## Uncalibrated Geometry \& Stratification

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## Overview

- Calibration with a rig
- Uncalibrated epipolar geometry
- Ambiguities in image formation
- Stratified reconstruction
- Autocalibration with partial scene knowledge


## Uncalibrated Camera



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## Uncalibrated Camera

$$
\mathbf{X}=[X, Y, Z, W]^{T} \in \mathbb{R}^{4}, \quad(W=1)
$$

## Calibrated camera

- Image plane coordinates $\mathbf{x}=[x, y, 1]^{T}$
- Camera extrinsic parameters $g=(R, T)$
- Perspective projection $\lambda \mathrm{x}=[R, T] \mathbf{X}$

Uncalibrated camera


## Taxonomy on Uncalibrated Reconstruction

$$
\lambda \mathbf{x}^{\prime}=[K R, K T] \mathbf{X}
$$

- $K$ is known, back to calibrated case $\mathrm{x}=K^{-1} \mathrm{x}^{\prime}$
- $K$ is unknown
- Calibration with complete scene knowledge (a rig) estimate $K$
- Uncalibrated reconstruction despite the lack of knowledge of $K$
- Autocalibration (recover $K$ from uncalibrated images)
- Use partial knowledge
- Parallel lines, vanishing points, planar motion, constant intrinsic
- Ambiguities, stratification (multiple views)


## Calibration with a Rig

Use the fact that both 3-D and 2-D coordinates of feature points on a pre-fabricated object (e.g., a cube) are known.


## Calibration with a Rig

- Given 3-D coordinates on known object $\mathbf{X}$ $\lambda \mathrm{x}^{\prime}=[K R, K T] \mathbf{X} \longrightarrow \lambda \mathrm{x}^{\prime}=\Pi \mathbf{X}$

$$
\lambda\left[\begin{array}{c}
x^{i} \\
y^{i} \\
1
\end{array}\right]=\left[\begin{array}{c}
\pi_{1}^{T} \\
\pi_{2}^{T} \\
\pi_{3}^{T}
\end{array}\right]\left[\begin{array}{c}
X^{i} \\
Y^{i} \\
Z^{i} \\
1
\end{array}\right]
$$

$$
\begin{aligned}
x^{i}\left(\pi_{3}^{T} \mathbf{X}\right) & =\pi_{1}^{T} \mathbf{X} \\
y^{i}\left(\pi_{3}^{T} \mathbf{X}\right) & =\pi_{2}^{T} \mathbf{X}
\end{aligned}
$$

- Recover projection matrix $\Pi=[K R, K T]=\left[R^{\prime}, T^{\prime}\right]$

$$
\begin{aligned}
& \Pi^{s}=\left[\pi_{11}, \pi_{21}, \pi_{31}, \pi_{12}, \pi_{22}, \pi_{32}, \pi_{13}, \pi_{23}, \pi_{33}, \pi_{14}, \pi_{24}, \pi_{34}\right]^{T} \\
& \min \left\|M \Pi^{s}\right\|^{2} \quad \text { subject to } \quad\left\|\Pi^{s}\right\|^{2}=1
\end{aligned}
$$

- Factor the $K R$ into $R \in S O$ (3) and $K$ using QR decomposition
- Solve for translation $T=K^{-1} T^{\prime}$


## Uncalibrated Camera vs. Distorted Space

- Inner product in Euclidean space: compute distances and angles

$$
\langle u, v\rangle=u^{T} v
$$

- Calibration $K$ transforming spatial coordinates

$$
\phi: \mathbb{R}^{3} \rightarrow \mathbb{R}^{3} ; \quad \mathrm{X} \rightarrow \mathbf{X}^{\prime}=K \mathbf{X}
$$

- Transformation induced a new inner product

$$
\left\langle\phi^{-1}(u), \phi^{-1}(v)\right\rangle=u^{T} K^{-T} K^{-1} v=u^{T} S v
$$

- $S$ (the metric of the space) and $K$ are equivalent

$$
\left\langle\phi^{-1}(u), \phi^{-1}(v)\right\rangle=u^{T} K^{-T} K^{-1} v
$$

## Calibrated vs. Uncalibrated Space



Figure 6.1. Effect of the matrix $K$ as a map $K: v \mapsto u=K v$, where points on the sphere $\|v\|^{2}=1$ is mapped to points on an ellipsoid $\|u\|_{S}^{2}=1$ (a "unit sphere" under the metric $S)$. Principal axes of the ellipsoid are exactly the eigenvalues of $S$.

## Calibrated vs. Uncalibrated Space



Distances and angles are modified by $S$

## Motion in the Distorted Space

$$
\mathbf{X}(t)=R(t) \mathbf{X}\left(t_{0}\right)+T(t) \quad K \mathbf{X}(t)=K R(t) \mathbf{X}\left(t_{0}\right)+K T(t)
$$

Calibrated space Uncalibrated space

$$
\mathbf{X}(t)=R(t) \mathbf{X}\left(t_{0}\right)+T(t) \quad \mathbf{X}^{\prime}(t)=K R(t) K^{-1} \mathbf{X}^{\prime}\left(t_{0}\right)+K T(t)
$$

- Uncalibrated coordinates are related by

$$
G^{\prime}=\left\{\left.g^{\prime}=\left[\begin{array}{cc}
K R K^{-1} & T^{\prime} \\
0 & 1
\end{array}\right] \right\rvert\, T^{\prime} \in \mathbb{R}^{3}, R \in S O(3)\right\}
$$

- Conjugate of the Euclidean group


## Uncalibrated Camera or Distorted Space

Uncalibrated camera with a calibration matrix K viewing points in Euclidean space and moving with $(R, T)$ is equivalent to a calibrated camera viewing points in distorted space governed by S and moving with a motion conjugate to ( $\mathrm{R}, \mathrm{T}$ )


## Uncalibrated Epipolar Geometry

$$
\lambda_{2} K \mathbf{x}_{2}=K R \lambda_{1} \mathbf{x}_{1}+K T \quad \lambda_{2} \mathbf{x}_{2}^{\prime}=K R K^{-1} \lambda_{1} \mathbf{x}_{1}^{\prime}+T^{\prime}
$$



- Epipolar constraint $\mathbf{x}_{2}^{\prime T} \underbrace{K^{-T} \widehat{T} R K^{-1}} \mathbf{x}^{\prime}{ }_{1}=0$
- Fundamental matrix $F=K^{-T} \widehat{T} R K^{-1}$
- Equivalent forms of $F=K^{-T} \widehat{T} R K^{-1}=\widehat{T}^{\prime} K R K^{-1}$


## Properties of the Fundamental Matrix

$$
\mathrm{x}^{\prime}{ }_{2}^{T} F \mathrm{x}^{\prime}{ }_{1}=0
$$

- Epipolar lines $l_{1}, l_{2}$
- Epipoles $\mathrm{e}_{1}, \mathrm{e}_{2}$


$$
\begin{array}{lll}
l_{1} \sim F^{T} \mathbf{x}_{2}^{\prime} & l_{i}^{T} \mathbf{x}_{i}^{\prime}=0 & l_{2} \sim F \mathbf{x}_{1}^{\prime} \\
F \mathbf{e}_{1}=0 & l_{i}^{T} \mathbf{e}_{i}=0 & \mathbf{e}_{2}^{T} F=0
\end{array}
$$

## Properties of the Fundamental Matrix

A nonzero matrix $F \in \mathbb{R}^{3 \times 3}$ is a fundamental matrix if $F$ has a singular value decomposition (SVD) $F=U \Sigma V^{T}$ with

$$
\Sigma=\operatorname{diag}\left\{\sigma_{1}, \sigma_{2}, 0\right\}
$$

for some $\sigma_{1}, \sigma_{2} \in \mathbb{R}_{+}$.
There is little structure in the matrix $F$ except that

$$
\operatorname{det}(F)=0
$$

## What Does F Tell Us?

- $F$ can be inferred from point matches (eight-point algorithm)
- Cannot extract motion, structure and calibration from one fundamental matrix (two views)
- $F$ allows reconstruction up to a projective transformation (as we will see soon)
- $F$ encodes all the geometric information among two views when no additional information is available


## Decomposing the Fundamental Matrix

$$
F=K^{-T} \widehat{T} R K^{-1}=\widehat{T}^{\prime} K R K^{-1}
$$

- Decomposition of the fundamental matrix into a skew symmetric matrix and a nonsingular matrix

$$
F \mapsto \Pi=\left[R^{\prime}, T^{\prime}\right] \quad \Rightarrow \quad F=\widehat{T^{\prime}} R^{\prime}
$$

- Decomposition of $F$ is not unique

$$
\mathrm{x}_{2}^{\prime} \hat{T}^{\prime}\left(T^{\prime} v^{T}+K R K^{-1}\right) \mathrm{x}_{1}^{\prime}=0 \quad T^{\prime}=K T
$$

- Unknown parameters - ambiguity

$$
v=\left[v_{1}, v_{2}, v_{3}\right]^{T} \in \Re^{3}, \quad v_{4} \in \Re
$$

- Corresponding projection matrix

$$
\Pi=\left[K R K^{-1}+T^{\prime} v^{T}, v_{4} T^{\prime}\right]
$$

## Ambiguities in Image Formation

Potential ambiguities $\lambda \mathbf{x}^{\prime}=K \Pi_{0} g \mathbf{X} \quad K=\left[\begin{array}{ccc}f s_{x} & f x_{y} & o_{x} \\ 0 & f s_{y} & o_{y} \\ 0 & 0 & 1\end{array}\right]$

$$
\lambda \mathbf{x}^{\prime}=\Pi \mathbf{X}=K \Pi_{0} g \mathbf{X}=\underbrace{K R_{0}^{-1} R_{0} \Pi_{0} H^{-1}}_{\tilde{\Pi}} \underbrace{H g g_{w}^{-1} g_{w} \mathbf{X}}_{\tilde{\mathbf{X}}}
$$

- Ambiguity ir $K$ (can be recovered uniquely - QR)

$$
\lambda \mathbf{x}^{\prime}=K \Pi_{0} g \mathbf{X}=K R_{0}^{-1} R_{0}[R, T] \mathbf{X} \doteq \widetilde{K} \Pi_{0} \tilde{g} \mathbf{X}
$$

- Structure of the motion parameters

$$
g \mathbf{X}=g g_{w}^{-1} g_{w} \mathbf{X}
$$

- Just an arbitrary choice of reference coordinate frame


## Ambiguities in Image Formation

Structure of motion parameters


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## Ambiguities in Image Formation

Structure of the projection matrix $\Pi=[K R, K T]$

$$
\lambda \mathrm{x}^{\prime}=\Pi \mathbf{X}=\left(\Pi H^{-1}\right)(H \mathbf{X})=\tilde{\Pi} \tilde{\mathbf{X}}
$$

- For any invertible $4 \times 4$ matri>H
- In the uncalibrated case we cannot distinguish between camera imaçXı word fro $\tilde{\Pi}_{\text {l }}$ camera imaging disto $\tilde{X}_{2} d$ world

$$
H
$$

- In general,

$$
\begin{aligned}
& \text { is of th- } H^{-1}=\left[\begin{array}{cc}
G & b \\
v^{T} & v_{4}
\end{array}\right]
\end{aligned}
$$

- In order to preserve th $H$ choice of the first reference frame we can restrict some DOF of

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## Structure of the Projective Ambiguity

- For i-th frame

$$
\lambda_{i} \mathbf{x}_{i}^{\prime}=K_{i} \Pi_{0} g_{i e} \mathbf{X}_{e}=\left(K_{i} \Pi_{0} g_{i e} H^{-1}\right)\left(H \mathbf{X}_{e}\right) \doteq \Pi_{i p} \mathbf{X}_{p}
$$

- ${ }^{\text {st }}$ frame as reference $\lambda_{1} \mathrm{x}^{\prime}{ }_{1}=K_{1} \Pi_{0} \mathbf{X}_{e}$

$$
K_{1} \Pi_{0} H^{-1} H \mathbf{X}_{e}=\Pi_{1 p} \mathbf{X}_{p}
$$

- Choose the projective reference frame
$\Pi_{1 p}=\left[I_{3 \times 3}, 0\right]$ then ambiguity is $H^{-1}=\left[\begin{array}{cc}K_{1}^{-1} & 0 \\ v^{T} & v_{4}\end{array}\right]$
- $H^{-1}$ can be further decomposed as

$$
\begin{aligned}
H^{-1}=\left[\begin{array}{cc}
K_{1}^{-1} & 0 \\
v^{T} & v_{4}
\end{array}\right] & =\left[\begin{array}{cc}
K_{1}^{-1} & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{cc}
I & 0 \\
v^{T} & v_{4}
\end{array}\right] \doteq H_{a}^{-1} H_{p}^{-1} \\
\mathbf{X}_{p} & =H_{p} \overbrace{H_{a}} \underbrace{\mathbf{X}_{a}}_{\mathbf{X}_{e}}
\end{aligned}
$$

## Geometric Stratification (cont)

|  | Camera projection | 3-D structure |
| :--- | :--- | :--- |
| Euclid. | $\Pi_{1 e}=[K, 0], \Pi_{2 e}=[K R, K T]$ | $\boldsymbol{X}_{e}=g_{e} \boldsymbol{X}=\left[\begin{array}{cc}R_{e} & T_{e} \\ 0 & 1\end{array}\right] \boldsymbol{X}$ |
| Affine | $\Pi_{2 a}=\left[K R K^{-1}, K T\right]$ | $\boldsymbol{X}_{a}=H_{a} \boldsymbol{X}_{e}=\left[\begin{array}{cc}K & 0 \\ 0 & 1\end{array}\right] \boldsymbol{X}_{e}$ |
| Project. | $\Pi_{2 p}=\left[K R K^{-1}+K T v^{T}, v_{4} K T\right]$ | $\boldsymbol{X}_{p}=H_{p} \boldsymbol{X}_{a}=\left[\begin{array}{cc}I & 0 \\ -v^{T} v_{4}^{-1} & v_{4}^{-1}\end{array}\right] \boldsymbol{X}_{a}$ |



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## Projective Reconstruction

- From points, extraci $F$, from which extract $\Pi$ ancX $X_{p}$

$$
\Pi_{1 p}=[I, 0], \Pi_{2 p}=[B, b]
$$

- Canonical decomposition

$$
F \quad \mapsto \quad \Pi_{1 p}=[I, 0], \Pi_{2 p}=\left[\left(\widehat{T^{\prime}}\right)^{T} F, T^{\prime}\right]
$$

- Projection matrices

$$
\begin{aligned}
& \lambda_{1} \mathbf{x}_{1}^{\prime}=\Pi_{1 p} \mathbf{X}_{p}=[I, 0] \mathbf{X}_{p} \\
& \lambda_{2} \mathbf{x}_{2}^{\prime}=\Pi_{2 p} \mathbf{X}_{p}=\left[\left(\widehat{T^{\prime}}\right)^{T} F, T^{\prime}\right] \mathbf{X}_{p}
\end{aligned}
$$

Theorem 7.6 (Projective reconstruction). Let $F\left(\Pi_{1}, \Pi_{2}\right)$ and $\left(\Pi_{1}, \tilde{\Pi}_{2}\right)$ possible pairs of projection matrices that yield the same Fundamental matrix $F$. Then there exists a nonsingular transformation matrix $H_{p}$ such that $\Pi_{2}=\Pi_{2} H_{p}^{-1}$ or equivalently $\Pi_{2}=\Pi_{2} H_{p}$.

## Projective Reconstruction

- Given projection matrices recover projective structure

$$
\begin{array}{ll}
\left(x_{1} \pi_{1}^{3 T}\right) \mathbf{X}_{p}=\pi_{1}^{1 T} \mathbf{X}_{p}, & \left(y_{1} \pi_{1}^{3 T}\right) \mathbf{X}_{p}=\pi_{1}^{2 T} \mathbf{X}_{p}, \\
\left(x_{2} \pi_{2}^{3 T}\right) \mathbf{X}_{p}=\pi_{2}^{1 T} \mathbf{X}_{p}, & \left(y_{2} \pi_{2}^{3 T}\right) \mathbf{X}_{p}=\pi_{2}^{2 T} \mathbf{X}_{p},
\end{array}
$$

- This is a linear problem and can be solve using leastsquares techniques.
- Given 2 images and no prior information, the scene can be recovered up a 4 -parameter family of solutions. This is the best one can do without knowing calibration!



## Affine Upgrade

- Upgrade projective structure to an affine structure

$$
H_{p}^{-1}=\left[\begin{array}{cc}
I & 0 \\
v^{T} & v_{4}
\end{array}\right] \quad \mathbf{X}_{a}=H_{p}^{-1} \mathbf{X}_{p}
$$

- Exploit partial scene knowledge
- Vanishing points, no skew, known principal point
- Special motions
- Pure rotation, pure translation, planar motion, rectilinear motion
- Constant camera parameters (multi-view)



## Affine Upgrade Using Vanishing Points

$$
\begin{gathered}
H_{p}^{-1}=\left[\begin{array}{cc}
I & 0 \\
v^{T} & v_{4}
\end{array}\right] \text { maps points on the plane } \\
{\left[v, v_{4}\right]^{T} \mathbf{X}_{p}=0}
\end{gathered}
$$

to points $\mathbf{X}_{a}=H_{p}^{-1} \mathbf{X}_{p}$ with affine coordinates

$$
\mathbf{X}_{a}=[X, Y, Z, 0]^{Y}
$$



## Vanishing Point Estimation from Parallelism



## Euclidean Upgrade

- Exploit special motions (e.g. pure rotation)

$$
R_{a}=K R K^{-1} \Rightarrow R_{a}\left(K K^{T}\right) R_{a}^{T}=\left(K K^{T}\right)
$$

- If Euclidean is the goal, perform Euclidean reconstruction directly (no stratification)
- Direct autocalibration (Kruppa's equations)
- Multiple-view case (absolute quadric)



## Direct Autocalibration Methods

The fundamental matrix

$$
F=K^{-T} \widehat{T} R K^{-1}=\widehat{T}^{\prime} K R K^{-1}
$$

satisfies the Kruppa's equations

$$
F K K^{T} F^{T}=\widehat{T^{\prime}} K K^{T}{\widehat{T^{\prime}}}^{T}
$$

If the fundamental matrix is known up to scale

$$
F K K^{T} F^{T}=\lambda^{2} \widehat{T^{\prime}} K K^{T}{\widehat{T^{\prime}}}^{T}
$$

Under special motions, Kruppa's equations become linear.
Solution to Kruppa's equations is sensitive to noises.

## Direct Stratification from Multiple Views

From the recovered projective projection matrix

$$
\Pi_{i p}=\Pi_{i e} H^{-1}=\left[B_{i}, b_{i}\right], \quad B_{i} \in \mathbb{R}^{3 \times 3}, b_{i} \in \mathbb{R}^{3}
$$

we obtain the absolute quadric contraints

$$
\left(B_{i}-b_{i} v^{T^{\prime}}\right) K K^{T^{\prime}}\left(B_{i}-b_{i} v^{T}\right)^{T}=\lambda K K^{T}
$$

Partial knowledge in $K$ (e.g. zero skew, square pixel) renders the above constraints linear and easier to solve.

The projection matrices can be recovered from the multiple-view rank method to be introduced later.

## Direct Methods - Summary

|  | Kruppa's equations | Modulus constraint | Absolute quadric constraint |
| :--- | :---: | :---: | :---: |
| Known | $F$ | $F$ | $\Pi_{i p}=\Pi_{i} H^{-1}$ |
| Unknowns | $S^{-1}=K K^{T}$ | $v=\left[v_{1}, v_{2}, v_{3}\right]^{T}$ | $S^{-1}$ and $v$ |
| \# of equations | 2 | 1 | 5 |
| Orders | $2^{n d}$ order | $4^{t h}$ order | $3^{r d}$ order |

## Summary of (Auto)calibration Methods

$\left.\begin{array}{|l|c|c|c}\hline & \text { Euclidean } & \text { Affine } & \text { Projective } \\ \hline \hline \text { Structure } & \mathbf{X}_{e}=g_{e} \mathbf{X} & \mathbf{X}_{a}=H_{a} \mathbf{X}_{e} & \mathbf{X}_{p}=H_{p} \mathbf{X}_{a} \\ \hline \text { Transformation } & g_{e}=\left[\begin{array}{cc}R & T \\ 0 & 1\end{array}\right] & H_{a}=\left[\begin{array}{cc}K & 0 \\ 0 & 1\end{array}\right] & H_{p}=\left[\begin{array}{cc}I \\ -v^{T} v_{4}^{-1} & 0 \\ v_{4}^{-1}\end{array}\right] \\ \hline \text { Projection } & \Pi_{e}=[K R, K T] & \Pi_{a}=\Pi_{e} H_{a}^{-1} & \Pi_{p}=\Pi_{a} H_{p}^{-1}\end{array}\right]$

