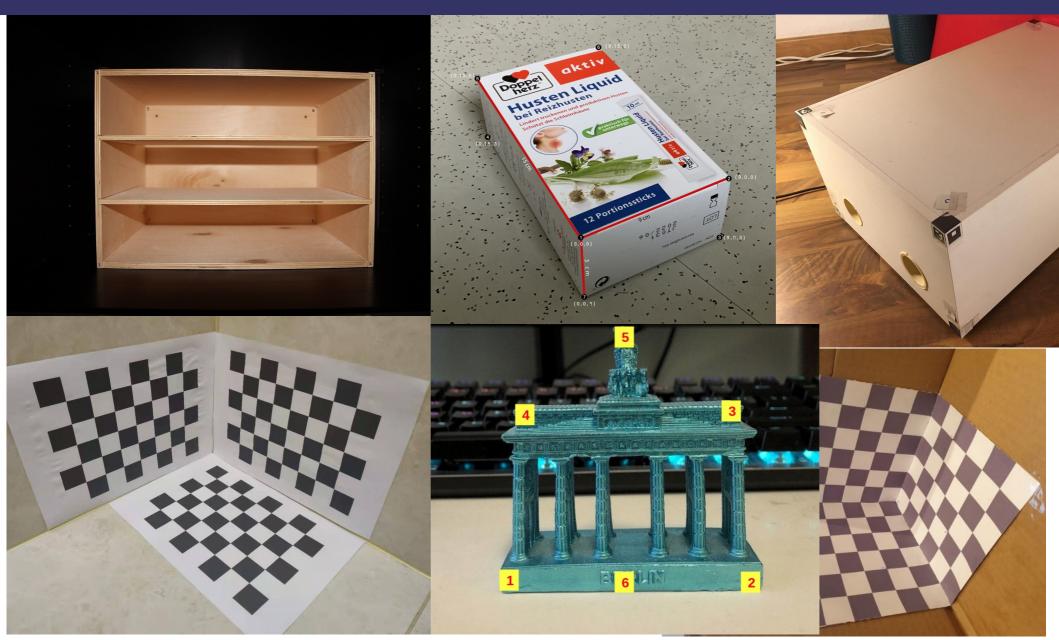
# Photogrammetric Computer Vision

Berlin University of Technology (TUB), Computer Vision and Remote Sensing Group Berlin, Germany



## **Last Exercise**

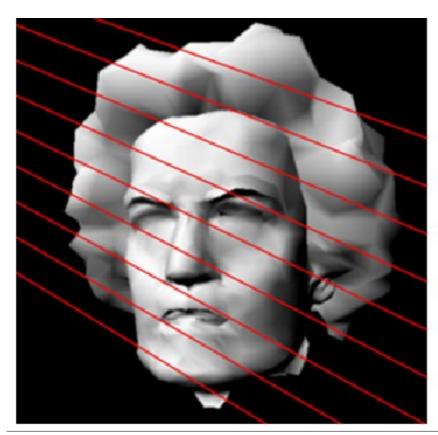


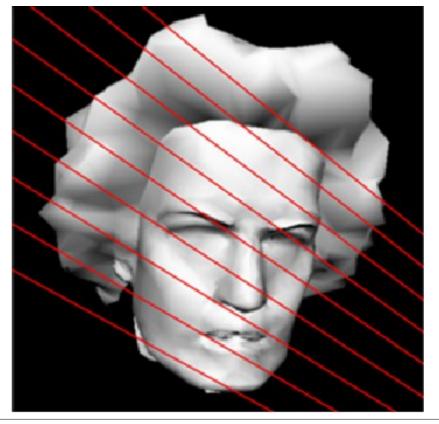
## **Relative Orientation**

#### Orientation of an image pair

The relative orientation of an image pair is defined by the epipolar geometry.

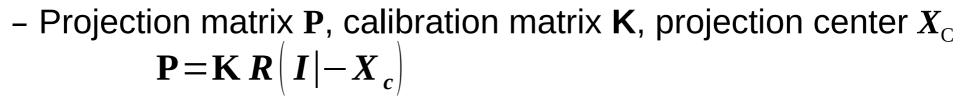
Using algebraic projective geometry the epipolar geometry can be represented by the fundamental matrix.





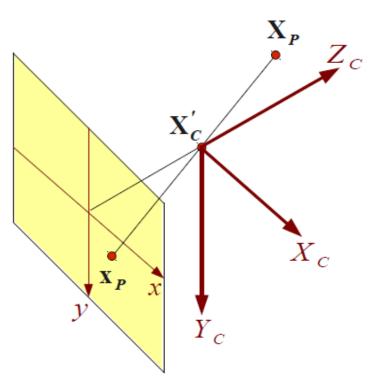
### What we have treated so far:

- Algebraic projective geometry
  - Homogeneous coordinates
- Object space coordinate system
- Camera coordinate system
- Image coordinate system
- Orientation of a single image



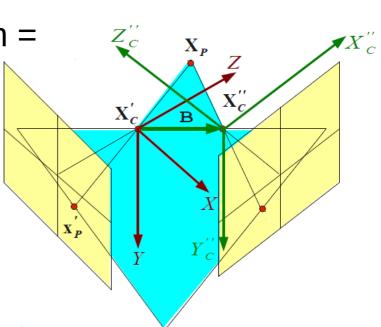
• Projection of object point  $X_P$  to image point  $X_P$ :

$$\mathbf{x}_{P} = \mathbf{K} R (I - X_{c}) \mathbf{X}_{P} = \mathbf{P} \mathbf{X}_{P}$$



### What we want to achieve now:

- Derivation of relative orientation:
  - Where is the second camera w.r.t. the first one?
  - Into which direction does it look, relative to the first camera?
- Important: Invariance of the image pair:
  - Cameras do not determine scale!
- Selection of parametrization of relative orientation:
  - Setting: object space coordinate system =
     coordinate system of the first camera
- Wanted:
  - Baseline (direction): B
  - Rotation of the second camera R''

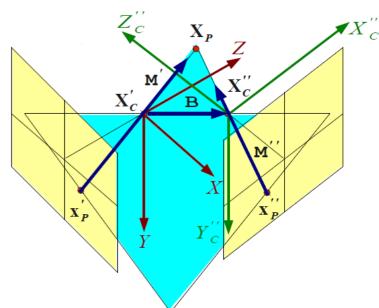


## **Coplanarity Condition**

 If three 3D vectors are coplanar, the enclosed volume, i.e. the scalar triple product, is zero:

$$\mathbf{M}'' \cdot (\mathbf{B} \times \mathbf{M}') = \mathbf{0}$$

 The three vectors must be given in the same coordinate system:



- M' is direction from projection center to image point in object space coordinate system

$$\mathbf{M}' = (\mathbf{R}')^{-1} (\mathbf{K}')^{-1} \mathbf{x}_{\mathbf{P}}'$$

- As 
$$\mathbf{R}'=\mathbf{I}$$
, for the first camera note e.g.:
$$\mathbf{M}' = \begin{bmatrix} 1/c \\ 1/c \end{bmatrix} \begin{bmatrix} x_P \\ y_P \\ 1 \end{bmatrix} = \begin{bmatrix} x_P \\ y_P \\ c \end{bmatrix}$$
- analogously  $\mathbf{M}'' - (\mathbf{R}'')^{-1}(\mathbf{K}'')^{-1}\mathbf{x}''$ 

- analogously 
$$\mathbf{M}'' = (\mathbf{R}'')^{-1} (\mathbf{K}'')^{-1} \mathbf{x}_{P}''$$
  
- Base line  $\mathbf{B} = \mathbf{X}_{C}'' - \mathbf{X}_{C}'$ 

## Derivation of the General Formulation of the Coplanarity Condition

- We note  $M'' \cdot (B \times M') = 0 = M''^T S_B M'$ 
  - with the skew symmetric matrix

$$\mathbf{S}_{\mathbf{B}} = \begin{bmatrix} 0 & -B_Z & B_Y \\ B_Z & 0 & -B_X \\ -B_Y & B_X & 0 \end{bmatrix} \text{ where } \mathbf{B} = \begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix}$$

Insertion results in

$$\mathbf{x}_{P}^{''T}(\mathbf{K}'')^{-T}(\mathbf{R}'')^{-T} \mathbf{S}_{B}(\mathbf{R}')^{-1}(\mathbf{K}')^{-1} \mathbf{x}_{P}' = 0$$

With the Fundamental Matrix

we get 
$$\mathbf{F} = (\mathbf{K}^{''})^{-T} \mathbf{R}^{''} \mathbf{S}_{\mathbf{B}} \mathbf{R}^{'T} (\mathbf{K}^{'})^{-1}$$

$$\mathbf{x}^{''}\mathbf{F}\mathbf{x}'=0$$

## **Coplanarity Condition**of Calibrated Cameras

 If the calibration matrix in known, normalized image coordinates can be computed:

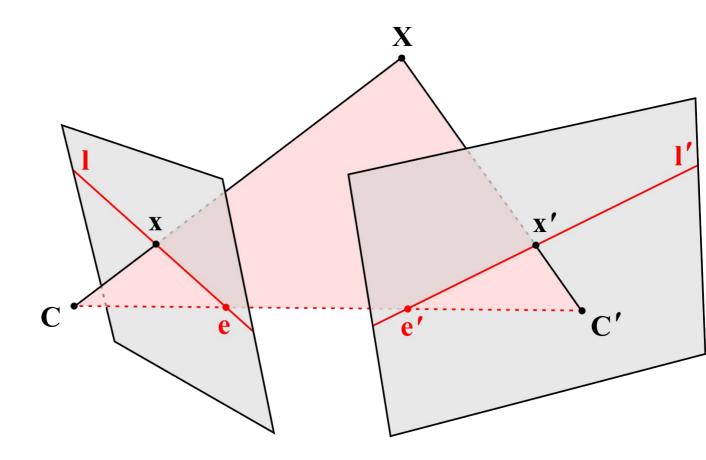
$$\mathbf{x}' = (\mathbf{K}')^{-1} \mathbf{x}_{p}'$$

 With these coordinates as a specialized version of the fundamental matrix we get the Essential Matrix
 E

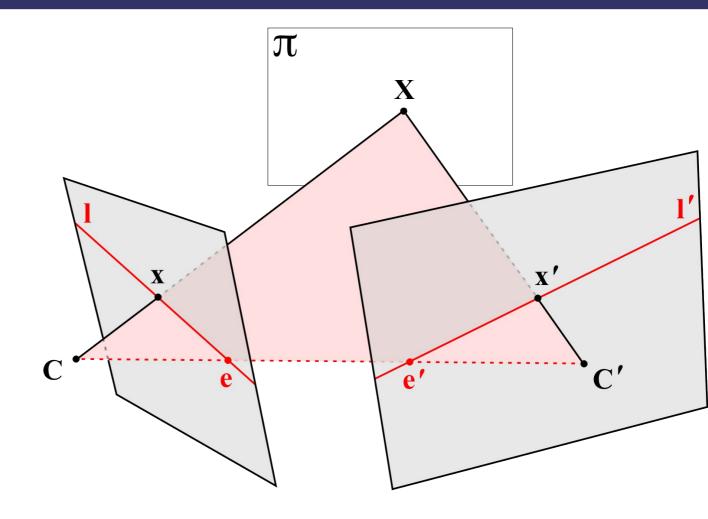
$$\mathbf{E} = \mathbf{R}'' \mathbf{S}_{\mathbf{B}} \mathbf{R}'^{\mathrm{T}}$$

Then the coplanarity condition is noted as

$$\mathbf{x}^{\mathsf{T}}\mathbf{E}\mathbf{x}^{\mathsf{T}}=0$$

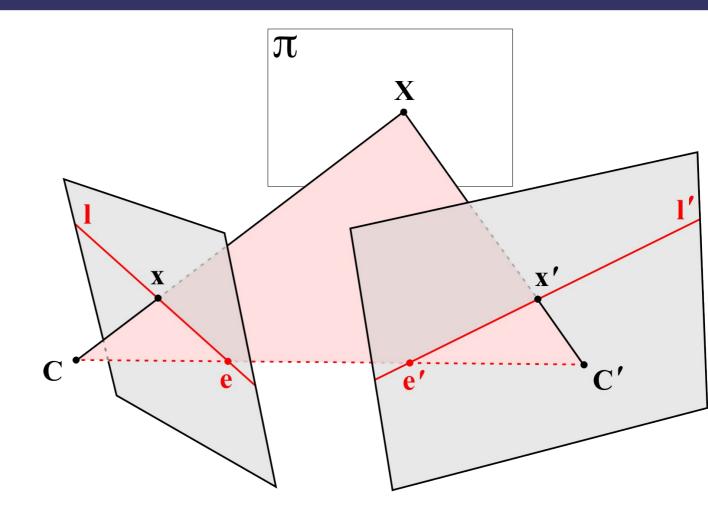


$$x' = H_{\pi} x$$



$$x' = H_{\pi} x$$

$$l' = e' \times x'$$
$$= [e']_{\times} x'$$

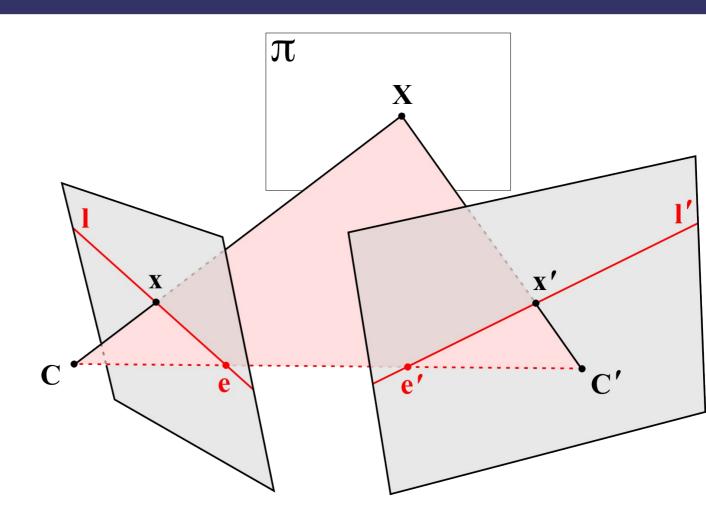


$$x' = H_{\pi} x$$

$$l' = e' \times x'$$

$$= [e']_{\times} x'$$

$$= [e']_{\times} H_{\pi} x$$



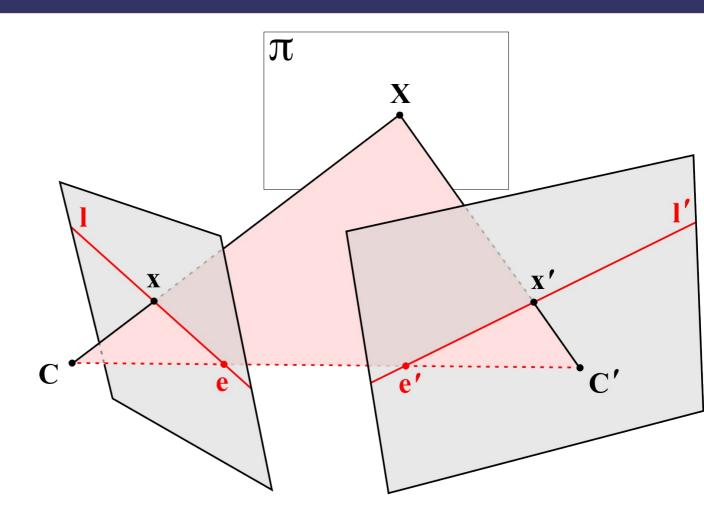
$$x' = H_{\pi} x$$

$$l' = e' \times x'$$

$$= [e']_{\times} x'$$

$$= [e']_{\times} H_{\pi} x$$

$$= Fx$$



$$x' = H_{\pi} x$$

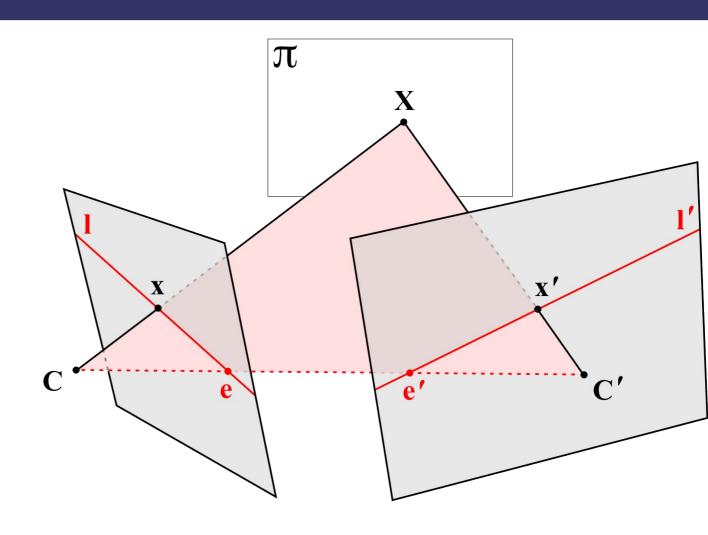
$$l' = e' \times x'$$

$$= [e']_{\times} x'$$

$$= [e']_{\times} H_{\pi} x$$

$$= Fx$$

$$0 = x'^T \cdot l'$$



#### **The fundamental matrix**

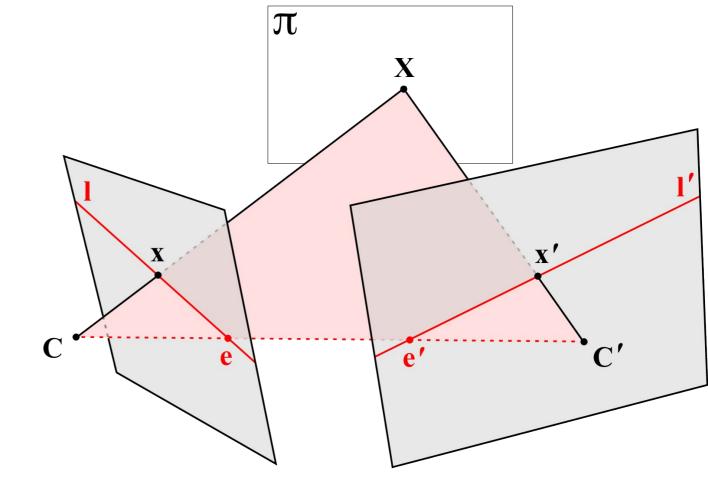
$$x' = H_{\pi} x$$

$$l' = e' \times x'$$

$$= [e']_{\times} x'$$

$$= [e']_{\times} H_{\pi} x$$

$$= Fx$$



$$0 = x'^T \cdot l'$$
$$= x'^T F x$$

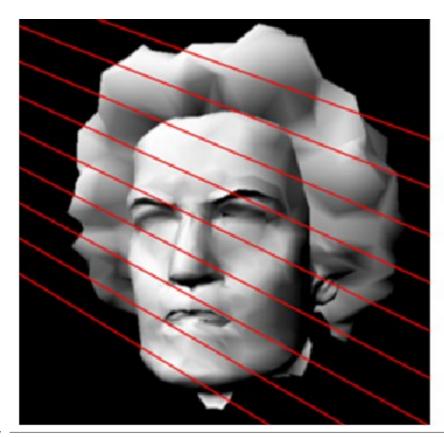
**Epipolar constraint** 

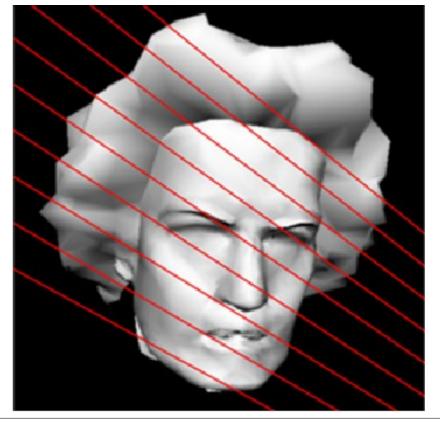
## **Relative Orientation**

#### Orientation of an image pair

The relative orientation of an image pair is defined by the epipolar geometry.

Using algebraic projective geometry the epipolar geometry can be represented by the fundamental matrix.







## **Fundamental Matrix Estimation**

How can F be used? → Next exercise

How can F be estimated? → This exercise

#### Two parts:

- 1) Using manually clicked point pairs
  - Point pairs assumed "correct"
  - How to estimate F from point pairs?
    - Estimation very similar to previous exercises
- 2) Using automatically determined point pairs
  - How to get point pairs automatically?
  - How to deal with outliers?

Part 1 F from (Manual) Point Pairs

#### 1. Image Acquisition:

Take a picture of a spatially structured object from two different views. Use thereby a general convergent image arrangement.

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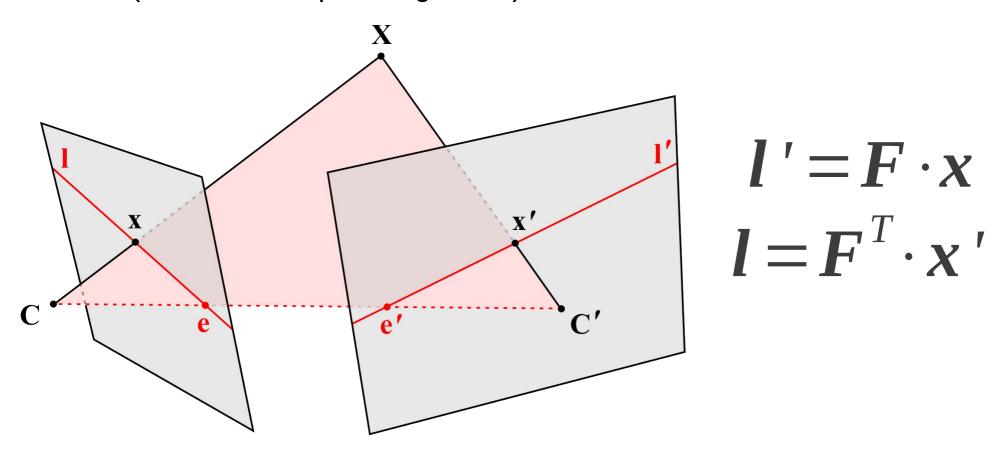
Take a picture of a spatially structured object from two different views. Use thereby a general convergent image arrangement.

#### 2. Homologous points:

Measure manually at least 8 homologous points  $x \leftrightarrow x'$  in the image pair.

#### 3. Computation of the fundamental matrix:

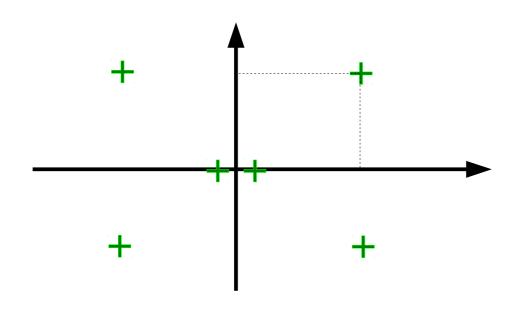
Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).



#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 1. Conditioning



$$T = \begin{bmatrix} \frac{1}{s_x} & 0 & \frac{-t_x}{s_x} \\ 0 & \frac{1}{s_y} & \frac{-t_y}{s_y} \\ 0 & 0 & 1 \end{bmatrix}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

$$0 = \hat{\boldsymbol{x}}'_{i}^{T} \boldsymbol{F} \hat{\boldsymbol{x}}_{i}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

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

$$0 = \begin{bmatrix} x'_{i} & y'_{i} & w'_{i} \end{bmatrix} \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} \\ f_{2,1} & f_{2,2} & f_{2,3} \\ f_{3,1} & f_{3,2} & f_{3,3} \end{bmatrix} \begin{bmatrix} x_{i} \\ y_{i} \\ w_{i} \end{bmatrix}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

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

$$0 = \begin{bmatrix} x'_{i} & y'_{i} & w'_{i} \end{bmatrix} \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} \\ f_{2,1} & f_{2,2} & f_{2,3} \\ f_{3,1} & f_{3,2} & f_{3,3} \end{bmatrix} \begin{bmatrix} x_{i} \\ y_{i} \\ w_{i} \end{bmatrix}$$

$$0 = \begin{bmatrix} x_{i}^{'} & y_{i}^{'} & w_{i}^{'} \end{bmatrix} \begin{bmatrix} f_{1,1} x_{i} + f_{1,2} y_{i} + f_{1,3} w_{i} \\ f_{2,1} x_{i} + f_{2,2} y_{i} + f_{2,3} w_{i} \\ f_{3,1} x_{i} + f_{3,2} y_{i} + f_{3,3} w_{i} \end{bmatrix}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

$$0 = \hat{x}_{i}^{T} F \hat{x}_{i}$$

$$0 = \begin{bmatrix} x_{i}^{'} & y_{i}^{'} & w_{i}^{'} \end{bmatrix} \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} \\ f_{2,1} & f_{2,2} & f_{2,3} \\ f_{3,1} & f_{3,2} & f_{3,3} \end{bmatrix} \begin{bmatrix} x_{i} \\ y_{i} \\ w_{i} \end{bmatrix}$$

$$0 = f_{1,1} x_{i} x_{i}^{'} + f_{1,2} y_{i} x_{i}^{'} + f_{1,3} w_{i} x_{i}^{'} + f_{2,1} x_{i} y_{i}^{'} + f_{2,2} y_{i} y_{i}^{'} + f_{2,3} w_{i} y_{i}^{'} + f_{3,1} x_{i} w_{i}^{'} + f_{3,2} y_{i} w_{i}^{'} + f_{3,3} w_{i} w_{i}^{'}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

$$0 = \hat{\mathbf{x}}_{i}^{T} \mathbf{F} \hat{\mathbf{x}}_{i}$$

$$0 = \begin{bmatrix} x_{i} & y_{i} & w_{i} \end{bmatrix} \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} \\ f_{2,1} & f_{2,2} & f_{2,3} \\ f_{3,1} & f_{3,2} & f_{3,3} \end{bmatrix} \begin{bmatrix} x_{i} \\ y_{i} \\ w_{i} \end{bmatrix}$$

$$0 = \begin{bmatrix} x_{i} x_{i} & y_{i} x_{i} & w_{i} x_{i} & x_{i} y_{i} & y_{i} y_{i} & w_{i} y_{i} & x_{i} w_{i} & y_{i} w_{i} & w_{i} w_{i} \end{bmatrix} \begin{bmatrix} f_{1,1} \\ f_{1,2} \\ f_{1,3} \\ \vdots \\ f_{3,3} \end{bmatrix}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

$$A = \begin{bmatrix} \hat{x}_1 \hat{x}_1' & \hat{y}_1 \hat{x}_1' & \hat{w}_1 \hat{x}_1' & \hat{x}_1 \hat{y}_1 & \hat{y}_1 \hat{y}_1' & \hat{w}_1 \hat{y}_1' & \hat{x}_1 \hat{w}_1' & \hat{y}_1 \hat{w}_1' & \hat{w}_1 \hat{w}_1' \\ \vdots & \vdots \\ \hat{x}_n \hat{x}_n' & \hat{y}_n \hat{x}_n' & \hat{w}_n \hat{x}_n' & \hat{x}_n \hat{y}_n' & \hat{y}_n \hat{y}_n' & \hat{w}_n \hat{y}_n' & \hat{x}_n \hat{w}_n' & \hat{y}_n \hat{w}_n' & \hat{w}_n \hat{w}_n' \end{bmatrix}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 2. Create design matrix

$$A = \begin{bmatrix} \hat{x}_{1} \hat{x}_{1}^{\prime} & \hat{y}_{1} \hat{x}_{1}^{\prime} & \hat{w}_{1} \hat{x}_{1}^{\prime} & \hat{x}_{1} \hat{y}_{1}^{\prime} & \hat{y}_{1} \hat{y}_{1}^{\prime} & \hat{w}_{1} \hat{y}_{1}^{\prime} & \hat{x}_{1} \hat{w}_{1}^{\prime} & \hat{y}_{1} \hat{w}_{1}^{\prime} & \hat{w}_{1} \hat{w}_{1}^{\prime} \\ \vdots & \vdots \\ \hat{x}_{n} \hat{x}_{n}^{\prime} & \hat{y}_{n} \hat{x}_{n}^{\prime} & \hat{w}_{n} \hat{x}_{n}^{\prime} & \hat{x}_{n} \hat{y}_{n}^{\prime} & \hat{y}_{n} \hat{y}_{n}^{\prime} & \hat{y}_{n} \hat{y}_{n}^{\prime} & \hat{w}_{n} \hat{y}_{n}^{\prime} & \hat{x}_{n} \hat{w}_{n}^{\prime} & \hat{y}_{n} \hat{w}_{n}^{\prime} & \hat{w}_{n} \hat{w}_{n}^{\prime} \end{bmatrix}$$

#### 3. Solve equation system with SVD and reshape

$$\mathbf{A}f = \mathbf{0} \qquad \qquad \mathbf{\tilde{F}} = \begin{bmatrix} f_1 & f_2 & f_3 \\ f_4 & f_5 & f_6 \\ f_7 & f_8 & f_9 \end{bmatrix}$$



#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 4. Enforce singularity

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Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 4. Enforce singularity

$$\mathbf{\tilde{F}} = \mathbf{\tilde{U}} \ diag (d_1, d_2, d_3) \mathbf{\tilde{V}}^T$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 4. Enforce singularity

$$||\mathbf{F} - \mathbf{F}^*|| = min$$
$$|\mathbf{F}^*| = 0$$

Wanted: 
$$\begin{aligned} & \left\| \boldsymbol{F} - \boldsymbol{F}^* \right\| = min \\ & \left| \boldsymbol{F}^* \right| = 0 \end{aligned} \end{aligned} \qquad \begin{aligned} & \tilde{\boldsymbol{F}} = \tilde{\boldsymbol{U}} \ diag \left( d_1, d_2, d_3 \right) \tilde{\boldsymbol{V}}^T \\ & \tilde{\boldsymbol{F}}^* = \tilde{\boldsymbol{U}} \ diag \left( d_1, d_2, 0 \right) \tilde{\boldsymbol{V}}^T \end{aligned}$$

#### 3. Computation of the fundamental matrix:

Implement a function in C++ for the linear computation of the fundamental matrix F (normalized 8-point-algorithm).

#### 4. Enforce singularity

Wanted: 
$$\|F\|$$

$$\|\mathbf{F} - \mathbf{F}^*\| = min$$
 $|\mathbf{F}^*| = 0$ 

Wanted: 
$$\begin{aligned} & \left\| \boldsymbol{F} - \boldsymbol{F}^* \right\| = min \\ & \left| \boldsymbol{F}^* \right| = 0 \end{aligned} \end{aligned} \qquad \begin{aligned} & \tilde{\boldsymbol{F}} = \tilde{\boldsymbol{U}} \ diag \left( d_1, d_2, d_3 \right) \tilde{\boldsymbol{V}}^T \\ & \tilde{\boldsymbol{F}}^* = \tilde{\boldsymbol{U}} \ diag \left( d_1, d_2, 0 \right) \tilde{\boldsymbol{V}}^T \end{aligned}$$

#### <u>5. Deconditioning</u>

$$F = T^{T} \tilde{F}^{T}$$

#### 4. Visualization of the fundamental matrix by epipolar lines:

- a) Mark the used points in both images
- b) and draw the associated epipolar lines in the corresponding image.

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- a) Mark the used points in both images
- b) and draw the associated epipolar lines in the corresponding image.

#### 5. Evaluation:

- a) Show the image pair and comment the line characteristics in brief.
- b) Calculate the (average) geometric image error (symmetric epipolar distance) of F for all points.

$$d = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(\mathbf{x_i^{T}} \mathbf{F} \mathbf{x_i}\right)^2}{\left(\mathbf{F} \mathbf{x_i}\right)_a^2 + \left(\mathbf{F} \mathbf{x_i}\right)_b^2 + \left(\mathbf{F}^T \mathbf{x_i'}\right)_a^2 + \left(\mathbf{F}^T \mathbf{x_i'}\right)_b^2}$$

c) Count the number of inliers. Inliers are point pairs whose error is smaller than a predefined threshold (e.g. 2 pixels)

## Part 2 Automatic Point Pairs and Robust Estimation

# **Keypoints**





How to automatically establish points correspondences?

# Keypoints



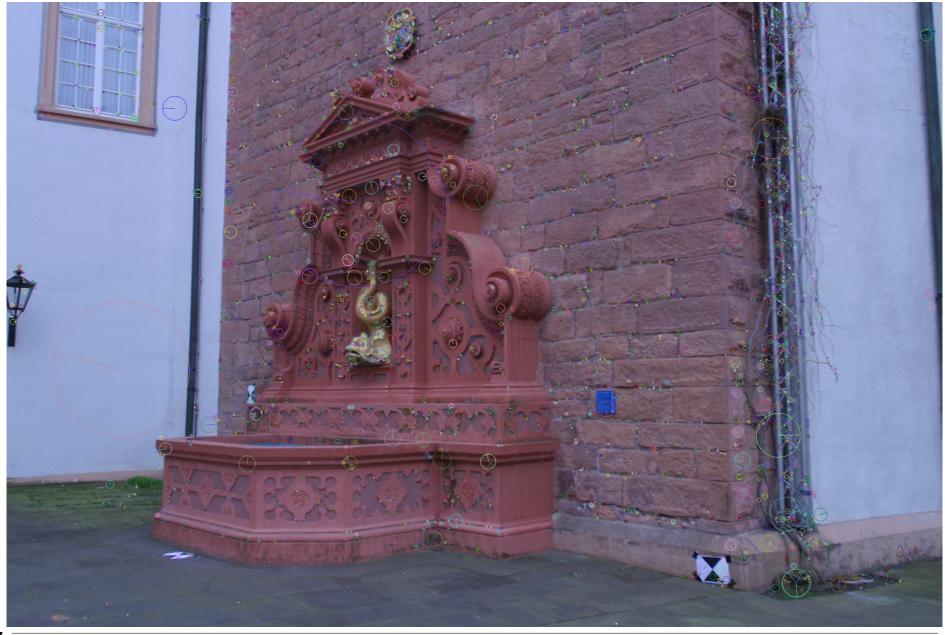


#### **Step 1: Keypoint detection** (in each image)

- → Find "salient" points (landmarks)
- → In a reproducible way
- → Usually:
  - Bright spots on dark ground (and vice versa)
  - Corners



# **Keypoint Detection**





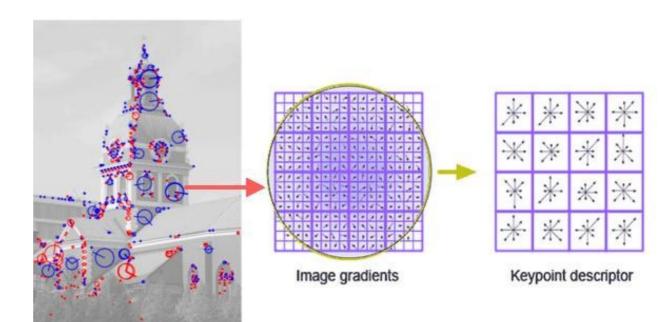
# **Keypoint Description**

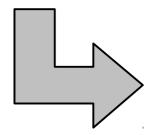
#### Step 2: Keypoint Description (for each image and keypoint)

- → Use information from detector (location, scale, angle)
- → Compute "descriptor" (vector) that describes surroundings
- → Again, in a stable, reproducible way

#### **SIFT Detection**

- → Position
- → Scale
- → Orientation





#### **SIFT Description**

- → gradient histogram
- → 128 dimensional vector





# **Keypoint Matching**

#### Step 3: Keypoint Matching (for each image pair)

- For each keypoint (descriptor) in first image find most similar keypoint (descriptor) in second image
- Similarity metric depends on descriptor
  - Real valued descriptors: Euclidean distance or dot product
  - Binary descriptors: Hamming distance
- Optimizations:
  - → Run in parallel
  - → Data structures (trees, grids)
  - → Partial distance computation

# **Keypoints**





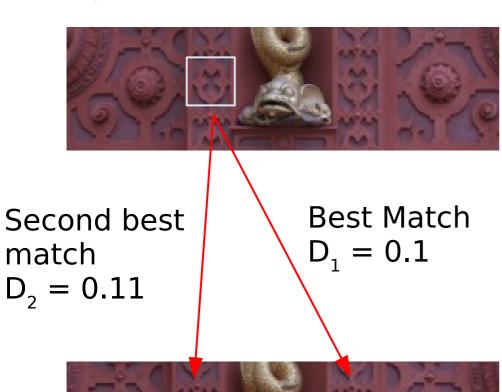
How to automatically establish points correspondences?

# **Keypoint Matching**



Large amount of gross errors (outliers)!

#### 1) Ratio Test



#### 1) Ratio Test



Second best match  $D_2 = 0.11$ 

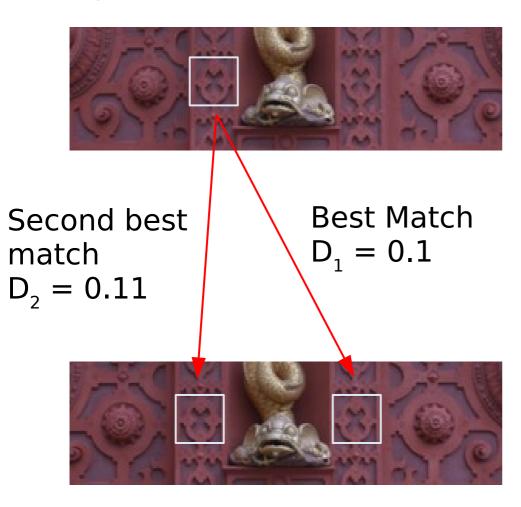
**Best Match**  $D_1 = 0.1$ 



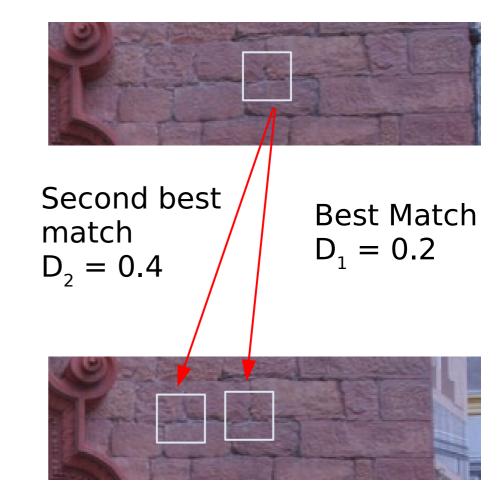
 $D_1/D_2 = 0.91 > 0.75 \rightarrow Reject$ 



#### 1) Ratio Test



 $D_1/D_2 = 0.91 > 0.75 \rightarrow Reject$ 



$$D_1/D_2 = 0.5 < 0.75 \rightarrow Accept$$



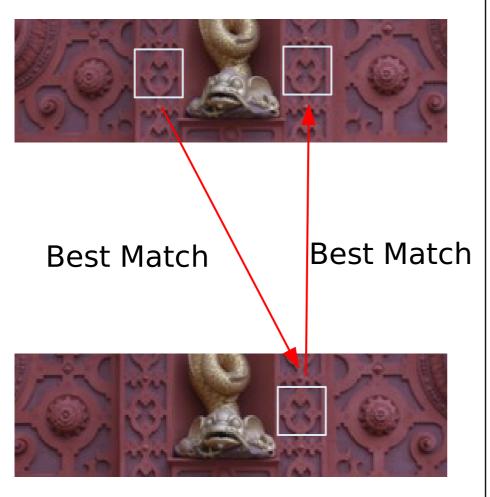
### 2) Cross Consistency Check



**Best Match** 



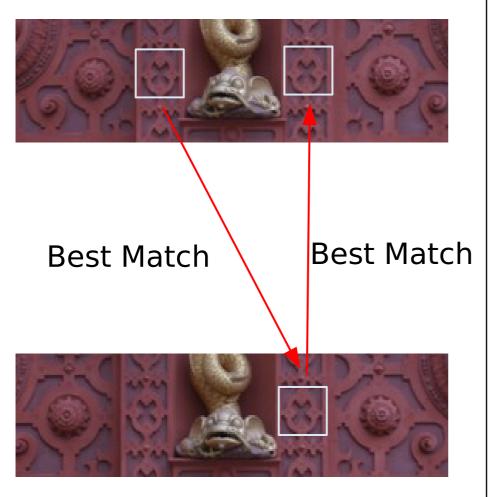
#### 2) Cross Consistency Check



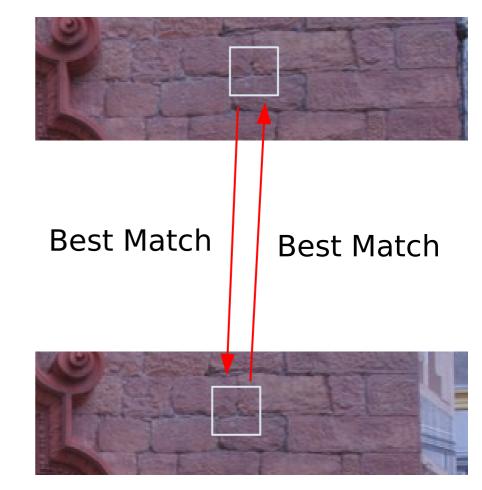
Matches inconsistent → Reject



#### 2) Cross Consistency Check



Matches inconsistent → Reject



Matches consistent → Accept





#### **RANdom Sampling Consensus**

#### Requirements:

- A model to be estimated from few data points
- Lots more data points than necessary

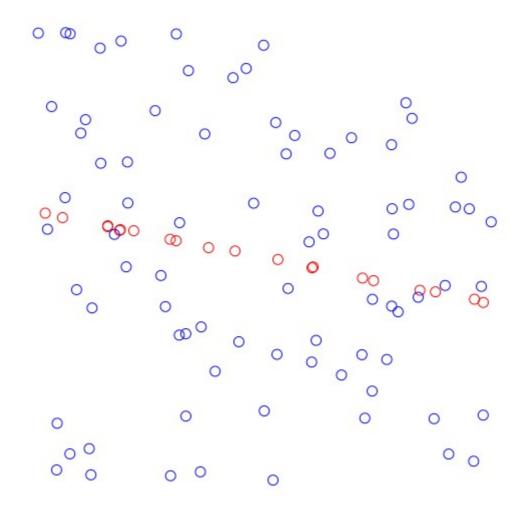
#### Steps:

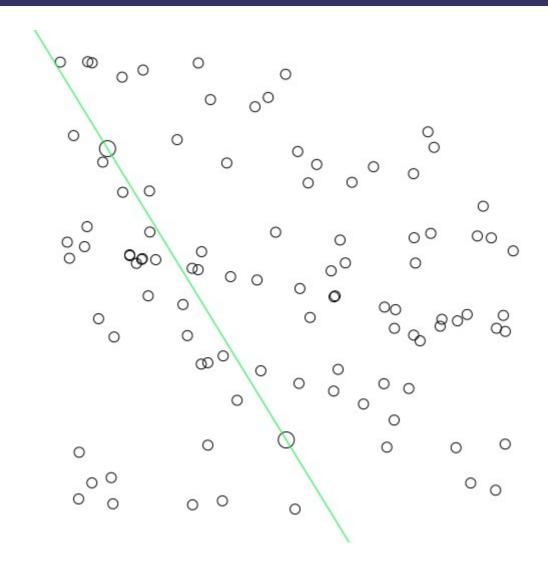
- 1) Select random subset
- 2) Estimate model from subset
- 3) Evaluate model on all data (e.g. count inliers)
- 4) Repeat couple thousand times and keep the best model

#### Key idea:

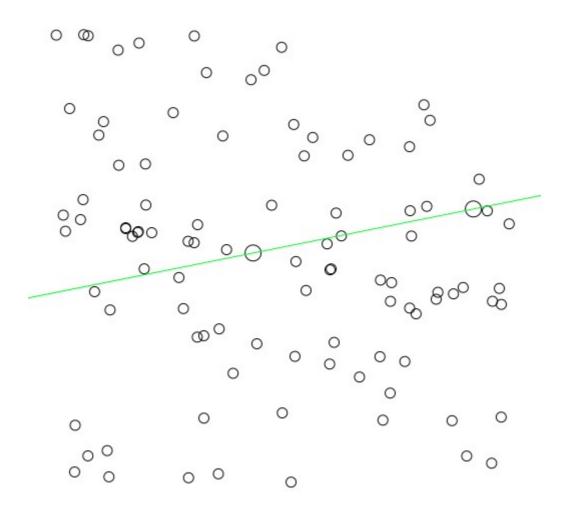
- 1) Outliers don't agree on a model!
- 2) Sooner or later, the small, random subset will be all inliers

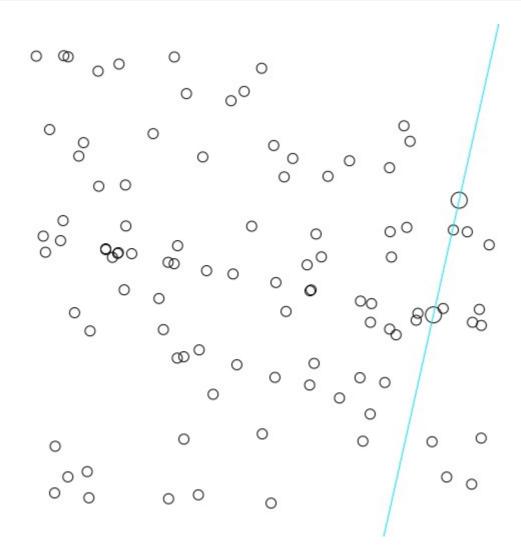


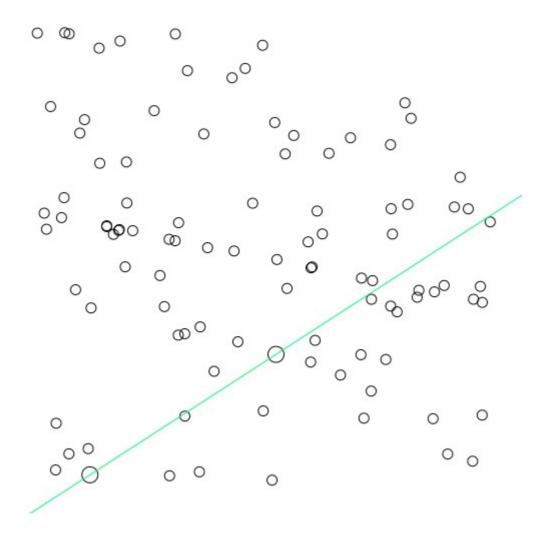


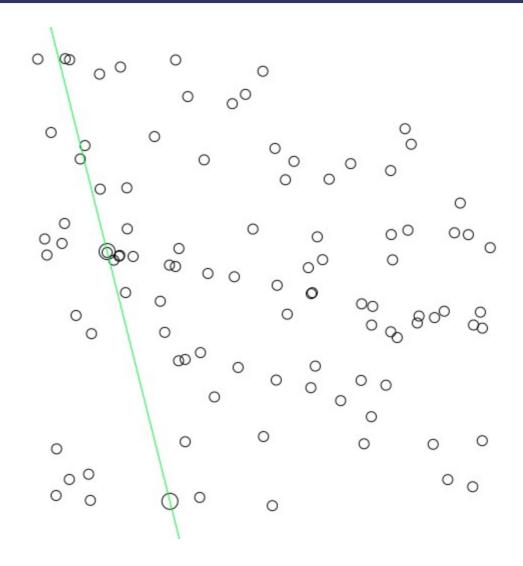


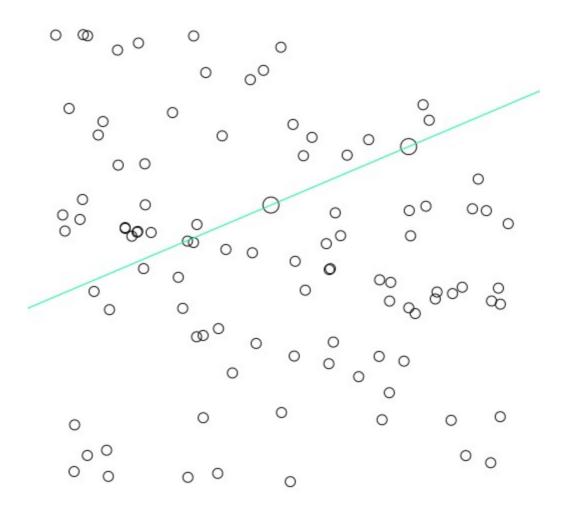


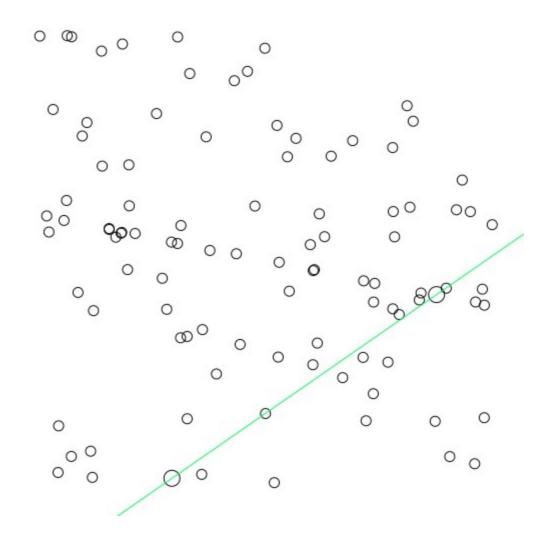


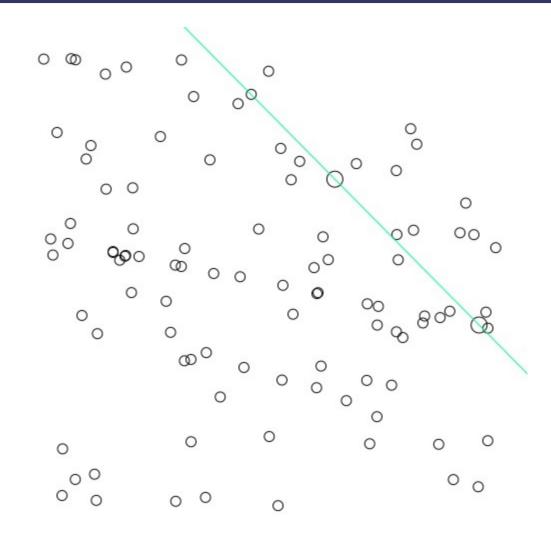


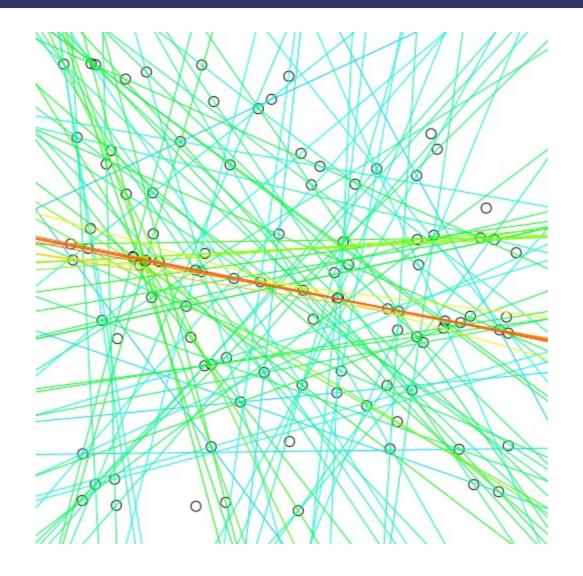












## 4. Exercise

#### **6. Automatically Detect Point Pairs:**

- a) Detect keypoints and match descriptors
- b) Filter matches based on ratio test and cross consistency check
- c) Estimate Fundamental matrix
- d) Compute average error, count number of inliers, and draw epipolar lines

#### 7. Robust Estimation:

- a) Implement RANSAC to estimate fundamental matrix robustly
- b) Estimate fundamental matrix via RANSAC
- c) Again compute average error, count number of inliers, and draw epipolar lines

# 4. Exercise - Theory

Two cameras  $c_1$  and  $c_2$  observe the same 3D scene in a general convergent constellation.

A human operator marked interesting points within a 3D scene. Two of those points are projected to  $x_1 = (1,0,1)^T$  and  $x_2 = (2,1,1)^T$  within the first view. What can you say about the position of those points within the second view, if the Fundamental matrix F of this system is given by

$$\mathbf{F} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -1 & 0 \\ 1 & -1 & 0 \end{bmatrix}$$

Using this information, derive the exact position of the epipole  $e_2$  within the second view.

How does the position of the epipole change, if the stereo-system is changed from a <u>convergent</u> to a <u>stereo-normal</u> view?

## 4. Exercise

#### **Relative Orientation**

#### Given:

- Main function for manual part (main\_manual.cpp)
- Main function for automatic part (main\_automatic.cpp)
- Unit tests (unit\_test.cpp)
- Header of individual functions

#### Todo:

- Individual functions
  - Fill in the necessary function body parts (Pcv4.cpp)

## Given

img1: Data of first imageimg2: Data second image

**p1:** Output: points in first image (homogeneous coordinates)

**p2:** Output: points in second image (homogeneous coordinates)

- Displays the two images in two individual windows.

- Catches left mouse clicks, stores position in corresponding matrix and marks points in images by green circles.

void drawEpiLine(Mat& img, double a, double b, double c)

**img:** Image in which lines are to be drawn

a, b, c: Epipolar line in homogeneous representation

- Draws epipolar line into image



## Given

#### RawOrbMatches extractRawOrbMatches(Mat& img1, Mat& img2)

```
img1: Data of first imageimg2: Data second image
```

- Runs ORB (keypoint detector and feature extractor) on both images
- Matches the features (both ways)
- Returns keypoint locations and closest and second closest matches

```
struct RawOrbMatches {
   std::vector<cv::Vec3f> keypoints1; /// Location of keypoints in first image
   std::vector<cv::Vec3f> keypoints2; /// Location of keypoints in second image

struct Match {
    unsigned closest; /// Index of the closest match
    float closestDistance; /// Feature distance of closest match
    unsigned secondClosest; /// Index of the second closest match
   float secondClosestDistance; /// Feature distance of second closest match
};

/// For each keypoint in first images which keypoints are similar in second image
std::map<unsigned, Match> matches_1_2;
/// For each keypoint in second images which keypoints are similar in first image
std::map<unsigned, Match> matches_2_1;
};
```

#### Matx33f getCondition2D(vector<Vec3f>& p)

**p:** Array of points

return: The 3x3 matrix for point conditioning

$$T = \begin{bmatrix} \frac{1}{s_x} & 0 & \frac{-t_x}{s_x} \\ 0 & \frac{1}{s_y} & \frac{-t_y}{s_y} \\ 0 & 0 & 1 \end{bmatrix}$$

- Computes the transformation matrix to move centroid to origin and scale mean distance to origin to one

#### 

geomObj: the geometric objects, that have to be transformed

H: the homography of the transformation

type : determines the type of the geometric object (point/line)

return: the transformed objects

- Reuse your implementation from exercise 1

**p1:** Set of 2D points within first image

**p2:** Set of 2D points within second image

return: Output: Design matrix to compute fundamental matrix

- Takes corresponding point pairs (already conditioned)
- Generates design matrix to compute fundamental matrix

$$A = \begin{bmatrix} \hat{x}_{1}\hat{x}_{1}^{'} & \hat{y}_{1}\hat{x}_{1}^{'} & \hat{w}_{1}\hat{x}_{1}^{'} & \hat{x}_{1}\hat{y}_{1}^{'} & \hat{y}_{1}\hat{y}_{1}^{'} & \hat{w}_{1}\hat{y}_{1}^{'} & \hat{x}_{1}\hat{w}_{1}^{'} & \hat{y}_{1}\hat{w}_{1}^{'} & \hat{w}_{1}\hat{w}_{1}^{'} \\ \vdots & \vdots \\ \hat{x}_{n}\hat{x}_{n}^{'} & \hat{y}_{n}\hat{x}_{n}^{'} & \hat{w}_{n}\hat{x}_{n}^{'} & \hat{x}_{n}\hat{y}_{n}^{'} & \hat{y}_{n}\hat{y}_{n}^{'} & \hat{y}_{n}\hat{y}_{n}^{'} & \hat{w}_{n}\hat{y}_{n}^{'} & \hat{x}_{n}\hat{w}_{n}^{'} & \hat{y}_{n}\hat{w}_{n}^{'} & \hat{w}_{n}\hat{w}_{n}^{'} \end{bmatrix}$$

**p1:** Set of 2D points within first image

**p2:** Set of 2D points within second image

return: Output: Design matrix to compute fundamental matrix

- Takes corresponding point pairs (already conditioned)
- Generates design matrix to compute fundamental matrix

Matx33f solve\_dlt\_fundamental(Mat\_<float>& A)

A: Design matrix representing homogenous equation system Af = 0

return: Fundamental matrix

- Uses SVD to solve homogeneous equation system



#### Matx33f forceSingularity(Matx33f& F)

**F:** Conditioned fundamental matrix (has to be transformed in-place)

Enforces rank 2 property of the fundamental matrix

$$\widetilde{\boldsymbol{F}}^* = \widetilde{\boldsymbol{U}} \operatorname{diag}(d_1, d_2, 0) \widetilde{\boldsymbol{V}}^T$$

#### Matx33f forceSingularity(Matx33f& F)

**F:** Conditioned fundamental matrix (has to be transformed in-place)

Enforces rank 2 property of the fundamental matrix

$$\widetilde{\boldsymbol{F}}^* = \widetilde{\boldsymbol{U}} \operatorname{diag}(d_1, d_2, 0) \widetilde{\boldsymbol{V}}^T$$

Matx33f decondition\_fundamental(

Matx33f& T\_fst, Matx33f& T\_snd, Matx33f& F)

**T\_fst:** Conditioning matrix of set of 2D image points from first image

**T\_snd:** Conditioning matrix of set of 2D image points from second image

**F:** Conditioned fundamental matrix

$$F = T^{'T} \widetilde{F}^* T$$

- Deconditions fundamental matrix



```
Matx33f getFundamentalMatrix(vector<Vec3f>& p1,
                                vector<Vec3f>& p2)
        N points from first image
p1:
   N points from second image
p1:
            Output: 3x3 fundamental matrix
return:
- Estimates fundamental matrix from given set of point pairs
- Calls:
   getCondition2D(...)
   applyH_2d(...)
   getDesignMatrix_fundamental(...)
   solve_dlt_fundamental(...)
   forceSingularity(...)
   decondition_fundamental(...)
```

```
void visualize(cv::Mat& img1, cv::Mat& img2,
    vector<Vec3f>& p1, vector<Vec3f>& p2, cv::Matx33f& F)
```

**img1:** Image data of first image

**img2:** Image data of second image

**p1:** Points in first image (homogeneous coordinates)

**p2:** Points in second image (homogeneous coordinates)

F: Calculated fundamental matrix

$$l' = F \cdot x$$

$$l = F^T \cdot x'$$

- Draws points
  - use cv::circle(...)
- Calculates and draws epipolar lines
  - use drawEpiLine(...)

float getError(Vec3f& p\_fst, Vec3f& p\_snd, Matx33f& F)

p\_fst: Point in first image (homogeneous coordinates)

p\_snd: Point in second image (homogeneous coordinates)

**F:** Calculated fundamental matrix

- Calculates Sampson errror for a single point pair

$$d = \frac{\left(\mathbf{x}_{i}^{\prime} \mathbf{F} \mathbf{x}_{i}\right)^{2}}{\left(\mathbf{F} \mathbf{x}_{i}\right)_{a}^{2} + \left(\mathbf{F} \mathbf{x}_{i}\right)_{b}^{2} + \left(\mathbf{F}^{T} \mathbf{x}_{i}^{\prime}\right)_{a}^{2} + \left(\mathbf{F}^{T} \mathbf{x}_{i}^{\prime}\right)_{b}^{2}}$$

**p1:** Array of points in first image (homogeneous coordinates)

**p2:** Array of points in second image (homogeneous coordinates)

F: Calculated fundamental matrix

- Calculates the average Sampson error for all point pairs

$$d = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(\mathbf{x}_{i}' \mathbf{F} \mathbf{x}_{i}\right)^{2}}{\left(\mathbf{F} \mathbf{x}_{i}\right)_{a}^{2} + \left(\mathbf{F} \mathbf{x}_{i}\right)_{b}^{2} + \left(\mathbf{F}'' \mathbf{x}_{i}'\right)_{a}^{2} + \left(\mathbf{F}'' \mathbf{x}_{i}'\right)_{b}^{2}}$$

**p1:** Array of points in first image (homogeneous coordinates)

**p2:** Array of points in second image (homogeneous coordinates)

F: Calculated fundamental matrix

- Calculates the average Sampson error for all point pairs

**p1:** Points in first image (homogeneous coordinates)

**p2:** Points in second image (homogeneous coordinates)

**F:** Calculated fundamental matrix

threshold: Maximal Sampson error of an inlier

- Count pairs with Sampson error smaller than threshold





Matx33f estimateFundamentalRANSAC(vector<Vec3f>& p vector<Vec3f>& p2, unsigned numIters, float thresh)

**p1:** Points in first image (homogeneous coordinates)

**p2:** Points in second image (homogeneous coordinates)

**numIters:** Number of attempts

thresh: Threshold on Sampson error for inliers

- for numlters:
  - pick a random subset of 8 points
  - estimate fundamental matrix of subset
  - count total number of inliers
- return fundamental matrix with most inliers

Code snipped for random number generation in source code.



rawOrbMatches: keypoint locations and closest and second closest matches

**p1:** Output: points in first image (homogeneous coordinates)

**p2:** Output: points in second image (homogeneous coordinates)

- Loops over raw matches and extracts those that satisfy:
  - Ratio test (ratio of 0.75)
  - Cross Consistency Check
- Pairs returned in p1 and p2

img1: Data of first image

img2: Data second image

**p1:** Output: points in first image (homogeneous coordinates)

**p2:** Output: points in second image (homogeneous coordinates)

- Runs extraction, matching, and filtering
- Calls:
  - extractRawOrbMatches(...)
  - filterMatches(...)
- Optional: Visualize with drawMatches(...) (in Helper.h/.cpp)

## Midterm

Available **From**: Tuesday 12.01.2021  $\sim$ 12:00

**Until:** Tuesday 19.01.2021 23.59

- 3 attempts
  - → Can be taken anytime during the available period
- Best attempt is taken as final result
- Multiple Choice
  - → Multiple correct answers possible
- 45 min
- 50% of points are required for pass
- Wrong choices give -0.5 Points
  - You can get negative points on a question
  - → Only select answers if you are confident