## Affine Structure from Motion

## EECS 598-08 Fall 2014 <br> Foundations of Computer Vision

## Readings: FP 8.2

Date: 11/5/14

## Plan

- What is affine SFM?
- Algebraic Methods from Two Views
- Factorization


## Application

Courtesy of Oxford Visual Geometry Group


## Structure from motion problem



Given $m$ images of $n$ fixed 3D points

$$
\cdot \mathbf{x}_{i j}=\mathbf{M}_{i} \mathbf{X}_{j}, \quad i=1, \ldots, m, \quad j=1, \ldots, n
$$

## Structure from motion problem



From the $m \times n$ correspondences $\mathbf{x}_{i j}$, estimate:

- m projection matrices $\mathbf{M}_{i}$
$\cdot n$ 3D points $\mathbf{X}_{j}$


## Affine structure from motion (simpler problem)



From the $m \times n$ correspondences $\mathbf{x}_{i j}$, estimate:

- $m$ projection matrices $\mathbf{M}_{i}$ (affine cameras)
-n 3D points $\mathbf{X}_{j}$



## Question:

$$
\left[\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{array}\right]\left[\begin{array}{ll}
R & T \\
0 & 1
\end{array}\right]=? ?
$$



Canonical perspective projection matrix


## Projective \& Affine cameras

$$
x=K\left[\begin{array}{ll}
R & T
\end{array}\right] X
$$

Projective case

$$
\mathrm{K}=\left[\begin{array}{ccc}
\boldsymbol{\alpha}_{\mathrm{x}} & \mathrm{~s} & \mathrm{x}_{\mathrm{o}} \\
0 & \boldsymbol{\alpha}_{\mathrm{y}} & \mathrm{y}_{\mathrm{o}} \\
0 & 0 & 1
\end{array}\right] \quad \mathrm{M}=\mathrm{K}\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{array}\right]\left[\begin{array}{cc}
\mathrm{R} & \mathrm{~T} \\
0 & 1
\end{array}\right]
$$

## Weak perspective projection

When the relative scene depth is small compared to its distance from the camera
$\left\{\begin{array}{l}x^{\prime}=-m x \\ y^{\prime}=-m y\end{array}\right.$



## Orthographic (affine) projection

When the camera is at a (roughly constant) distance from the scene


## Transformation in 2D

$$
\left[\begin{array}{c}
x^{\prime} \\
\mathrm{y}^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{cc}
\mathrm{a} & \mathrm{t} \\
0 & 1
\end{array}\right]\left[\begin{array}{l}
\mathrm{x} \\
\mathrm{y} \\
1
\end{array}\right]=\mathrm{H}_{\mathrm{a}}\left[\begin{array}{l}
\mathrm{x} \\
\mathrm{y} \\
1
\end{array}\right]
$$



## Projective \& Affine cameras

$$
x=K\left[\begin{array}{ll}
R & T
\end{array}\right] X
$$

Projective case

$$
K=\left[\begin{array}{ccc}
\boldsymbol{\alpha}_{\mathrm{x}} & \mathrm{~s} & \mathrm{x}_{\mathrm{o}} \\
0 & \boldsymbol{\alpha}_{\mathrm{y}} & \mathrm{y}_{\mathrm{o}} \\
0 & 0 & 1
\end{array}\right] \quad \mathrm{M}=\mathrm{K}\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{array}\right]\left[\begin{array}{cc}
\mathrm{R} & \mathrm{~T} \\
0 & 1
\end{array}\right]
$$

Affine case


Magnification (scaling term)


Parallel projection matrix
(points at infinity are mapped as points at infinity)

## Affine cameras

$$
\begin{aligned}
& \mathrm{X}=\mathrm{K}\left[\begin{array}{ll}
\mathrm{R} & \mathrm{~T}
\end{array}\right] \mathrm{X} \quad \text { [Homogeneous] } \\
& K=\left[\begin{array}{ccc}
\alpha_{x} & 0 & 0 \\
0 & \alpha_{y} & 0 \\
0 & 0 & 1
\end{array}\right] \quad \mathrm{M}=\mathrm{K}\left[\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{ll}
\mathrm{R} & \mathrm{~T} \\
0 & 1
\end{array}\right] \\
& M=[3 \times 3 \text { affine }]\left[\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1
\end{array}\right][4 \times 4 \text { affine }]=\left[\begin{array}{cccc}
a_{11} & a_{12} & a_{13} & b_{1} \\
a_{21} & a_{22} & a_{23} & b_{2} \\
0 & 0 & 0 & 1
\end{array}\right]=\left[\begin{array}{cc}
\mathbf{A} & \mathbf{b} \\
\mathbf{0} & \mathbf{1}
\end{array}\right] \\
& \mathbf{x}=\binom{x}{y}=\left[\begin{array}{lll}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23}
\end{array}\right]\left(\begin{array}{l}
X \\
Y \\
Z
\end{array}\right)+\binom{b_{1}}{b_{2}}=\mathbf{A X}+\mathbf{b}=M_{E u c}\left[\begin{array}{l}
\mathbf{X} \\
1
\end{array}\right]=M_{E u c}\left[\begin{array}{l}
\mathbf{P} \\
1
\end{array}\right] ; \\
& \left.\mathrm{M}_{\mathrm{Euc}}=\mathrm{M}=\left[\begin{array}{ll}
\mathrm{A} & \mathrm{~b}
\end{array}\right] \begin{array}{l}
\text { [nonhomogeneous } \\
\text { image coordinates }
\end{array}\right]
\end{aligned}
$$

## Affine cameras



To recap:
from now on we define $M$ as the camera matrix for the affine case

$$
\mathbf{p}=\binom{u}{v}=\mathbf{A P}+\mathbf{b}=M\left[\begin{array}{l}
\mathbf{P} \\
1
\end{array}\right] ; \quad \mathbf{M}=\left[\begin{array}{ll}
\mathbf{A} & \mathbf{b}
\end{array}\right]
$$

## The Affine Structure-from-Motion Problem

Given $m$ images of $n$ fixed points $P_{j}\left(=\mathrm{X}_{\mathrm{i}}\right)$ we can write

$$
\boldsymbol{p}_{i j}=\mathcal{M}_{i}\binom{\boldsymbol{P}_{j}}{1}=\mathcal{A}_{i} \boldsymbol{P}_{j}+\boldsymbol{b}_{i} \text { for } i=1, \ldots, \sqrt{m} \text { and } j=1, \ldots, n .
$$

Problem: estimate the $m 2 \times 4$ matrices $M_{i}$ and the $n$ positions $P_{j}$ from the $m \times n$ correspondences $p_{i j}$.

How many equations and how many unknown?
$2 \mathrm{~m} \times \mathrm{n}$ equations in $8 \mathrm{~m}+3 \mathrm{n}$ unknowns

## Two approaches:

- Algebraic approach (affine epipolar geometry; estimate F; cameras; points)
- Factorization method


## Algebraic analysis (2-view case)

- Derive the fundamental matrix $F_{A}$ for the affine case
- Compute $\mathrm{F}_{\mathrm{A}}$
- Use $\mathrm{F}_{\mathrm{A}}$ to estimate projection matrices
- Use projection matrices to estimate 3D points


## 1. Deriving the fundamental matrix $F_{A}$



Homogeneous system

$$
\left\{\begin{array}{l}
\boldsymbol{p}=\mathcal{A} \boldsymbol{P}+\boldsymbol{b} \\
\boldsymbol{p}^{\prime}=\mathcal{A}^{\prime} \boldsymbol{P}+\boldsymbol{b}^{\prime}
\end{array} \quad \square \quad\left(\begin{array}{cc}
\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\
\mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}
\end{array}\right)\binom{\boldsymbol{P}}{-1}=\mathbf{0}\right.
$$

Dim $=? 4 \times 4$
$\Rightarrow \operatorname{Det}\left(\begin{array}{cc}\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\ \mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}\end{array}\right)=\Rightarrow \alpha^{\alpha u+\beta v+\alpha^{\prime} u^{\prime}+\beta^{\prime} v^{\prime}+\delta=0}$ Affine Epipolar Constraint

## Deriving the fundamental matrix $\mathrm{F}_{\mathrm{A}}$

$$
\alpha u+\beta v+\alpha^{\prime} u^{\prime}+\beta^{\prime} v^{\prime}+\delta=0
$$



$$
(u, v, 1) \mathcal{F}\left(\begin{array}{c}
u^{\prime} \\
v^{\prime} \\
1
\end{array}\right)=0 \quad \text { where } \quad \mathcal{F} \stackrel{\text { def }}{=}\left(\begin{array}{ccc}
0 & 0 & \alpha \\
0 & 0 & \beta \\
\alpha^{\prime} & \beta^{\prime} & \delta
\end{array}\right)
$$

The Affine Fundamental Matrix!

Are the epipolar lines parallel or converging?


Affine Epipolar Geometry


## Estimating $\mathrm{F}_{\mathrm{A}}$

$$
\alpha u+\beta v+\alpha^{\prime} u^{\prime}+\beta^{\prime} v^{\prime}+\delta=0
$$

- Measurements: u, u', v, v’
- From $n$ correspondences, we obtain a linear system on the unknown alpha, beta, etc...

$$
\left[\begin{array}{ccccc}
\mathrm{u}_{1}^{\prime} & \mathrm{v}_{1}^{\prime} & \mathrm{u}_{1} & \mathrm{v}_{1} & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\mathrm{u}_{\mathrm{n}}^{\prime} & \mathrm{v}_{\mathrm{n}}^{\prime} & \mathrm{u}_{\mathrm{n}} & \mathrm{v}_{\mathrm{n}} & 1
\end{array}\right] \mathbf{f}=0
$$

- Computed by least square and by enforcing $|f|=1$
- SVD


## Estimating projection matrices from $\mathrm{F}_{\mathrm{A}}$



## Affine ambiguity



## 2. Estimating projection matrices from epipolar constraints

If $M_{i}$ and $P_{i}$ are solutions,
then $M_{i}^{\prime}$ and $P_{i}^{\prime}$ are also solutions,
where

$$
\mathcal{M}_{i}^{\prime}=\mathcal{M}_{i} \mathcal{Q} \quad \text { and } \quad\binom{\boldsymbol{P}_{j}^{\prime}}{1}=\mathcal{Q}^{-1}\binom{\boldsymbol{P}_{j}}{1}
$$

and

$$
\mathcal{Q}=\left(\begin{array}{cc}
\mathcal{C} & \boldsymbol{d} \\
\mathbf{0}^{T} & 1
\end{array}\right) \quad \begin{aligned}
& Q \text { is an affine } \\
& \text { transformation } .
\end{aligned}
$$

Proof:

$$
\boldsymbol{p}_{i j}=\mathcal{M}_{i}\binom{\boldsymbol{P}_{j}}{1}=\left(\mathcal{M}_{i} \mathcal{Q}\right)\left(\mathcal{Q}^{-1}\binom{\boldsymbol{P}_{j}}{1}\right)=\mathcal{M}_{i}^{\prime}\binom{\boldsymbol{P}_{j}^{\prime}}{1} \boldsymbol{\square}
$$

3. Estimating projection matrices from $\mathrm{F}_{\mathrm{A}}$


Estimating projection matrices from $\mathrm{F}_{\mathrm{A}}$

Choose Q such
that..

$$
\begin{gathered}
\mathcal{M}=\left(\begin{array}{ll}
\mathcal{A} & b
\end{array}\right) \\
\boldsymbol{\nabla}
\end{gathered}
$$

$$
\mathcal{M}^{\prime}=\left(\begin{array}{ll}
\mathcal{A}^{\prime} & b^{\prime}
\end{array}\right)
$$

$$
P
$$

$$
\downarrow
$$

$$
\tilde{\mathcal{M}}^{\prime}=\mathcal{M}^{\prime} \mathcal{Q}
$$

$$
\begin{gathered}
\boldsymbol{\nabla} \\
\tilde{\mathcal{M}}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0
\end{array}\right)
\end{gathered}
$$

$$
\begin{gathered}
\boldsymbol{\nabla} \\
\tilde{\mathcal{M}}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0
\end{array}\right)
\end{gathered}
$$

Where $a, b, c, d$ can be expressed as function of the parameters of $F_{A}$

## 4. Estimating the structure from $F_{A}$

> A b
> $A^{\prime} b^{\prime}$

$$
\begin{aligned}
& \left(\begin{array}{cc}
\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\
\mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}
\end{array}\right)\binom{\boldsymbol{P}}{-1}=\mathbf{0} \quad \boldsymbol{\square} \\
& \left(\begin{array}{cccc}
1 & 0 & 0 & u \\
0 & 1 & 0 & v \\
0 & 0 & 1 & u^{\prime} \\
a & b & c & v^{\prime}-d
\end{array}\right)\binom{\tilde{\boldsymbol{P}}}{-1}=0 \quad \boldsymbol{} \quad \tilde{\boldsymbol{P}}=\left(\begin{array}{c}
u \\
v \\
u^{\prime}
\end{array}\right)
\end{aligned}
$$

Can be solved by least square again
3. Estimating projection matrices from epipolar constraints

$$
\mathcal{M}=\left(\begin{array}{ll}
\mathcal{A} & b
\end{array}\right)
$$

$$
\begin{gathered}
\\
.
\end{gathered}
$$

$$
\downarrow
$$

$$
\tilde{\mathcal{M}}=\mathcal{M} \mathcal{Q}
$$

$$
\begin{gathered}
\tilde{\mathcal{M}}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0
\end{array}\right) \\
\boldsymbol{\nabla}
\end{gathered}
$$

$$
\widetilde{\mathrm{A}}=\left[\begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 0
\end{array}\right]
$$

$$
\widetilde{\mathrm{b}}=\left[\begin{array}{ll}
0 & 0
\end{array}\right]^{\mathrm{T}}
$$

$$
\mathcal{M}^{\prime}=\left(\begin{array}{ll}
\mathcal{A}^{\prime} & b^{\prime}
\end{array}\right)
$$

$$
P
$$

$$
\sqrt{5}
$$

$$
\downarrow
$$

$$
\tilde{\mathcal{M}}^{\prime}=\mathcal{M}^{\prime} \mathcal{Q}
$$

$$
\tilde{\boldsymbol{P}}=\mathcal{Q}^{-1} \boldsymbol{P}
$$

$$
\square
$$

$$
\downarrow
$$

$$
\tilde{\mathcal{M}}^{\prime}=\left(\begin{array}{llll}
0 & 0 & 1 & 0 \\
a & b & c & d
\end{array}\right) \quad \tilde{\boldsymbol{P}}
$$

$$
\downarrow
$$

$$
\widetilde{\mathrm{A}}^{\prime}=\left[\begin{array}{lll}
0 & 0 & 1 \\
\mathrm{a} & \mathrm{~b} & \mathrm{c}
\end{array}\right]
$$

Canonical affine cameras

Estimating projection matrices from epipolar constraints

$$
\begin{array}{ccc}
\mathcal{M}=\left(\begin{array}{ll}
\mathcal{A} & b
\end{array}\right) & \mathcal{M}^{\prime}=\left(\begin{array}{ll}
\mathcal{A}^{\prime} & \boldsymbol{b}^{\prime}
\end{array}\right) & \boldsymbol{P} \\
\boldsymbol{\nabla} & \boldsymbol{\downarrow} & \boldsymbol{\downarrow} \\
\tilde{\mathcal{M}}=\mathcal{M} \mathcal{Q} & & \tilde{\mathcal{M}}^{\prime}=\mathcal{M}^{\prime} \mathcal{Q}
\end{array}
$$

Choose Q such
that..

By re-enforcing the epipolar constraint, we can compute $a, b, c, d$ directly from the measurements

## Reminder: epipolar constraint



Homogeneous system

$$
\left\{\begin{array}{l}
\boldsymbol{p}=\mathcal{A} \boldsymbol{P}+\boldsymbol{b} \\
\boldsymbol{p}^{\prime}=\mathcal{A}^{\prime} \boldsymbol{P}+\boldsymbol{b}^{\prime}
\end{array} \quad \square \quad\left(\begin{array}{lc}
\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\
\mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}
\end{array}\right)\binom{\boldsymbol{P}}{-1}=\mathbf{0}\right.
$$

$\operatorname{Det}\left(\begin{array}{cc}\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\ \mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}\end{array}\right)=0 \Rightarrow$
$\alpha u+\beta v+\alpha^{\prime} u^{\prime}+\beta^{\prime} v^{\prime}+\delta=0$

## Estimating projection matrices from epipolar constraints

$$
\begin{gathered}
\mathcal{M}=\left(\begin{array}{ll}
\mathcal{A} & b
\end{array}\right) \\
\boldsymbol{\downarrow} \\
\tilde{\mathcal{M}}=\mathcal{M} \mathcal{Q}
\end{gathered}
$$

$$
\tilde{\mathcal{M}}^{\prime}=\mathcal{M}^{\prime} \mathcal{Q}
$$

Choose $Q$ such that... $\downarrow$

$$
\downarrow
$$

$$
\tilde{\mathcal{M}}=\left(\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1 & 0
\end{array}\right] \quad \tilde{\mathcal{M}}^{\prime}=\left(\begin{array}{llll}
0 & 0 & 1 & 0 \\
a & b & c & d
\end{array}\right) \quad \tilde{\boldsymbol{P}}
$$

$$
\widetilde{A} \bar{\square}
$$

Re-enforce the Epipolar constraint
$\operatorname{Det}\left(\begin{array}{cc}\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\ \mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}\end{array}\right)=0 \longrightarrow \operatorname{Det}\left(\begin{array}{cccc}0 & 1 & 0 & v \\ 0 & 0 & 1 & u^{\prime} \\ a & b & c & v^{\prime}-d\end{array}\right)=0$

Estimating projection matrices from epipolar constraints

$$
\begin{aligned}
& \mathcal{M}=\left(\begin{array}{ll}
\mathcal{A} & b
\end{array}\right) \\
& \mathcal{M}^{\prime}=\left(\begin{array}{ll}
\mathcal{A}^{\prime} & b^{\prime}
\end{array}\right) \\
& \text { P } \\
& \sqrt{\square} \\
& \tilde{\mathcal{M}}=\mathcal{M} \mathcal{Q} \\
& \tilde{\mathcal{M}}^{\prime}=\mathcal{M}^{\prime} \mathcal{Q} \\
& \tilde{\boldsymbol{P}}=\mathcal{Q}^{-1} \boldsymbol{P} \\
& \text { Choose } Q \text { such that... } \boldsymbol{\downarrow} \\
& \tilde{\mathcal{M}}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0
\end{array}\right) \\
& \tilde{\mathcal{M}}^{\prime}=\left(\begin{array}{llll}
0 & 0 & 1 & 0 \\
a & b & c & d
\end{array}\right) \quad \tilde{\boldsymbol{P}} \\
& \text { A b }
\end{aligned}
$$

$$
\operatorname{Det}\left(\begin{array}{cccc}
1 & 0 & 0 & u \\
0 & 1 & 0 & v \\
0 & 0 & 1 & u^{\prime} \\
a & b & c & v^{\prime}-d
\end{array}\right)=a u-b v+c u^{\prime}+v^{\prime}-d=0
$$

## Estimating projection matrices from epipolar constraints

$$
\operatorname{Det}\left(\begin{array}{cccc}
1 & 0 & 0 & u \\
0 & 1 & 0 & v \\
0 & 0 & 1 & u^{\prime} \\
a & b & c & v^{\prime}-d
\end{array}\right)=a u-b v+c u^{\prime}+v^{\prime}-d=0
$$

- Linear relationship between measurements and unknown

Unknown: a, b, c, d Measurements: u, u', v, v’

- From at least 4 correspondences, we can solve this linear system and compute a, b, c, d (via least square)
- The cameras can be computed
- How about the structure?


## 4. Estimating the structure from $F_{A}$

$$
\tilde{\mathcal{M}}=\left(\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1 & 0 \\
\mathrm{~A}
\end{array}\right) \quad \tilde{\mathrm{O}}^{\prime}=\left(\begin{array}{llll}
0 & 0 & 1 & 0 \\
a & b & c & d
\end{array}\right) \quad \tilde{\boldsymbol{P}}
$$

$$
\left(\begin{array}{cc}
\mathcal{A} & \boldsymbol{p}-\boldsymbol{b} \\
\mathcal{A}^{\prime} & \boldsymbol{p}^{\prime}-\boldsymbol{b}^{\prime}
\end{array}\right)\binom{\boldsymbol{P}}{-1}=\mathbf{0}
$$

$$
\left(\begin{array}{cccc}
1 & 0 & 0 & u \\
0 & 1 & 0 & v \\
0 & 0 & 1 & u^{\prime} \\
a & b & c & v^{\prime}-d
\end{array}\right)\binom{\tilde{\boldsymbol{P}}}{-1}=0 \quad \Rightarrow \quad \tilde{\boldsymbol{P}}=\left(\begin{array}{c}
u \\
v \\
u^{\prime}
\end{array}\right)
$$

Can be solved by least square again


First reconstruction. Mean reprojection error: 1.6pixel



Second reconstruction. Mean re-projection error: 7.8pixel

# A factorization method Tomasi \& Kanade algorithm 

C. Tomasi and T. Kanade.

Shape and motion from image streams under orthography: A factorization method. IJCV, 9(2):137-154, November 1992.

- Centering the data
- Factorization


## A factorization method - Centering the data

- Centering: subtract the centroid of the image points

$$
\hat{\mathbf{x}}_{\mathrm{ij}}=\mathbf{x}_{\mathrm{ij}}-\frac{1}{\mathrm{n}} \sum_{\mathrm{k}=1}^{\mathrm{n}} \mathbf{x}_{\mathrm{ik}}-\overline{\mathbf{x}}_{\mathrm{i}}
$$



## A factorization method - Centering the data

- Centering: subtract the centroid of the image points

$$
\begin{aligned}
& \hat{\mathbf{x}}_{\mathrm{ij}}=\mathbf{x}_{\mathrm{ij}}-\frac{1}{\mathrm{n}} \sum_{\mathrm{k}=1}^{\mathrm{n}} \mathbf{x}_{\mathrm{ik}}=\mathbf{A}_{\mathrm{i}} \mathbf{X}_{\mathrm{j}}+\mathbf{b}_{\mathrm{i}}-\frac{1}{\mathrm{n}} \sum_{\mathrm{k}=1}^{\mathrm{n}}\left(\mathbf{A}_{\mathrm{i}} \mathbf{X}_{\mathrm{k}}+\mathbf{b}_{\mathrm{i}}\right) \\
& \mathbf{x}_{i j}=\mathbf{A}_{i} \mathbf{X}_{j}+\mathbf{b}_{i}
\end{aligned}
$$

## A factorization method - Centering the data

- Centering: subtract the centroid of the image points

$$
\begin{aligned}
\hat{\mathbf{x}}_{i j} & =\mathbf{x}_{i j}-\frac{1}{n} \sum_{k=1}^{n} \mathbf{x}_{i k}=\mathbf{A}_{i} \mathbf{X}_{j}+\mathbf{b}_{i}-\frac{1}{n} \sum_{k=1}^{n}\left(\mathbf{A}_{i} \mathbf{X}_{k}+\mathbf{b}_{i}\right) \\
& =\mathbf{A}_{i}\left(\mathbf{X}_{j}-\frac{1}{n} \sum_{k=1}^{n} \mathbf{X}_{k}\right)
\end{aligned}
$$

Assume that the origin of the world coordinate system is at the centroid pf the 3D points

After centering, each normalized point $\mathbf{x}_{i j}$ is related to the 3D point $\mathbf{X}_{i}$ by

$$
\hat{\mathbf{x}}_{i j}=\mathbf{A}_{i} \mathbf{X}_{j}
$$

A factorization method - Centering the data


$$
\hat{\mathbf{x}}_{i j}=\mathbf{A}_{i} \mathbf{X}_{j}
$$

## A factorization method - factorization

Let's create a $2 \mathrm{~m} \times \mathrm{n}$ data (measurement) matrix:

$$
\left.\mathbf{D}=\underbrace{\left[\begin{array}{llll}
\hat{\mathbf{x}}_{11} & \hat{\mathbf{x}}_{12} & \cdots & \hat{\mathbf{x}}_{1 n} \\
\hat{\mathbf{x}}_{21} & \hat{\mathbf{x}}_{22} & \cdots & \hat{\mathbf{x}}_{2 n} \\
& & \ddots & \\
\hat{\mathbf{x}}_{m 1} & \hat{\mathbf{x}}_{m 2} & \cdots & \hat{\mathbf{x}}_{m n}
\end{array}\right]}_{\text {points }(n)} \right\rvert\, \begin{gathered}
\text { cameras } \\
(2 m)
\end{gathered}
$$

## A factorization method - factorization

- Let's create a $2 \mathrm{~m} \times \mathrm{n}$ data (measurement) matrix:


The measurement matrix $\mathbf{D}=\mathbf{M} \mathbf{S}$ has rank 3 (it's a product of a $2 m x 3$ matrix and $3 x n$ matrix)

## Factorizing the measurement matrix



## Factorizing the measurement matrix

- Singular value decomposition of $D$ :



## Factorizing the measurement matrix

- Singular value decomposition of $D$ :


Since rank (D)=3, there are only 3 non-zero singular values 3


## Factorizing the measurement matrix

- Obtaining a factorization from SVD:

$S=$ structure
$\mathrm{M}=$ Motion (cameras)

What is the issue here?
D has rank $>3$ because of - measurement noise

- affine approximation


## Factorizing the measurement matrix

- Obtaining a factorization from SVD:


$S=$ structure

$$
\mathrm{M}=\text { motion }
$$

Theorem: When D has a rank greater than $p, \mathcal{U}_{p} \mathcal{W}_{p} \mathcal{V}_{p}^{T}$ is the best possible rank- $p$ approximation of D in the sense of the Frobenius norm.

$$
\mathcal{D}=\mathcal{U}_{3} \mathcal{W}_{3} \mathcal{V}_{3}^{T} \quad\left\{\begin{array}{l}
\mathcal{A}_{0}=\mathcal{U}_{3} \\
\mathcal{P}_{0}=\mathcal{W}_{3} \nu_{3}^{T}
\end{array}\right.
$$

## Affine ambiguity



- The decomposition is not unique. We get the same D by using any $3 \times 3$ matrix $\mathbf{C}$ and applying the transformations $\mathbf{M} \rightarrow \mathbf{M C}, \mathbf{S} \rightarrow \mathbf{C}^{-1} \mathbf{S}$
- We can enforce some Euclidean constraints to resolve
- this ambiguity (more on next lecture!)


## Algorithm summary

1. Given: $m$ images and $n$ features $\mathbf{x}_{i j}$
2. For each image $i$, center the feature coordinates
3. Construct a $2 m \times n$ measurement matrix $\mathbf{D}$ :

- Column $j$ contains the projection of point $j$ in all views
- Row $i$ contains one coordinate of the projections of all the $n$ points in image $i$

4. Factorize $\mathbf{D}$ :

- Compute SVD: D=U W V ${ }^{\top}$
- Create $\mathbf{U}_{3}$ by taking the first 3 columns of $\mathbf{U}$
- Create $\mathbf{V}_{3}$ by taking the first 3 columns of $\mathbf{V}$
- Create $\mathbf{W}_{3}$ by taking the upper left $3 \times 3$ block of $\mathbf{W}$

5. Create the motion and shape matrices:
$-\quad \begin{aligned} & \mathbf{M}=\mathbf{M}=\mathbf{U}_{3} \text { and } \mathbf{S}=\mathbf{W}_{3} \mathbf{V}_{3}{ }^{\top} \text { (or } \mathbf{U}_{3} \mathbf{W}_{3}{ }^{\top}{ }^{1 / 2} \text { and } \mathbf{S}=\mathbf{W}_{3}^{1 / 2},\end{aligned}$
6. Eliminate affine ambiguity

## Reconstruction results



1


120


60


150
poin1s.graph


C. Tomasi and T. Kanade. Shape and motion from image streams under orthography: A factorization method. IJCV, 9(2):137-154, November 1992.

## Next Lecture: Perspective SFM

- Readings: FP 8.3

