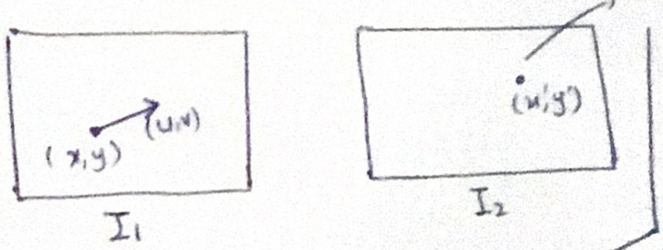
⇒ Generally, most approaches are supervised but problem is to fine tune on new data. So, new data collection with accurate disparity maps is an issue. Therefore domain adaptation is problem. Many approaches then use semi-/unsupervised approaches. These use left-right consistency and mapping.

⇒ synthesize left view according to estimated left disparity (and right for computing a loss function.
↳ becomes vulnerable when stereo pairs are imperfect.
→ i.e. both views have different photogrammetric distortions.

Zoom & learn → CVPR 2018
↳ mat-cattle.

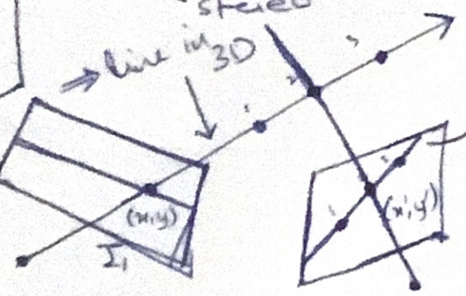
Epipolar Geometry

optical flow case → correspondence is not restricted
correspondence for (x,y)
→ correspondence



→ Static scenes (camera moves)
→ 2 pictures of same scene taken at same time.
↑ stereo

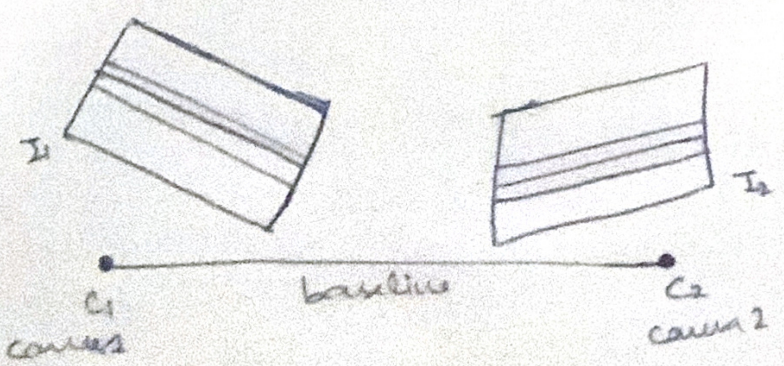
→ line in 3D

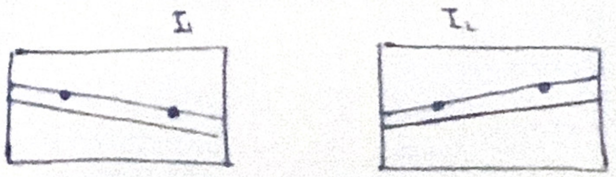


→ constraint our search in/along to one line.

⇒ for every point in I_1, there is some ray in space where there is 3D correspondence could be and then that produces a constrainted set of possible correspondences in I_2.

→

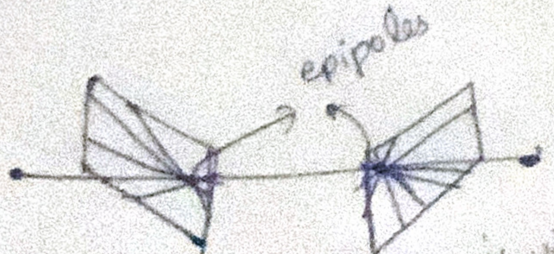




→ line in I_1 and I_2, every point in I_1 has correspondence in I_2 and vice versa. These are conjugate epipolar lines.

⇒ Generally slanted

→ Rectification makes it horizontal and then you can find correspondences along the rows of image.



↳ one camera is visible (in the field) of view of another.

The fundamental matrix

F 3x3 matrix

$$[x' \; y' \; 1] \, F \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = 0$$

⇒ For any $(x,y) \leftrightarrow (x',y')$ correspondence, this matrix eq. has to be true.

Getting epipolar lines from F

$$\underbrace{\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}^T}_{1\times3} \underbrace{F}_{3\times3} \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{3\times1} = 0 \quad \to \text{fixed } (x,y)$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}^T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = 0$$

$ax' + by' + c = 0$
↳ Epipolar line in I_2

→ All epipolar lines intersect at epipole.

⇒ In I_1 (x_e, y_e) is on every epipole line

$$\underbrace{\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}^T}_{\text{point in } I_2} F \underbrace{\begin{bmatrix} x_e \\ y_e \\ 1 \end{bmatrix}}_{\text{epipole in } I_1} = 0$$

$$\Rightarrow F \begin{bmatrix} x_e \\ y_e \\ 1 \end{bmatrix} = 0$$

→ Epipole can be found as eigenvector of F that has 0 eigen value.

⇒ F is 3x3 but has 7 degrees of freedom.

⇒ Estimating the F

1) Obtain feature correspondences (Harris corners, Swift-features)
2) Normalize correspondences to have $\delta = 0$, S.D = 1.
3) Each correspondence generates 1 constraint on F.

$$\underbrace{\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}^T}_{1\times3} \underbrace{\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}}_{3\times3} \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{3\times1} = 0$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}^T \begin{bmatrix} f_{11}x + f_{12}y + f_{13} \\ \vdots \end{bmatrix} = 0$$

$x'f_{11}x + x'f_{12}y + x'f_{13} + y'f_{11}x + y'f_{12}y + y'f_{13} + f_{11}x + f_{12}y + f_{13} = 0$

$$N \underbrace{\begin{bmatrix} x_1x_1' & y_1x_1' & \cdots \\ & & \\ & & \end{bmatrix}}_{N\times9} \underbrace{\begin{bmatrix} f_{11} \\ f_{12} \\ \vdots \\ f_{33} \end{bmatrix}}_{9\times1} = 0$$

4) $AF = 0$

⇒ compute singular value decomposition of A.

⇒ $A = UDV^T$

D → 9x9 Diagonal matrix

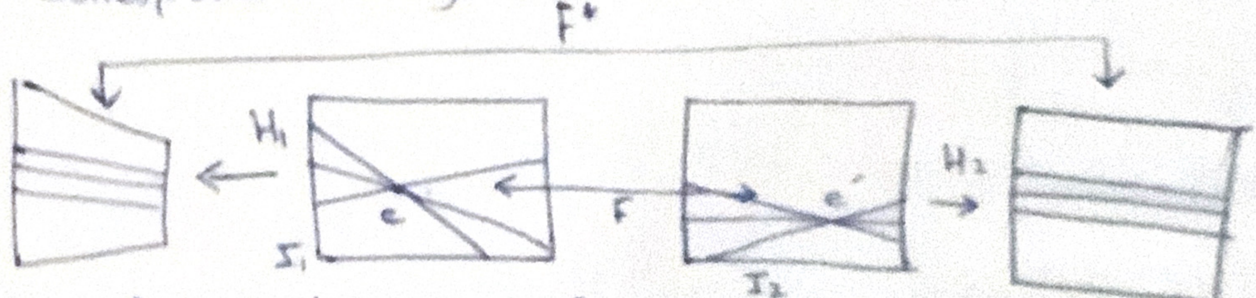
5) Let f be last column of V (9x1).
Reshape into 3x3 matrix $\hat{F}$.

6) Compute SVD of $\hat{F} = \hat{U}\hat{D}\hat{V}^T$ zero out lowest singular value of D
Then recompute $F = \hat{U}\hat{D}\hat{V}^T$ ↳ 3x3 diagonal matrix

7) Renormalization F.

$\boxed{\text{8-point algorithm}}$

Rectification → warp images so that conjugate epipolar lines correspond to image rows (scanlines)



→ Each image has a rectifying projective transformation H applied to it.

→ What will be F^*?

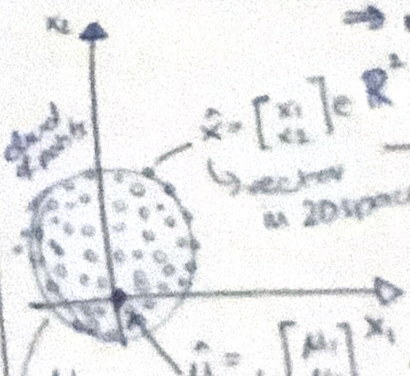
$$F^* = \begin{bmatrix}0&0&0\\0&0&1\\0&-1&0\end{bmatrix}$$

$$\begin{bmatrix}x'\\y'\\1\end{bmatrix}^T \begin{bmatrix}0&0&0\\0&0&1\\0&-1&0\end{bmatrix}\begin{bmatrix}x\\y\\1\end{bmatrix}=0$$

$$\begin{bmatrix}x'\\y'\\1\end{bmatrix}\begin{bmatrix}0\\1\\y\end{bmatrix}=0$$

$$y' - y = 0 \Rightarrow y' = y$$

Gaussian Process



→ multivariate gaussian
use → fit gaussians to the data.

$\hat{x} = \begin{bmatrix}x_1\\x_2\end{bmatrix} \in \mathbb{R}^2$ ↳ vector in 2D space

— process of fitting a Gaussian to the points and then the Gaussian will describe most points

At any point, $\hat{\mu} = \begin{bmatrix}\mu_1\\\mu_2\end{bmatrix}$

→ Mean and covariance (correlation) should describe the data.

$$\begin{bmatrix}x_1\\x_2\end{bmatrix} \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1&0\\0&1\end{bmatrix}\right) \quad E(x_1x_2) \text{ (expectation)}$$

→ information about x_1 doesn't help get more information about x_2. Not correlated

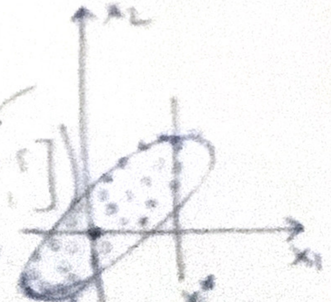
$$\rho_{x_1x_2} = \frac{\text{covariance}(x_1,x_2)}{\sigma_1(x_1)\,\sigma_2(x_2)}$$

$$\sigma_1(x_1) = \sqrt{E(x_1^2) - \mu}$$

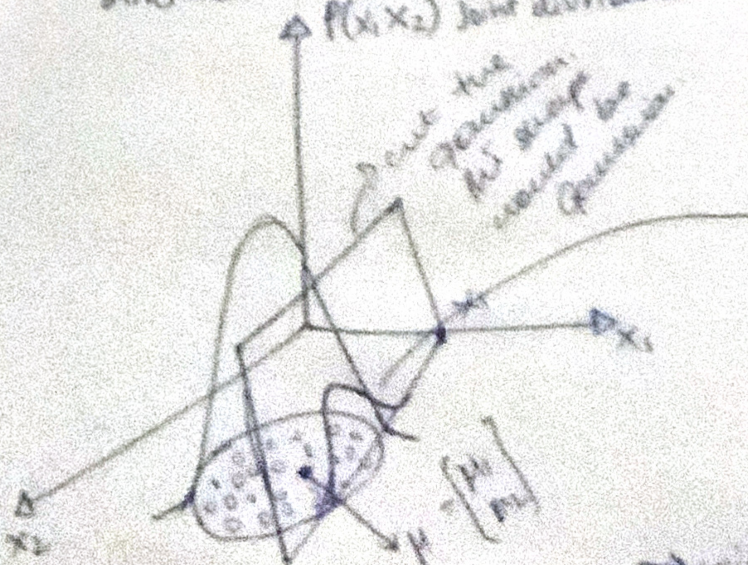
⇒ dot product measures similarity
↳ if two points are similar, the dot product will be similar

$$\begin{bmatrix}x_1\\x_2\end{bmatrix} \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1&0.5\\0.5&1\end{bmatrix}\right)$$

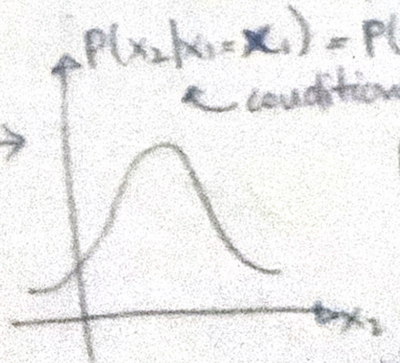
some +ve number



→ If non-zero, then means dependence is there.



$P(x_2|x_1=X_1) = P(x_2|x_1)$ ← conditional



$$\begin{bmatrix}x_1\\x_2\end{bmatrix} \sim N\left(\begin{bmatrix}\mu_1\\\mu_2\end{bmatrix}, \Sigma\right) \quad \Sigma(x_1,x_2)$$

assume joint distribution is gaussian

⇒ width of Gaussian should be +ve.