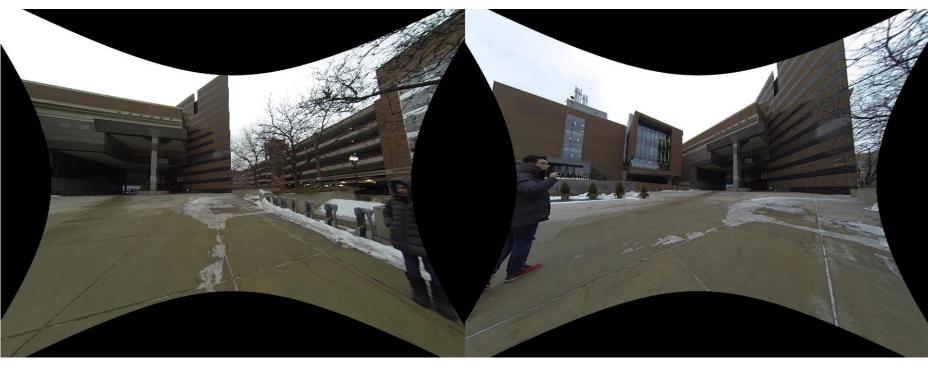
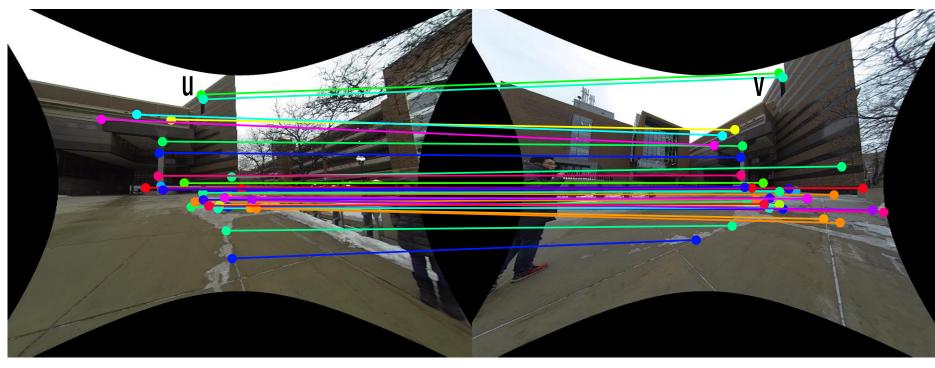


2D Correspondences



Bob's image Alice's image

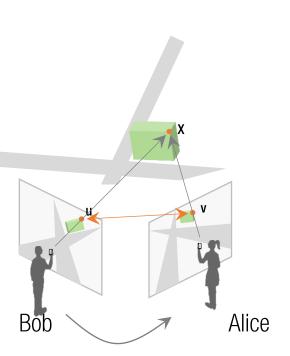
2D Correspondences

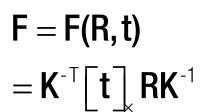


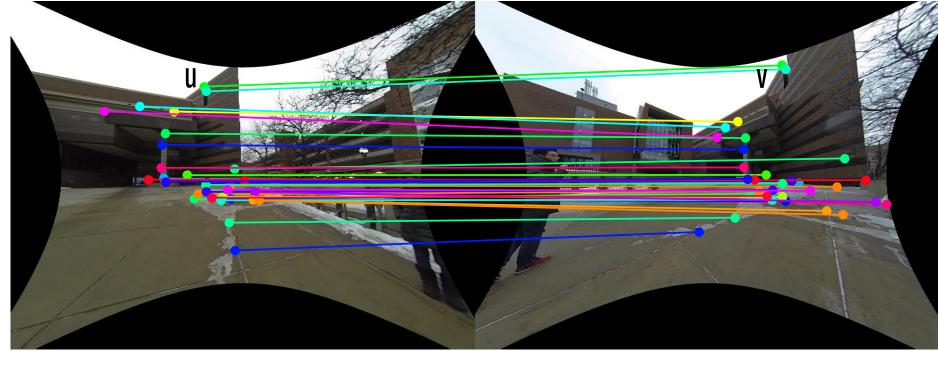
Bob's image Alice's image

$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u}=0$$

2D Correspondences







Bob's image Alice's image

 $\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u}=0$

How to compute fundamental matrix?

8 Point Algorithm (Longuet-Higgins, Nature 1981)

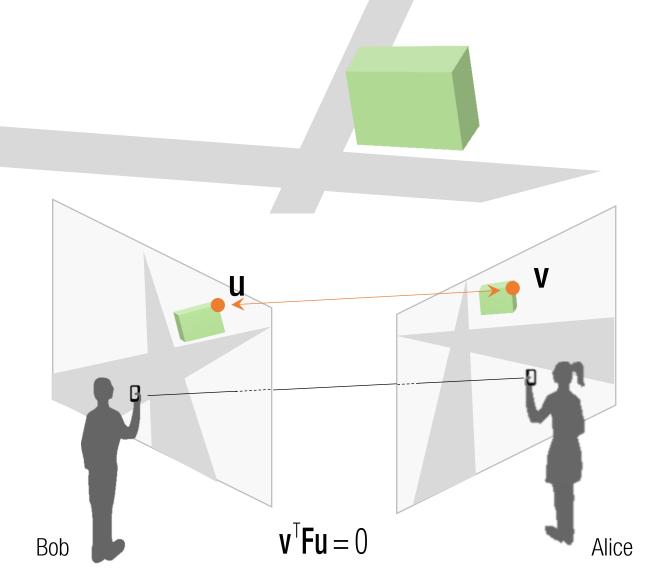


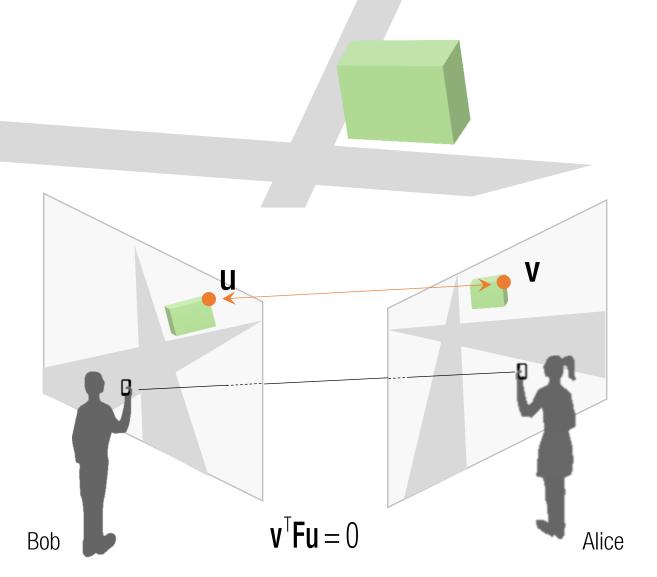
A computer algorithm for reconstructing a scene from two projections

H. C. Longuet-Higgins

Laboratory of Experimental Psychology, University of Sussex, Brighton BN1 9QG, UK

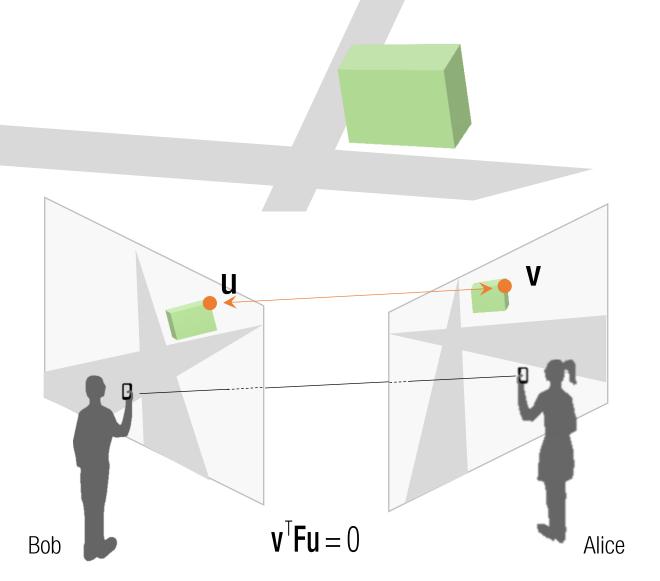
A simple algorithm for computing the three-dimensional ture of a scene from a correlated pair of perspective projections described here, when the spatial relationship between a projections is unknown. This problem is relevant not photographic surveying but also to binocular vision, who non-visual information available to the observer about





$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$$

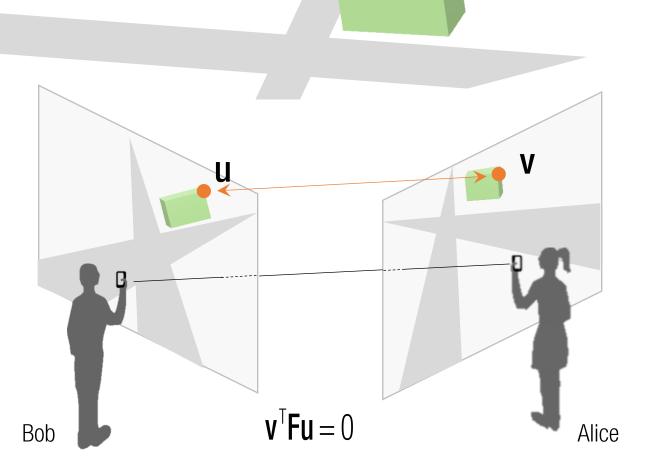
Degree of freedom of fundamental matrix:



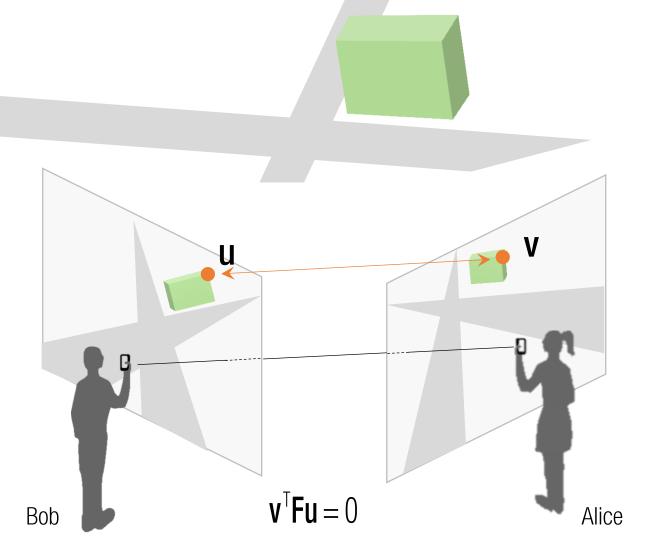
$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$$

Degree of freedom of fundamental matrix: 7 = 9 (3x3 matrix) - 1(scale) - 1 (rank 2)

We will estimate fundamental matrix with 8 parameter by ignoring rank constraint and then project onto rank 2 matrix:

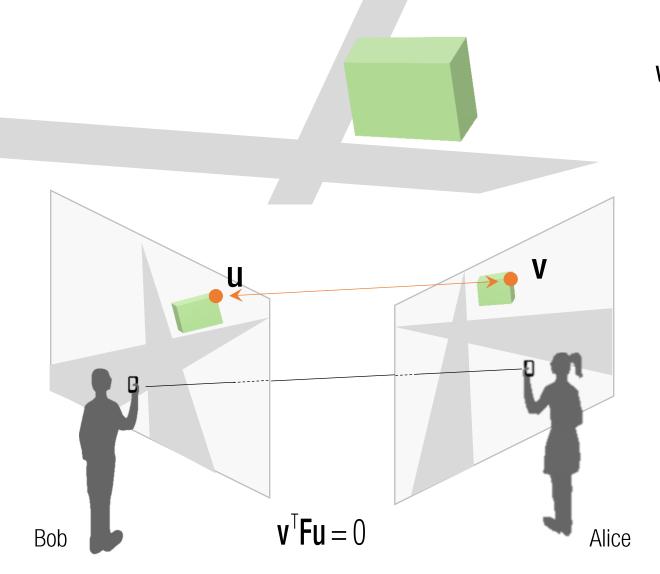


$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{X}} & v^{\mathsf{y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{X}} \\ u^{\mathsf{y}} \\ 1 \end{bmatrix}$$



$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{x}} & v^{\mathsf{y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{x}} \\ u^{\mathsf{y}} \\ 1 \end{bmatrix}$$

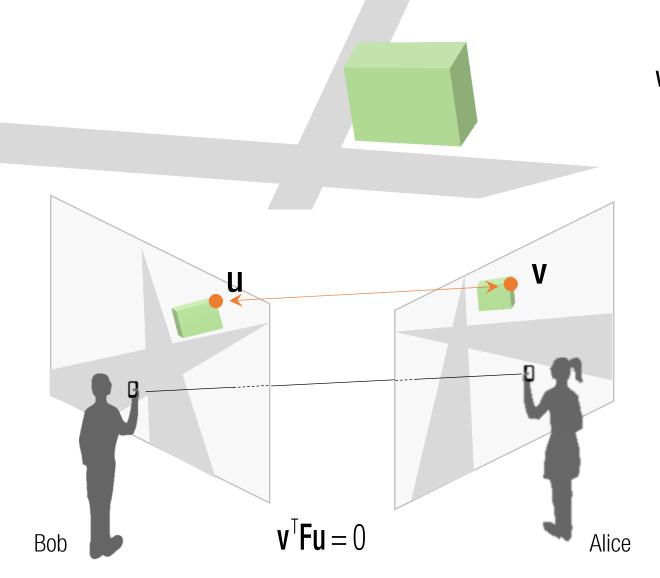
$$= f_{11}U^{x}V^{x} + f_{12}U^{y}V^{x} + f_{13}V^{x} + f_{21}U^{x}V^{y} + f_{22}U^{y}V^{y} + f_{23}V^{y} + f_{31}U^{x} + f_{32}U^{y} + f_{33}U^{y} + f_{33}U^{y} + f_{34}U^{y} + f_{34}$$



$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{x}} & v^{\mathsf{y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{x}} \\ u^{\mathsf{y}} \\ 1 \end{bmatrix}$$

$$= f_{11}u^{\mathsf{x}}v^{\mathsf{x}} + f_{12}u^{\mathsf{y}}v^{\mathsf{x}} + f_{13}v^{\mathsf{x}} + f_{21}u^{\mathsf{x}}v^{\mathsf{y}} + f_{22}u^{\mathsf{y}}v^{\mathsf{y}} + f_{23}v^{\mathsf{y}} + f_{31}u^{\mathsf{x}} + f_{32}u^{\mathsf{y}} + f_{33}$$

$$= 0 \qquad \qquad \qquad \text{Linear in } \mathbf{F}.$$



$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{x}} & v^{\mathsf{y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{y}} \\ 1 \end{bmatrix}$$

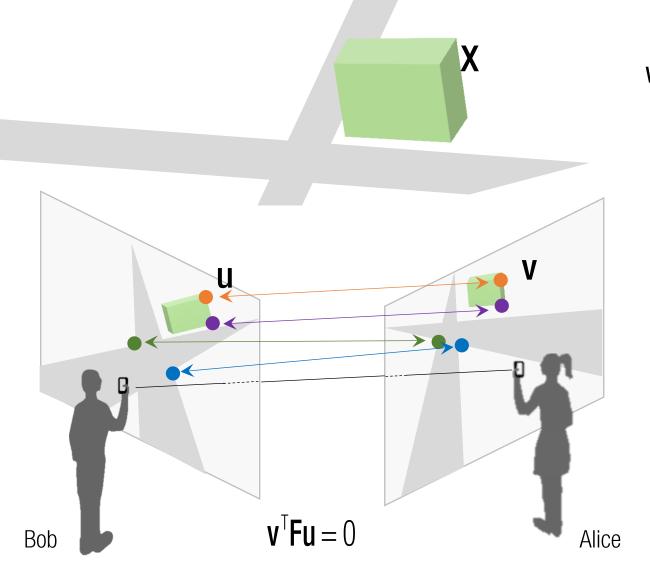
$$= f_{11}u^{\mathsf{x}}v^{\mathsf{x}} + f_{12}u^{\mathsf{y}}v^{\mathsf{x}} + f_{13}v^{\mathsf{x}} + f_{21}u^{\mathsf{x}}v^{\mathsf{y}} + f_{22}u^{\mathsf{y}}v^{\mathsf{y}} + f_{23}v^{\mathsf{y}} + f_{31}u^{\mathsf{x}} + f_{32}u^{\mathsf{y}} + f_{33}$$

$$= 0 \qquad \qquad \text{Linear in } \mathbf{F}.$$

$$\begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{13} \end{bmatrix}$$

of unknowns: 9

of equations per correspondence: 1

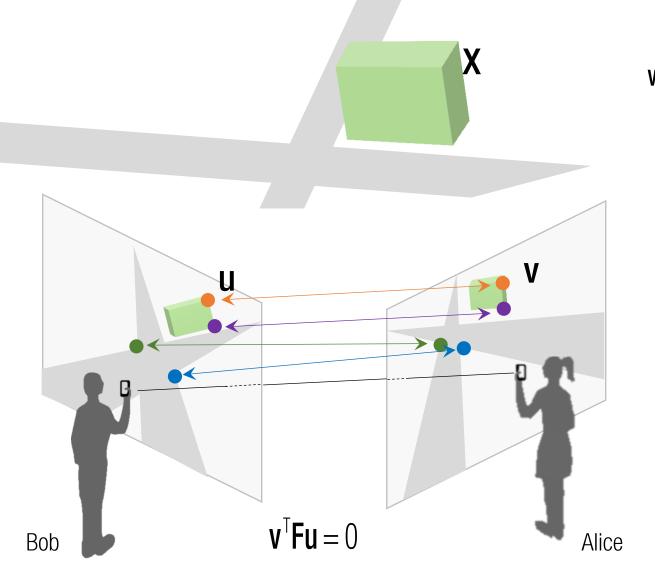


$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{X}} & v^{\mathsf{Y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{X}} \\ u^{\mathsf{Y}} \\ 1 \end{bmatrix}$$

$$= \underbrace{f_{11}u^{\mathsf{X}}v^{\mathsf{X}} + f_{12}u^{\mathsf{Y}}v^{\mathsf{X}} + f_{13}v^{\mathsf{X}} + f_{21}u^{\mathsf{X}}v^{\mathsf{Y}} + f_{22}u^{\mathsf{Y}}v^{\mathsf{Y}} + f_{23}v^{\mathsf{Y}} + f_{31}u^{\mathsf{X}} + f_{32}u^{\mathsf{Y}} + f_{33}}_{= 0}$$

$$= 0$$
Linear in **F**.
$$\begin{bmatrix} u_{1}^{\mathsf{X}}v_{1}^{\mathsf{X}} & u_{1}^{\mathsf{Y}}v_{1}^{\mathsf{X}} & v_{1}^{\mathsf{X}} & u_{1}^{\mathsf{X}}v_{1}^{\mathsf{Y}} & u_{1}^{\mathsf{Y}}v_{1}^{\mathsf{Y}} & v_{1}^{\mathsf{Y}} & u_{1}^{\mathsf{Y}} & u_{1}^{\mathsf{Y}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u_{m}^{\mathsf{X}}v_{m}^{\mathsf{X}} & u_{m}^{\mathsf{Y}}v_{m}^{\mathsf{X}} & v_{m}^{\mathsf{X}} & u_{m}^{\mathsf{X}}v_{m}^{\mathsf{Y}} & u_{m}^{\mathsf{Y}}v_{m}^{\mathsf{Y}} & v_{m}^{\mathsf{Y}} & u_{m}^{\mathsf{X}} & u_{m}^{\mathsf{Y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \end{bmatrix}$$

What is minimum m?

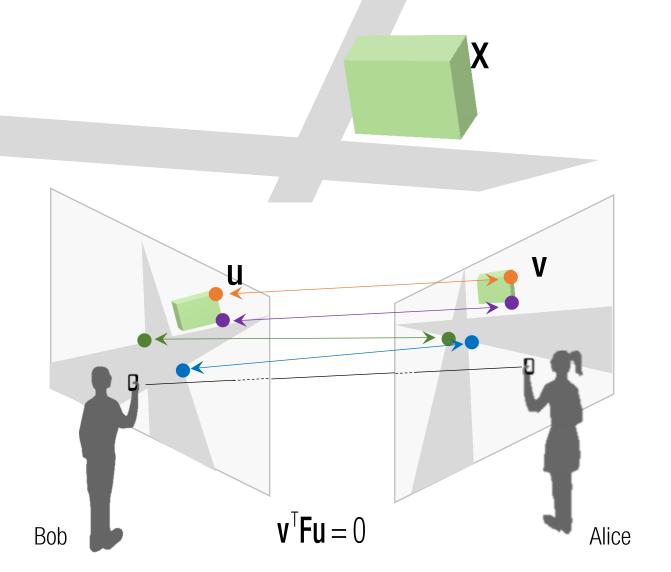


$$\mathbf{v}^{\mathsf{T}}\mathbf{F}\mathbf{u} = \begin{bmatrix} v^{\mathsf{x}} & v^{\mathsf{y}} & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^{\mathsf{x}} \\ u^{\mathsf{y}} \\ 1 \end{bmatrix}$$

$$= f_{11}u^{\mathsf{x}}v^{\mathsf{x}} + f_{12}u^{\mathsf{y}}v^{\mathsf{x}} + f_{13}v^{\mathsf{x}} + f_{21}u^{\mathsf{x}}v^{\mathsf{y}} + f_{22}u^{\mathsf{y}}v^{\mathsf{y}} + f_{23}v^{\mathsf{y}} + f_{31}u^{\mathsf{x}} + f_{32}u^{\mathsf{y}} + f_{33} \\ = 0 \qquad \qquad \text{Linear in } \mathbf{F}.$$

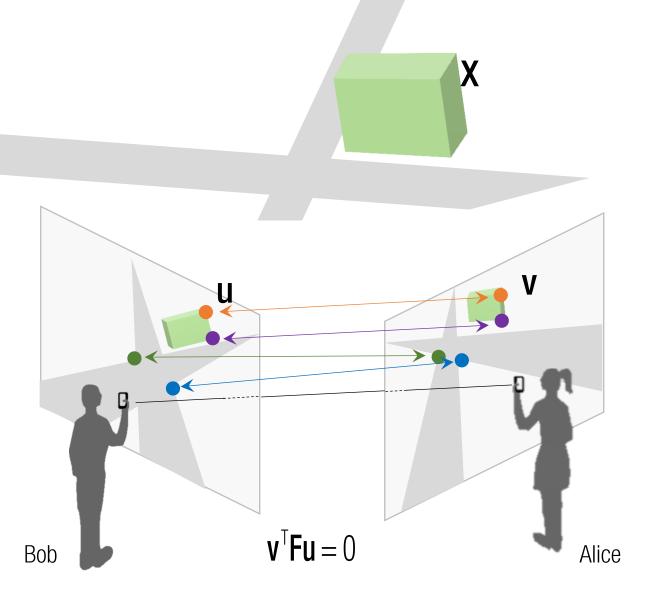
$$\downarrow u_{\mathsf{m}}^{\mathsf{x}}v_{\mathsf{m}}^{\mathsf{x}} & u_{\mathsf{m}}^{\mathsf{y}}v_{\mathsf{m}}^{\mathsf{x}} & v_{\mathsf{m}}^{\mathsf{x}} & u_{\mathsf{m}}^{\mathsf{y}}v_{\mathsf{m}}^{\mathsf{y}} & v_{\mathsf{m}}^{\mathsf{y}} & v_{\mathsf{m}}^{\mathsf{y}} & u_{\mathsf{m}}^{\mathsf{y}} & u_{\mathsf{$$

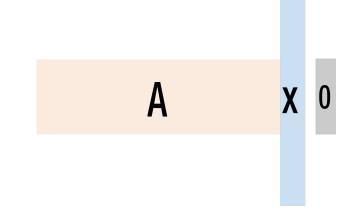
What is minimum m?





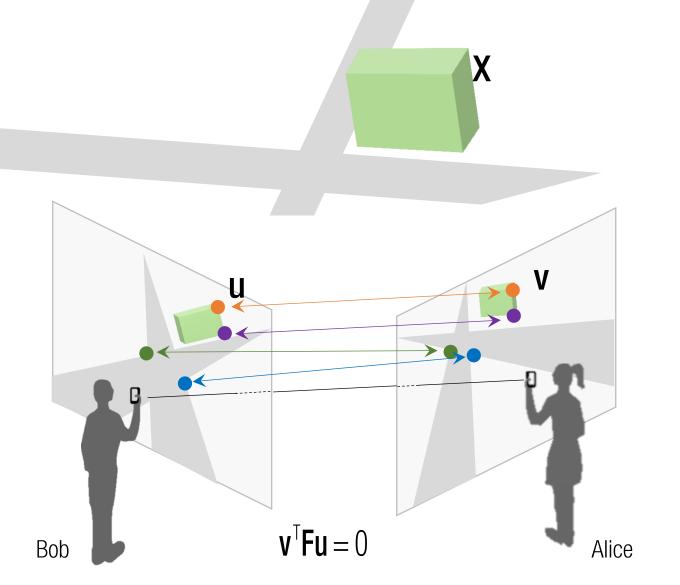
The solution is not necessarily satisfy rank 2 constraint.

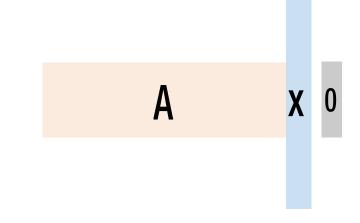




The solution is not necessarily satisfy rank 2 constraint.

$$\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} = \mathbf{U}$$

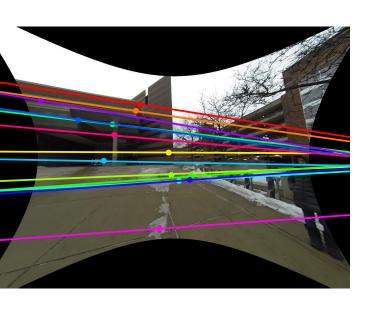


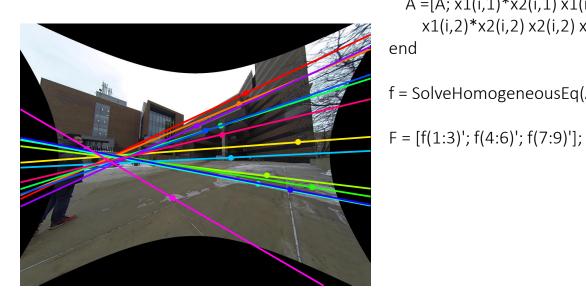


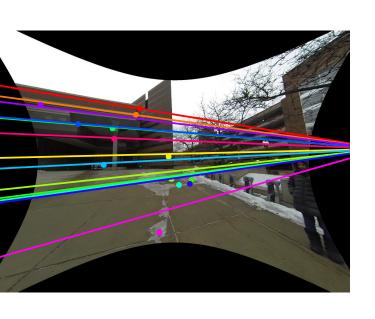
The solution is not necessarily satisfy rank 2 constraint.

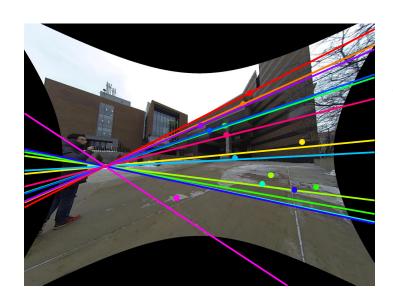
$$\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} = \begin{bmatrix} \mathbf{U} & \mathbf{D} & \mathbf{V}^{\mathsf{T}} \\ \mathbf{D} & \mathbf{D} & \mathbf{V}^{\mathsf{T}} \end{bmatrix}$$

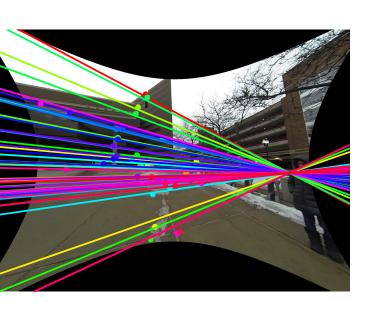
$$\approx \mathbf{F}_{\text{rank2}} = \begin{bmatrix} \mathbf{U} & \mathbf{D} & \mathbf{D} & \mathbf{V}^{\mathsf{T}} \\ \mathbf{D} & \mathbf{D} & \mathbf{V}^{\mathsf{T}} \end{bmatrix}$$
SVD cleanup

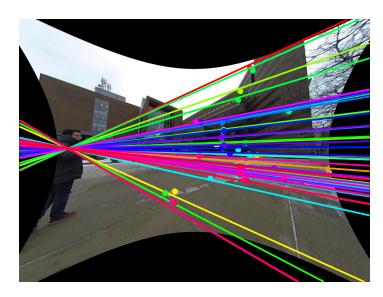










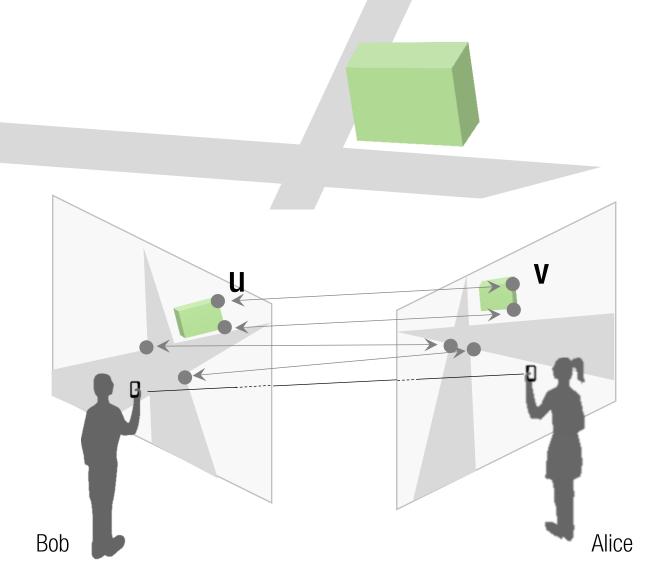


```
function [F F1] = ComputeFundamentalMatrix(x1, x2)
A = [];
for i = 1 : size(x1,1)
    A = [A; x1(i,1)*x2(i,1) x1(i,2)*x2(i,1) x2(i,1) x1(i,1)*x2(i,2) ...
        x1(i,2)*x2(i,2) x2(i,2) x1(i,1) x1(i,2) 1];
end

f = SolveHomogeneousEq(A);

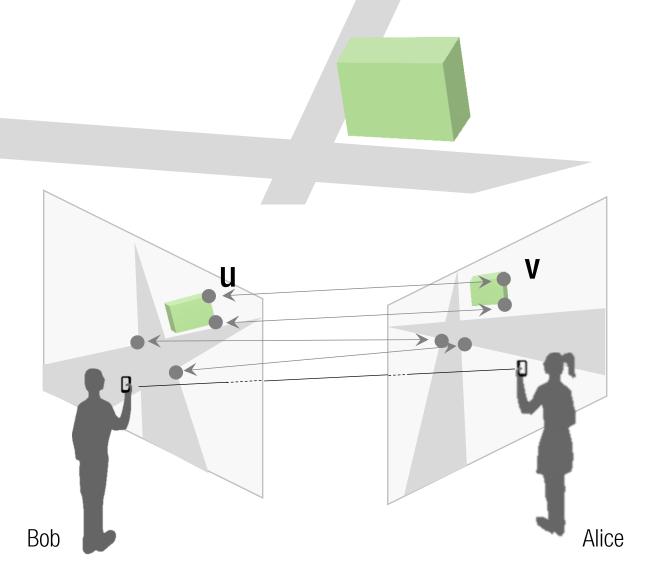
F = [f(1:3)'; f(4:6)'; f(7:9)'];

[u d v] = svd(F);
F1 = F;
d(3,3) = 0;
F = u*d*v';
SVD cleanup
```



$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} [\mathbf{t}] \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

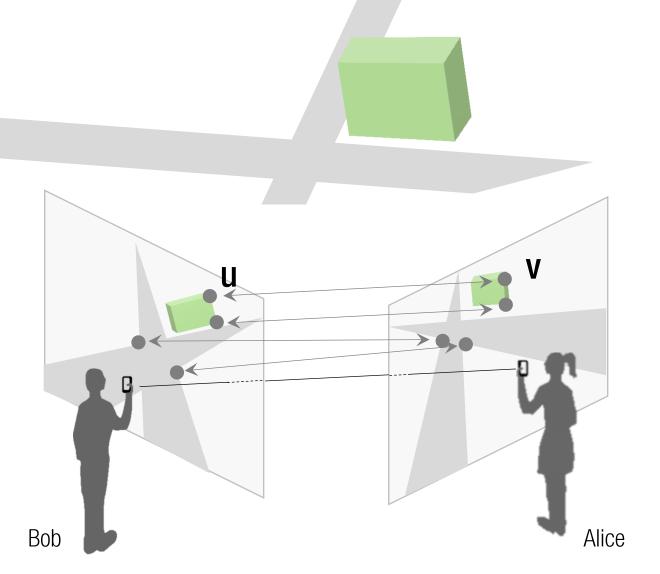


Essential Matrix:

$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} [\mathbf{t}] \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

$$\longrightarrow \mathbf{E} = \mathbf{K}^{\mathsf{T}} \mathbf{F} \mathbf{K}$$
 where $\mathbf{E} = [\mathbf{t}]_{\mathsf{K}} \mathbf{R}$ Calibrated fundamental matrix



Essential Matrix:

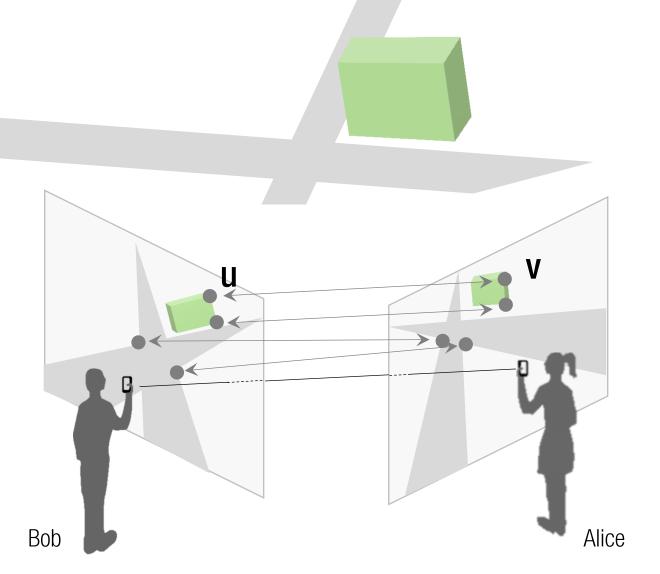
$$F = F(R,t)$$

$$= K^{-T} [t] RK^{-1} = K^{-T}EK^{-1}$$

$$\rightarrow E = K^{T}FK \qquad \text{where} \quad E = [t] R$$
Calibrated fundamental matrix

Property of essential matrix:

$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$



Essential Matrix:

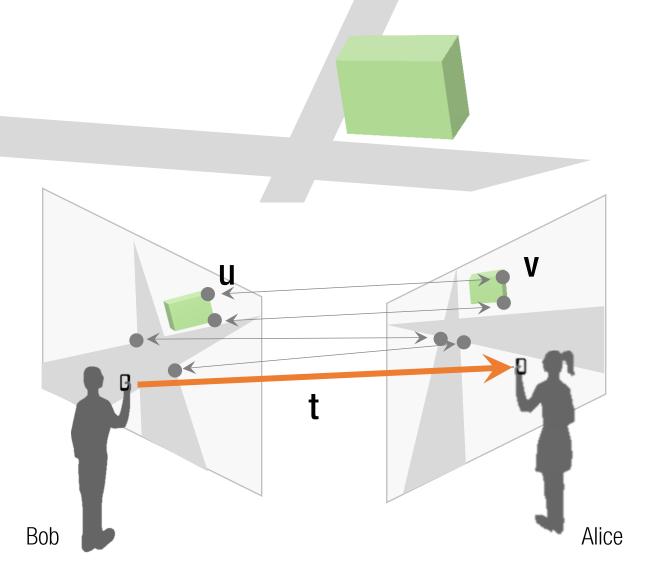
$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

$$\rightarrow \mathbf{E} = \mathbf{K}^{T} \mathbf{F} \mathbf{K} \qquad \text{where } \mathbf{E} = \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R}$$
Calibrated fundamental matrix

Property of essential matrix:

$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{bmatrix} \mathbf{1} \\ \mathbf{0} \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

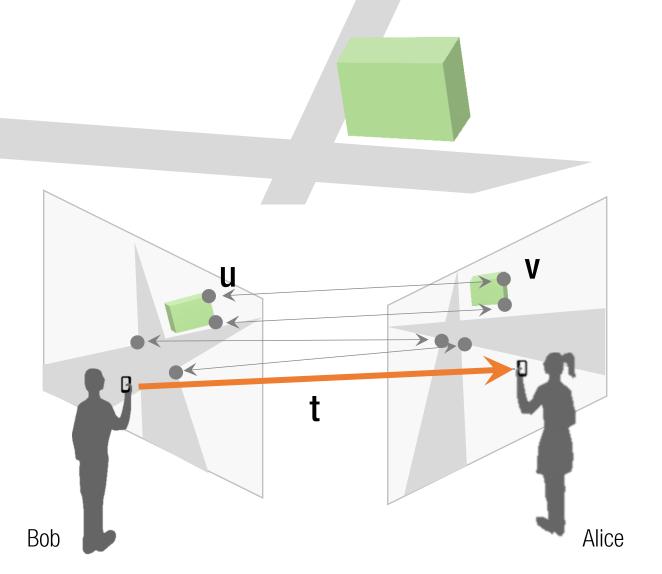


Essential Matrix:

$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} [\mathbf{t}] \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

$$t =$$



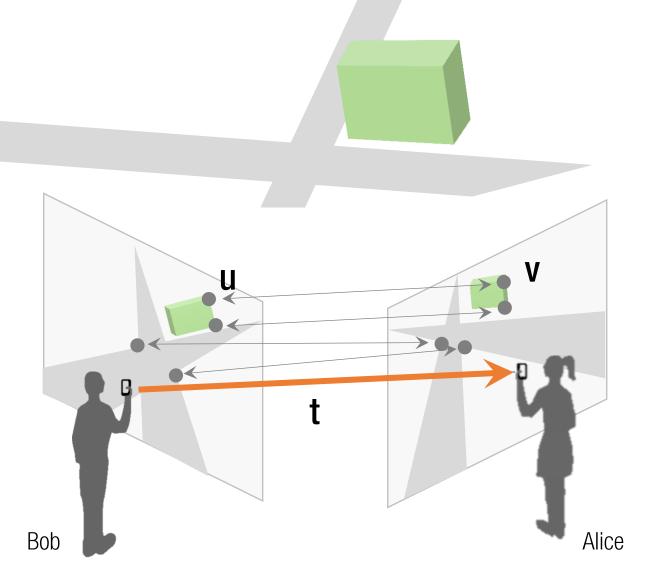
Essential Matrix:

$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} [\mathbf{t}] \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

$$\longrightarrow \mathbf{E} = \mathbf{K}^{\mathsf{T}} \mathbf{F} \mathbf{K}$$
 where $\mathbf{E} = \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R}$ Calibrated fundamental matrix

$$t =$$



Essential Matrix:

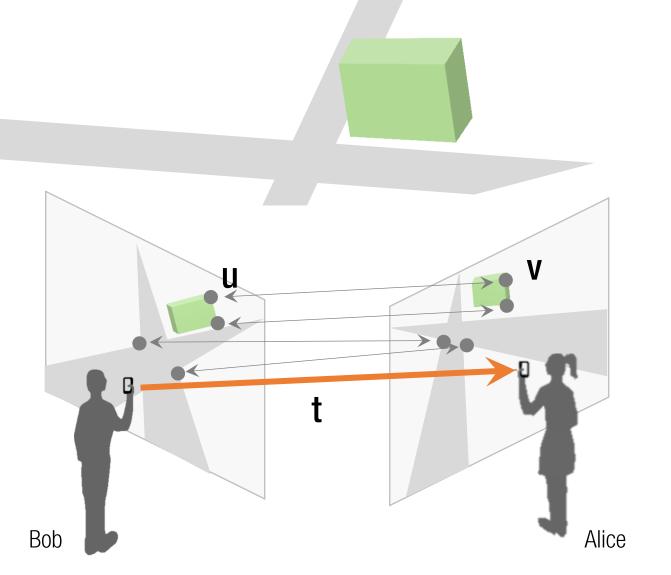
$$F = F(R,t)$$

$$= K^{-T} [t] RK^{-1} = K^{-T}EK^{-1}$$

$$\rightarrow E = K^{T}FK \qquad \text{where} \quad E = [t] R$$

Calibrated fundamental matrix

$$\mathbf{t} = \pm \text{null}(\mathbf{E}^{\mathsf{T}}) = \pm \text{null}(([\mathbf{t}], \mathbf{R})^{\mathsf{T}})$$



Essential Matrix:

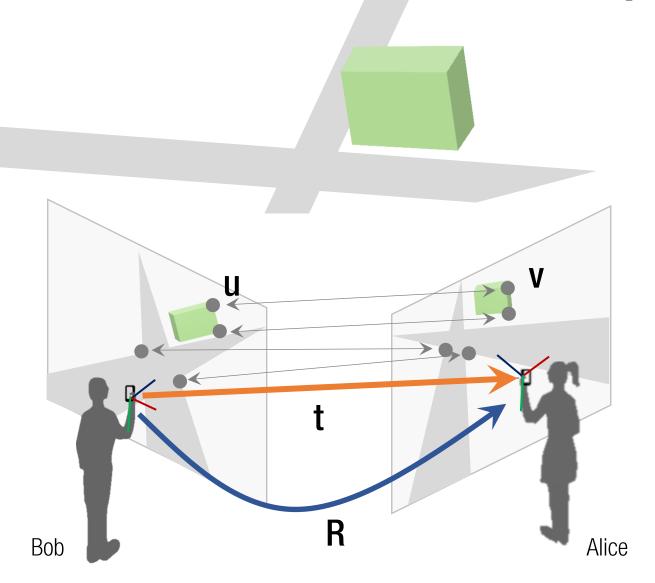
$$\mathbf{F} = \mathbf{F}(\mathbf{R}, \mathbf{t})$$

$$= \mathbf{K}^{-T} \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1}$$

$$\rightarrow \mathbf{E} = \mathbf{K}^{T} \mathbf{F} \mathbf{K} \qquad \text{where } \mathbf{E} = \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R}$$
Calibrated fundamental matrix

$$\mathbf{t} = \pm \text{null}(\mathbf{E}^{\mathsf{T}}) = \pm \text{null}(\left(\left[\mathbf{t}\right] \mathbf{R}\right)^{\mathsf{T}})$$

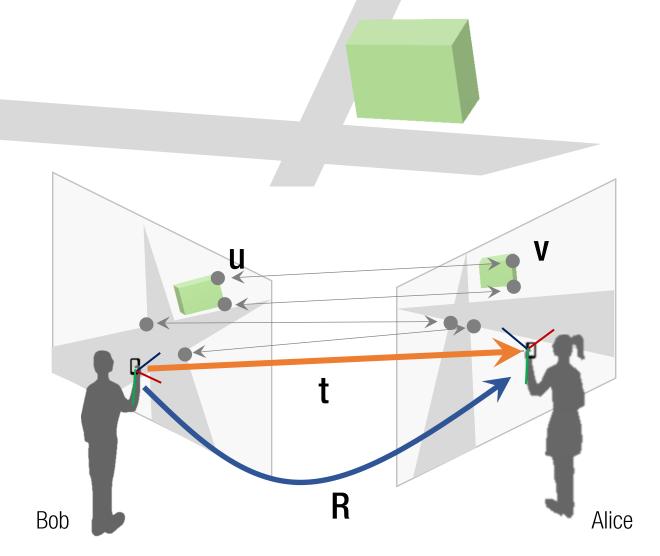
$$\mathbf{t}^{\mathsf{T}} \left[\mathbf{t}\right] \mathbf{R} = -\left(\left[\mathbf{t}\right] \mathbf{t}\right)^{\mathsf{T}} \mathbf{R} = -\left(\mathbf{t} \times \mathbf{t}\right)^{\mathsf{T}} \mathbf{R} = 0$$
Self-cross product



Left null space of E is translation vector, t:

$$\mathbf{t} = \text{null}(\mathbf{E}^{\mathsf{T}}) = \text{null}((\mathbf{t}, \mathbf{R})^{\mathsf{T}})$$

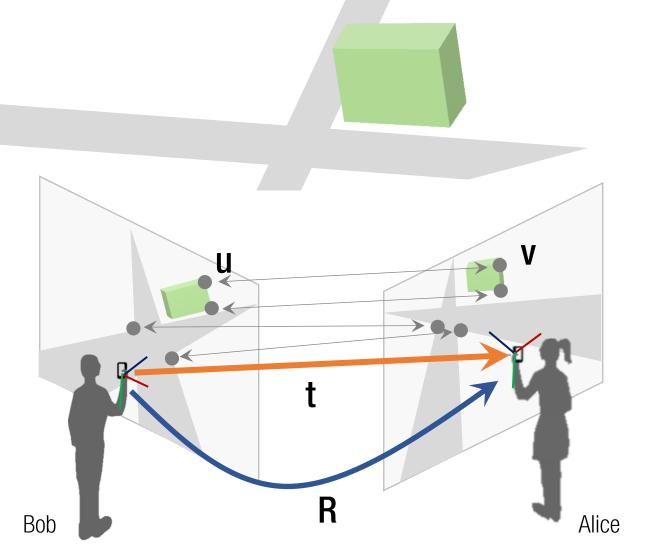
Can I invert [t]?



$$\mathbf{t} = \text{null}(\mathbf{E}^{\mathsf{T}}) = \text{null}((\mathbf{t}, \mathbf{R})^{\mathsf{T}})$$

$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_3$ where $\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 \end{bmatrix}$

$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

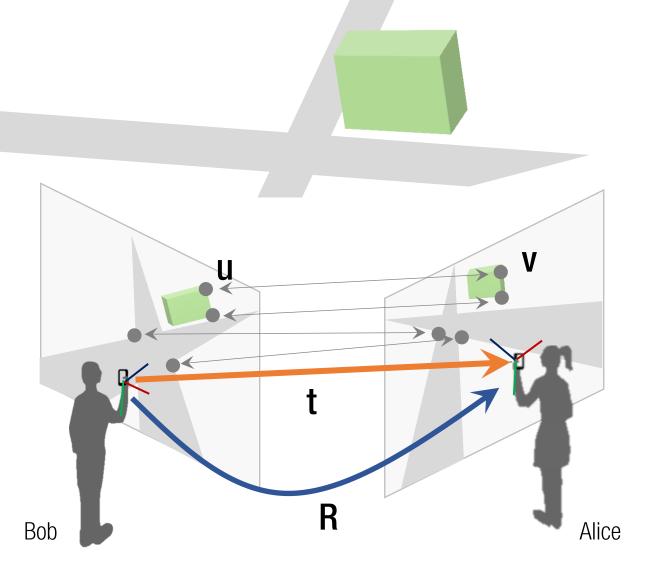


$$\mathbf{t} = \text{null}(\mathbf{E}^{\mathsf{T}}) = \text{null}((\mathbf{t}, \mathbf{R})^{\mathsf{T}})$$

$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_3$ where $\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 \end{bmatrix}$

$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{vmatrix} 1 & & & \\ & 1 & & \\ & & 0 \end{vmatrix} \mathbf{V}^{\mathsf{T}}$$

$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2$ (orthogonal matrix, \mathbf{U})



Left null space of E is translation vector, t:

$$\mathbf{t} = \text{null}(\mathbf{E}^{\mathsf{T}}) = \text{null}((\mathbf{t}, \mathbf{R})^{\mathsf{T}})$$

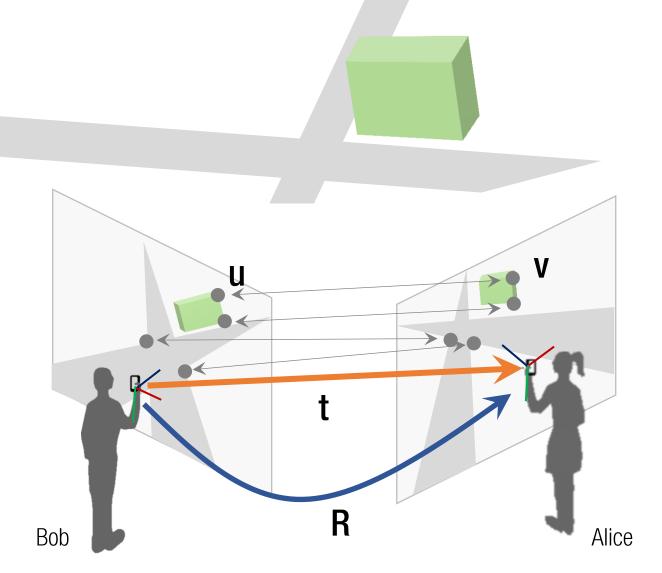
$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_3$ where $\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 \end{bmatrix}$

$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{vmatrix} 1 & & & \\ & 1 & & \\ & & 0 \end{vmatrix} \mathbf{V}^{\mathsf{T}}$$

$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2$ (orthogonal matrix, \mathbf{U})

$$\boxed{\mathbf{t}} = \boxed{\mathbf{u}_1 \times \mathbf{u}_2} = \mathbf{u}_2 \mathbf{u}_1^{\mathsf{T}} - \mathbf{u}_1 \mathbf{u}_2^{\mathsf{T}}$$

:



Left null space of E is translation vector, **t**:

$$\mathbf{t} = \text{null}(\mathbf{E}^{\mathsf{T}}) = \text{null}((\mathbf{t}, \mathbf{R})^{\mathsf{T}})$$

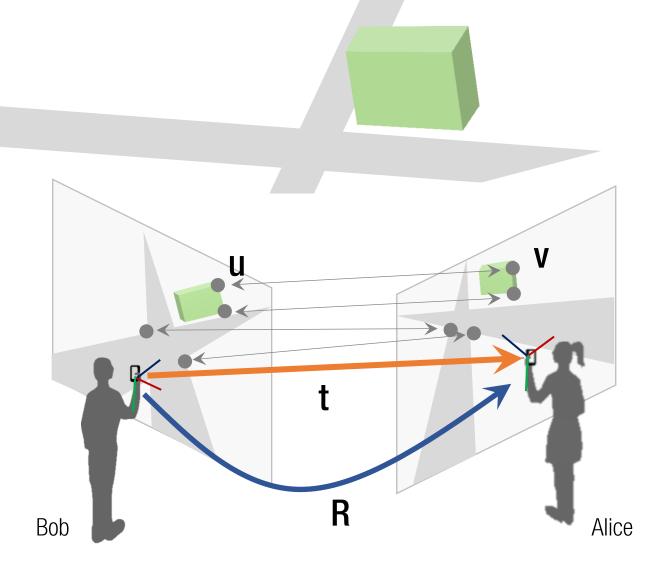
$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_3$ where $\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 \end{bmatrix}$

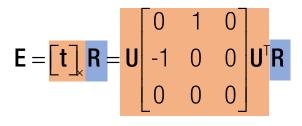
$$\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}} = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

$$\longrightarrow$$
 $\mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2$ (orthogonal matrix, \mathbf{U})

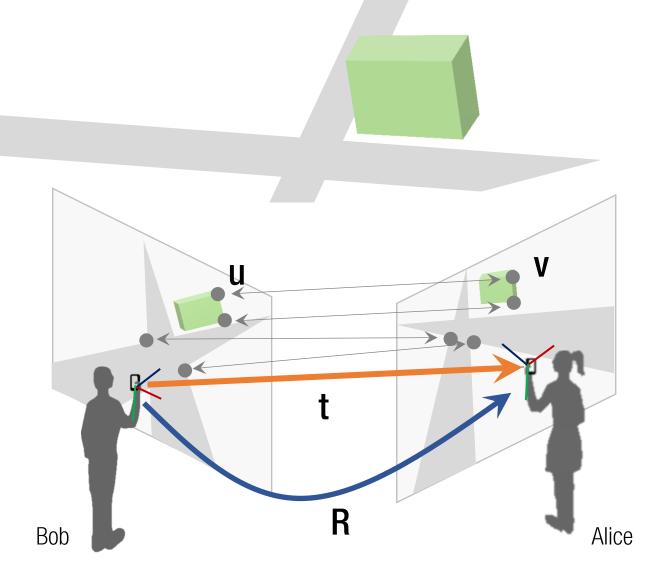
$$\begin{bmatrix} \mathbf{t} \end{bmatrix} = \begin{bmatrix} \mathbf{u}_1 \times \mathbf{u}_2 \end{bmatrix}_{\times} = \mathbf{u}_2 \mathbf{u}_1^{\mathsf{T}} - \mathbf{u}_1 \mathbf{u}_2^{\mathsf{T}}$$
$$= \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{U}^{\mathsf{T}}$$

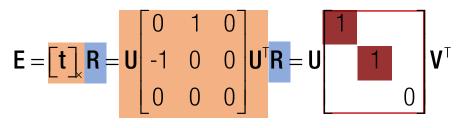
Prove!



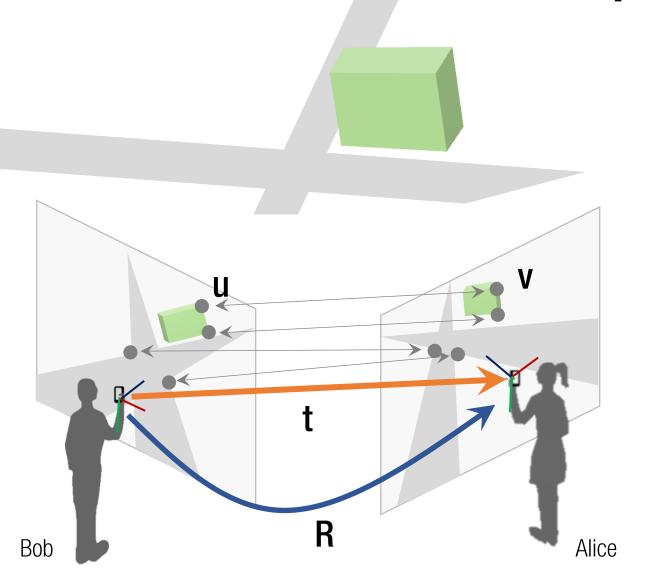


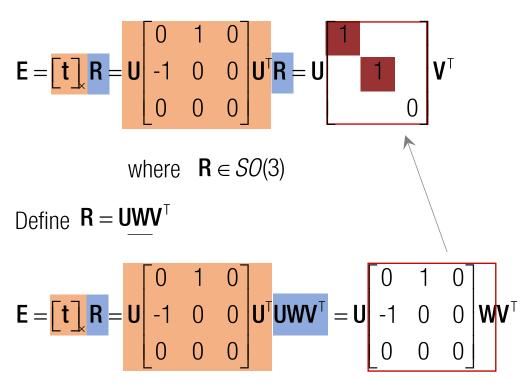
where $\mathbf{R} \in SO(3)$



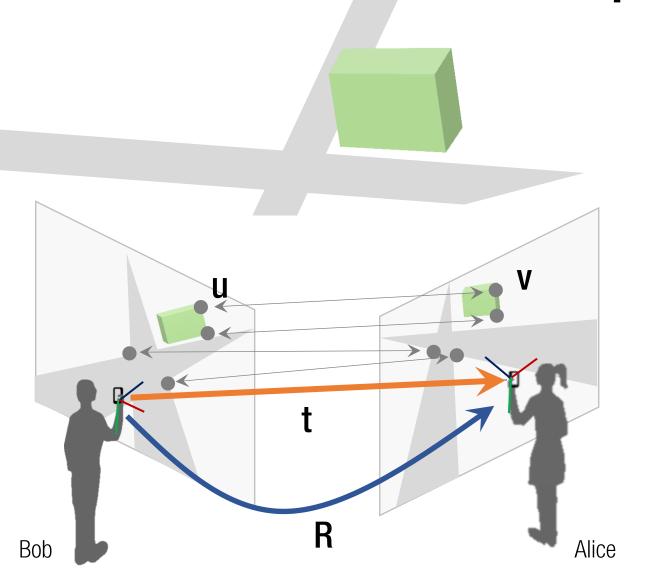


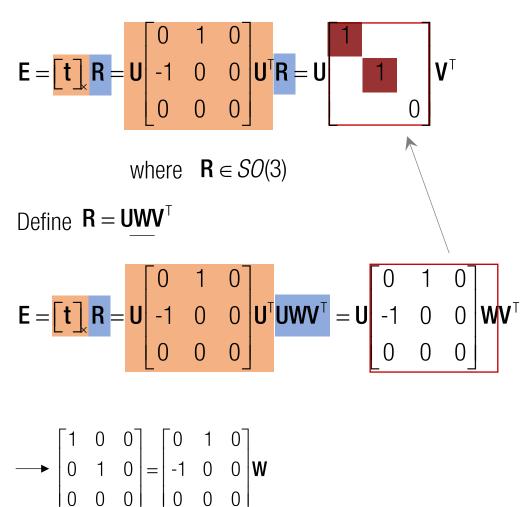
where $\mathbf{R} \in SO(3)$



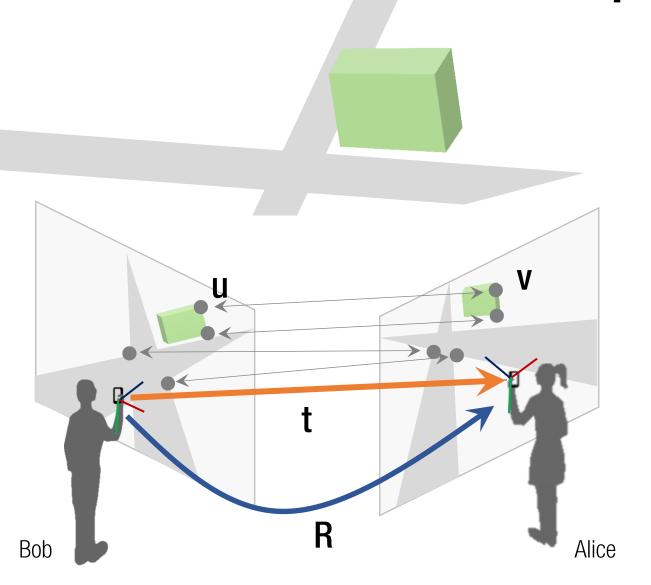


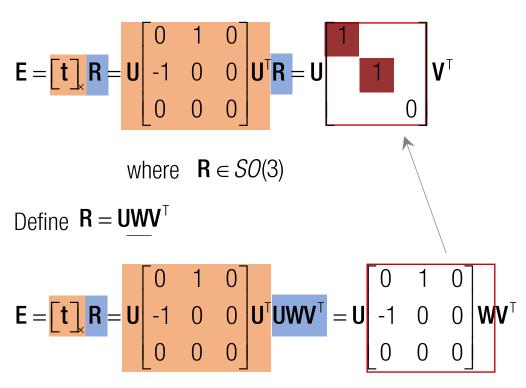
Essential Matrix Decomposition



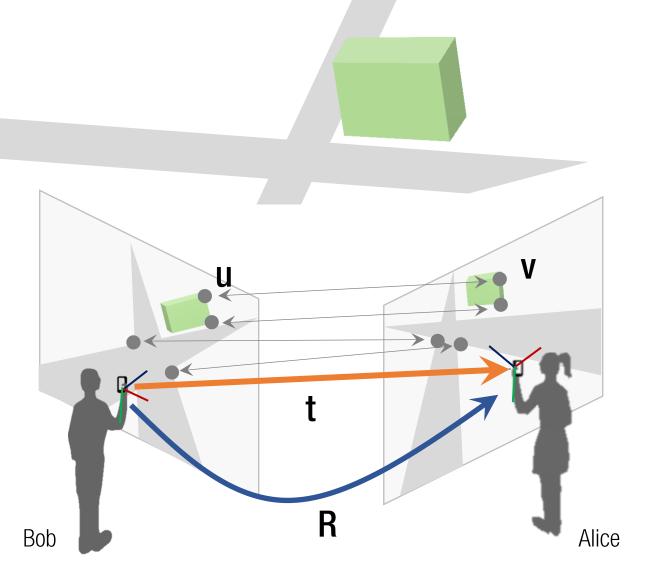


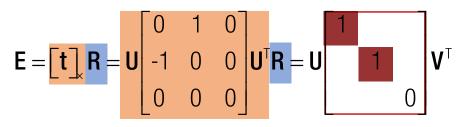
Essential Matrix Decomposition





Camera Pose from Essential Matrix (Rotation)

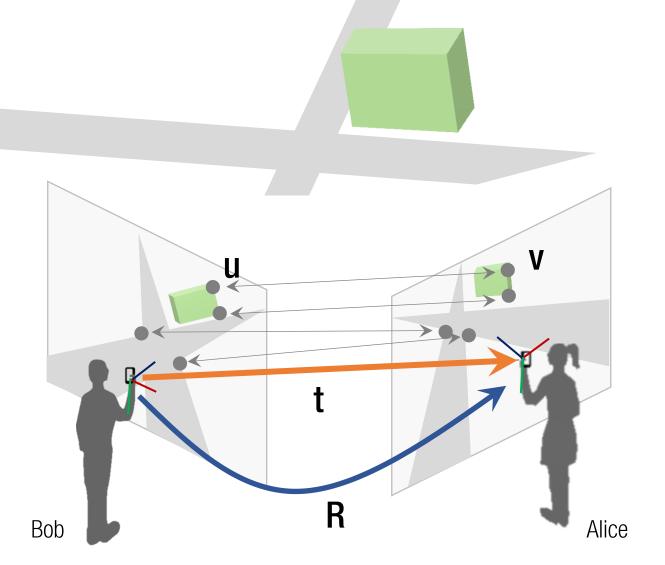




where $\mathbf{R} \in SO(3)$

$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}} , \text{ or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

Where Am I?

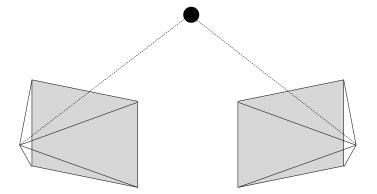


$$\mathbf{E} = \begin{bmatrix} \mathbf{t} \end{bmatrix} \mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{U}^{\mathsf{T}} \mathbf{R} = \mathbf{U} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

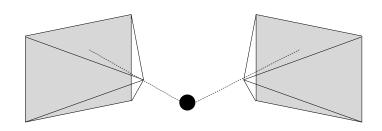
$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}} , \text{ or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

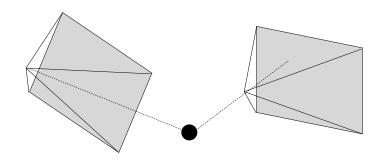
→ Four configurations

Four Configurations

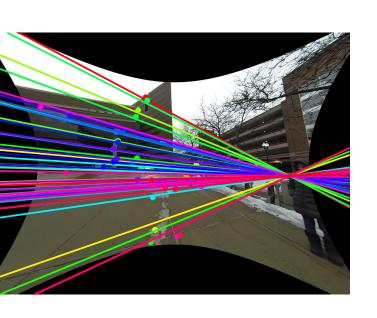


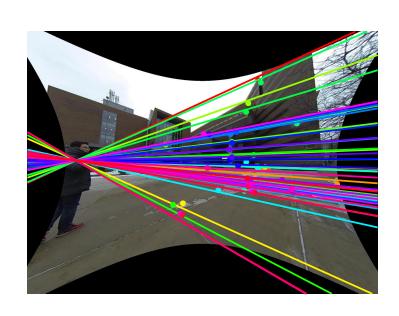
$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}} \text{, or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$





Camera Pose Estimation





$\mathbf{E} = \mathbf{K}^{\mathsf{T}} \mathbf{F} \mathbf{K}$

```
function E = ComputeEssentialMatrix(F, K)
```

$$E = K' * F * K;$$

$$[u d v] = svd(E);$$

$$d(1,1) = 1;$$

$$d(2,2) = 1;$$

E = u * d * v';

$$d(3,3) = 0;$$

$$u(3,3) - c$$

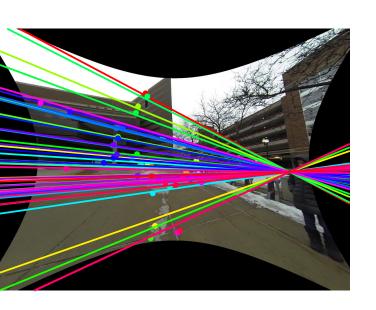
SVD cleanup

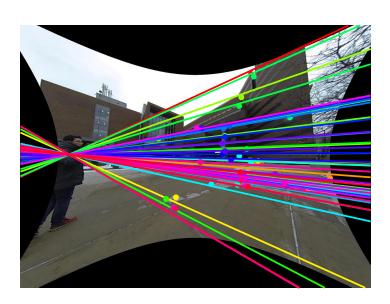
1.0000 0 1.0000 0.0000

Before cleanup

After cleanup

Camera Pose Estimation

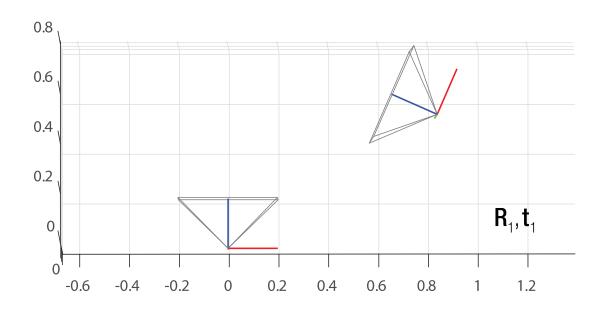


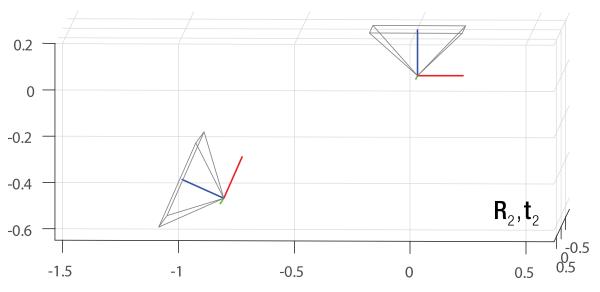


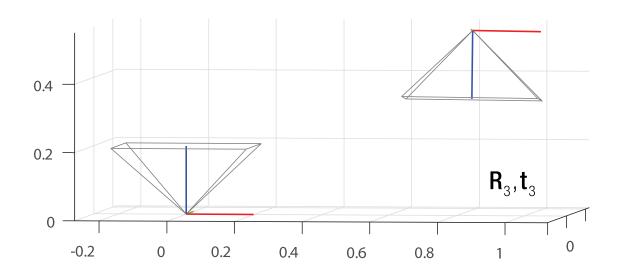
$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}}, \text{ or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^{\mathsf{T}}$$

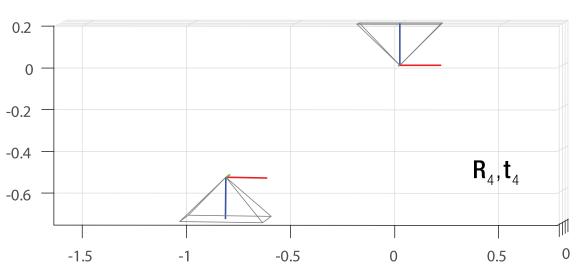
function [R1 t1, R2, t2, R3, t3, R4, t4] = ... CameraPoseFromEssentialMatrix(E)

...

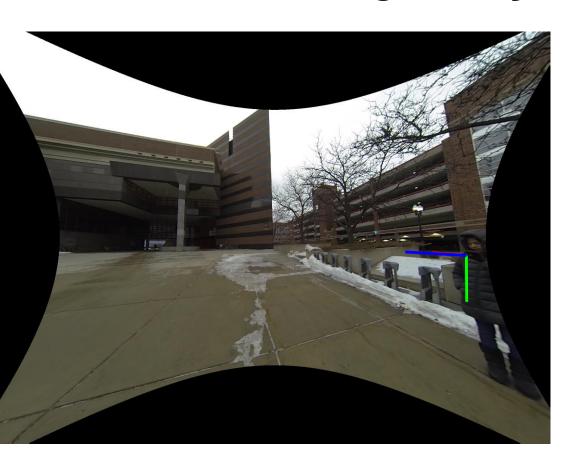


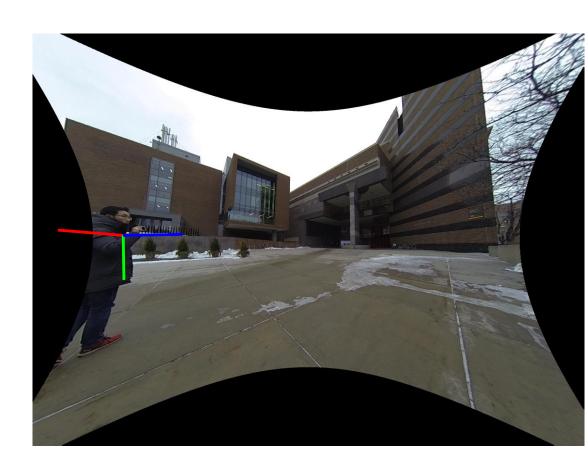






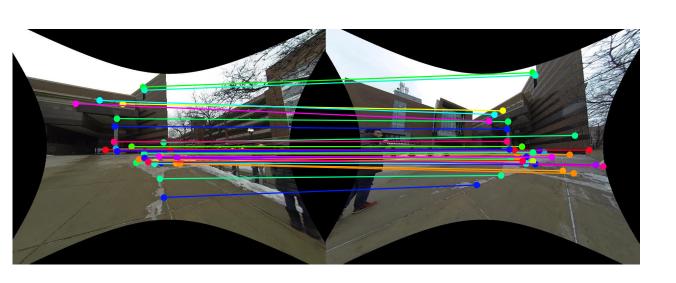
Camera Image Projection

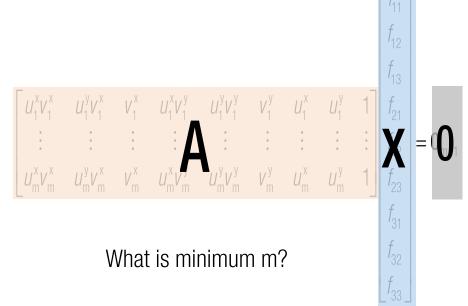






How Many Correspondences?







Local Patch



Local Patch (Scale)





Local Patch (Scale)



Local Patch (Scale)



Local Visual Descriptor



Desired properties:

- Repeatability: the same point is repeatedly detected.
- Discriminativity: the point is unique.

Local Visual Descriptor



Desired properties:

- Repeatability: the same point is repeatedly detected.
- Discriminativity: the point is unique.
- Orientation aware

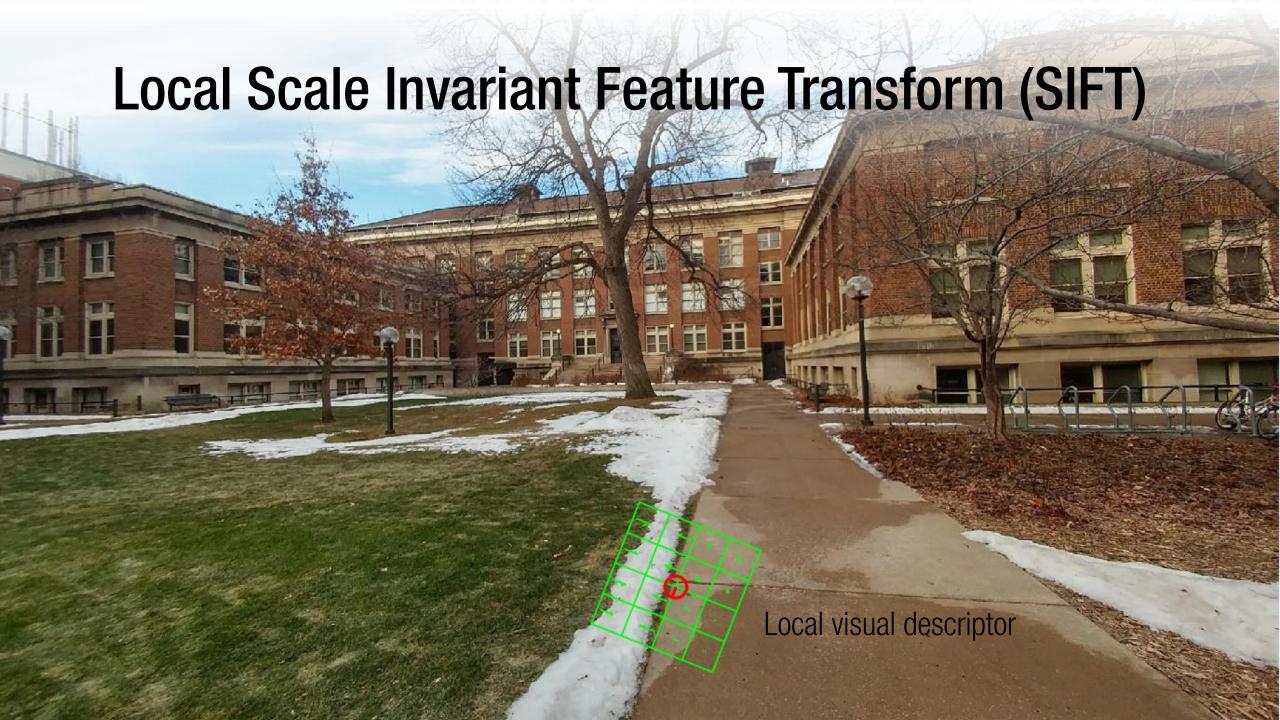
Local Scale Invariant Feature Transform (SIFT)



Desired properties:

- Repeatability: the same point is repeatedly detected.
- Discriminativity: the point is unique.
- Orientation aware





Local Scale Invariant Feature Transform (SIFT)





Local Scale Invariant Feature Transform (SIFT)

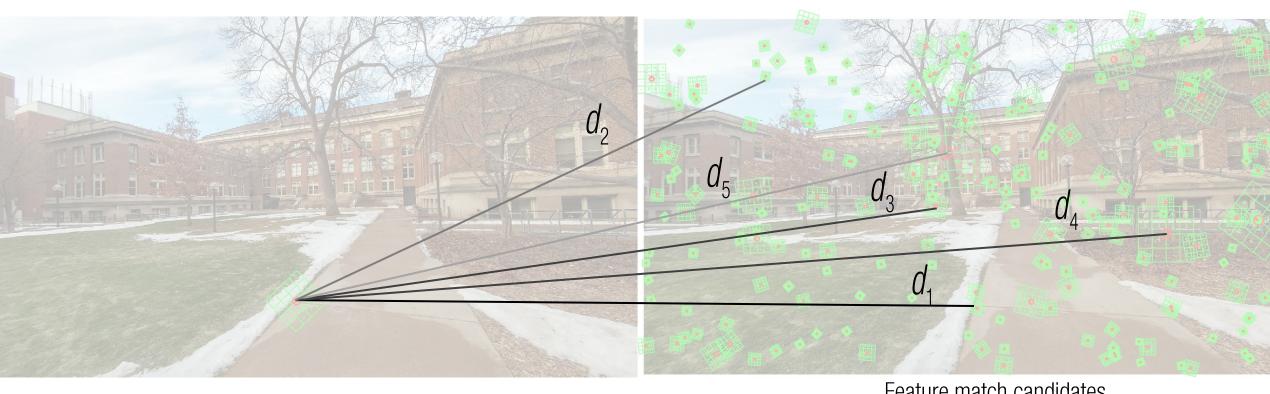






Feature match candidates

Nearest Neighbor Search

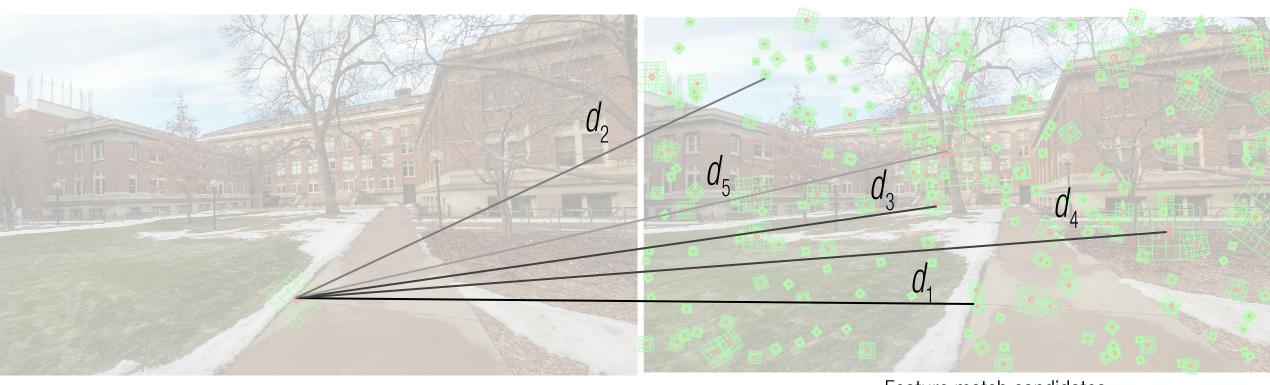






Feature match candidates

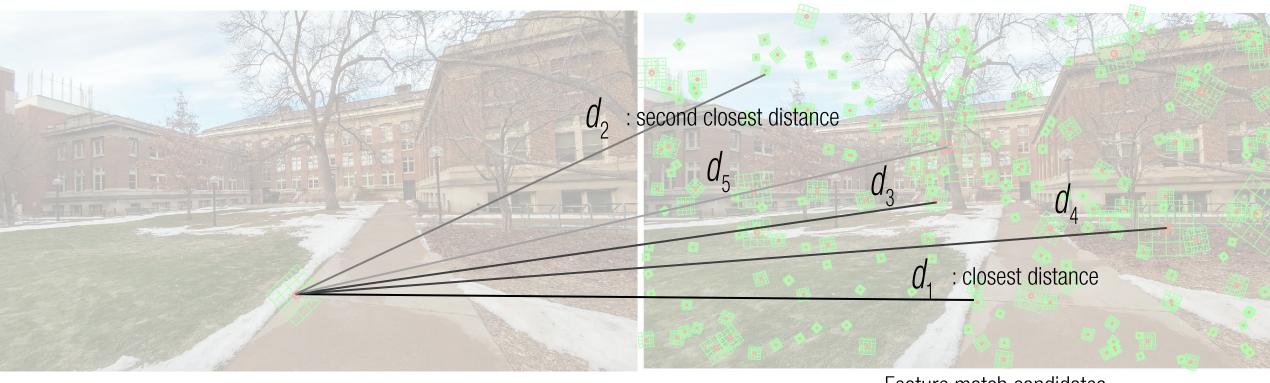
Nearest Neighbor Search



Discriminativity: how is the feature point unique?

Feature match candidates

Nearest Neighbor Search w/ Ratio Test

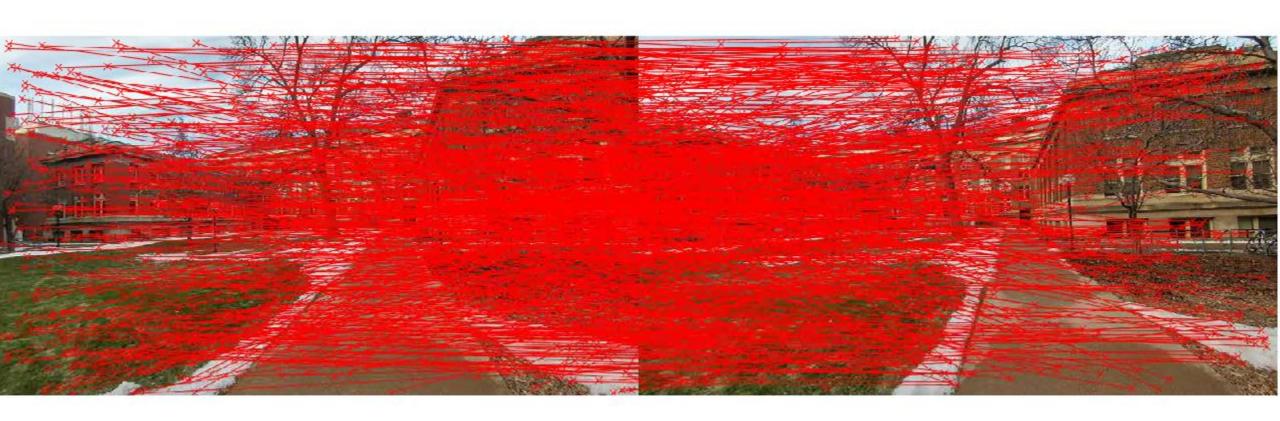


Discriminativity: how is the feature point unique?

$$\frac{d_1}{d_2} < 0.7$$

Feature match candidates

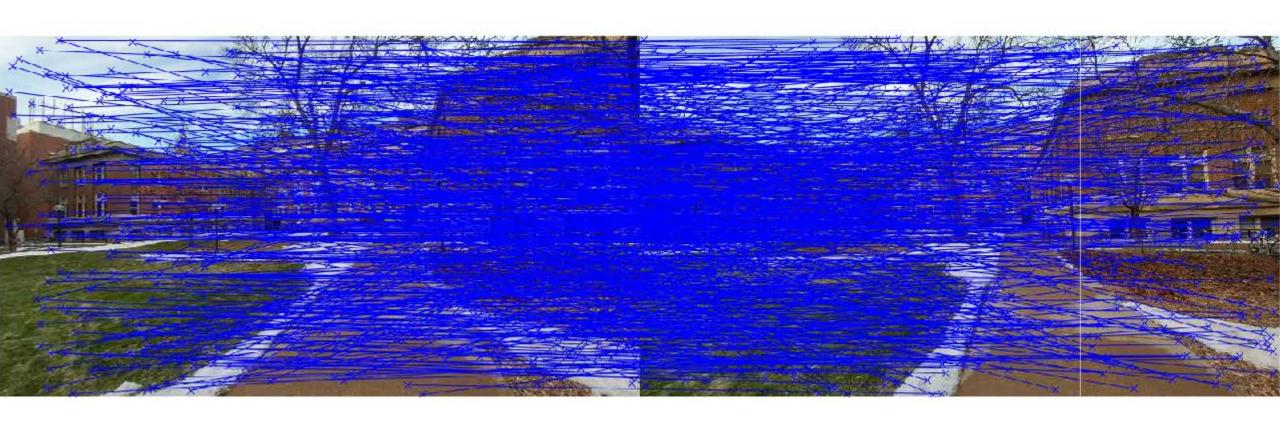
Nearest Neighbor Search w/o Ratio Test



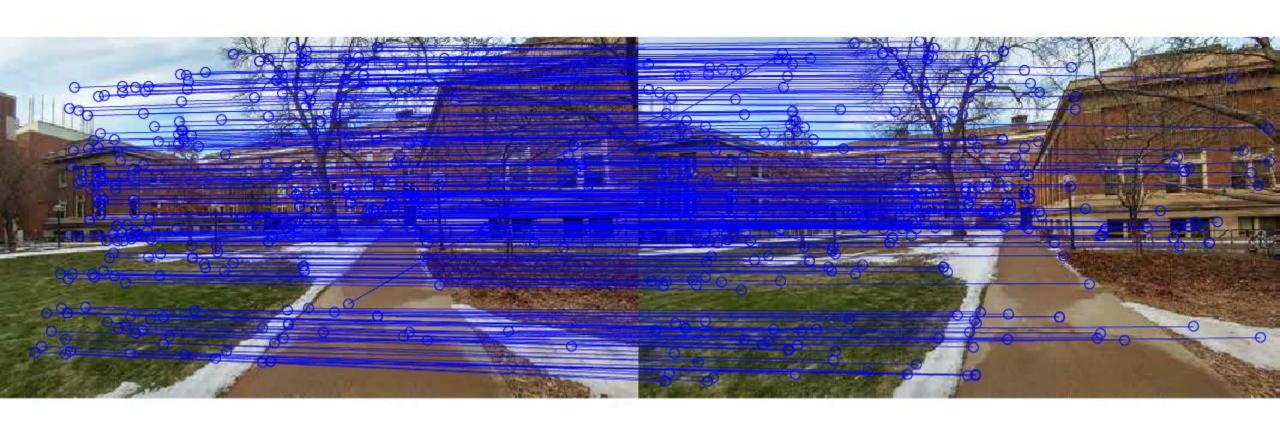
Nearest Neighbor Search w/ Ratio Test



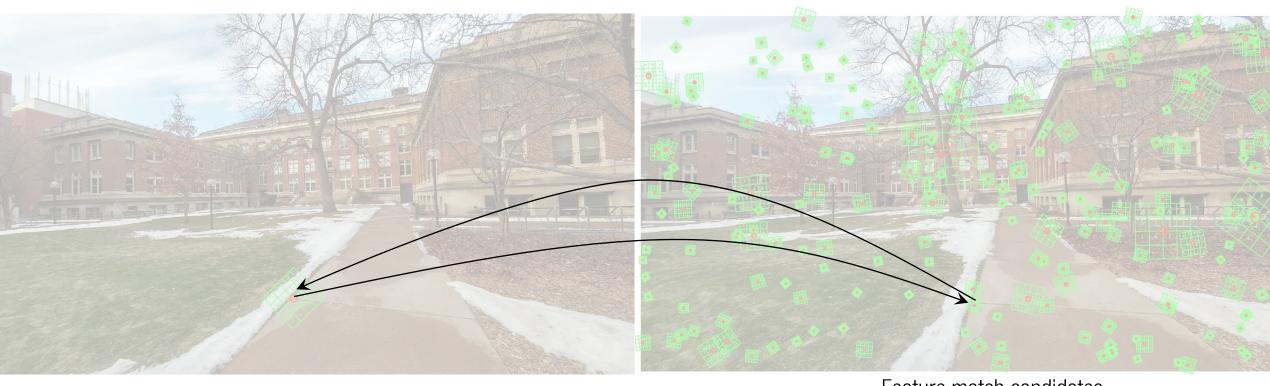
Nearest Neighbor Search w/o Ratio Test



Nearest Neighbor Search w/ Ratio Test



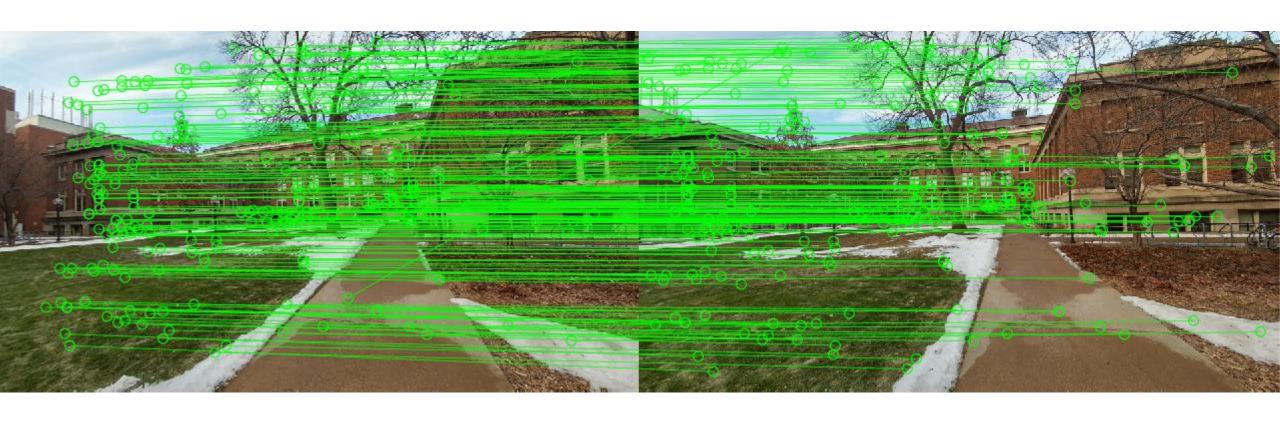
Bi-directional Consistency Check



Consistency: would a feature match correspond to each other?

Feature match candidates

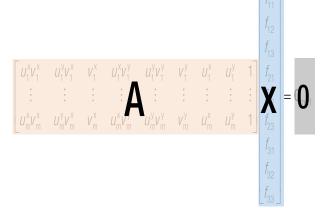
Bi-directional Consistency Check

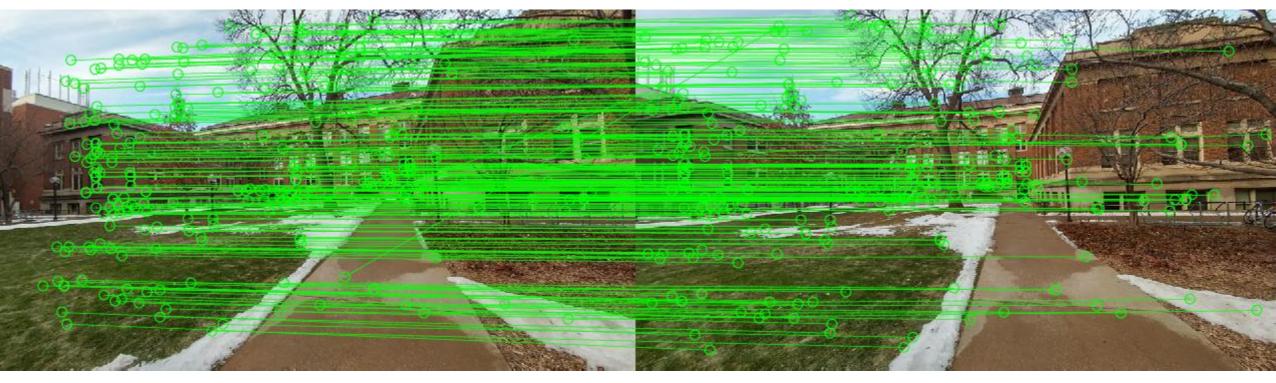


RANSAC: Random Sample Consensus

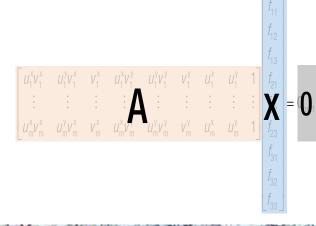


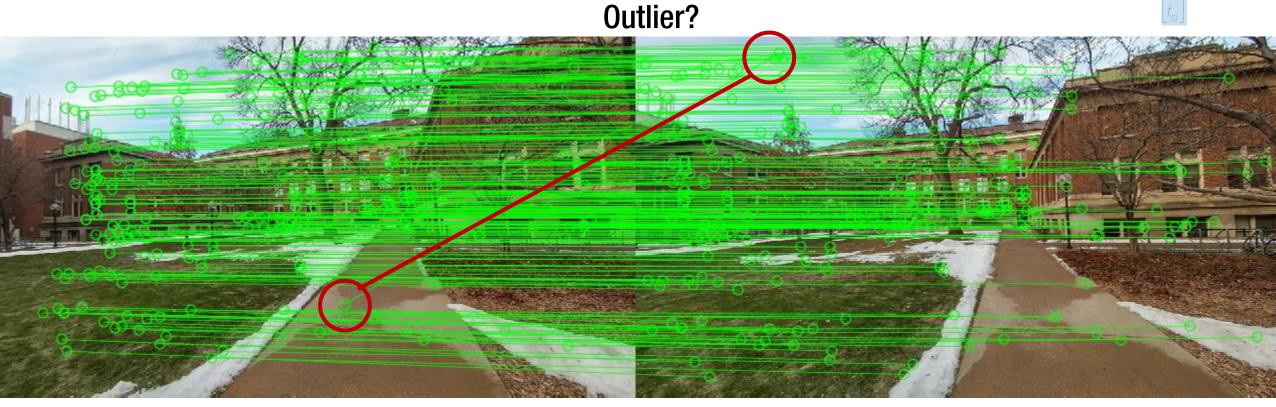
Fundamental Matrix Computation: Linear Least Squares



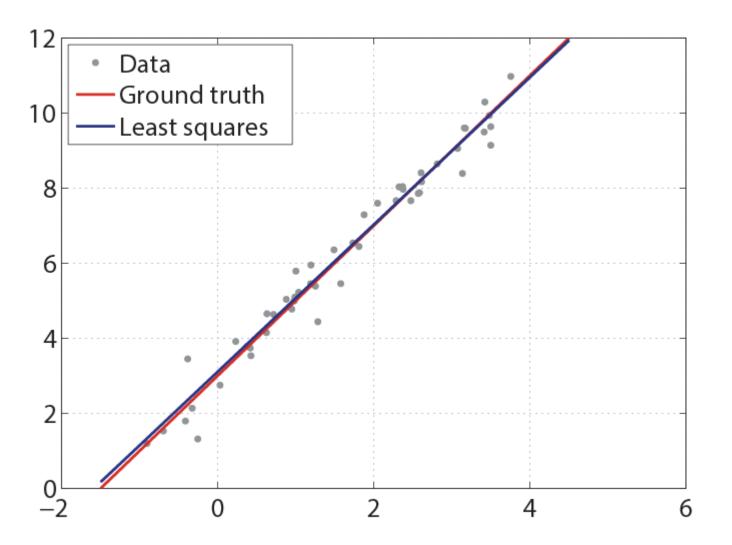


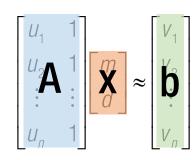
Fundamental Matrix Computation: Linear Least Squares





Recall: Line Fitting (Ax=b)

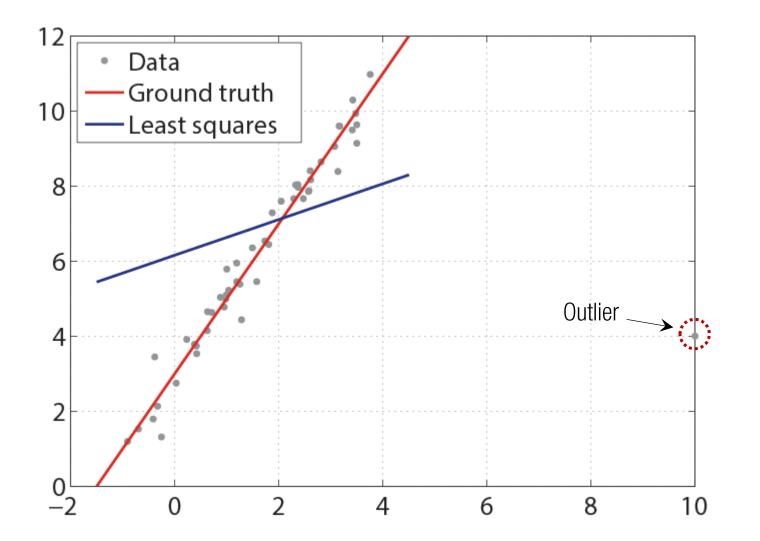


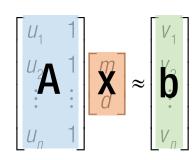


$$\mathbf{A}^{\mathsf{T}}$$
 \mathbf{A} \mathbf{X} = \mathbf{A}^{T} \mathbf{b}

$$\mathbf{X} = \begin{bmatrix} \mathbf{A}^{\mathsf{T}} & \mathbf{A} \end{bmatrix}^{-1} \mathbf{A}^{\mathsf{T}} \mathbf{b}$$

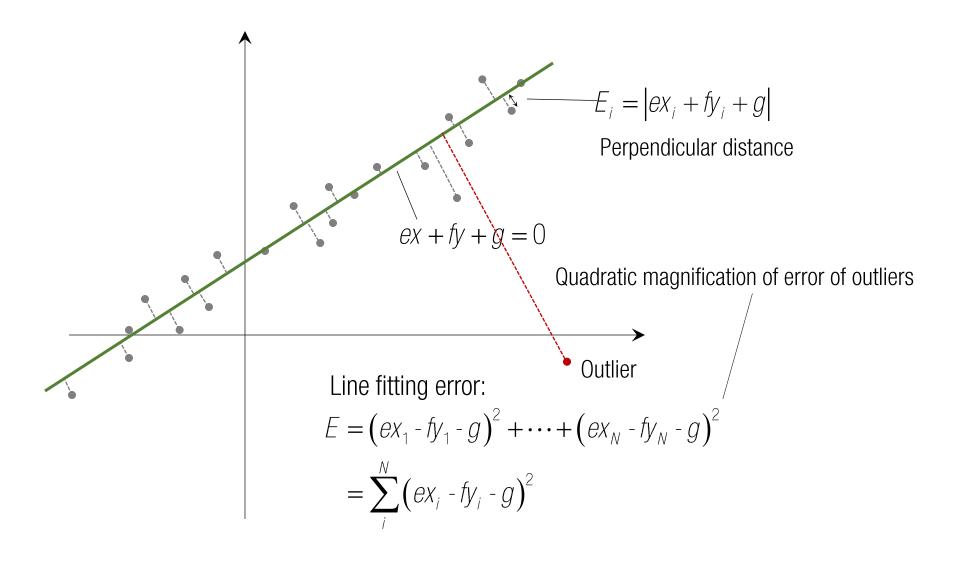
Outlier

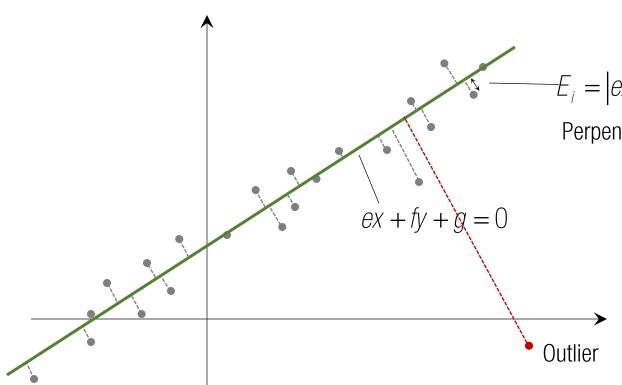




$$\mathbf{A}^{\mathsf{T}}$$
 \mathbf{A} \mathbf{X} = \mathbf{A}^{T} \mathbf{b}

$$\mathbf{X} = \begin{bmatrix} \mathbf{A}^{\mathsf{T}} & \mathbf{A} \end{bmatrix}^{-1} \mathbf{A}^{\mathsf{T}} \mathbf{b}$$



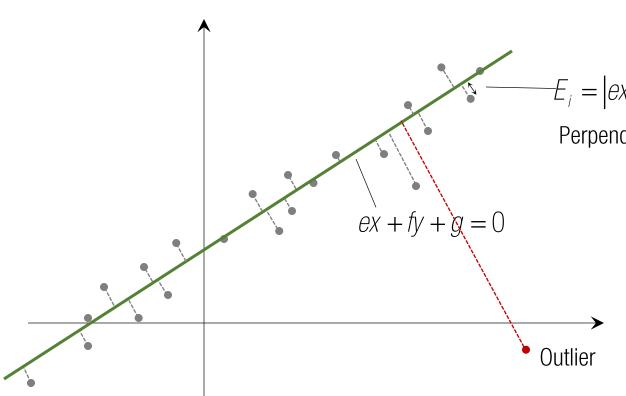


$-E_i = |ex_i + fy_i + g|$

Perpendicular distance

Outlier rejection strategy:

To find the best line that explanes the <u>maximum</u> number of points.



$$E_i = \left| ex_i + fy_i + g \right|$$

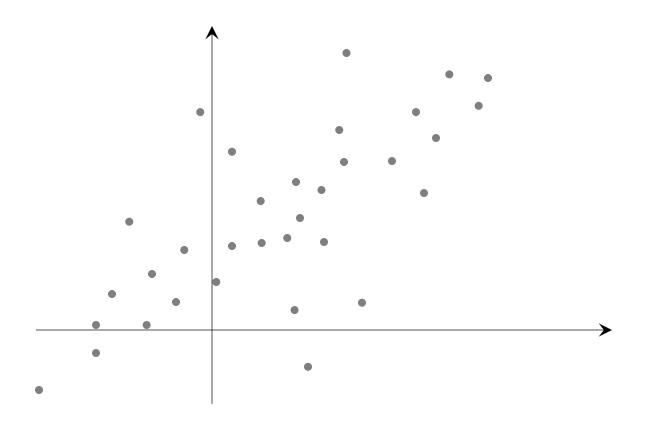
Perpendicular distance

Outlier rejection strategy:

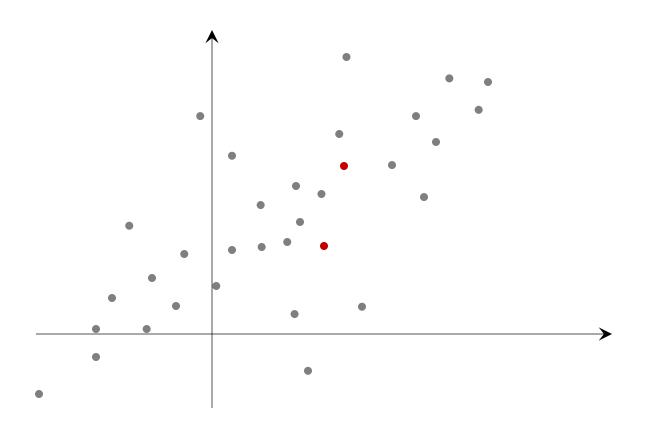
To find the best line that explanes the <u>maximum</u> number of points.

Assumptions:

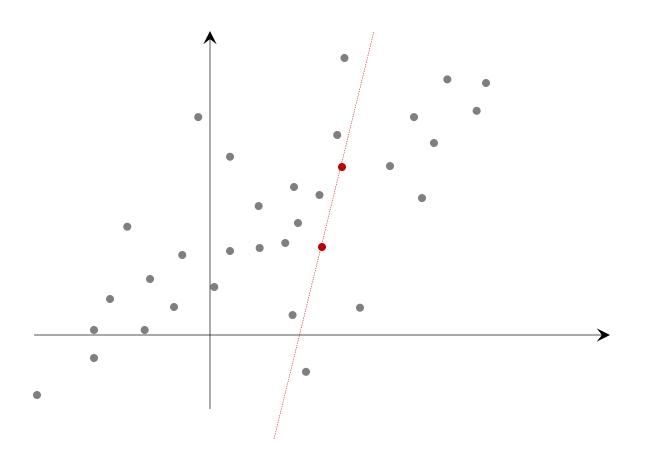
- 1. Majority of good samples agree with the underlying model (good apples are same and simple.).
- 2. Bad samples does not consistently agree with a single model (all bad apples are different and complicated.).



RANSAC: Random Sample Consensus

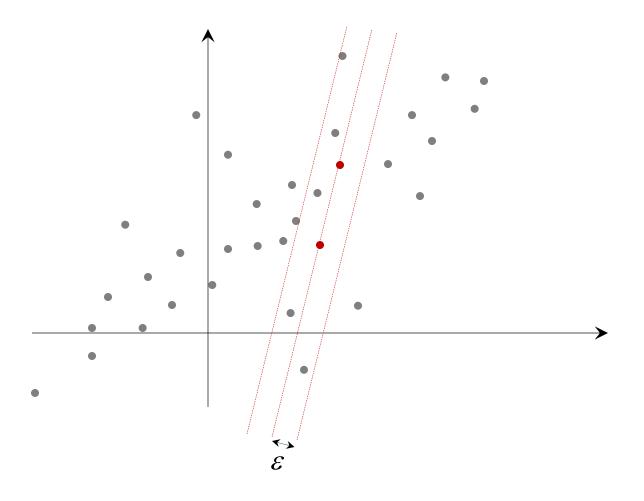


1. Random sampling



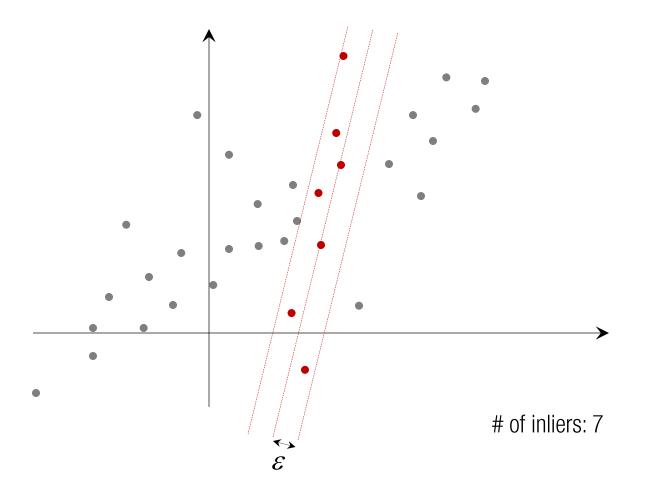
- 1. Random sampling
- 2. Model building

RANSAC: Random Sample Consensus

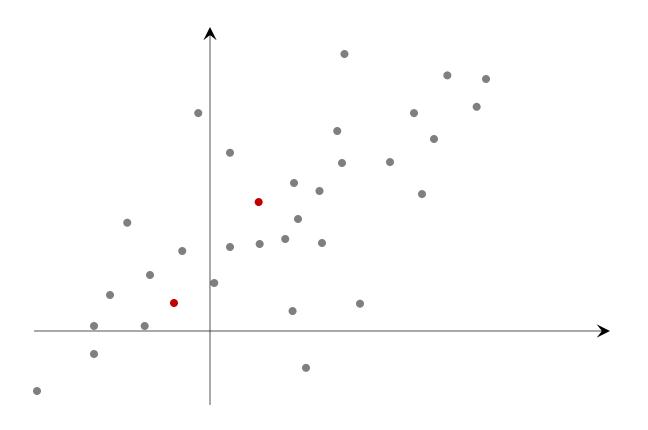


- 1. Random sampling
- 2. Model building
- 3. Thresholding

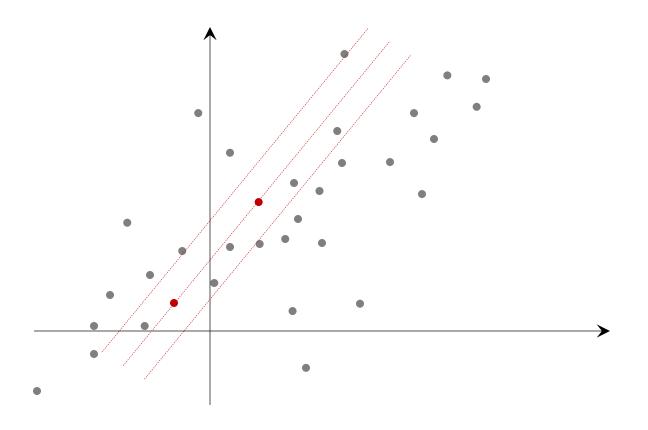
RANSAC: Random Sample Consensus



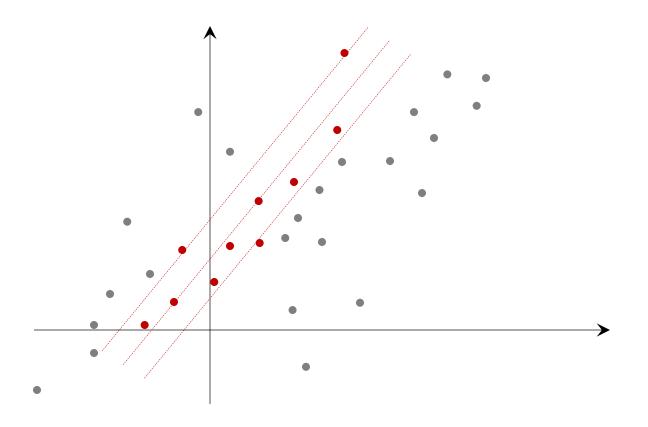
- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting



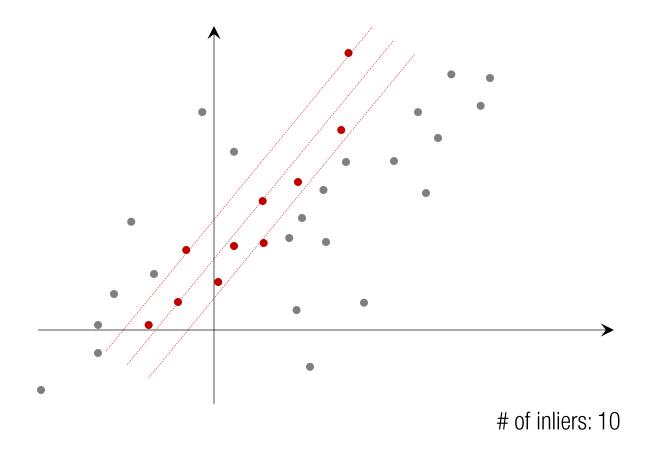
- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting



- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting

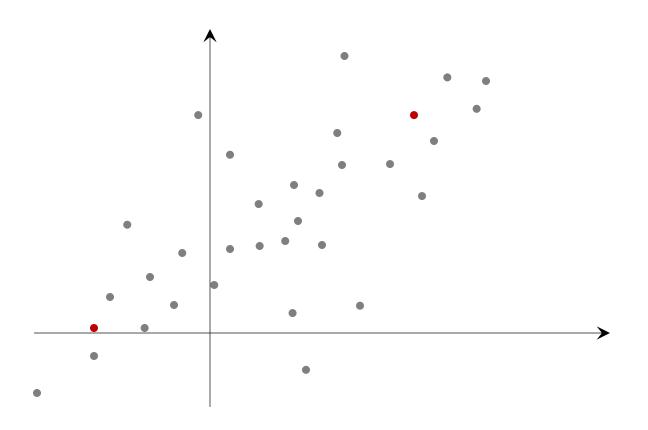


- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting

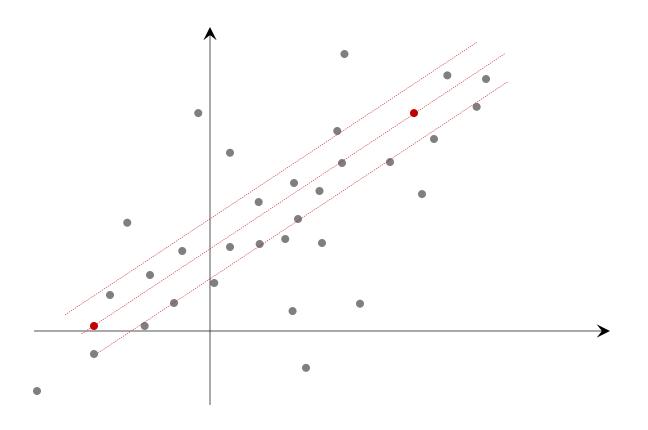


- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting

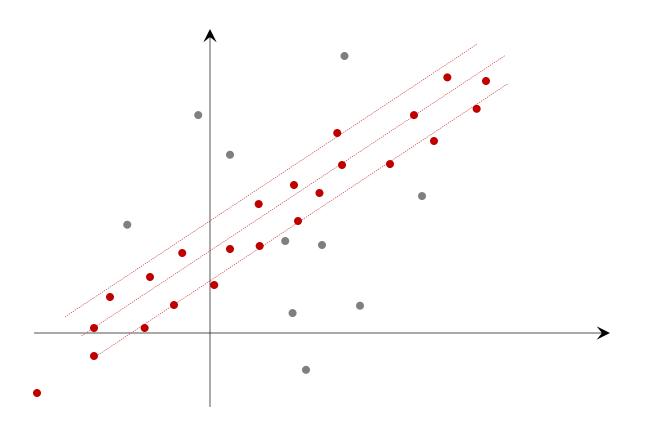
RANSAC: Random Sample Consensus



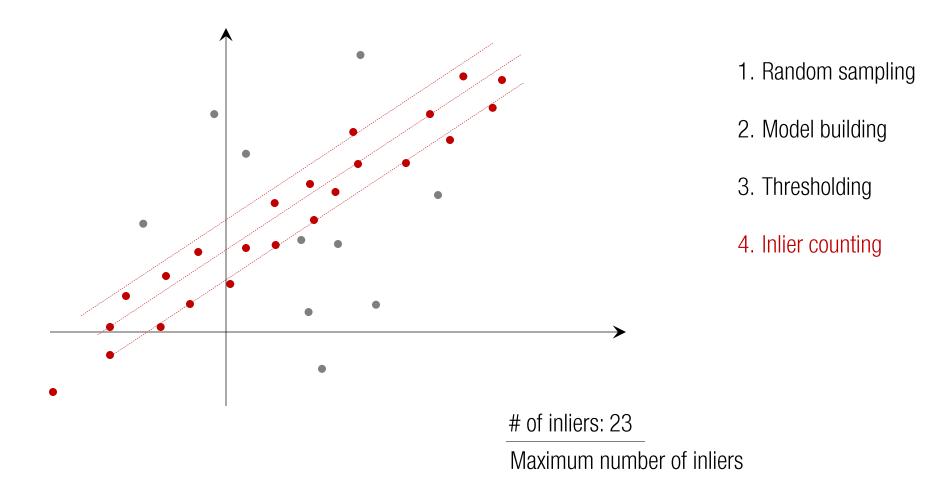
- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting



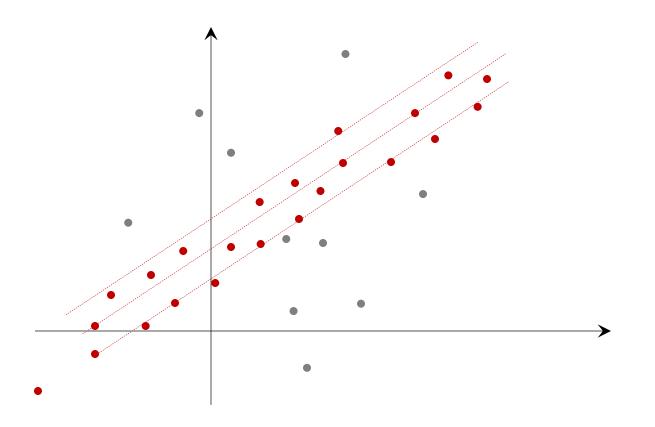
- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting

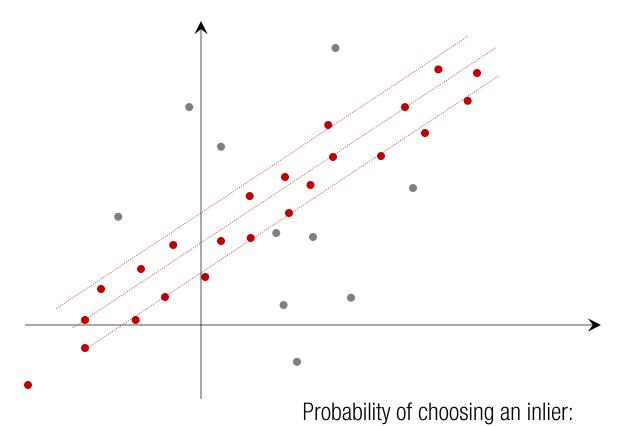


- 1. Random sampling
- 2. Model building
- 3. Thresholding
- 4. Inlier counting

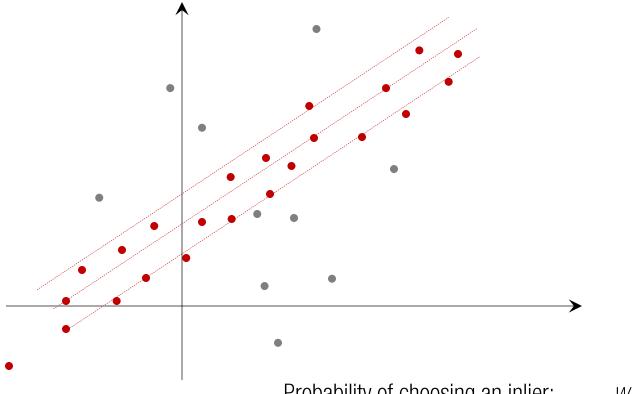


RANSAC: Random Sample Consensus





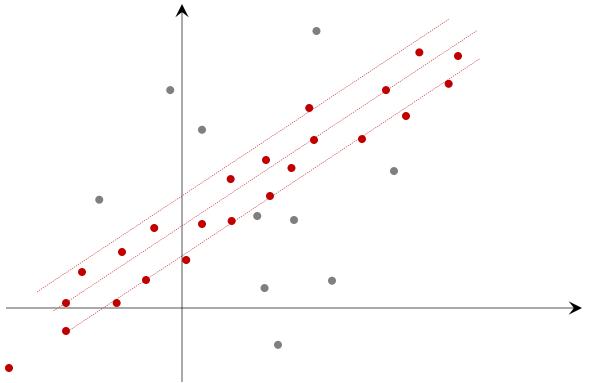
$$w = \frac{\text{\# of inliers}}{\text{\# of samples}}$$



Probability of choosing an inlier:

$$w = \frac{\text{# of inliers}}{\text{# of samples}}$$

Probability of building a correct model: W^n where n is the number of samples to build a model.

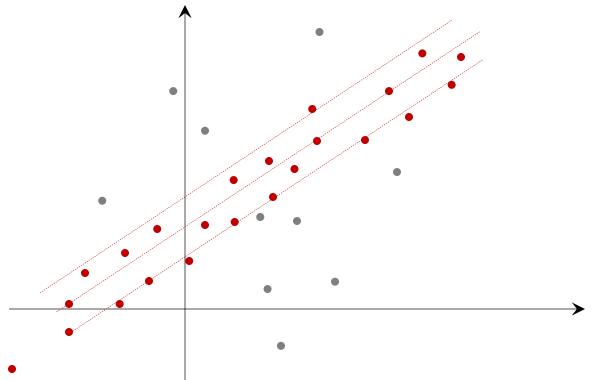


Probability of choosing an inlier:

$$w = \frac{\text{# of inliers}}{\text{# of samples}}$$

Probability of building a correct model: W^n where n is the number of samples to build a model.

Probability of not building a correct model during *k* iterations: $(1-w^n)^k$



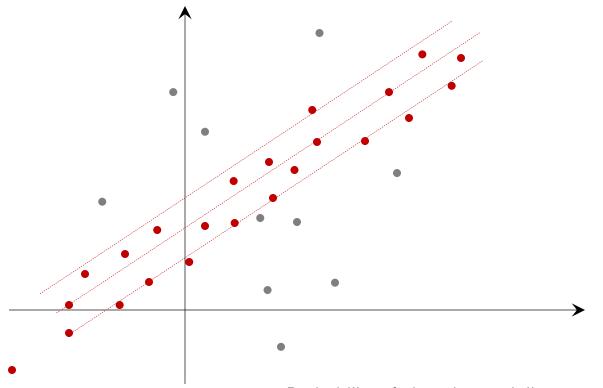
Probability of choosing an inlier:

$$w = \frac{\text{# of inliers}}{\text{# of samples}}$$

Probability of building a correct model: W^n where n is the number of samples to build a model.

Probability of not building a correct model during
$$k$$
 iterations: $(1-w^n)^k$

$$(1-w^n)^k = 1-p \quad \text{where } p \text{ is desired RANSAC success rate.} \qquad k = \frac{\log(1-p)}{\log(1-w^n)^k}$$



$$k = \frac{\log(1-p)}{\log(1-w^n)} \quad \text{where } w = \frac{\text{\# of inliers}}{\text{\# of samples}}$$

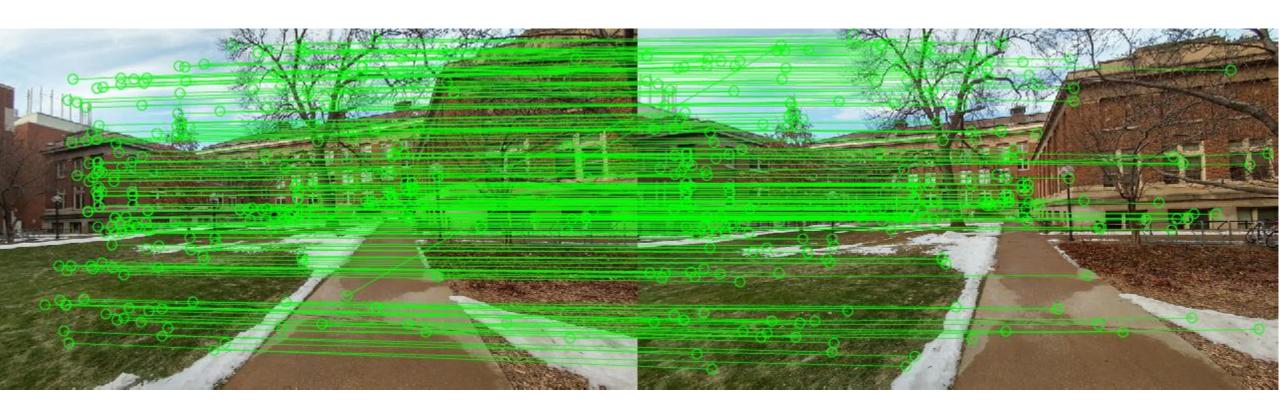
Probability of choosing an inlier:

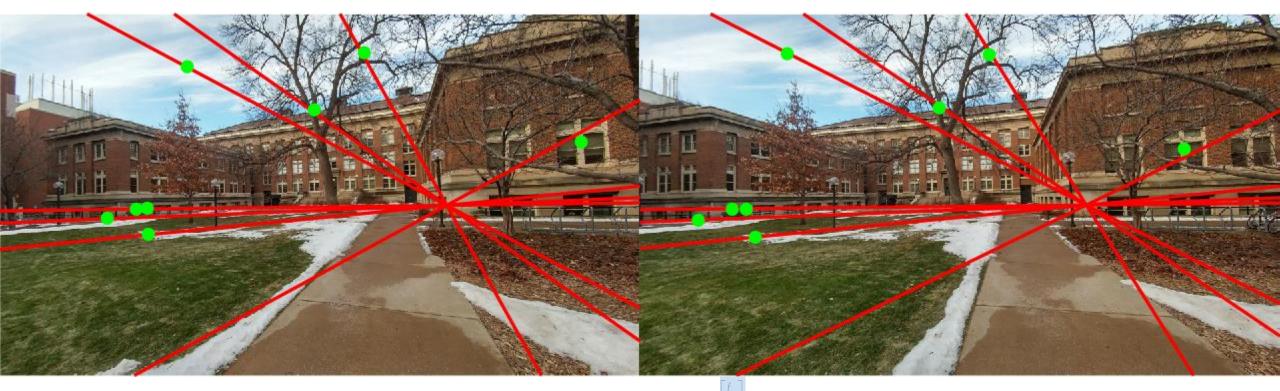
$$w = \frac{\text{# of inliers}}{\text{# of samples}}$$

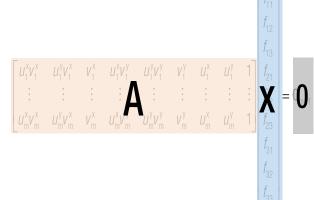
Probability of building a correct model: W^n where n is the number of samples to build a model.

Probability of not building a correct model during
$$k$$
 iterations: $(1-w^n)^k$

$$(1-w^n)^k = 1-p \quad \text{where } p \text{ is desired RANSAC success rate.} \qquad k = \frac{\log(1-p)}{\log(1-w^n)}$$









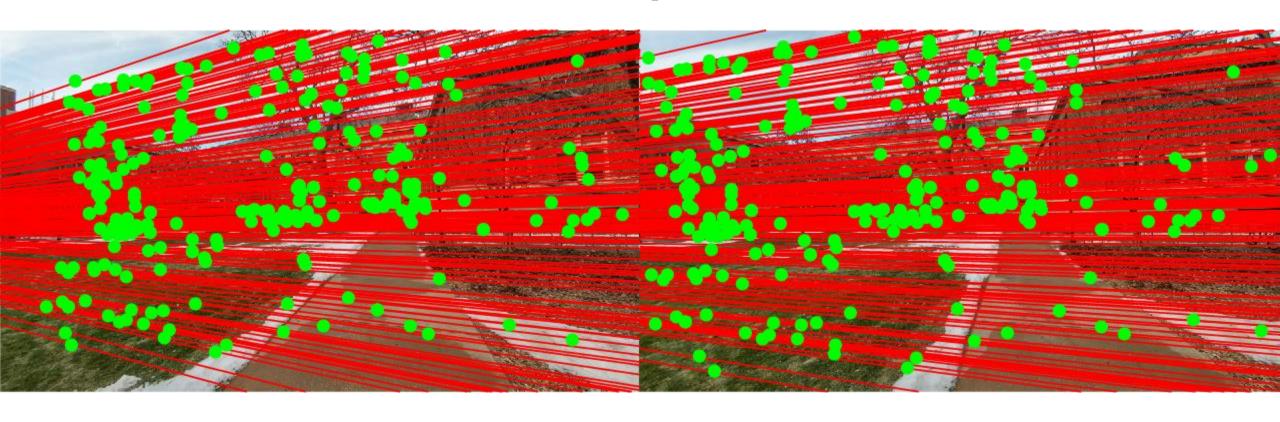
Epipolar line:
$$I_{u} = F\iota$$



of inliers: 65 out of 260



of inliers: 65 out of 260



of inliers: 186 out of 260

Four Camera Pose Config. From Essential Matrix

