

# Image-based Modeling and Rendering

## 6. Basic Concepts of 3D Modeling from Images

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# Objectives

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- Estimate  $R$ ,  $T$  from  $E$ .
- 3D position estimation
- Feature matching and extraction

# Introduction

- How to determine geometry from images?
  - Passive approaches
    - Reconstruction from stereo images
    - Reconstruction from motion
  - Active approaches
    - Structured-light-based modeling

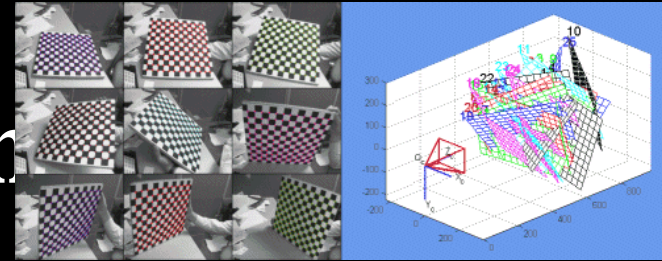
## Ref:

- Image-based Modeling and Rendering, SIGGRAPH'99 course notes.
- J. Weng, T.S. Huang, N. Ahuja, Motion and Structure from Image Sequences, 1993.
- Camera calibration toolbox for matlab
- D. Frolova, D. Simakov, Slides of "Matching with Invariant Features".
- , IEEE T. PAMI, IJCV, Proc. ICCV, Proc. CVPR ....

# 3D Geometry from Images

- Computer vision is the inverse of computer graphics.
- This talk describes some techniques for recovering 3D geometry from images.
- These techniques will be extended for image-based modeling.

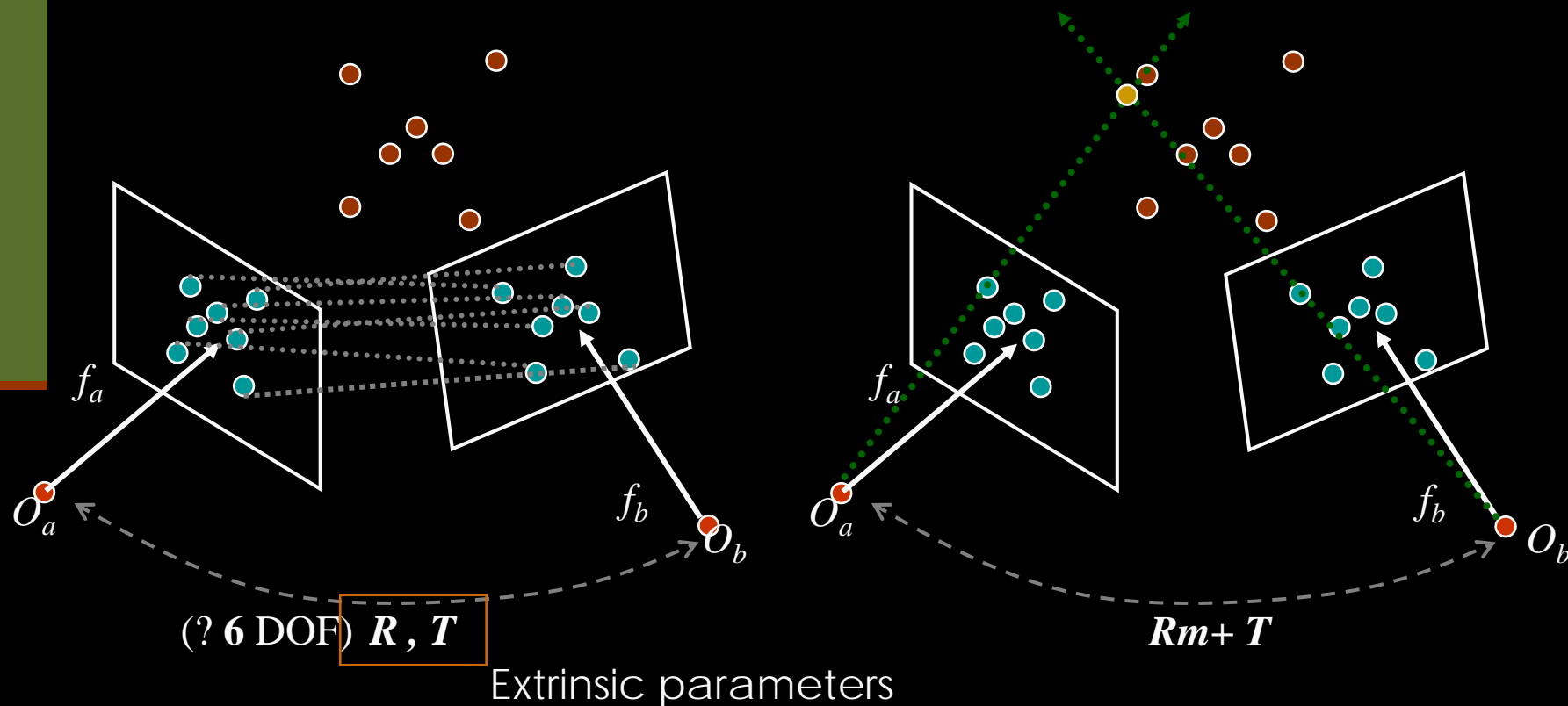
# Camera Calibration



- Public camera calibration tools
  - A flexible new technique for camera calibration
    - <http://research.microsoft.com/~zhang/calib/>
    - Z. Zhang. A flexible new technique for camera calibration. IEEE Trans. Pattern Analysis and Machine Intelligence, 22(11):1330-1334, 2000.
  - Camera calibration toolbox for matlab
    - [http://www.vision.caltech.edu/bouguetj/calib\\_doc/](http://www.vision.caltech.edu/bouguetj/calib_doc/)
  - Tsai's camera model
    - <http://www.cs.cmu.edu/~rgw/TsaiDesc.html>
    - "A versatile Camera Calibration Technique for High-Accuracy 3D Machine Vision Metrology Using Off-the-Shelf TV Cameras and Lenses", Roger Y. Tsai, IEEE J. Robotics and Automation, Vol. RA-3, No. 4, 1987, pages 323-344.

# Triangulation (Stereo)

- Given some points in **correspondence** across two or more images (**taken from calibrated cameras**),  $\{(u_j, v_j)\}$ , compute the 3D location  $X$



# Triangulation (Stereo)

- Constructing 3D structure from two views.
  - H.C. Longuet-Higgins (Nature'81).
  - J.Weng et al. **The two-view approach** (PAMI'89).
- Given some points in **correspondence** across two images (in a normalized camera model),  $\{(u_j, v_j)\}$ ,
  - Estimate  $R, T$  from corresponding points.
  - 3D position estimation from triangulation.
  - (optional) non-linear optimization

# The Two-view Approach

- Without loss of generality, the images of different view direction  $d_1, d_2$  is regarded as a rigid-body motion of an object between  $t_1, t_2$ .

$\mathbf{x}_i = (x_i, y_i, z_i)$  is the 3D position of point  $P_i$  at time  $t_1$ .

$\mathbf{x}_i' = (x_i', y_i', z_i')$  is the 3D position of point  $P_i$  at time  $t_2$ .

$\mathbf{X}_i = (u_i, v_i, 1)$  is the projected vector of  $P_i$  at time  $t_1$ .

$\mathbf{X}_i' = (u_i', v_i', 1) = (x_i'/z_i', y_i'/z_i', 1)$  is the projected vector of  $P_i$  at time  $t_2$ .



# The Two-view Approach (1)

- Step (1). Solving for essential matrix E.

$$A = \begin{bmatrix} u_1 u'_1 & u_1 v'_1 & u_1 & v_1 u'_1 & v_1 v'_1 & v_1 & u'_1 & v'_1 & 1 \\ u_2 u'_2 & u_2 v'_2 & u_2 & v_2 u'_2 & v_2 v'_2 & v_2 & u'_2 & v'_2 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u_n u'_n & u_n v'_n & u_n & v_n u'_n & v_n v'_n & v_n & u'_n & v'_n & 1 \end{bmatrix}$$

- $\min_h \|Ah\| = 1$ , subject to  $\|h\| = 1$ .

$$E = [E_1 \quad E_2 \quad E_3] = \sqrt{2} \begin{bmatrix} h_1 & h_4 & h_7 \\ h_2 & h_5 & h_8 \\ h_3 & h_6 & h_9 \end{bmatrix}$$

The solution of  $h$  is the unit eigenvector of  $A^t A$  associated with the smallest eigenvalue.

# The Two-view Approach (2)

- Step (2). Determining a unit vector  $T_s$  with  $T_0 = \pm T_s$ .
  - $\min_{T_s} \| E^t T_s \|$ , subject to  $\| T_s \| = 1$ .

The solution of  $T_s$  is the unit eigenvector of  $EE^t$  associated with the smallest eigenvalue.

$$E = T_{\times} R = [E_1 \ E_2 \ E_3] = [T_{\times} R_1 \ T_{\times} R_2 \ T_{\times} R_3]$$
$$\therefore E_1, E_2, E_3 \perp T \Rightarrow E^t T_s = 0$$

- if  $(\sum_i (T_s \times X_i') \cdot (E X_i) < 0)$ ,  $T_s = -T_s$ .

# The Two-view Approach (3)

- Step (3). Determining rotation matrix  $R$ .

- Without noise,  $W=R$

$$W = [(E_1 \times T_s + E_2 \times E_3) \quad (E_2 \times T_s + E_3 \times E_1) \quad (E_3 \times T_s + E_1 \times E_2)]$$

Using the identity equation:  $(a \times b) \times c = (a \cdot c) b - (b \cdot c) a$

- With noise,

$\min_R \| R - W \|$ , subject to:  $R$  is a rotation matrix.

# The Two-view Approach (3 app.)

- $\min_R \|RC - D\|$ , subject to:  $R$  is a rotation matrix.

- Define a 4x4 matrix  $B$  by 
$$B = \sum_{i=1}^3 B_i^t B_i$$

where 
$$B_i = \begin{bmatrix} 0 & (C_i - D_i)^t \\ D_i - C_i & [D_i + C_i]_{\times} \end{bmatrix}_{4 \times 4}$$

- $\mathbf{q} = (q_0, q_1, q_2, q_3)^t$  is the unit eigenvector of  $B$  associated with the smallest eigenvalue.

$$R = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1q_2 + q_0q_3) & 2(q_1q_3 - q_0q_2) \\ 2(q_2q_1 + q_0q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_3q_1 - q_0q_2) & 2(q_3q_2 + q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix}$$

# The Two-view Approach (4)

- Step (4). Checking  $T = 0$ , If  $T \neq 0$ , determine the sign of  $T_0$ .  
if for all  $i = 1 \sim n$ , then report  $T \approx 0$ .  
else if  $(\sum_i (T_s \times X_i') \cdot (R X_i) > 0)$ , then  $T_0 = T_s$ , otherwise  $T_0 = -T_s$ .

# The Two-view Approach (5)

- Step (5). If  $T \neq 0$ , estimate relative depths.

- To find  $Z_i = \left( \frac{z'_i}{\|T\|}, \frac{z_i}{\|T\|} \right)^t = (\tilde{z}'_i, \tilde{z}_i)$

by  $\min \left\| \begin{bmatrix} X'_i & -RX_i \end{bmatrix} Z_i - T^0 \right\|$

# The Nonlinear Optimization

- Two-view linear algorithms are often easily disturbed by noise.
  - More calibration points.
  - Nonlinear optimization.
- First, take the result of the two-view linear algorithm as an initial guess.
- Approximate the  $R, T$  by  $\min_m \{ \|f(u, m)\| \}$  in a nonlinear least square approach
  - E.g. the Levenberg-Marquardt method, or the Gauss-Newton method.
  - $f(u, m) = \text{prj}(m, y(u, m)) - u$

where  $u$  is the observed projected position,  
 $m$  is the motion parameters( $R, T$ ),  $y(u, m)$  is the best 3D positions of  $P$ ,  
and  $\text{prj}(m, x)$  is the projected position of the input structure  $x$  and motion  $m$ .

# Triangulation limits

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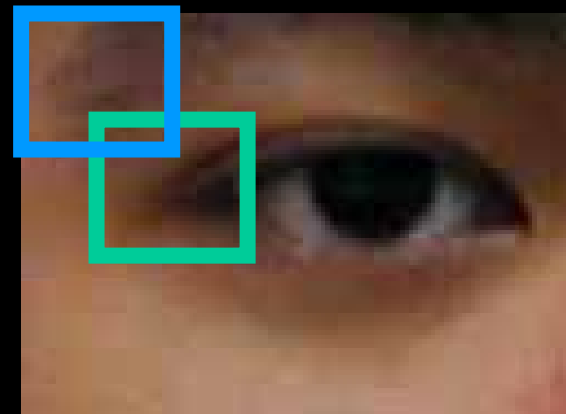
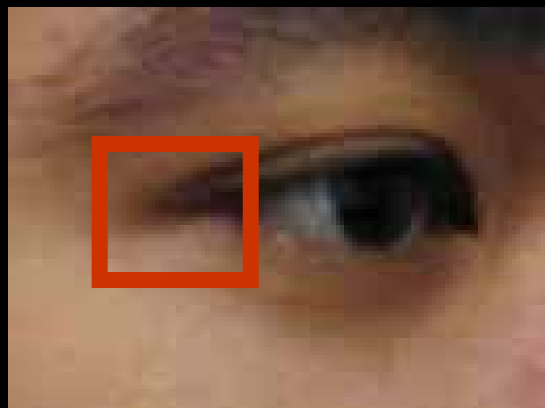
- Difficult to reliably estimate structure and motion unless:
  - large ( $x$  or  $y$ ) rotation
  - large field of view and depth variation
- Camera calibration is important
- Need good feature trackers or manual assistance
- Post-processing of the resulting 3-D points?



# Feature Matching (correlation)

- Find corresponding points in image video sequence
  - one simple technique: find two patches with minimal summed squared error.

$$E_{x,y}(u,v) = \sum_{k=x-w}^{x+w} \sum_{l=y-w}^{y+w} [I_1(k+u, l+v) - I_0(k, l)]^2$$

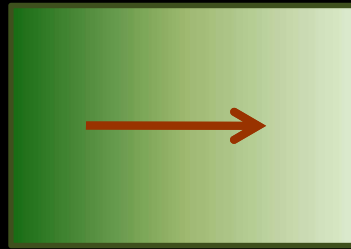


# Feature Extraction

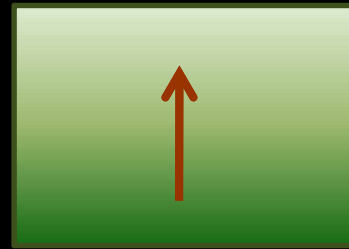
- The gradient of an image:

- E.g.

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}$$



$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} & 0 \end{bmatrix}$$



$$\nabla f = \begin{bmatrix} 0 & \frac{\partial f}{\partial y} \end{bmatrix}$$



$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}$$

- The gradient direction:

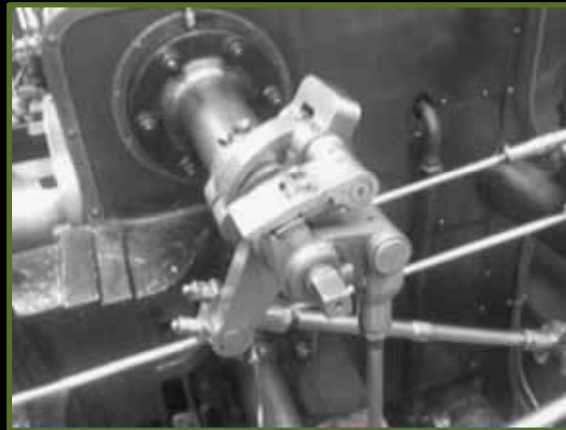
$$\theta = \tan^{-1} \left( \frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}} \right)$$

- The gradient magnitude:

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

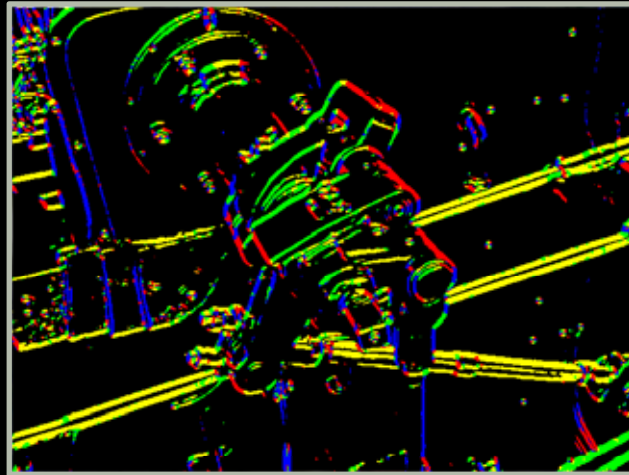
# Sobel Edge Detection

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * A \quad \text{and} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

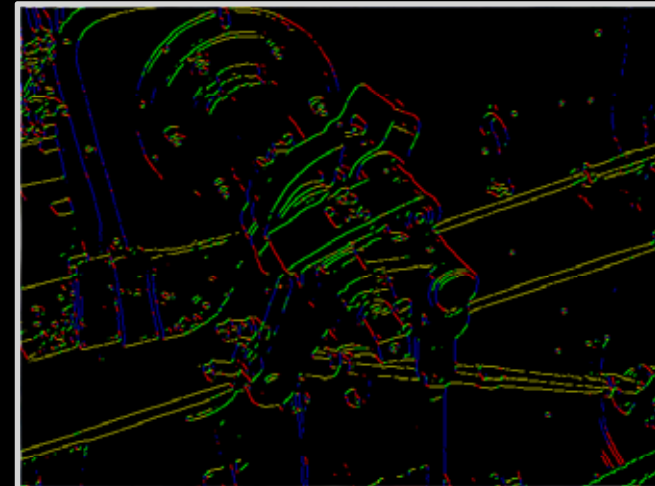


# Canny Edge Detection

- Noise removal (Gaussian filtering)
- Gradients of the image (similar to Sobel)
- Non-maximum suppression
  - Check whether a pixel is a local maximum along gradient direction



Yellow for 0 degrees; green for 45 degrees; blue for 90 degrees ; red for 135 degrees



After non-maximum suppression

# Corner Detection (Harris)

- Consider the matrix for a small square around  $(x,y)$

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

- The simplest case

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

- If  $\lambda_1 = 0$  and  $\lambda_2 = 0$  then there are no features of interest at this pixel  $(x,y)$ .
- If  $\lambda_1$  and  $\lambda_2$  is some large positive values, then an edge is found.
- If  $\lambda_1$  and  $\lambda_2$  are both large, distinct positive values, then a corner is found.

# Corner Detection (Harris)

- More general cases:

$$A = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

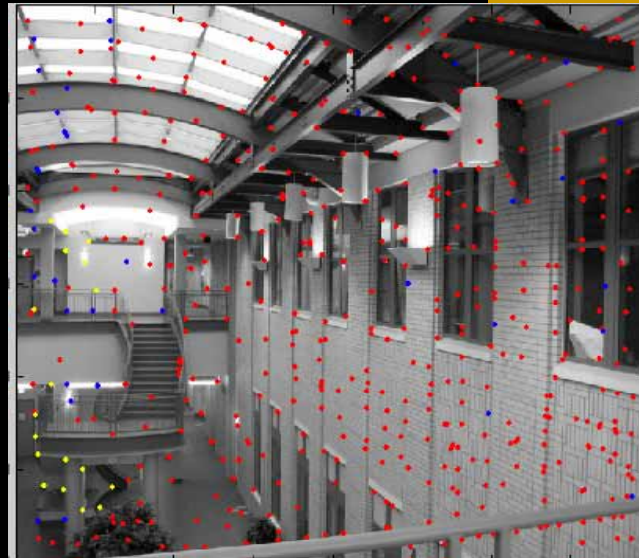
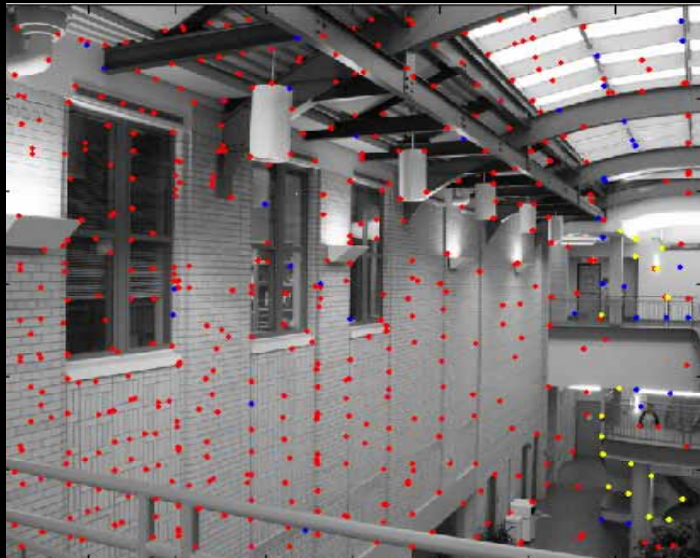
where R is a rotation matrix.

- Remind “Eigenvalues” or “Singular Value Decomposition (SVD)”.

- Process steps

- Apply Gaussian filter.
- Evaluate magnitudes of the gradients.
- Construct A.
- Find  $\lambda_1$  and  $\lambda_2$  by evaluation of eigen values or SVD.
- If they are both big, we have a corner.

# Matching with Features



Figures from Alexei Efros,  
Computational Photography