#### 55:148 Digital Image Processing

Chapter 11 3D Vision, Geometry

## **Topics:**

**Basics of projective geometry** 

Points and hyperplanes in projective space

Homography

**Estimating homography from point correspondence** 

The single perspective camera

An overview of single camera calibration

Calibration of one camera from the known scene

Scene reconstruction from multiple views

**Triangulation** 

**Projective reconstruction** 

Matching constraints

**Bundle adjustment** 

Two cameras, stereopsis

The geometry of two cameras. The fundamental matrix

Relative motion of the camera; the essential matrix

Estimation of a fundamental matrix from image point correspondences

**Camera Image rectification** 

Applications of the epipolar geometry in vision

Three and more cameras

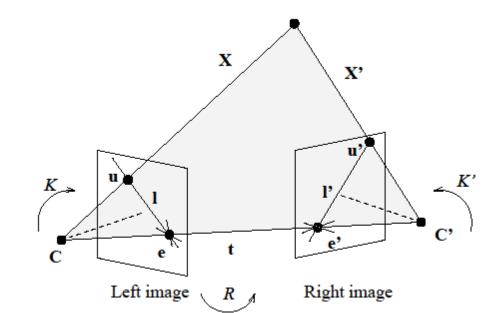
Stereo correspondence algorithms

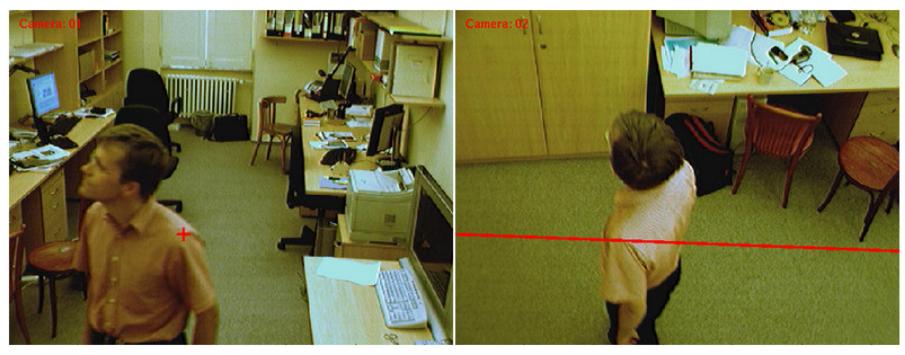
## **Epipolar geometry and Fundamental matrix**

Fundamental matrix relates corresponding points in two stereo images

$$\mathbf{u}^{\prime \mathrm{T}} F \mathbf{u} = 0$$

What does it mean? A point on the left image ≈ a line on the right image What is this line called





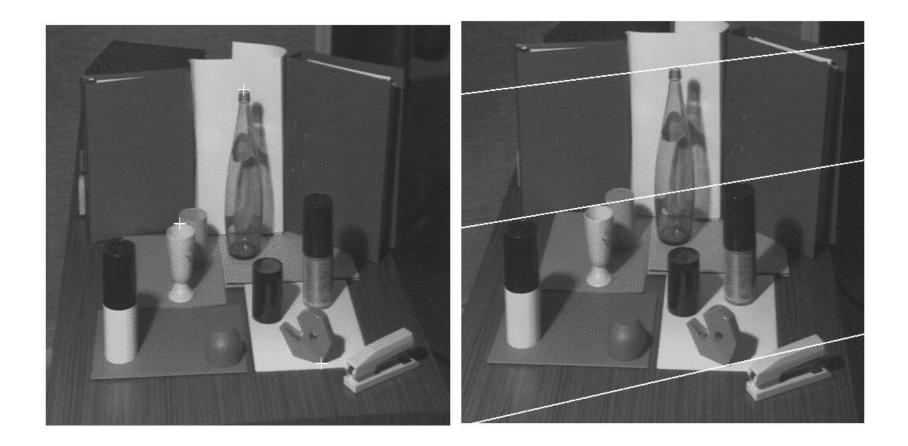




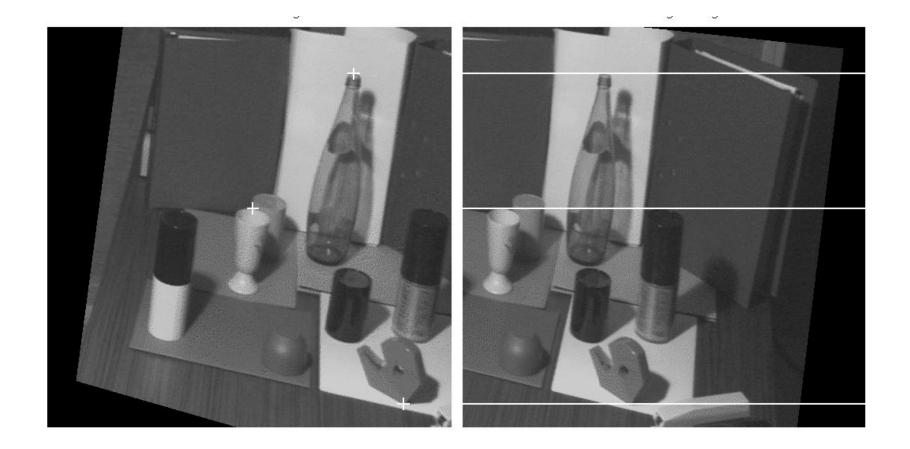




# Image rectification (before)



# Image rectification (after)



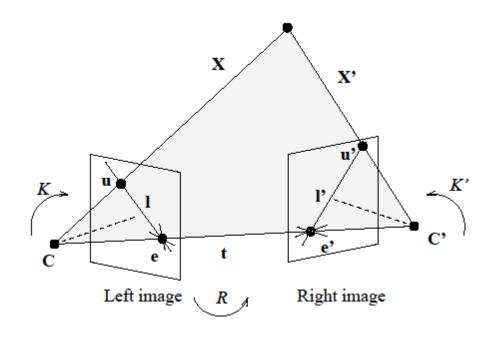
#### Image rectification

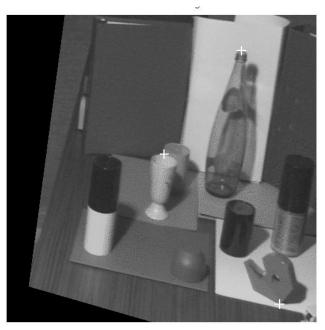
What happens in terms of epipolar geometry?

Where are the two epipoles?

What is the relation between the baseline and the camera matrix?

Can we solve it using a homographic transformation on each camera image?







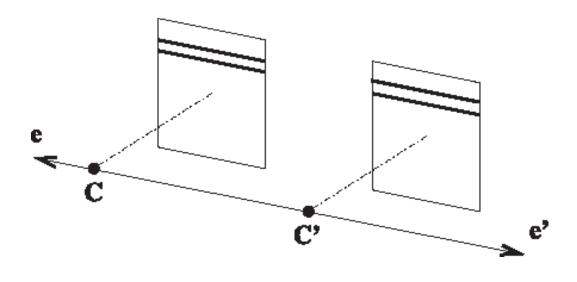
### **Image rectification**

What happens in terms of epipolar geometry?

Where are the two epipoles?

What is the relation between the baseline and the camera matrix?

Can we solve it using a homographic transformation on each camera image?







## Image rectification: advantages

3D reconstruction becomes easier

Image stitching to generate a panoramic view





## Panoramic view



### So, how to accomplish image rectification?

- Learn how to determine the fundamental matrix
- Relative camera motion and essential matrix
- Relation between fundamental matrix and camera matrix
- Compute image rectification

#### **Relative camera motion and essential matrix**

In the previous class, we have seen:  $F = K'^{-T}RS(\mathbf{t})K^{-1}$ 

K' and K are intrinsic camera parameters that maps Euclidean image plane to image pixels; primarily plays a role to correct the shear distortion between the x- and y-axes.

It's very difficult to determine K' and K without use of a known 3D scene and just by using the correspondence between two acquired images

Thus, if we ignore this shear component, the epipolar constraint in the image Euclidean plane translates to

$$\mathbf{u}_i^{T} RS(\mathbf{t}) \mathbf{u}_i = 0 \Rightarrow \mathbf{u}_i^{T} E \mathbf{u}_i = 0, \quad \text{where } E = RS(\mathbf{t})$$

*E* is called the **essential matrix** that defines the relative motion between two camera position

Application: Determine camera movements from a video image (http://www.2d3.com/)

Relation between fundamental matrix and essential matrix (when we know K' and K)  $E = K'^{T}FK$ 

#### **Decomposition of essential matrix**

Note that the vector **t** in the essential matrix  $E = RS(\mathbf{t})$  tells us about the relative location of the two optical centers. i.e., the baseline.

Also, assuming that the camera matrix  $M = [I | \mathbf{0}]$  for the first camera, R and  $\mathbf{t}$  together determine M' -- the camera matrix of the second camera

Now, assume that, somehow, we have computed the essential matrix EBut, it does not immediately give us the translation vector **t** or the rotation matrix R

So, we need to <u>decompose *E*</u>

Singular value decomposition of E gives  $E = UDV^{T}$ , U and V are rotation matrices.

Following that the rows of  $S(\mathbf{t})$  are coplanar (why), it has a rank of two and the two singular values are equal (follows from the formulation of  $S(\mathbf{t})$ ); so

$$D = diag[\sigma, \sigma, 0]$$

We will later see that scale factor in the actual computation of E is arbitrarily set

## Decomposition of the essential matrix

#### continued ...

Denote

$$\bar{\mathbf{t}} = \begin{bmatrix} 0\\0\\1 \end{bmatrix}$$
 and  $\bar{R} = \begin{bmatrix} 0 & 1 & 0\\-1 & 0 & 0\\0 & 0 & 1 \end{bmatrix}$ 

Then the translation vector is given by

$$S(\mathbf{t}) = VS(\bar{\mathbf{t}})V^{\mathrm{T}}$$

The rotation matrix is not given uniquely, we have

$$R = U\bar{R}V^{\mathrm{T}}$$
 or  $R = U\bar{R}^{\mathrm{T}}V^{\mathrm{T}}$ 

#### Before getting into image rectification, we need to learn

- Relation between the fundamental matrix and the camera matrix
- How to compute the fundamental matrix

Camera matrices:

 $M = [I \mid \mathbf{0}]$  $M' = [S(\mathbf{e}')F \mid \mathbf{e}']$ 

## Computation of the fundamental matrix using point correspondence

Number of unknowns:

9 parameters in F minus one for scale standardization minus one for rank of F is two

$$9 - 1 - 1 = 7$$

So, we can solve F with  $m \ge 8$  corresponding point pairs in two images.

We have to solve the following linear system:

 $\mathbf{u}_i^{\prime \mathrm{T}} F \mathbf{u}_i = 0, \qquad i = 1, 2, ..., m$ Use Kronecker product identity:  $AB\mathbf{c} = (\mathbf{c}^{\mathrm{T}} \otimes A)\mathbf{b}$ 

$$\mathbf{u}_i^{\prime \mathrm{T}} F \mathbf{u}_i = \left[ \mathbf{u}_i^{\mathrm{T}} \otimes \mathbf{u}_i^{\prime \mathrm{T}} \right] \mathbf{f} = 0$$

Put together all point correspondences

$$\begin{bmatrix} \mathbf{u}_{i,1}^{\mathrm{T}} \otimes \mathbf{u}_{i,1}^{\prime \mathrm{T}} \\ \vdots \\ \mathbf{u}_{i,m}^{\mathrm{T}} \otimes \mathbf{u}_{i,m}^{\prime \mathrm{T}} \end{bmatrix} \mathbf{f} = W\mathbf{f} = 0$$

Compute  $W^T W$  and apply singular value decomposition; choose **f** along the eigenvector corresponding to the smallest eigenvalue

#### **Computation of the fundamental matrix using maximum likelihood estimation**

$$\min_{\substack{F,u_i,v_i,u'_i,v'_i}} [(u_i - \hat{u}_i)^2 + (v_i - \hat{v}_i)^2 + (u'_i - \hat{u}'_i)^2 + (v'_i - \hat{v}'_i)^2]$$
  
Given  $[u'_i, v'_i, 1]F[u_i, v_i, 1]^T = 0$  and det  $F = 0$ 

## Use Lagrange multiplier

maximize f(x, y), given g(x, y) = c

is equivalent to optimizing the Lagrange function

$$\Lambda(x, y, \lambda) = f(x, y) + \lambda \cdot (g(x, y) - c)$$

where  $\lambda$  is the new variable called <u>Lagrange multiplier</u>