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## Stereo Vision: Epipolar Geometry

Some slides courtesy of
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## Stereovision

- In stereovision, two or more views of the scene are available from different vantage points, for example
- From two separate cameras
- A single camera that is translated
- By finding matches (correspondences) between the images, the relative distance of objects from the camera (depth) can be determined.
- The human visual system achieves stereopsis with binocular vision.
- Two images of the world are captured by the eyes (~65 mm apart)
- Receptive fields fuse images and recognise different positions
- Disparity (the amount of displacement) is used to infer depth


## Finding correspondences

- Given a point in one image, how do we find its match in the other image?


Left image


Right image

- Brute force: search every pixel in the right image to find a match.
- Actually we can do better...


## Epipolar geometry

- Epipolar geometry can be used to constrain the search to a line.

$\Rightarrow$ Potential matches for $\mathbf{x}$ must be on the line $\ell^{\prime}$. Similarly, potential matches for $\mathbf{x}^{\prime}$ ' have to be on the line $\ell$.


## An example


$\Rightarrow$ This example shows epipolar lines in both images

## Terminology

- Epipolar geometry can be used to constrain the search to a line.

- C, C', and $\mathbf{X}$ are three 3D points that form the epipolar plane.
- The baseline connects the two camera centres. The epipoles e and e' are where the baseline intersects the image plane.
- All epipolar lines in an image will go through the epipole, regardless of $\mathbf{X}$.


## The fundamental matrix

- If the images are uncalibrated, one can compute the fundamental matrix, $\mathbf{F}$. This $3 \times 3$ matrix is the algebraic representation of the epipolar geometry.
- The fundamental matrix allows us to find the epipolar line $\ell^{\prime}=\mathbf{F x}$.
- Since $\mathbf{x}^{\prime}$ is on the line $\ell^{\prime}, \mathbf{x}^{\prime \top} \mathbf{F} \mathbf{x}=0$.

Properties of the fundamental matrix:

- If $\mathbf{F}$ is the fundamental matrix going from image 1 to image 2 , then $\mathbf{F}^{\top}$ is the fundamental matrix going from image 2 to image 1 .
- $\mathrm{Fe}=0$
- The fundamental matrix has rank 2


## Reading Assignments for Epipolar Geometry

Hartley Zissermann: Multiple View Geometry Book:
Chapter 9:
https://www.robots.ox.ac.uk/~vgg/hzbook/hzbook2/HZepipolar.pdf

Ma, Soatto et al book (An Invitation to 3D Vision):
Chapter 5.1, 5.2, 5.3 and Chapter 6.1, 6.2, 6.A

For 3D Triangulation, see: G. Slabaugh, R. Schafer, and M. Livingston, "Optimal ray intersection for computing 3d points from n-
 view correspondences," Technical Report, 2001.
http://www.staff.city.ac.uk/~sbbh653/publications/opray.pdf
C. Loop and Z. Zhang: Computing Rectifying Homographies for Stereo Vision, Technical Report, Microsoft Research, 1999.

## Estimating the fundamental matrix

- There are several approaches to estimate $\mathbf{F}$. The best-known approach is called the eight point algorithm, as it requires eight correspondences.
- One can write out the epipolar constraint as

$$
\mathbf{x}^{\prime T} F \mathbf{x}=\left[\begin{array}{lll}
x^{\prime} & y^{\prime} & 1
\end{array}\right]\left[\begin{array}{lll}
f_{11} & f_{12} & f_{13} \\
f_{21} & f_{22} & f_{23} \\
f_{31} & f_{32} & f_{33}
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=0
$$

multiplying this out, one gets

$$
x^{\prime} x f_{11}+x^{\prime} y f_{12}+x^{\prime} f_{13}+y^{\prime} x f_{21}+y^{\prime} y f_{22}+y^{\prime} f_{23}+x f_{31}+y f_{32}+f_{33}=0
$$

for each correspondence, we have one such equation.

## Estimating the fundamental matrix

- So with $N$ correspondences, we can write

$$
\left[\begin{array}{ccccccccc}
x_{1}^{\prime} x_{1} & x_{1}^{\prime} y_{1} & x_{1}^{\prime} & x_{1} y_{1}^{\prime} & y_{1} y_{1}^{\prime} & y_{1}^{\prime} & x_{1} & y_{1} & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x_{N}^{\prime} x_{N} & x_{N}^{\prime} y_{N} & x_{N}^{\prime} & x_{N} y_{N}^{\prime} & y_{N} y_{N}^{\prime} & y_{N}^{\prime} & x_{N} & y_{N} & 1
\end{array}\right]\left[\begin{array}{c}
f_{11} \\
f_{12} \\
f_{13} \\
f_{21} \\
f_{22} \\
f_{23} \\
f_{31} \\
f_{32} \\
f_{33}
\end{array}\right]=\mathbf{0}
$$

- and solve for $\mathbf{F}$. However, we can set $\|\operatorname{det}(\mathbf{F})\|=1$, so this can be reduced to eight correspondences.
- If there are more than eight correspondences, we can use all and solve to get a least squares solution.



## Recall RANSAC

- Note there is a chicken-and-egg problem here. To find correspondences, the fundamental matrix is really helpful. But to estimate the fundamental matrix, we need correspondences!
- Also, automation is desired, as manually finding corresponding points may not be practical.
- A common approach is to employ RANSAC, which stands for RANdom SAmple Consensus. Essentially, it is a "hypothesize and test" methodology.

Given a set of correspondences (e.g., matching SURF points) found in two images:

1. Randomly subsample a set of correspondences C , selecting eight called $\mathrm{C}^{*}$
2. Estimate the fundamental matrix $\mathbf{F}$ from $\mathrm{C}^{*}$
3. Score F by determining the fraction of inliers in C using a threshold
4. Go to 1 until a best $\mathbf{F}$ is found

## Method for Fundamental Matrix Estimation

- Use SURF to find feature points in both images
- Match SURF features to generate possible correspondences
- Use RANSAC to find the best F using 8 point algorithm


## 3D estimation

- Compute the fundamental matrix $\mathbf{F}$ between the two views
- First camera matrix: [I\|0]
- If the intrinsics are known, the Matlab function
- [R, t] = cameraPose(F, cameraParams, inliers1, inliers2) can estimate the relative rotation and translation between views, and the second camera matrix is then $\mathrm{K}^{*}[\mathbf{R}, \mathrm{t}]$
- One can then triangulate the matching 2D points to compute 3D points $\mathbf{P}$.
- How can we triangulate to find the 3D Point $P$ ?


## Triangulation



Reference: G. Slabaugh, R. Schafer, and M. Livingston, "Optimal ray intersection for computing 3d points from n-view correspondences," Technical Report, 2001.
http://www.staff.city.ac.uk/~sbbh653/publications/opray.pdf

## Triangulation

- There are many ways to triangulate to determine at point $\mathbf{P}$ give two or more projections given matching points $\mathbf{p}$ and camera matrices $\mathbf{M}$ in each image.
- A common approach is to set up a system of linear equations in $\mathbf{P}$ which can then be solved.

$$
\begin{aligned}
\mathbf{p}=\mathbf{M P} & =\left[\begin{array}{l}
\mathbf{m}_{1}^{T} \\
\mathbf{m}_{2}^{T} \\
\mathbf{m}_{3}^{T}
\end{array}\right] \mathbf{P}
\end{aligned} \quad w\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{l}
\mathbf{m}_{1}^{T} \mathbf{P} \\
\mathbf{m}_{2}^{T} \mathbf{P} \\
\mathbf{m}_{3}^{T} \mathbf{P}
\end{array}\right] .
$$

- Can solve for two or more images. In Matlab, you can use
- $P$ = triangulate(matchedPoints1, matchedPoints2,cameraMatrix1,cameraMatrix2)


## Optimisation for Bundle Adjustment

- Optimise over all views and all points by minimising the reprojection error $R$ for each point. This is a non-linear least squares problem, and is known in the literature as bundle adjustment. Performed when $>2$ images.

$$
E(\mathbf{M}, \mathbf{P})=\sum_{i=1}^{M} \sum_{j=1}^{N} R\left(\mathbf{q}_{i j}, \mathbf{M}_{i} \mathbf{P}_{j}\right)
$$



