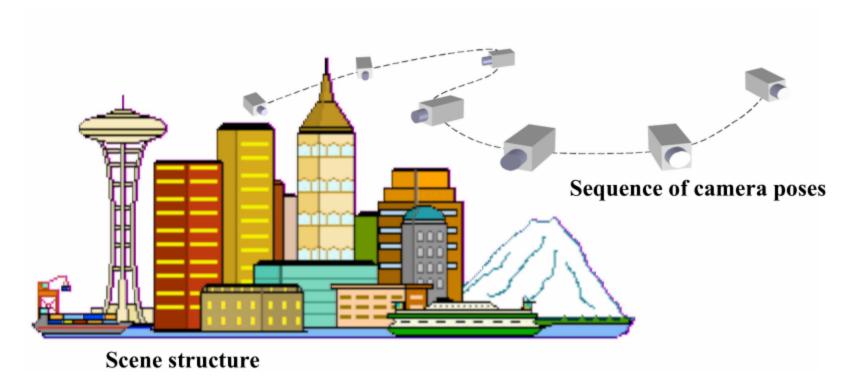
# Lecture 25: Structure from Motion

## **Structure from Motion**

Given a set of flow fields or displacement vectors from a moving camera over time, determine:

- the sequence of camera poses
- the 3D structure of the scene



# SFM "Killer App"

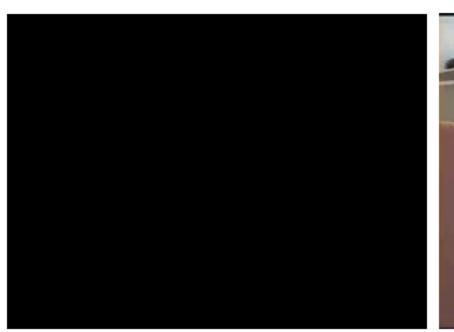
#### **Match Move**

Track a set of feature points through a movie sequence

Deduce where the cameras are and the 3D locations of the points that were tracked

Render synthetic objects with respect to the deduced 3D geometry of the scene / cameras

# **Match Move Examples**





"Harts' War" and "Graham Kimpton" examples from www.realviz.com MatchMover Professional gallery. Copyrighted.

## **Factorization**

Tomasi and Kanade, "Shape and Motion from Image Streams under Orthography," *International Journal of Computer Vision (IJCV)*, Vol 9, pp.137-154, 1992.

Goal: combine point correspondence information from multiple points over multiple frames to solve for scene structure and camera motion (structure from motion)

Approach: numerically stable approach based on using SVD to "factor" matrix of observed point positions.

Historical significance: until that time, most SFM work dealt with minimal configurations, and noise-free data. Factorization was one of the first "practical SFM algorithms"

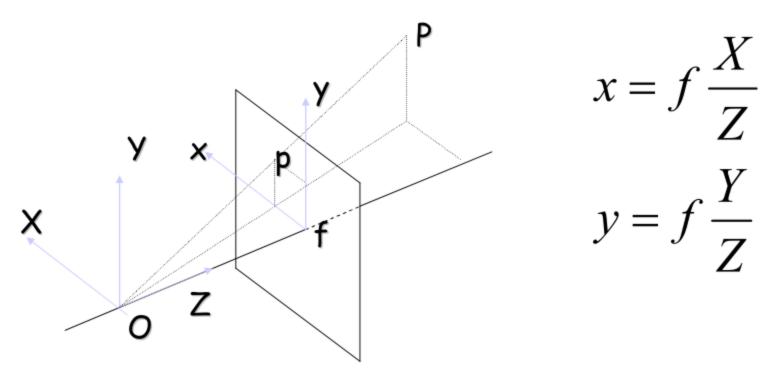
# CSE486, PRecall: World to Camera Transform

$$\mathbf{P}^{\mathbf{C}} = \mathbf{R} \left( \mathbf{P}^{\mathbf{W}} - \mathbf{C} \right)$$

$$\begin{pmatrix}
P_{x}^{C} \\
P_{y}^{C} \\
P_{z}^{C} \\
1
\end{pmatrix} = \begin{pmatrix}
r_{11} & r_{12} & r_{13} & 0 \\
r_{21} & r_{22} & r_{23} & 0 \\
r_{31} & r_{32} & r_{33} & 0 \\
0 & 0 & 0 & 1
\end{pmatrix} \begin{pmatrix}
1 & 0 & 0 & -c_{x} \\
0 & 1 & 0 & -c_{y} \\
0 & 0 & 1 & -c_{z} \\
0 & 0 & 0 & 1
\end{pmatrix} \begin{pmatrix}
P_{x}^{W} \\
P_{y}^{W} \\
P_{z}^{W} \\
1
\end{pmatrix}$$

$$P^C = M_{ext} \cdot P^W$$

# **Perspective Projection**

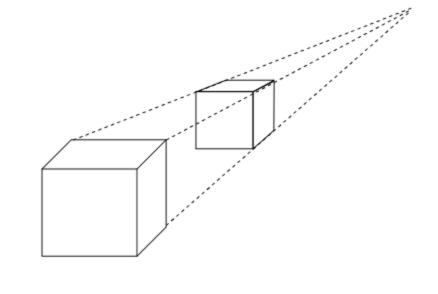


- ·Non-linear equations
- ·Any point on the ray OP has image p!!

# **Perspective Projection**

$$x = f \frac{X}{Z}$$

$$y = f \frac{Y}{Z}$$



Perspective Projection: parallel lines appear to meet at a vanishing point; farther objects seem smaller

# CSE486, Penn Stat Simplification: Weak Perspective

$$x = \frac{f}{Z_o} X$$

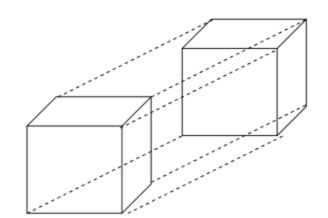
$$y = \frac{f}{Z_o} Y$$

Weak perspective = Parallel projection (parallel lines remain parallel) + Scaling to simulate change in size due to object distance.

# CSE486, Penn Sta Simpler: Orthographic Projection

$$x = X$$

$$y = Y$$



Pure parallel projection. Highly simplified case where we even ignore the scaling due to distance.

# CSE486, Penn State Perspective Matrix Equation

(Camera Coordinates)

Using homogeneous coordinates:

$$x = f \frac{X}{Z}$$

$$y = f \frac{Y}{Z}$$

$$x = f \frac{X}{Z}$$

$$y = f \frac{Y}{Z}$$

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$x = \frac{x'}{z'} \quad y = \frac{y'}{z'}$$

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# Weak Perspective Approximation

$$x = \frac{f}{Z_o} X$$

$$y = \frac{f}{Z_0} Y$$

$$x = \frac{f}{Z_o} X$$

$$y = \frac{f}{Z_o} Y$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} f/Z_0 & 0 & 0 & 0 \\ 0 & f/Z_0 & 0 & 0 \\ 0 & f/Z_0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

# CSE486, Penn State Let's Consider Orthographic

Using homogeneous coordinates:

$$x = X$$

$$y = Y$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

## CSE486, Penn State Combine with External Params

$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{r}_{11} & \mathbf{r}_{12} & \mathbf{r}_{13} & 0 \\ \mathbf{r}_{21} & \mathbf{r}_{22} & \mathbf{r}_{23} & 0 \\ \mathbf{r}_{31} & \mathbf{r}_{32} & \mathbf{r}_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & -c_x \\ 0 & 1 & 0 & -c_y \\ 0 & 0 & 1 & -c_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{P}_{\mathbf{x}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{y}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{z}}^{\mathbf{W}} \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_{11} & \mathbf{r}_{12} & \mathbf{r}_{13} & 0 \\ \mathbf{r}_{21} & \mathbf{r}_{22} & \mathbf{r}_{23} & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & -c_x \\ 0 & 1 & 0 & -c_y \\ 0 & 0 & 1 & -c_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{P}_{\mathbf{x}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{y}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{z}}^{\mathbf{W}} \\ 1 \end{bmatrix}$$

## CSE486, Penn State Combine with External Params

$$\begin{pmatrix} \mathbf{x} \\ \mathbf{y} \end{pmatrix} = \begin{pmatrix} \mathbf{r}_{11} & \mathbf{r}_{12} & \mathbf{r}_{13} & \mathbf{0} \\ \mathbf{r}_{21} & \mathbf{r}_{22} & \mathbf{r}_{23} & \mathbf{0} \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & -c_x \\ 0 & 1 & 0 & -c_y \\ 0 & 0 & 1 & -c_z \\ \hline \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \end{pmatrix} \begin{pmatrix} \mathbf{P}_{\mathbf{x}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{y}}^{\mathbf{W}} \\ \mathbf{P}_{\mathbf{z}}^{\mathbf{W}} \\ \mathbf{1} \end{pmatrix}$$

$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_{11} & \mathbf{r}_{12} & \mathbf{r}_{13} \\ \mathbf{r}_{21} & \mathbf{r}_{22} & \mathbf{r}_{23} \end{bmatrix} \begin{bmatrix} \mathbf{P}_{\mathbf{x}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{x}} \\ \mathbf{P}_{\mathbf{y}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{y}} \\ \mathbf{P}_{\mathbf{z}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{z}} \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_{11} & \mathbf{r}_{12} & \mathbf{r}_{13} \\ \mathbf{r}_{21} & \mathbf{r}_{22} & \mathbf{r}_{23} \end{bmatrix} \begin{bmatrix} \mathbf{P}_{\mathbf{x}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{x}} \\ \mathbf{P}_{\mathbf{y}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{y}} \\ \mathbf{P}_{\mathbf{z}}^{\mathbf{W}} - \mathbf{c}_{\mathbf{y}} \end{bmatrix}$$

$$x = \mathbf{i}^{T} (\mathbf{P} - \mathbf{T})$$
$$y = \mathbf{j}^{T} (\mathbf{P} - \mathbf{T})$$

# CSE486, Penn State Multiple Points, Multiple Frames

Notation (attack of the killer subscripts)

$$x = \mathbf{i}^{T} (\mathbf{P} - \mathbf{T})$$

$$y = \mathbf{j}^{T} (\mathbf{P} - \mathbf{T})$$

$$\begin{array}{c} N \text{ points} \\ P_1 \ P_2 \ ... \ P_j \ ... \ P_N \end{array}$$

$$x_{ij} = \mathbf{i}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

$$y_{ij} = \mathbf{j}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

Eq 8.31-8.32 T&V book

$$x_{ij} = \mathbf{i}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

$$y_{ij} = \mathbf{j}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

N points
$$P_1 P_2 \dots P_j \dots P_N$$
(We want to recover these)

Note that absolute position of the set of points is something that cannot be uniquely recovered, so...

**First Trick**: set the origin of the world coordinate system to be the center of pass of the N points!

$$\frac{1}{N}\sum_{i=1}^{N}P_{i}=0$$

$$x_{ij} = \mathbf{i}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

$$y_{ij} = \mathbf{j}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

Centroid at 0:

$$\frac{1}{N}\sum_{i=1}^{N}P_{i}=0$$

#### **Implication:**

$$\bar{x}_{it} = \frac{1}{N} \sum_{i=1}^{N} i_t^T (P_i - T_t) = \frac{1}{N} \sum_{i=1}^{N} i_t^T P_i - \frac{1}{N} \sum_{i=1}^{N} i_t^T T_t = 0 - i_t^T T_t$$

Note: this is the center of mass of x coordinates in frame t

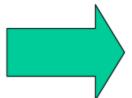
$$\bar{x}_{ti} = \frac{1}{n} \sum_{i=1}^{n} i_t^T (P_i - T_t) = -i_t^T T_t$$

$$\bar{y}_{ti} = \frac{1}{n} \sum_{i=1}^{n} j_t^T (P_i - T_t) = -j_t^T T_t$$

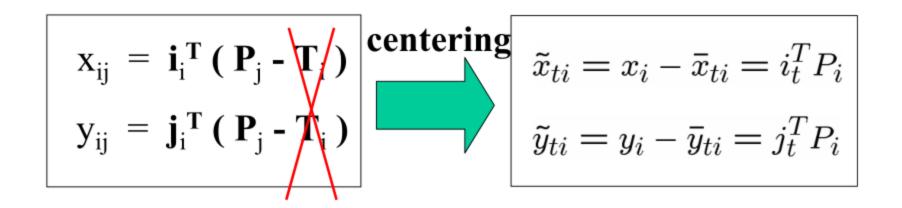
**Second Trick**: subtract off the center of mass of the 2D points in each frame. (Centering)

$$x_{ij} = \mathbf{i}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$

$$y_{ij} = \mathbf{j}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$



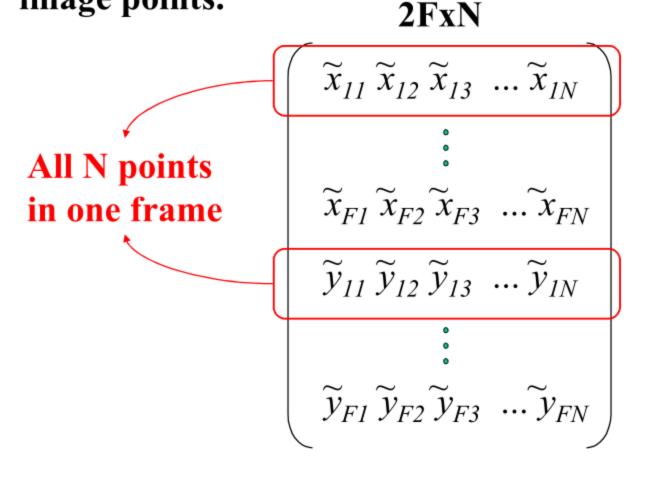
$$\mathbf{x}_{ij} = \mathbf{i}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$$
 $\mathbf{y}_{ij} = \mathbf{j}_{i}^{T} (\mathbf{P}_{j} - \mathbf{T}_{i})$ 
 $\tilde{y}_{ti} = y_{i} - \bar{y}_{ti} = j_{t}^{T} P_{i}$ 



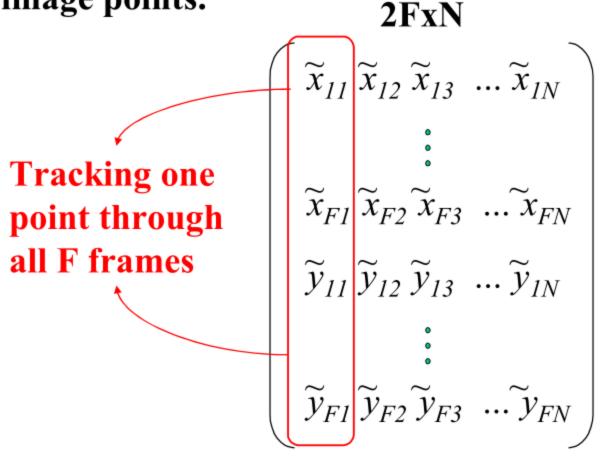
What have we accomplished so far?

- 1) Removed unknown camera locations from equations.
- 2) More importantly, we can now write everything As a big matrix equation...

Form a matrix of centered image points.



Form a matrix of centered image points.



# Robert Collins CSE486, Per actorization Approach $\tilde{x}_{it} = x_i - \bar{x}_{it} = i_t^T P_i$

# $\tilde{x}_{it} = x_i - \bar{x}_{it} = i_t^T P_i$ $\tilde{y}_{it} = y_i - \bar{y}_{it} = j_t^T P_i$

# matrix of centered image points:

#### 2FxN

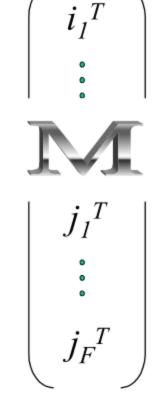
$$\widetilde{x}_{11} \widetilde{x}_{12} \widetilde{x}_{13} \dots \widetilde{x}_{1N}$$

$$\widetilde{x}_{F1} \widetilde{y}_{12} y_{13} \dots \widetilde{y}_{1N}$$

$$\widetilde{y}_{11} \widetilde{y}_{12} y_{13} \dots \widetilde{y}_{1N}$$

$$\widetilde{y}_{F1} \widetilde{y}_{F2} \widetilde{y}_{F3} \dots \widetilde{y}_{FN}$$

#### 2Fx3



#### 3xN

$$P_1 \longrightarrow P_N$$

2F x N

2F x 3

3 x N

W

M

S

Centered measurement matrix

"Motion" (camera rotation)

Structure (3D scene points)

W = M S

#### Rank Theorem:

The 2FxN centered observation matrix has at most rank 3.

#### **Proof:**

Trivial, using the properties:

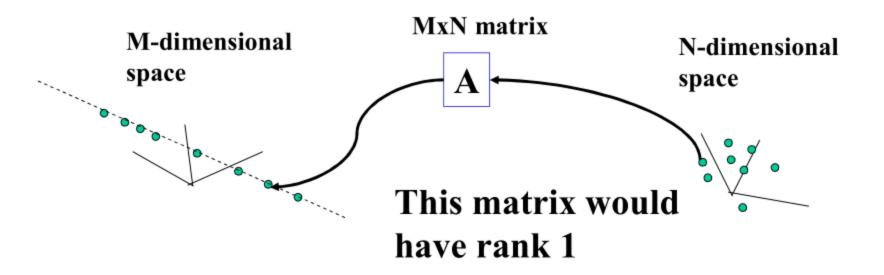
- rank of mxn matrix is at most min(m,n)
- rank of A\*B is at most min(rank(A),rank(B))

## Rank of a Matrix

What is rank of a matrix, anyways?

Number of columns (rows) that are linearly independent.

If matrix A is treated as a linear map, it is the <u>intrinsic</u> dimension of the space that is mapped into.

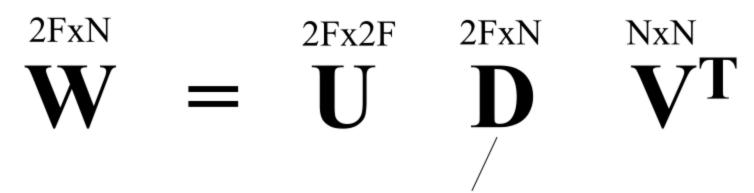


## **Factorization Rank Theorem**

#### Importance of rank theorem:

- •Shows that video data is highly redundant
- •Precisely quantifies the redundancy
- •Suggests an algorithm for solving SFM

#### Form SVD of measurement matrix W



Diagonal matrix with eigenvalues sorted in decreasing order:

$$d_{11} >= d_{22} >= d_{33} >= ...$$

#### Form SVD of measurement matrix W

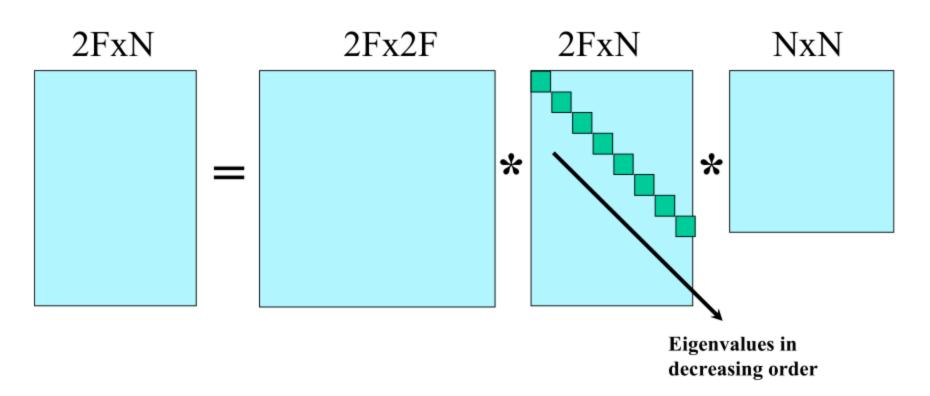


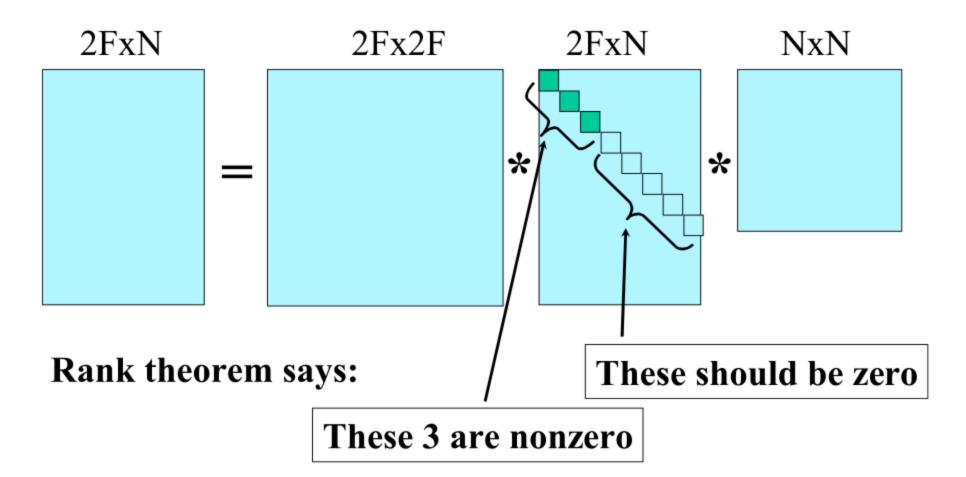
#### Another useful rank property:

Rank of a matrix is equal to the number of nonzero eigenvalues.

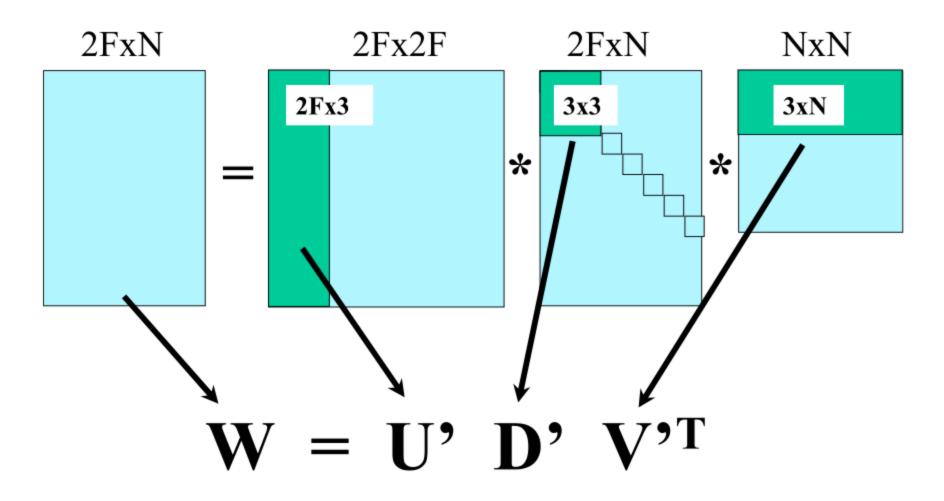


 $d_{11}$ ,  $d_{22}$ ,  $d_{33}$  are only nonzero eigenvalues (the rest are 0).





In practice, due to noise, there may be more than 3 nonzero eigenvalues, but rank theorem tells us to ignore all but the largest three.



**Observed image points** 

$$\mathbf{W} \stackrel{\text{SVD}}{=} \mathbf{U'} \mathbf{D'} \mathbf{V'}^{\mathsf{T}}$$

$$\mathbf{W} = \mathbf{U'} \mathbf{D'}^{1/2} \mathbf{D'}^{1/2} \mathbf{V'}^{\mathsf{T}}$$

$$\mathbf{W} = \mathbf{M} \mathbf{S}$$

$$\mathbf{Camera}_{\text{motion}} \mathbf{Scene}_{\text{structure}}$$

# **Annoying Details**

$$W = (U' D'^{1/2})(D'^{1/2} V'^{T})$$

$${}_{2FxN} {}_{2Fx3} {}_{3xN}$$

$$W = M S$$

#### **Problems:**

1) This is not a unique decomposition.

eg: 
$$(M Q) (Q^{-1} S) = M Q Q^{-1} S = M S$$

2) i<sup>T</sup>, j<sup>T</sup> pairs (rows of M) are not necessarily orthogonal

# Solving the Annoying Details

#### **Solution to both problems:**

Solve for Q such that appropriate rows of M satisfy

$$\left\{ egin{aligned} & \widehat{\mathbf{i}}_i^T Q Q^T \widehat{\mathbf{i}}_i = 1 \\ & \widehat{\mathbf{j}}_i^T Q Q^T \widehat{\mathbf{j}}_i = 1 \end{aligned} \right\} \quad \text{unit vectors} \\ & \widehat{\mathbf{i}}_i^T Q Q^T \widehat{\mathbf{j}}_i = 0 \quad \text{orthogonal} \end{aligned}$$

3N equations in 9 unknowns

But these are nonlinear equations linearize and iterate

(see Exercise 8.8 in book for Newton's method)

(alternative approach is to use Cholesky decomposition – outside our scope)

# **Factorization Summary**

#### Assumptions

- orthographic camera
- N non-coplanar points tracking in F>=3 frames

Form the centered measurement matrix W=[X;Y]

- where  $\tilde{\mathbf{x}}_{ij} = \mathbf{x}_{ij} \mathbf{m}\mathbf{x}_{j}$
- where  $\tilde{y}_{ij} = y_{ij} my_j$
- mx<sub>j</sub> and my<sub>j</sub> are mean of points in frame i
- j ranges over set of points

Rank theorem: The centered measurement matrix has a rank of at most 3

# **Factorization Algorithm**

- 1) Form the centered measurement matrix W from N points tracked over F frames.
- 2) Compute SVD of  $W = U D V^T$ 
  - U is 2Fx2F
  - D is 2FxN
  - VT is NxN
- 3) Take largest 3 eigenvalues, and form
  - D' = 3x3 diagonal matrix of largest eigenvalues
  - U' = 2Fx3 matrix of corresponding column vectors from U
  - $V^T = 3xN$  matrix of corresponding row vectors from  $V^T$
- 4) Define

$$M = U' D'^{1/2}$$
 and  $S = D'^{1/2} V'^{T}$ 

- 5) Solve for Q that makes appropriate rows of M orthogonal
- 6) Final solution is

$$\mathbf{M}^* = \mathbf{M} \mathbf{Q}$$
 and  $\mathbf{S}^* = \mathbf{Q}^{-1} \mathbf{S}$ 

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# **Sample Results**

QuickTime™ and a Cinepak decompressor are needed to see this picture.

