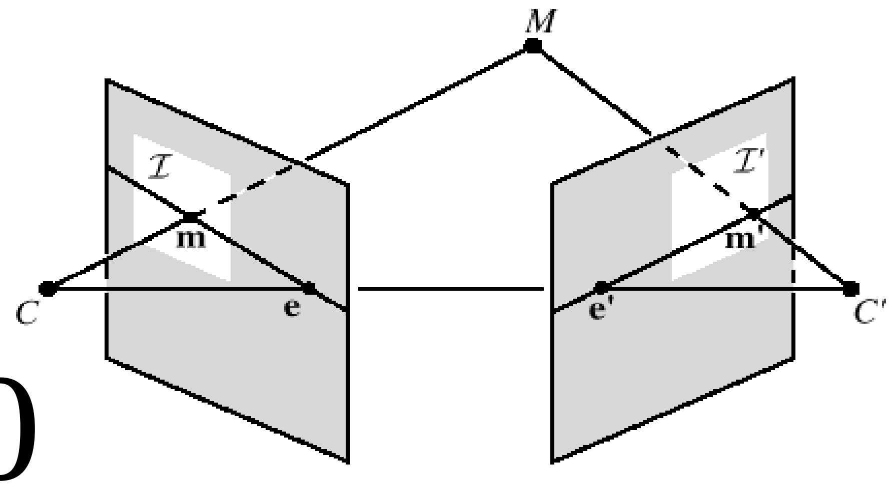
$$\mathbf{x}^T \mathbf{F} \mathbf{x}' = 0$$

$$\begin{pmatrix} x & y & 1 \end{pmatrix} \begin{bmatrix} f_1 & f_2 & f_3 \\ f_4 & f_5 & f_6 \\ f_7 & f_8 & f_9 \end{bmatrix} \begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = 0$$

6.2 RANSAC: Activity

- **Activity 2:**

- **Explain the process of RANSAC outlier removal for feature matching using epipolar constraint**



$$\mathbf{x}^T \mathbf{F} \mathbf{x}' = 0$$

$$\begin{pmatrix} x & y & 1 \end{pmatrix} \begin{bmatrix} f_1 & f_2 & f_3 \\ f_4 & f_5 & f_6 \\ f_7 & f_8 & f_9 \end{bmatrix} \begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = 0$$

6.1 RANSAC

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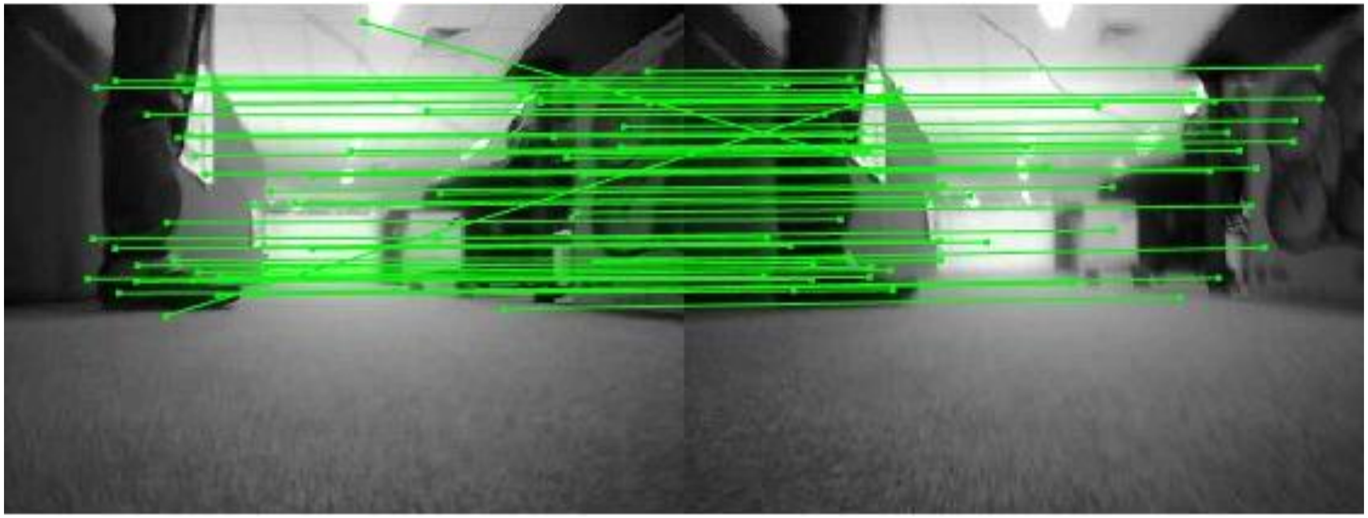
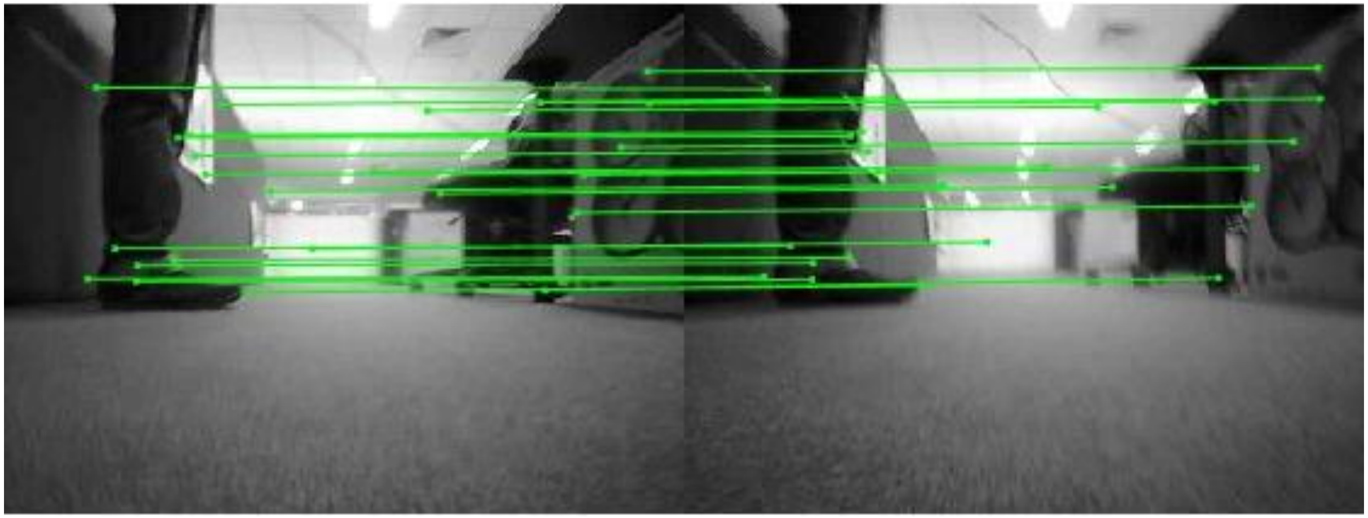
❖ **RANSAC outlier removal with epipolar constraint**





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41014 Sensors and Control for Mechatronic Systems

Next Lectures: Control

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THANK YOU

Questions?