

PS2 Review

CS231A

Computer Vision: From 3D Reconstruction to Recognition

Spring 2016

Outline

Q2: Estimating Fundamental Matrix

Q3: Affine Structure From Motion

Q4: Projective Triangulation in Structure From Motion

Least Squares Eight Point Algorithm

- ▶ Recall $p^T F p' = 0$
- ▶ Construct W matrix such that $W\hat{F} = 0$, where \hat{F} is F arranged as a vector
- ▶ Run SVD on W , such that $W = U\Sigma V^T$
- ▶ \hat{F} is equal to the last column of V .
- ▶ Rearrange \hat{F} into it's matrix form (now F_m will be this matrix)
- ▶ Find the closest rank 2 matrix to F_m . Do this by running SVD on F_m , such that $F_m = U\Sigma V^T$
- ▶ Set the smallest singular value to zero ($\Sigma_{3,3} = 0$) and we find $F = U\Sigma V^T$

Problems with Eight Point Algorithm

- ▶ W matrix is highly unbalanced and can ruin SVD computation
- ▶ Each entry in W should be around the same order of magnitude
- ▶ **Solution:** Need to normalize each of the correspondences and then denormalize returned F

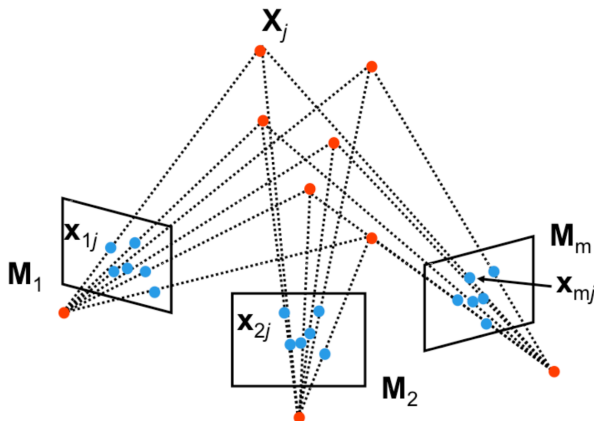
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Overall Structure From Motion Problem



- ▶ Given n 3D points and m images:
 - ▶ Motion: the projective matrices M_j
 - ▶ Structure: the 3D locations X_i

Affine Structure From Motion

- ▶ Simpler problem if we assume cameras are affine:

$$M = \begin{bmatrix} A_{2 \times 3} & b_{2 \times 1} \\ 0 & 1 \end{bmatrix}$$

$$x_{ij} = A_i X_j + b_i$$

- ▶ **Problem:** Find all A_i , X_j and b_i given correspondences x_{ij} .
- ▶ Unknowns: $3n$ from n 3D points and $8m$ from m camera parameters. In total, $3n + 8m$ variables
- ▶ Equations: $m \times n$ correspondences. Each correspondence gives 2 constraints. In total, $2mn$ constraints

Factorization Method Part 1

- Center the data:

$$\begin{aligned}\hat{x}_{ij} &= x_{ij} - \frac{1}{n} \sum_{k=1}^n x_{ik} \\ &= A_i X_j + b_i - \frac{1}{n} \sum_{k=1}^n A_i X_k - \frac{1}{n} \sum_{k=1}^n b_i \\ &= A_i \left(X_j - \frac{1}{n} \sum_{k=1}^n X_k \right)\end{aligned}$$

- Place world axes at centroid of 3D locations:

$$\sum_{k=1}^n X_k = 0$$

$$\hat{x}_{ij} = A_i X_j$$

Factorization Method Part 2

- Setup equation as follows:

$$\begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \dots & \hat{x}_{1n} \\ \hat{x}_{21} & \hat{x}_{22} & \dots & \hat{x}_{2n} \\ & & \ddots & \\ \hat{x}_{m1} & \hat{x}_{m2} & \dots & \hat{x}_{mn} \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{bmatrix} \begin{bmatrix} X_1 & X_2 & \dots & X_n \end{bmatrix}$$

$$D = MS$$

$$D = U\Sigma V^T$$

$$D = U_3 \Sigma_3 V_3^T$$

- Thus, $M = U_3$ and $S = \Sigma_3 V_3^T$

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Computing R, T From Essential Matrix E

- ▶ Recall $E = [T]_{\times} R$
- ▶ $[T]_{\times}$ is a skew-symmetric matrix and R is orthogonal
- ▶ Let $Z = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$ and $W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
- ▶ Note that $Z = \text{diag}(1, 1, 0)W$ or $\text{diag}(1, 1, 0)W^T$ up to sign
- ▶ Skew-symmetric matrices can be written as $kUZU^T$ for orthogonal matrix U and coefficient k
- ▶ Using SVD, $E = U\Sigma V^T$, with $\Sigma = \text{diag}(1, 1, 0)$

Computing R, T From Essential Matrix E

- ▶ If $E = U \text{diag}(1, 1, 0) V^T$, then

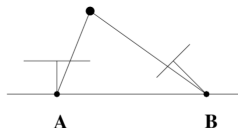
$$E = U Z U^T U W V^T$$

or

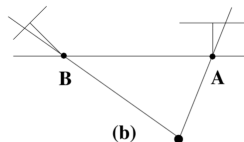
$$E = U Z U^T U W^T V^T$$

- ▶ Thus $[T]_{\times} = U Z U^T$ and $R = U W V^T$ or $U W^T V^T$
- ▶ Since Z is known up to sign, $T = u_3$ or $-u_3$ where u_3 is the 3rd column vector of U

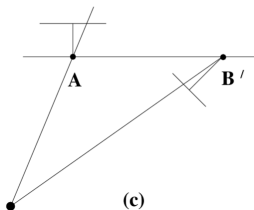
Disambiguating R, T



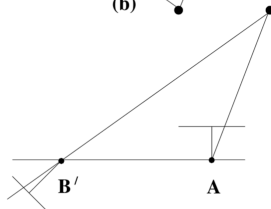
(a)



(b)



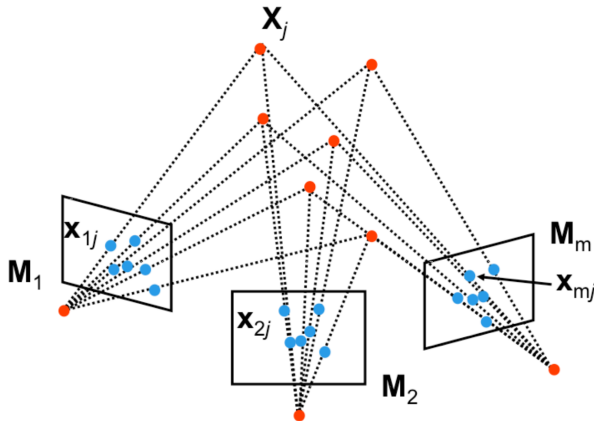
(c)



(d)

- Logically, what you're seeing has to be in front of both cameras

Relating Triangulation to Structure From Motion Problem



- Triangulation: Given motion M and image correspondences x , compute structure X

Linear Triangulation

- ▶ Want to find the least squares solution to triangulation
- ▶ Given $x_{ij} = M_i X_j$, then $x_{ij} \times M_i X_j = 0$
- ▶ Setup with form $AX_j = 0$

$$x_{ij} \times M_i X_j = 0$$

$$[x_{ij}]_{\times} M_i X_j = 0$$

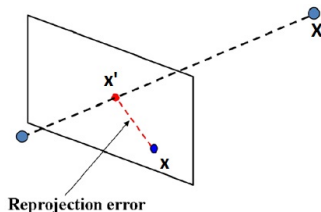
- ▶ Thus $A = [x_{ij}]_{\times} M_i$
- ▶ Because of noise, we minimize $\|AX_j\|$ subject to $\|X_j\| = 1$.
- ▶ Solved using SVD: If $A = U\Sigma V^T$, then X_j is the last column of V (proof in HZ 592)
- ▶ Use homogeneous coordinates to circumvent $\|X_j\| = 1$ constraint

Nonlinear Optimization

- ▶ Can also optimize finding structure using some objective function
- ▶ Common one is the reprojection error for image location x :

$$\text{error} = x' - x$$

where x' when you project 3D location X into some image.



- ▶ Newton step - covered in class prerequisites