## Structure from Motion and Multiview Geometry

Topics in Image-Based Modeling and Rendering CSE291 J00

Lecture 5

## Last lecture

S. J. Gortler, R. Grzeszczuk, R. Szeliski, M. F. Cohen The Lumigraph, SIGGRAPH, pp 43--54, 1996

## M. Levoy, P. Hanrahan, Light Field Rendering , SIGGRAPH, 1996

Aaron Isaksen, Leonard McMillan, Steven J. Gortler, Dynamically reparameterized light fields, SIGGRAPH 2000, pp 297-306
D. Wood, D. Azuma, W. Aldinger, B. Curless, T. Duchamp, D. Salesin, and W. Steutzle. Surface light fields for 3D photography, SIGGRAPH, 2000.

## A cube of light



- All light from an object can be represented as if it were coming from a cube
- Each point on the cube has a a 2-D set of rays emanating from the cube.



## Two plane parameterization

- Rays are parameterized by where they intersect these planes.


4D parameterization of rays

- Any point in the 4D Light field/Lumigraph is identified by its coordinates ( $\mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}$ )
- Continuous light field

$$
\mathbf{L}(\mathbf{s}, \mathbf{t}, \mathbf{u}, \mathbf{v})
$$

## - Cube around object - six

 slabs.Note that the lumigraph and light field papers interchange roles of $(\mathrm{s}, \mathrm{t})$ and ( $\mathrm{u}, \mathrm{v}$ )

## Rendering



- For each desired ray:
- Compute intersection with (u,v) and (s,t) planes
- Take radiance at closest ray
- Can be computed using texture mapping hardware


## Lumigraph Rendering

- Use rough depth information to improve rendering quality



## Light Slabs (Again)

- Two-plane parameterization impacts reconstruction filters
- Aperture filtering removes high frequency data
- But if plane is wrong place, only stores blurred version of scene



## Variable Aperture



- Real camera aperture produce depth-of-field effects
- Emulate depth-of-field effects by combining rays from several cameras
- Combine samples for each $D_{s, t}$ in the synthetic aperture to produce image

1. Render $r$ ' with aperture $A^{\prime}:$ in focus
2. Render $\mathrm{r}^{\prime \prime}$ with aperature $\mathrm{A}^{\prime \prime}$ : out of focus

## This lecture

- Motion contains useful information
- Epipolar constraint
- The motion field for a moving camera
- Factorization for orthographic cameras
- Perspective - 8 point algorithm

1. Multiple View Geometry in Computer Vision, by Richard Hartley,Andrew Zisserman, Cambridge University Press, 2000.
2. The Geometry of Multiple Images, by Olivier Faugeras, Quang-Tuan Luong, T. Papadopoulo, MIT Press, 2001.
3. C. Tomasi, T. Kanade, Shape and Motion from Image Streams: A Factorization Method, IJCV, 9(2), 1992, 137-154.
4. Longuet-Higgins, Prazdny, The Interpretation of a Moving Retinal Image, Proc. R. Soc. Long. B, 1980, pp. 385-397.
5. Longuet-Higgins, A computer algorithm for reconstructing a scene from two projections, Nature, Vol. 293, 1981, pp. 133-135.

## Motion Demo





## Motion

"When objects move at equal speed, those more remote seem to move more slowly."

- Euclid, 300 BC



## The Motion Field

Where in the image did a point move?


Down and left


## Motion Field Equation

$$
\begin{aligned}
& v_{x}=\frac{T_{z} x-T_{x} f}{Z}-\omega_{y} f+\omega_{z} y+\frac{\omega_{z} x y}{f}-\frac{\omega_{y} x^{2}}{f} \\
& v_{y}=\frac{T_{z} y-T_{y} f}{Z}+\omega_{x} f-\omega_{z} x-\frac{\omega_{y} x y}{f}+\frac{\omega_{x} y^{2}}{f} .
\end{aligned}
$$

- $\mathrm{v}_{\mathrm{x}}, \mathrm{v}_{\mathrm{y}}$ : Components of image motion
-T: Components of 3-D linear motion
- $\omega$ : Angular velocity vector
- (x,y): Image point coordinates
- Z: depth
- f: focal length


## Pure Translation

$$
\begin{aligned}
& v_{x}=\frac{T_{z} x-T_{x} f}{Z}-\omega_{y} f+\omega_{x} y+\frac{\omega_{x} x y}{f}-\frac{\omega_{y} z}{f} \\
& v_{y}=\frac{T_{z} y-T_{y} f}{Z}+\omega_{x}-\omega_{z} x-\frac{\omega_{y} x y}{f}+\frac{\omega_{x} y^{2}}{f} \\
& \omega=0
\end{aligned}
$$



## Pure Rotation: $\mathbf{T}=0$

$$
\begin{aligned}
& v_{x}=\frac{i_{i} x-T_{r}}{7}-\omega_{y} f+\omega_{z} y+\frac{\omega_{x} x y}{f}-\frac{\omega_{y} x^{2}}{f} \\
& v_{y}=\frac{T y-1_{y} f}{Z}+\omega_{x} f-\omega_{z} x-\frac{\omega_{y} x y}{f}+\frac{\omega_{x} y^{2}}{f}
\end{aligned}
$$

- Independent of $\mathrm{T}_{\mathrm{x}} \mathrm{T}_{\mathrm{y}} \mathrm{T}_{\mathrm{z}}$
- Independent of Z
- Only function of (x,y), f and $\omega$


## Pure Rotation: Motion Field on Sphere



## Epipolar Geometry

## Triangulation



Epipolar Constraint


- Potential matches for $p$ have to lie on the corresponding epipolar line $l$ '.
- Potential matches for $p$ ' have to lie on the corresponding epipolar line $l$.


## Epipolar Geometry



- Epipolar Plane • Baseline
- Epipoles
- Epipolar Lines



## Properties of the Essential Matrix

- E $\mathrm{p}^{\prime}$ is the epipolar line associated with $\mathrm{p}^{\prime}$.
- $E^{T} p$ is the epipolar line associated with $p$.
- $E e^{\prime}=0$ and $E\binom{\mathrm{~T}}{\mathrm{e}}$.
- $E$ is singular.
- E has two equal non-zero singular values (Huang and Faugeras, 1989).


## Rectification

Given a pair of images, transform both images so that epipolar lines are scan lines.


Estimate a Homography to apply to each image, given at least four corresponding points

$$
\left[\begin{array}{c}
u^{\prime} \\
v^{\prime} \\
w^{\prime}
\end{array}\right]=\left[\begin{array}{lll}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{array}\right]\left[\begin{array}{c}
u \\
v \\
w
\end{array}\right]
$$

## Rectification



All epipolar lines are parallel in the rectified image plane.

## Rectification

Given a pair of images, transform both images so that epipolar lines are scan lines.


## Rectification

Given a pair of images, transform both images so that epipolar lines are scan lines.


Rectified Images

## Features on same epipolar line



## E vs. F revisited

The Essential Matrix $\boldsymbol{E}$ :

- Encodes information on the extrinsic parameters only
- Has rank 2 since R is full rank and $\left[\mathrm{T}_{\mathrm{x}}\right]$ is skew \& rank 2
- Its two non-zero singular values are equal
- 5 degrees of freedom

The Fundamental Matrix $\boldsymbol{F}$ :

- Encodes information on both the intrinsic and extrinsic parameters
- Also has rank 2 since $E$ is rank 2
- 7 degrees of freedom

Epipolar Constraint: Uncalibrated Case


$$
\hat{\boldsymbol{p}}^{T} \mathcal{E} \hat{\boldsymbol{p}}^{\prime}=0
$$

$$
\boldsymbol{p}=\mathcal{K} \hat{\boldsymbol{p}} \quad \Longleftrightarrow \boldsymbol{p}^{T} \mathcal{F} \boldsymbol{p}^{\prime}=0 \quad \text { with } \mathcal{F}=\mathcal{K}^{-T} \mathcal{E} \mathcal{K}^{\prime-1}
$$

$$
\boldsymbol{p}^{\prime}=\mathcal{K}^{\prime} \hat{\boldsymbol{p}}^{\prime}
$$



## Properties of the Fundamental Matrix

- $\mathrm{F} \mathrm{p}^{\prime}$ is the epipolar line associated with $\mathrm{p}^{\prime}$.
- $\mathrm{F}^{\mathrm{T}} \mathrm{p}$ is the epipolar line associated with p .
- $\mathrm{Fe}^{\prime}=0$ and $\mathrm{F}^{\mathrm{T}}=0$.
- F is singular.


## E vs. F revisited

The Essential Matrix $\boldsymbol{E}$ :

- Encodes information on the extrinsic parameters only
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- 5 degrees of freedom

The Eight-Point Algorithm (Longuet-Higgins, 1981)


## Non-Linear Least-Squares Approach (Luong et al., 1993)

Minimize

$$
\sum_{i=1}^{n}\left[\mathrm{~d}^{2}\left(\boldsymbol{p}_{i}, \mathcal{F} \boldsymbol{p}_{i}^{\prime}\right)+\mathrm{d}^{2}\left(\boldsymbol{p}_{i}^{\prime}, \mathcal{F}^{T} \boldsymbol{p}_{i}\right)\right]
$$

with respect to the coefficients of $F$, using an appropriate rank-2 parameterization.

## Recovering Motion

## Recall epipolar constraint

$$
\boldsymbol{p}^{T} \mathcal{E} \boldsymbol{p}^{\prime}=0 \quad \text { with } \quad \mathcal{E}=\left[\boldsymbol{t}_{\times}\right] \mathcal{R}
$$

Where

$$
\left[t_{x}\right]=\left[\begin{array}{ccc}
0 & -t_{z} & t_{y} \\
t_{z} & 0 & -t_{x} \\
-t_{y} & t_{x} & 0
\end{array}\right]
$$

Solve for $\mathbf{R} \& \mathbf{t}$

## Structure from Motion:

Uncalibrated cameras and projective amibguity


The Eight-Point Algorithm (Longuet-Higgins, 1981)


## Non-Linear Least-Squares Approach (Luong et al., 1993)

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-t_{y} & t_{x} & 0
\end{array}\right]
$$

Solve for $\mathbf{R} \& \mathbf{t}$

## Structure from Motion:

Uncalibrated cameras and projective amibguity


## Projective Ambiguity

Theorem 1 Let $\left\{P_{1}, P_{2}\right\}$ and $\left\{P_{1}^{\prime} P_{2}^{\prime}\right\}$ be two pairs of camera transformations. Then $\left\{P_{1}, P_{2}\right\}$ and $\left\{P_{1}^{\prime} P_{2}^{\prime}\right\}$ correspond to the same essential matrix $F$ if and only if there exists a $4 \times 4$ non-singular matrix $H$ such that $P_{1} H \approx P_{1}^{\prime}$ and $P_{2} H \approx P_{2}^{\prime}$.

$$
\begin{gathered}
\mathbf{x}_{i}^{\prime}=H^{-1} \mathbf{x}_{i} \\
P_{j}^{\prime} \mathbf{x}_{i}^{\prime}=P_{j} H H^{-1} \mathbf{x}_{i}=P_{j} \mathbf{x}_{i}=\mathbf{u}_{i} \\
j=1,2
\end{gathered}
$$

- We see that the same set of corresponding image points could come from two different sets of real world points and therefore both sets satisfy:

$$
\mathbf{u}_{i}^{\prime \top} F \mathbf{u}_{i}=0
$$

## The "only if" part

- We would also like to show that if the cameras have the same fundamental matrix then there is a 4 by 4 matrix that relates them.
- If we take the camera matrices and multiply them by:
we get

$$
\left\{\left(M_{1} \mid-M_{1} T_{1}\right),\left(M_{2} \mid-M_{2} T_{2}\right)\right\}
$$

- The same is true for
$\left(\begin{array}{cc}M_{1}^{-1} & T_{1} \\ \mathbf{0} & 1\end{array}\right)$

$$
\left\{(I \mid 0),\left(M_{2} M_{1}^{-1} \mid-M_{2}\left(T_{2}-T_{1}\right)\right)\right\}
$$

$$
\left\{\left(M_{1}^{\prime} \mid-M_{1}^{\prime} T_{1}^{\prime}\right),\left(M_{2}^{\prime} \mid-M_{2}^{\prime} T_{2}^{\prime}\right)\right\}
$$

$$
\left\{(I \mid 0),\left(M_{2}^{\prime} M_{1}^{\prime-1} \mid-M_{2}^{\prime}\left(T_{2}^{\prime}-T_{1}^{\prime}\right)\right)\right\}
$$

## Factorization method/affine cameras

C. Tomasi, T. Kanade, Shape and Motion from Image Streams: A Factorization Method, IJCV, 9(2), 1992, 137-154.


## Origin of 3D Points at 3-D Centroid



Centroid
$\bar{P}=\frac{1}{n} \sum_{i=1}^{n} P_{j}$

Centered Data Points
$\widetilde{P}=P_{j}-\bar{P}$

## Origin of image at image Centroid



## Centered Image Points

$$
\left[\begin{array}{c}
\tilde{x}_{i, j} \\
\tilde{y}_{i, j}
\end{array}\right]=\left[\begin{array}{l}
x_{i, j}-\bar{x}_{i} \\
y_{i, j}-\bar{y}_{i}
\end{array}\right] \quad \begin{aligned}
& \text { is pentriod of image points } \\
&
\end{aligned}
$$

## Data Matrix

$\tilde{x}_{i, j}, \tilde{y}_{i, j}$ are the $\mathrm{i}, \mathrm{j}$-th element of the N by n data matrices $\mathrm{X}, \mathrm{Y}$
$\tilde{W}=\left[\begin{array}{c}\tilde{X} \\ --- \\ \tilde{Y}\end{array}\right] \quad 2 \mathrm{~N}$ by n registered data matrix

Rank Theorem: Without noise, the rank of W is less than or equal to 3.

## The Rank Theorem: Factorized

The registered measurement matrix can be expressed in a matrix form:

$$
\widetilde{W}=R S
$$

$$
R=\left[\begin{array}{c}
\mathbf{i}_{1}^{T} \\
\vdots \\
\mathbf{i}_{F}^{T} \\
\mathbf{j}_{1}^{T} \\
\vdots \\
\mathbf{j}_{F}^{T}
\end{array}\right] \quad \text { represents the camera rotation }
$$

$$
S=\left[\begin{array}{lll}
\mathbf{s}_{1} & \cdots & \mathbf{s}_{P}
\end{array}\right] \quad \text { is the shape matrix }
$$

## Factoring

Given a data matrix containing measured feature points, it can be factored using singular value decomposition as:

$$
\tilde{W}=U D V^{T}
$$

Where
D: n by n diagonal matrix, non-negative entries, called singular values
$\mathrm{U}: 2 \mathrm{~N}$ by n with orthogonal columns
$\mathrm{V}^{\mathrm{T}}$ : n by n with orthogonal columns

$$
D=\left[\begin{array}{cccc}
\sigma_{1} & 0 & \cdots & 0 \\
0 & \sigma_{2} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \sigma_{n}
\end{array}\right], \sigma_{1} \geq \sigma_{2} \geq \sigma_{3} \geq \sigma_{n} \quad \begin{aligned}
& \bullet \text { Without noise, } \sigma_{\mathrm{i}}=0, \mathrm{i}>3 \\
& \bullet \text { With noise, set } \sigma \mathrm{i}=0, \mathrm{i}>3
\end{aligned}
$$

## Factoring: After setting $\sigma_{i}=0, \mathrm{i}>3$

$$
\tilde{W}^{\prime}=U^{\prime} D^{\prime} V^{T}
$$

Where
D': 3 by 3 diagonal matrix, non-negative entries
U: 2 N by 3 with orthogonal columns
$\mathrm{V}^{\mathrm{T}}: 3$ by n with orthogonal columns

$$
\begin{aligned}
& \tilde{W}^{\prime}=U^{\prime} D^{\prime} V^{\prime T}=\hat{R} \hat{S} \\
& \text { where } \\
& \hat{R}=U^{\prime} D^{1 / 2} \\
& \hat{S}=D^{1 / 2} V^{\prime T}
\end{aligned}
$$

$$
\begin{gathered}
\text { Ambiguity } \\
\tilde{W}=\hat{R} \hat{S}=\hat{R} A A^{-1} \hat{S}=(\hat{R} A)\left(A^{-1} \hat{S}\right)
\end{gathered}
$$

- True for any A.
- So, find an A such that rows of RA are unit length and pairs corresponding to same image are orthogonal.

| $\hat{R} A$ | Estimated camera orientation |
| :--- | :--- |
| $A^{-1} \hat{S}$ | Estimated 3-D structure |

## Four of 150 input images



## Tracked Corner Features




## Building



40


80


## Reconstruction



- Triangulate
- Texture Map

