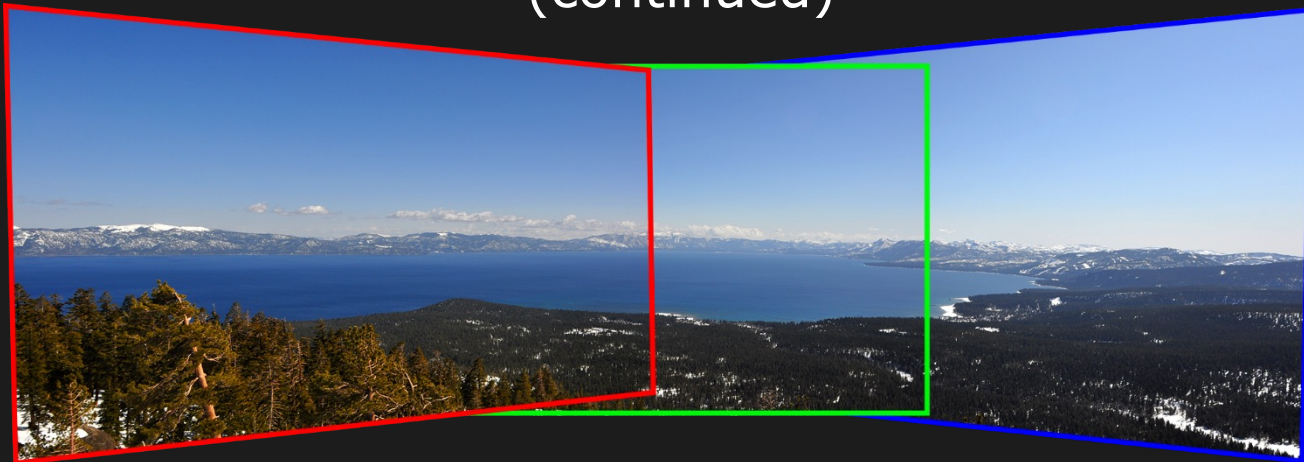


# CS/ECE 766 : Computer Vision

University of Wisconsin-Madison

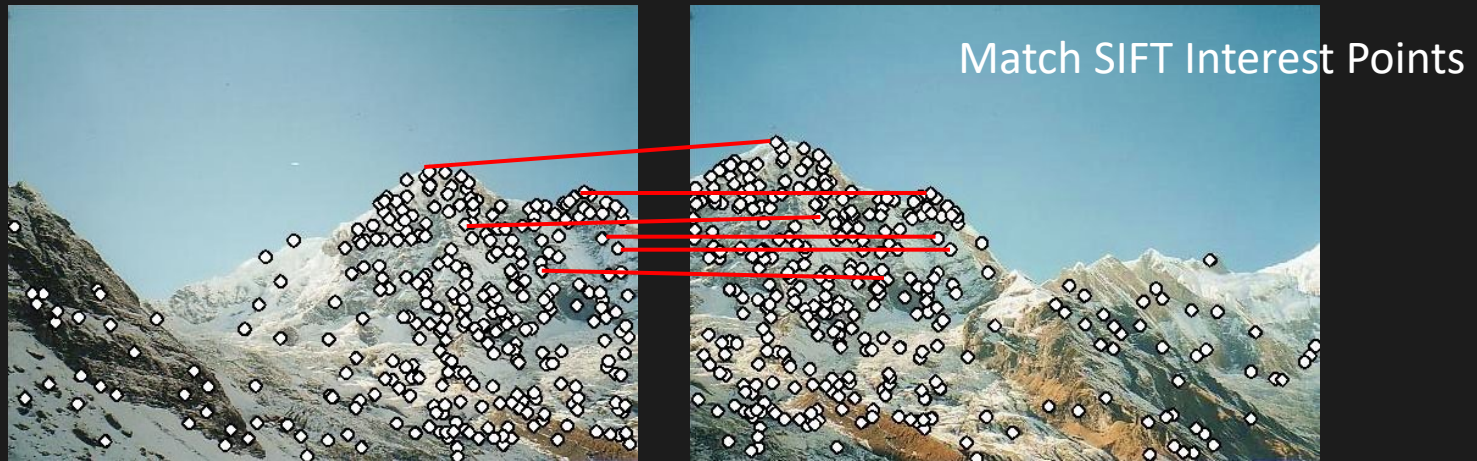
## Image Alignment and Stitching

(continued)



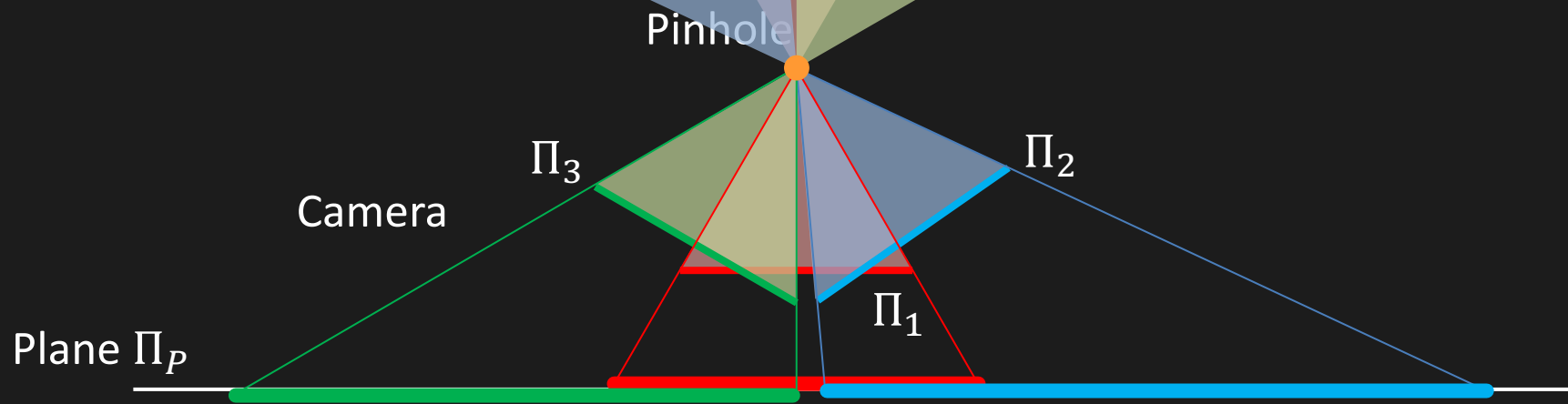
# (Review) Panorama Stitching

---



# (Review) Image Stitching Process

---



# (Review) Image Stitching Process

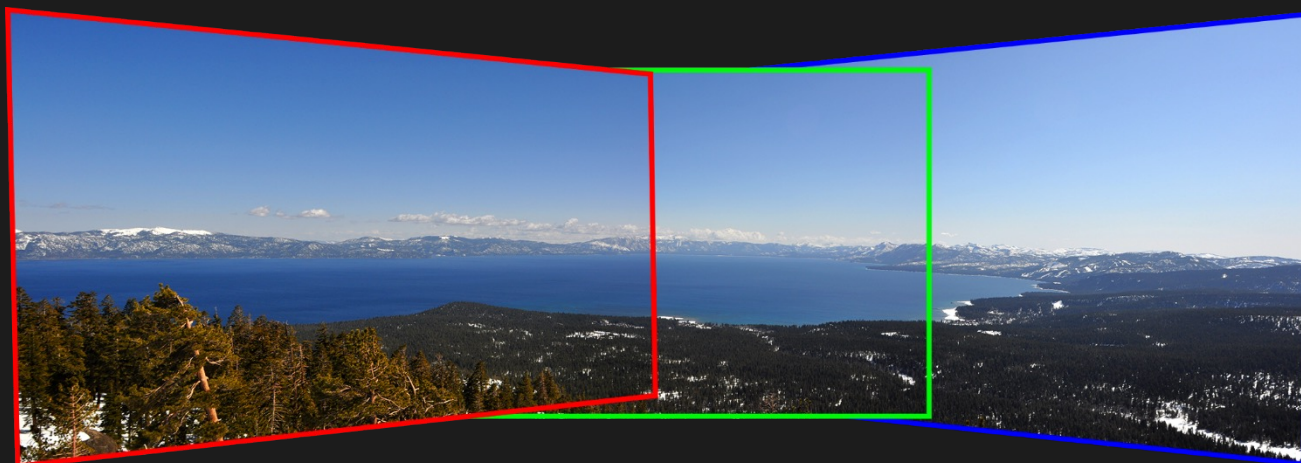
---



Source Image 1

Source Image 2

Source Image 3



Warp images so that corresponding points align.



# (Review) Global Warping/Transformation



Translation



Rotation



Scaling and Aspect

$$g(x, y) = f(T(x, y))$$



Affine



Perspective

Transformation  $T$  is the same over entire domain.  
Linear Transformation of Homogeneous Coordinates

# (Review) Scaling, Rotation, Skew, Translation

---

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

Scaling

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & m_x \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

Horizontal Skew

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

Rotation

Translations cannot be represented!

# (Review) 2x2 Matrix Transformations

---

Any transformation of the form:

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

- Origin maps to the origin
- Lines map to lines
- Parallel lines remain parallel
- Closed under composition

$$\left. \begin{array}{l} \mathbf{p}_2 = T_{21}\mathbf{p}_1 \\ \mathbf{p}_3 = T_{32}\mathbf{p}_2 \\ \mathbf{p}_3 = T_{31}\mathbf{p}_1 \end{array} \right\} \mathbf{p}_3 = T_{32}\mathbf{p}_2 = T_{32}T_{21}\mathbf{p}_1 \Rightarrow T_{31} = T_{32}T_{21}$$

# (Review) Homogenous Coordinates

---

The **homogenous** representation of a 2D point  $\mathbf{p} = (x, y)$  is a 3D point  $\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y}, \tilde{z})$ . The third coordinate  $\tilde{z} \neq 0$  is fictitious such that:

$$x = \frac{\tilde{x}}{\tilde{z}} \quad y = \frac{\tilde{y}}{\tilde{z}}$$

$$\mathbf{p} \equiv \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \equiv \begin{bmatrix} \tilde{z}x \\ \tilde{z}y \\ \tilde{z} \end{bmatrix} \equiv \begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{bmatrix} = \tilde{\mathbf{p}}$$

Converting **to** homogeneous:

$$(x, y) = \left( \frac{\tilde{x}}{\tilde{z}}, \frac{\tilde{y}}{\tilde{z}} \right)$$

Converting **from** homogeneous:

$$(\tilde{x}, \tilde{y}, \tilde{z}) = (x, y, 1)$$



# (Review) Scaling, Rotation, Skew, Translation

---

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

Scaling

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} 1 & m_x & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

Horizontal Skew

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

Translation

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

Rotation

# (Review) Projective Transformation

---

Any transformation of the form:

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{bmatrix} \quad \tilde{\mathbf{p}}_2 = H\tilde{\mathbf{p}}_1$$

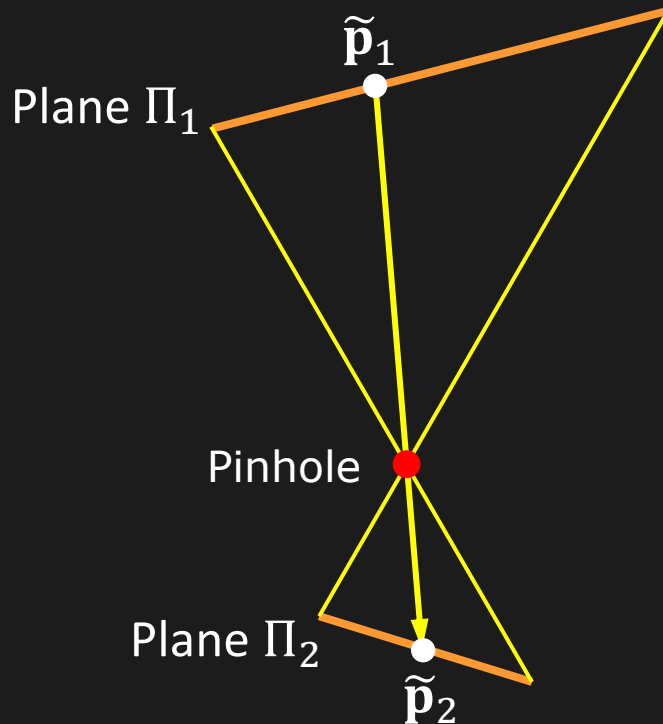


Also called **Homography**.

# (Review) Projective Transformation

---

Mapping of one plane to another through a pinhole



$$\tilde{\mathbf{p}}_2 = H\tilde{\mathbf{p}}_1$$

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{bmatrix}$$

Same as imaging a plane through a pinhole.

# (Review) Projective Transformation

---

Homography can only be defined up to a scale.

$$\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{bmatrix} \equiv \begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix}$$

Because homogeneous coordinates  
are only defined up to a scale.

If we fix scale such that  $\sqrt{\sum (h_{ij})^2} = 1$  then 8 free parameters

# (Review) Projective Transformation

---

Transformation that represents mapping a plane into another through a pinhole.

- Origin does not necessarily map to the origin
- Lines map to lines
- Parallel lines do not necessarily remain parallel
- Closed under composition

Plane  $\Pi_W$ 

World

# Pinhole

$$\Pi_3$$

# Camera

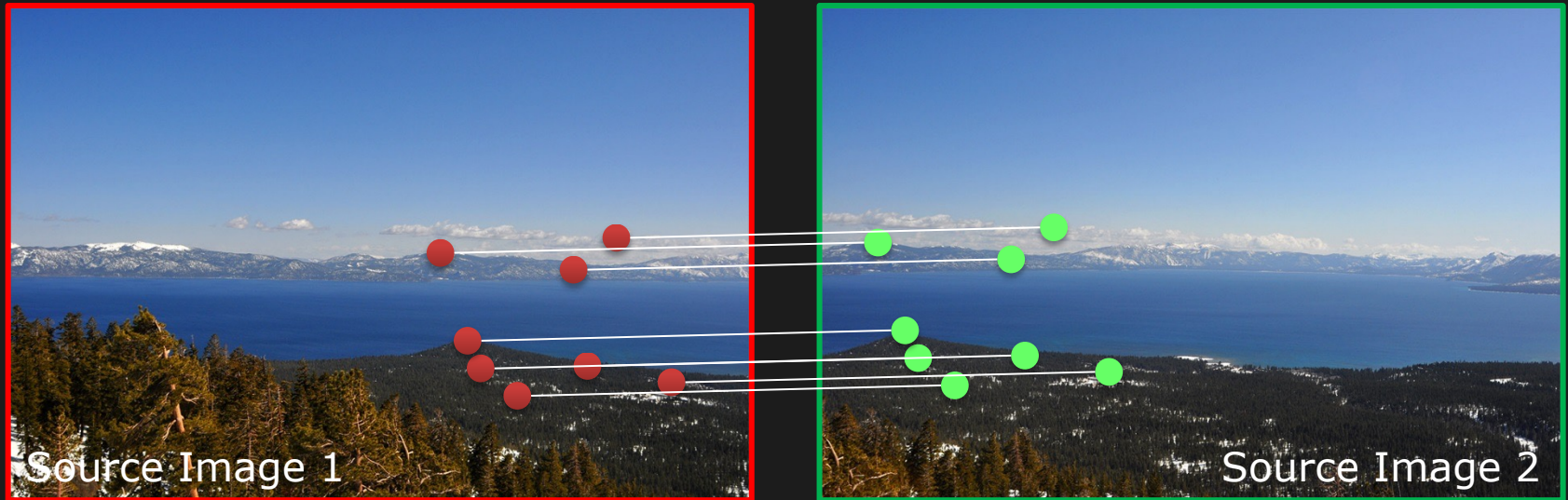
 $\Pi_2$  $\Pi_1$ Plane  $\Pi_p$ 
$$H_{P1}H_{13}$$
$$H_{P1}H_{12}$$

Useful in stitching planar panoramas.



# (Review) Computing Homography

---



Given a set of matching points between images 1 and 2, find the homography  $H$  that best “agrees” with the matches.

The scene points should lie on a plane, or be distant (plane at infinity), or imaged from the same point.

# (Review) Computing Homography



Source Image



Destination Image

$$\begin{bmatrix} x_d \\ y_d \\ 1 \end{bmatrix} \equiv \begin{bmatrix} \tilde{x}_d \\ \tilde{y}_d \\ \tilde{z}_d \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x_s \\ y_s \\ 1 \end{bmatrix}$$

How many pairs of points are needed to define the homography?

There are 9 unknowns, but only 8 degrees of freedom.

Each pair provides 2 constraints. So, 4 pairs are needed.

# (Review) Computing Homography

For a given pair  $i$  of corresponding points (2 constraints):

$$x_d^{(i)} = \frac{\tilde{x}_d^{(i)}}{\tilde{z}_d^{(i)}} = \frac{h_{11}x_s^{(i)} + h_{12}y_s^{(i)} + h_{13}}{h_{31}x_s^{(i)} + h_{32}y_s^{(i)} + h_{33}} \quad y_d^{(i)} = \frac{\tilde{y}_d^{(i)}}{\tilde{z}_d^{(i)}} = \frac{h_{21}x_s^{(i)} + h_{22}y_s^{(i)} + h_{23}}{h_{31}x_s^{(i)} + h_{32}y_s^{(i)} + h_{33}}$$

Rearranging the terms and writing as linear equation:

$$\begin{bmatrix} x_s^{(1)} & y_s^{(1)} & 1 & 0 & 0 & 0 & -x_d^{(1)}x_s^{(1)} & -x_d^{(1)}y_s^{(1)} & -x_d^{(1)} \\ 0 & 0 & 0 & x_s^{(1)} & y_s^{(1)} & 1 & -y_d^{(1)}x_s^{(1)} & -y_d^{(1)}y_s^{(1)} & -y_d^{(1)} \\ & & & & & \vdots & & & \\ x_s^{(i)} & y_s^{(i)} & 1 & 0 & 0 & 0 & -x_d^{(i)}x_s^{(i)} & -x_d^{(i)}y_s^{(i)} & -x_d^{(i)} \\ 0 & 0 & 0 & x_s^{(i)} & y_s^{(i)} & 1 & -y_d^{(i)}x_s^{(i)} & -y_d^{(i)}y_s^{(i)} & -y_d^{(i)} \\ & & & & & \vdots & & & \\ x_s^{(n)} & y_s^{(n)} & 1 & 0 & 0 & 0 & -x_d^{(n)}x_s^{(n)} & -x_d^{(n)}y_s^{(n)} & -x_d^{(n)} \\ 0 & 0 & 0 & x_s^{(n)} & y_s^{(n)} & 1 & -y_d^{(n)}x_s^{(n)} & -y_d^{(n)}y_s^{(n)} & -y_d^{(n)} \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

$A$  (Known)

$\mathbf{h}$  (Unknown)

# (Review) Constrained Least Squares

---

Solve for  $\mathbf{h}$ :  $A \mathbf{h} = \mathbf{0}$  such that  $\|\mathbf{h}\|^2 = 1$

Define least squares problem:

$$\min_{\mathbf{h}} (\mathbf{h}^T A^T A \mathbf{h}) \text{ such that } \mathbf{h}^T \mathbf{h} = 1$$

Solve (unconstrained) Lagrangian function  $L(\mathbf{h}, \lambda)$ :

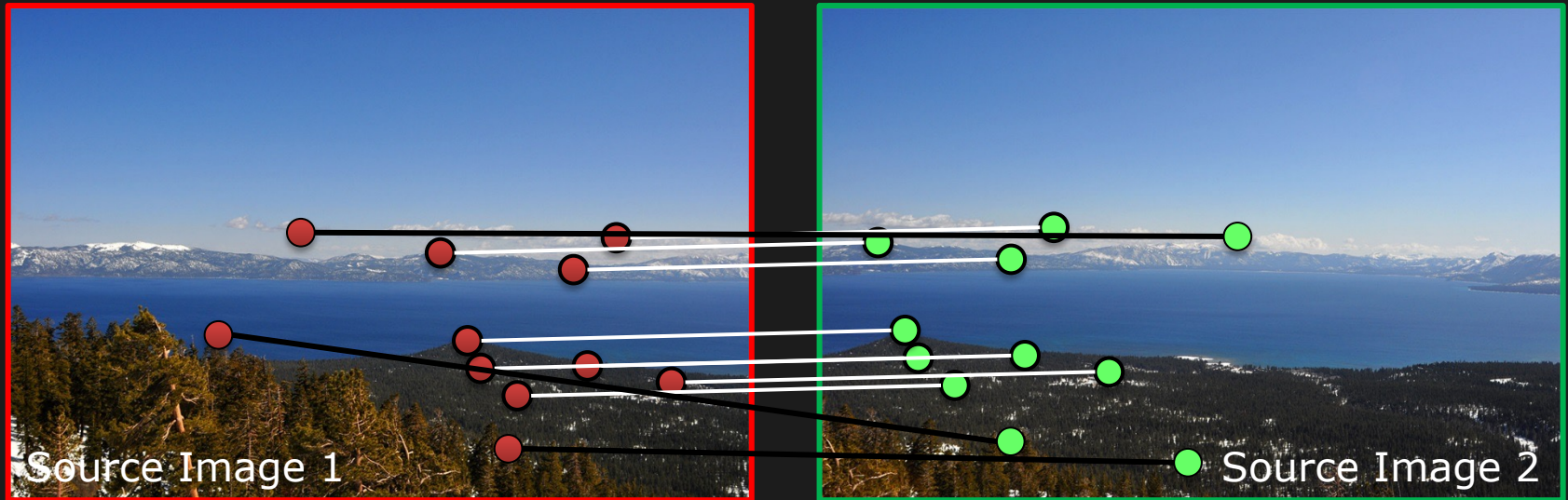
$$L(\mathbf{h}, \lambda) = \mathbf{h}^T A^T A \mathbf{h} - \lambda(\mathbf{h}^T \mathbf{h} - 1)$$

Taking derivatives of  $L(\mathbf{h}, \lambda)$  w.r.t  $\mathbf{h}$ :  $2A^T A \mathbf{h} - 2\lambda \mathbf{h} = \mathbf{0}$

$$A^T A \mathbf{h} = \lambda \mathbf{h} \quad \text{Eigenvalue Problem}$$

Eigenvector  $\mathbf{h}$  with smallest eigenvalue  $\lambda$  of matrix  $A^T A$  minimizes the loss function  $L(\mathbf{h})$ .

# What Could Go Wrong?



## Outliers!

We need to robustly compute transformation in the presence of wrong matches.

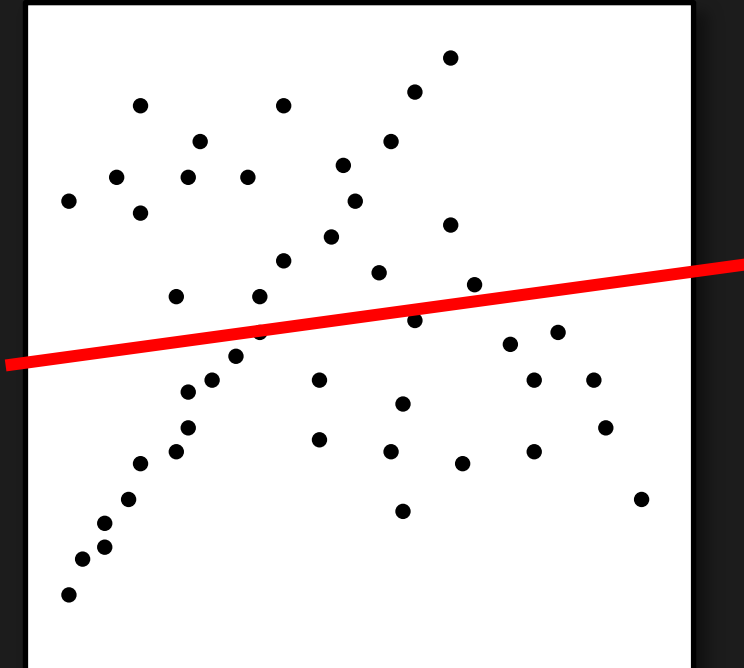
How?

If **number of outliers** < 50%, then **RANSAC** to the rescue!

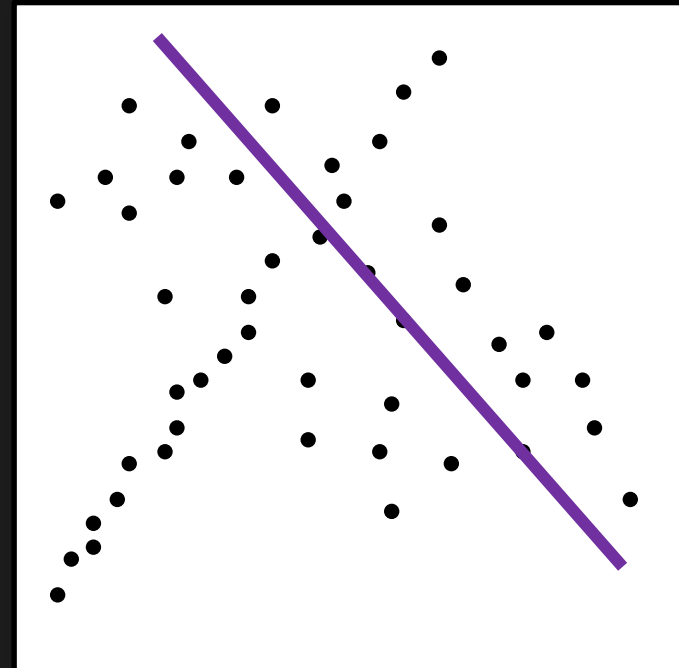
# RANSAC Example: Line Fitting

---

Robust line fitting:



Least Squares Fitting  
Inliers: 2



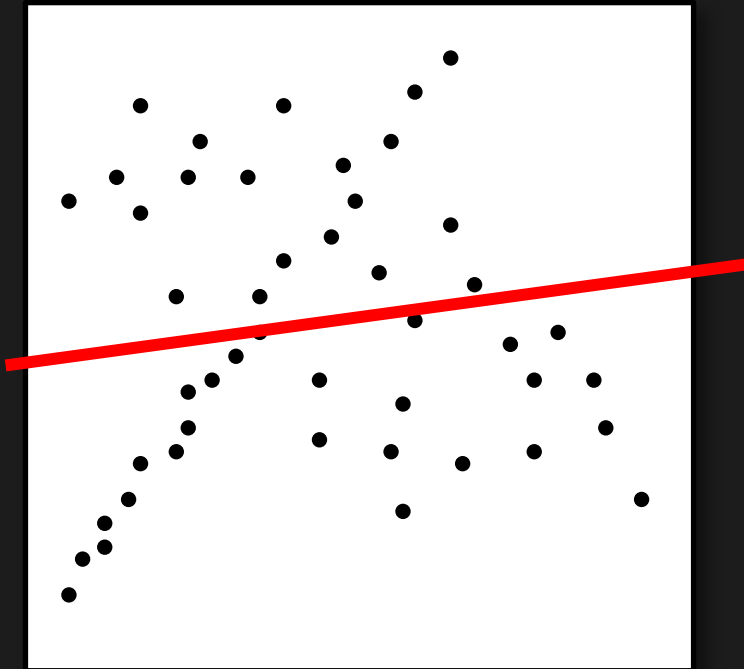
RANSAC Iteration 1  
Inliers: 4



# RANSAC Example: Line Fitting

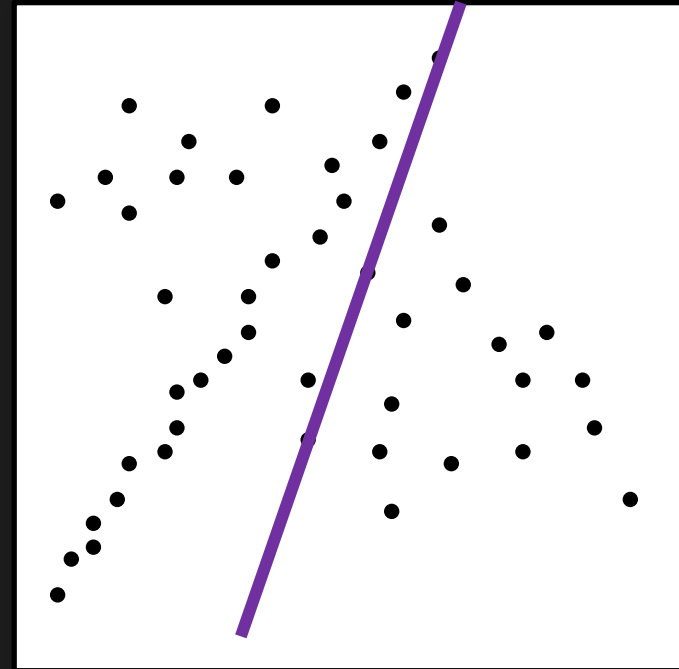
---

Robust line fitting:



Least Squares Fitting

Inliers: 2



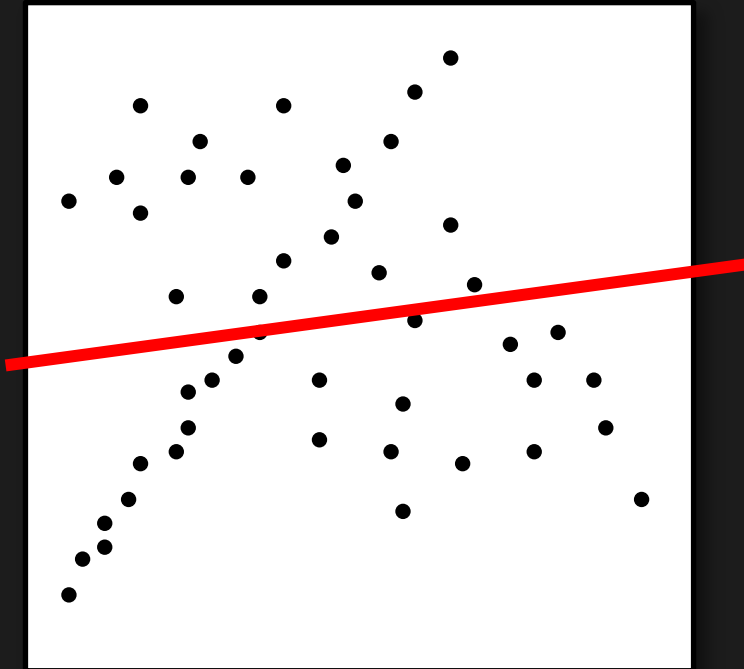
RANSAC Iteration 2

Inliers: 3

# RANSAC Example: Line Fitting

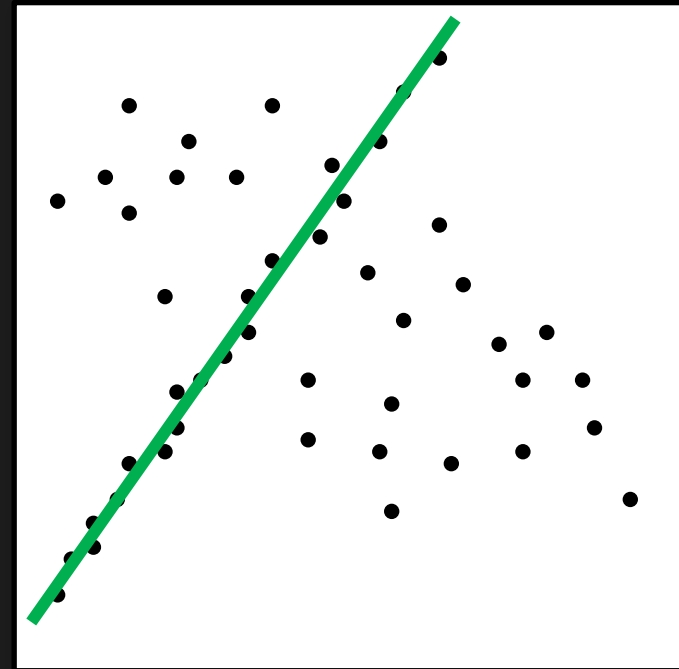
---

Robust line fitting:



Least Squares Fitting

Inliers: 2



RANSAC Iteration i

Inliers: 20

# RANdom SAmple Consensus

---

General RANSAC Algorithm:

1. Randomly choose  $s$  samples. Typically  $s$  is the minimum samples to fit a model.
2. Fit the model to the randomly chosen samples.
3. Count the number  $M$  of data points (inliers) that fit the model within a measure of error  $\epsilon$ .
4. Repeat Steps 1-3  $N$  times
5. Choose the model that has the largest number  $M$  of inliers.

For homography:

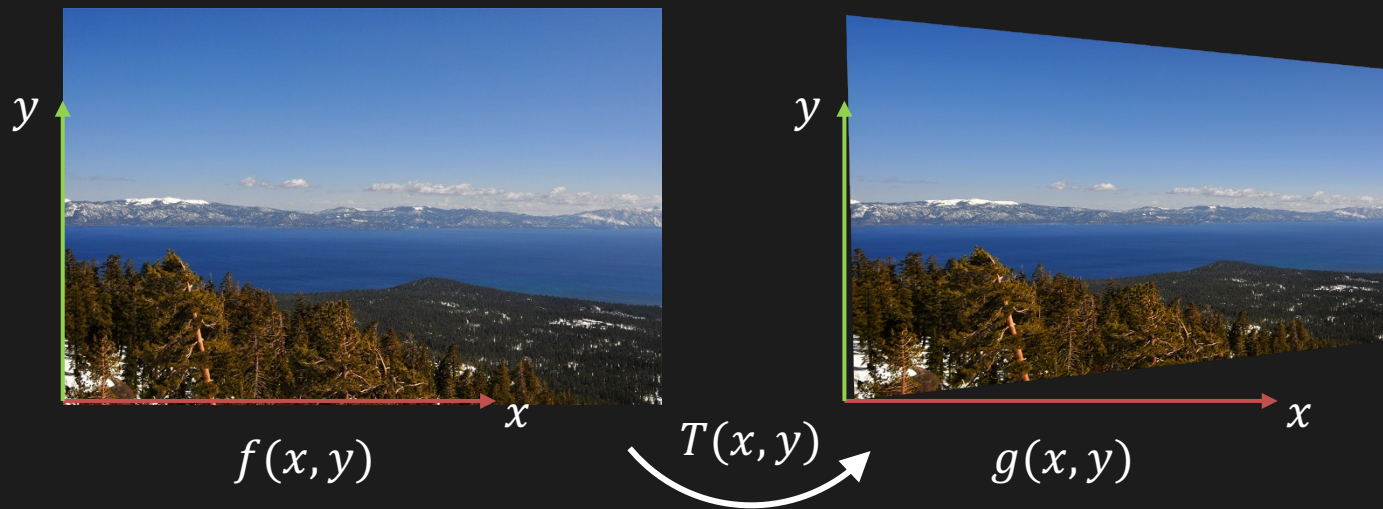
$s = 4$  points.  $\epsilon$  is acceptable alignment error in pixels.

# Back to Warping Images

---

Given a transformation  $T$  and a source image  $f(x, y)$ , compute the transformed image  $g(x, y)$

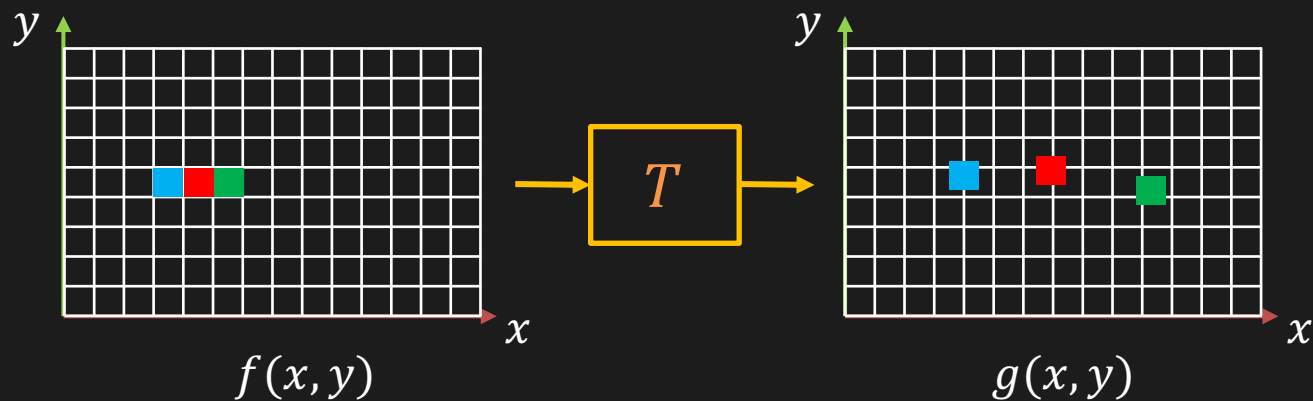
$$g(x, y) = f(T(x, y))$$



# Forward Warping

Send each pixel  $(x, y)$  in  $f(x, y)$  to its corresponding location  $T(x, y)$  in  $g(x, y)$

$$g(x, y) = f(T(x, y))$$



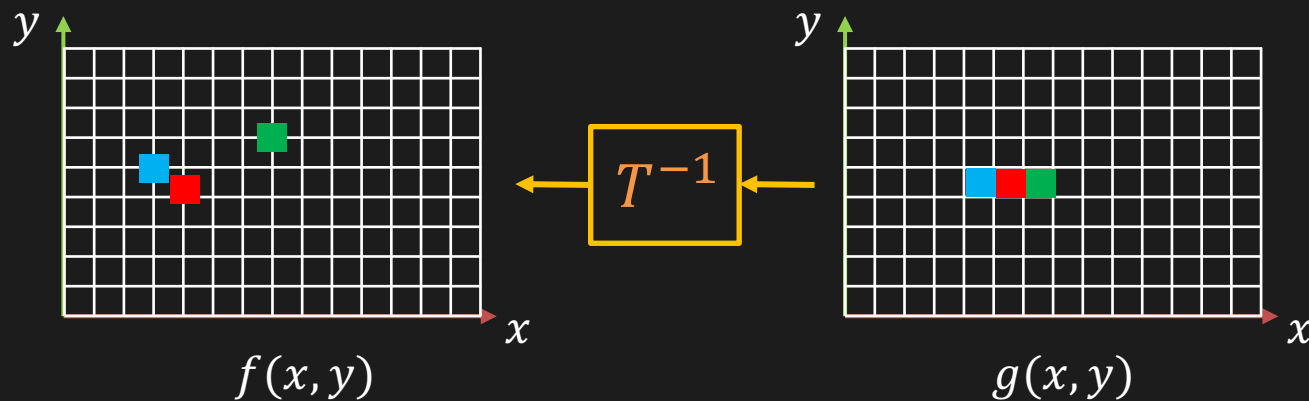
What if pixel lands in between pixels?  
What if not all pixels in  $g(x, y)$  are filled?

Can result in holes!

# Backward Warping

Get each pixel  $(x, y)$  in  $g(x, y)$  from its corresponding location  $T^{-1}(x, y)$  in  $f(x, y)$

$$g(x, y) = f(T(x, y))$$



What if pixel lands between pixels?

No problem. Use **Nearest Neighbor** or **Interpolate** (Weighted Average of Neighbors)!



# Image Alignment Process

---



Source Image 1



Source Image 2

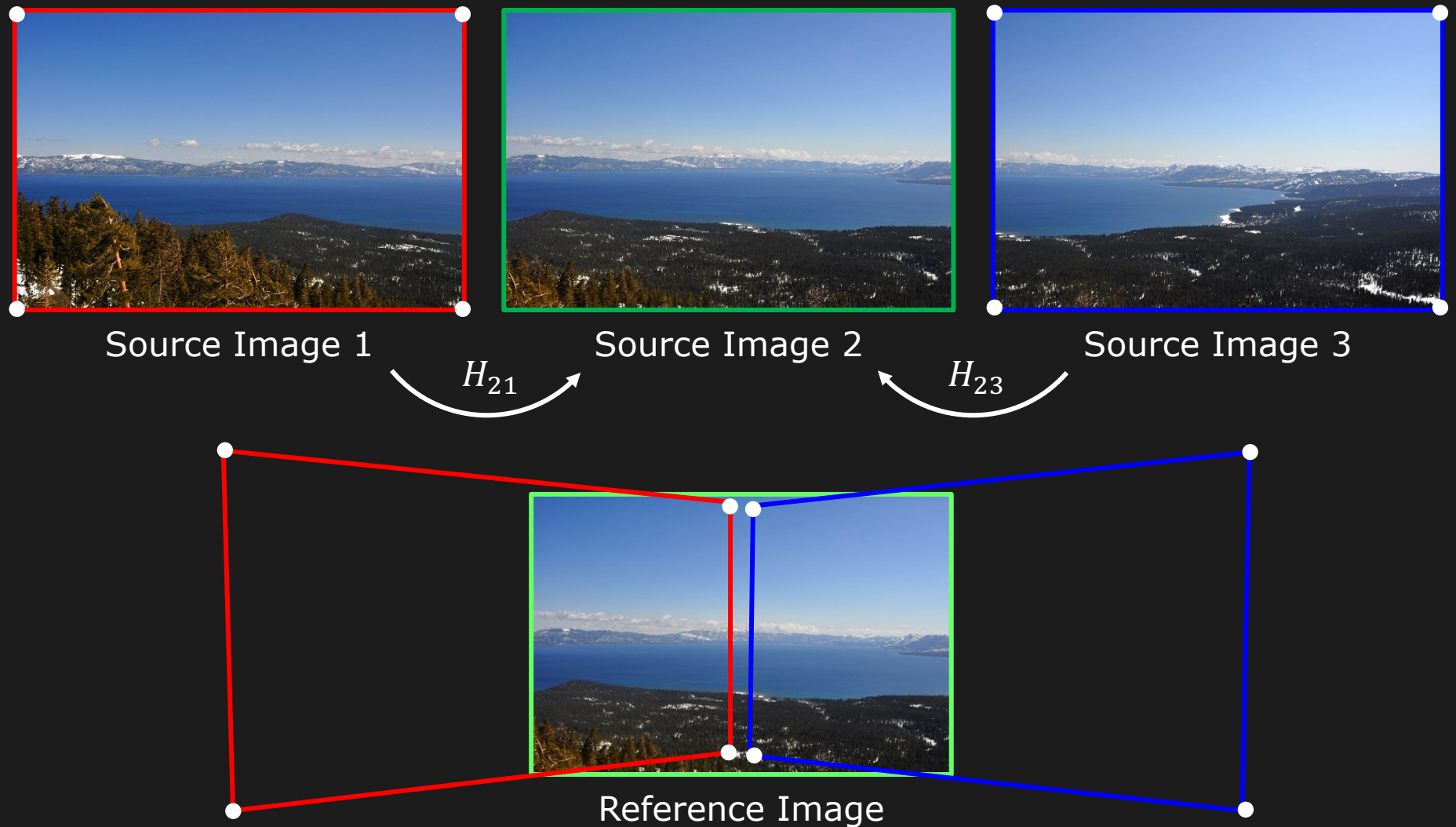


Source Image 3



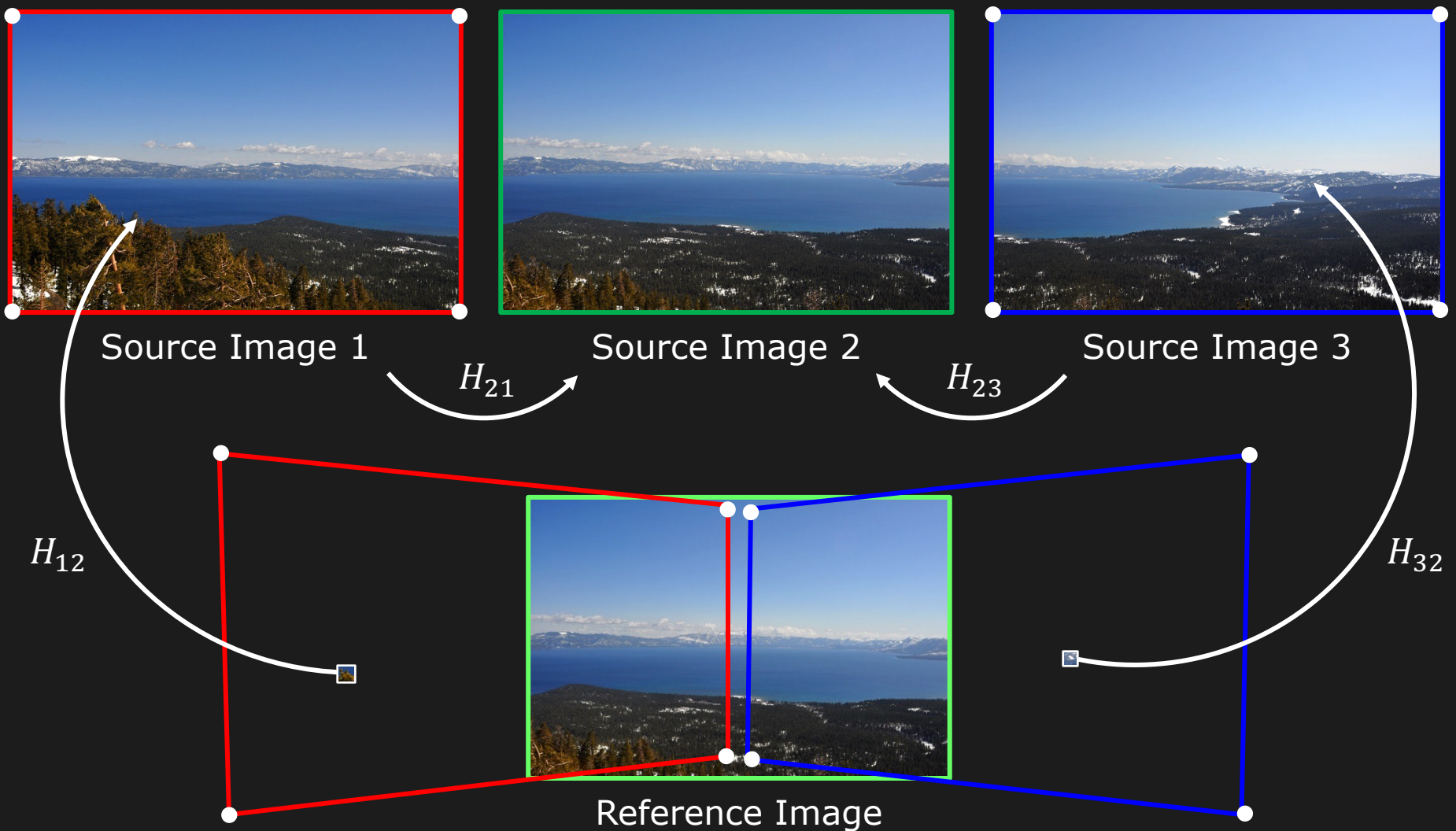
Reference Image  
(Source Image 2)

# Image Alignment Process



Compute the bounds of Image 1 and Image 3 in reference image space

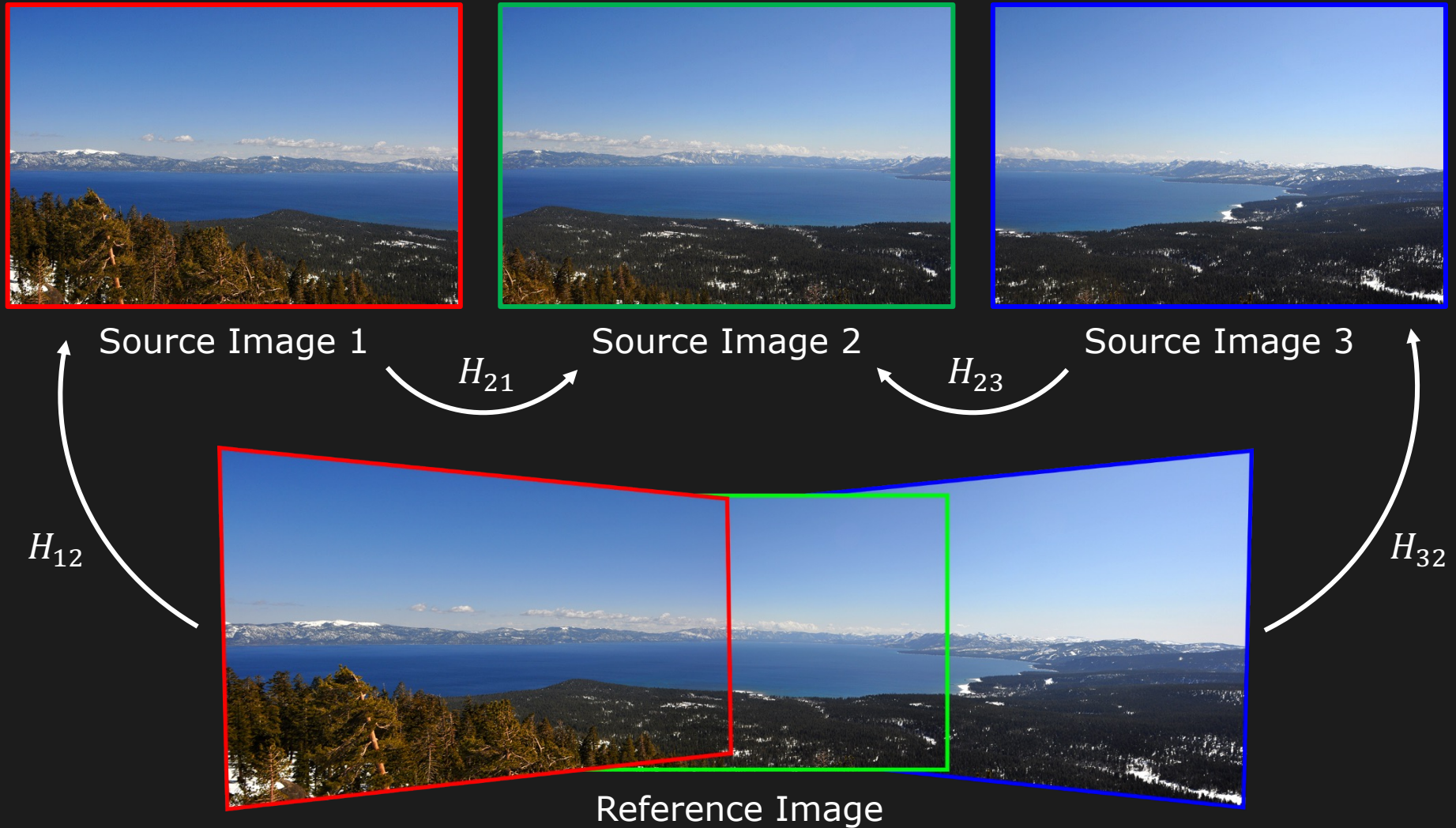
# Image Alignment Process



For each pixel within bounds, compute its location in source image



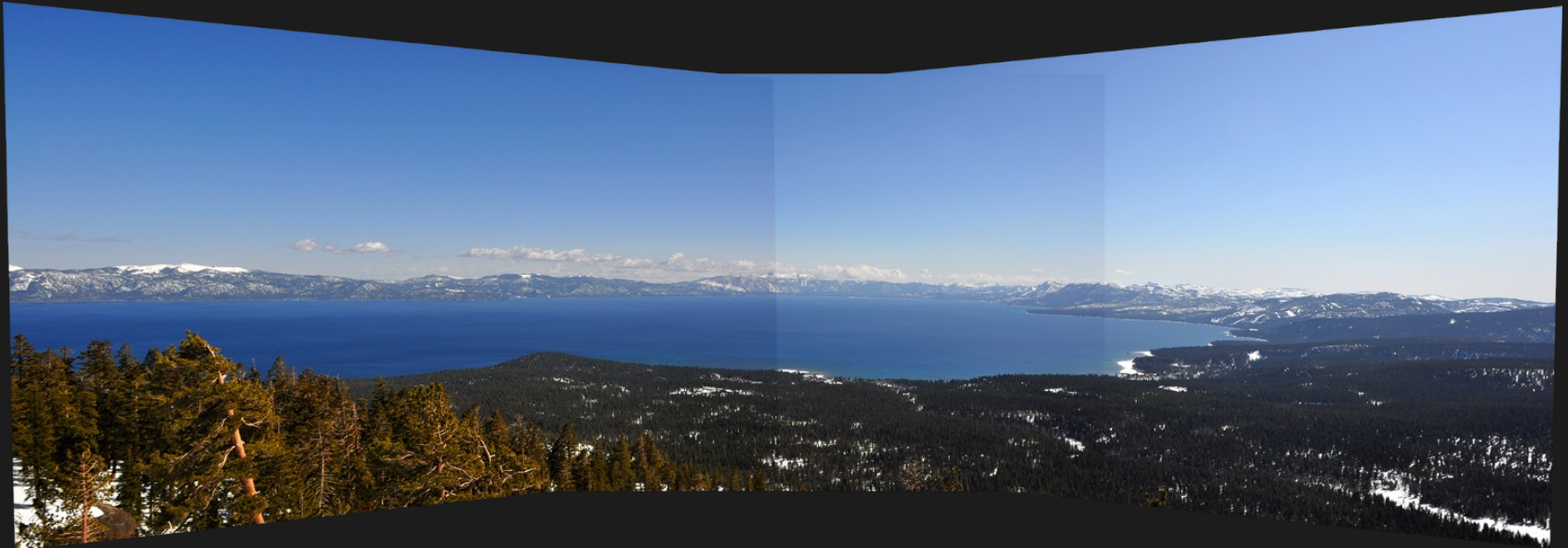
# Image Alignment Process



For each pixel within bounds, compute its location in source image

# Blending Images

---

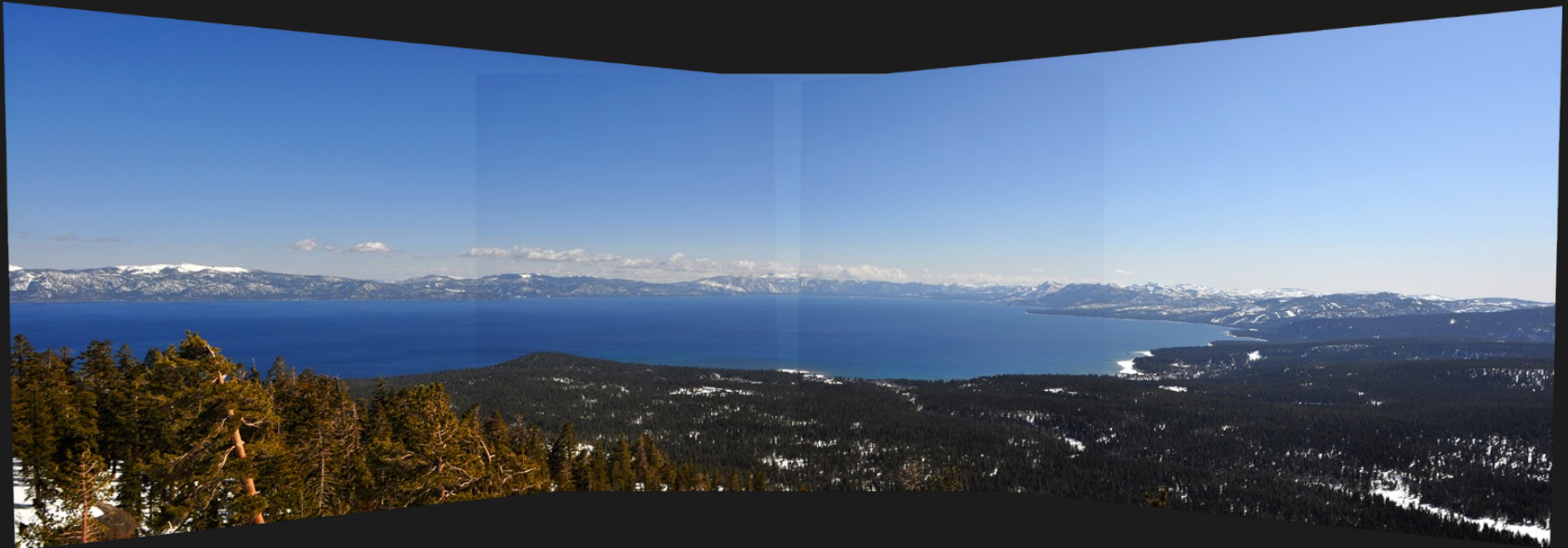


Overlaid Aligned Images

Hard seams due to vignetting, exposure differences, etc.

# Blending Images: Averaging

---



Averaged Images

Seams still visible.



# Blending Images



Image  $I_1$

+

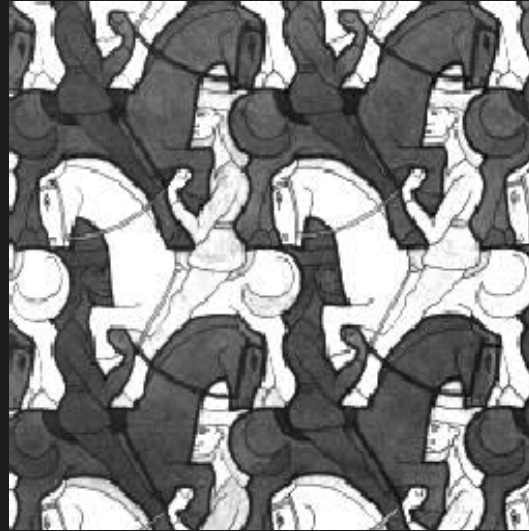
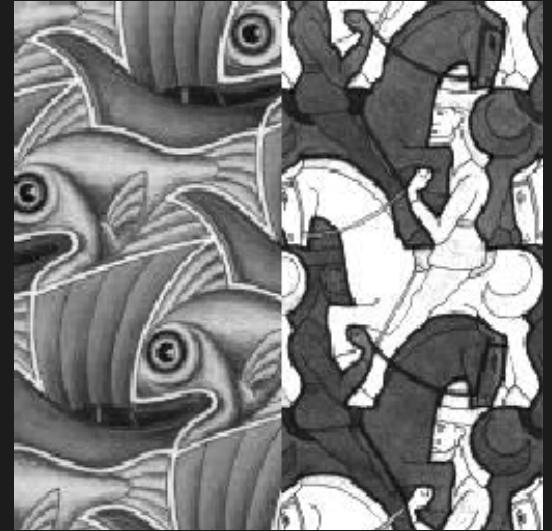


Image  $I_2$

=



Hard overlay



Say we want to blend images  $I_1$  and  $I_2$  at the center.

# Weighted Blending



Image  $I_1$

+

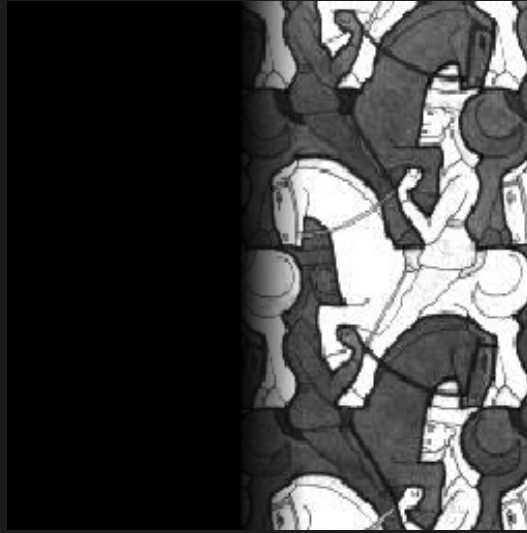


Image  $I_2$

=



Blended Image

$I_{blend}$



$$I_{blend} = \frac{w_1 I_1 + w_2 I_2}{w_1 + w_2}$$

# Weighted Blending

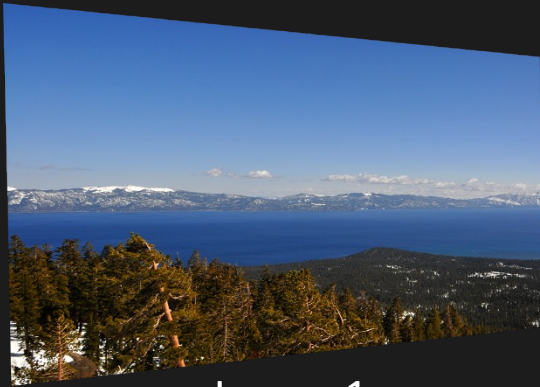


Image 1



Image 2

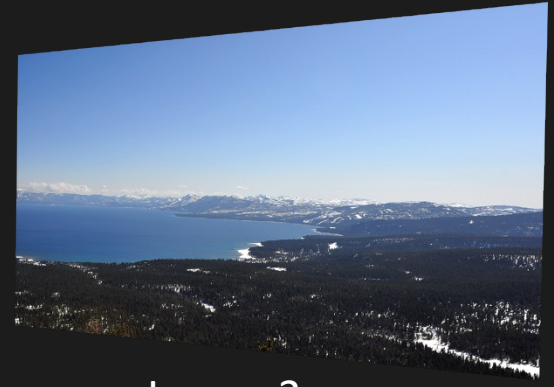
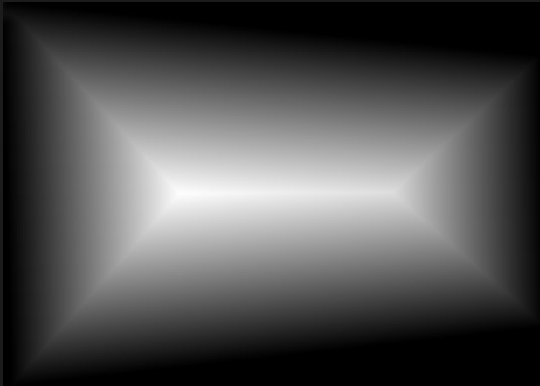


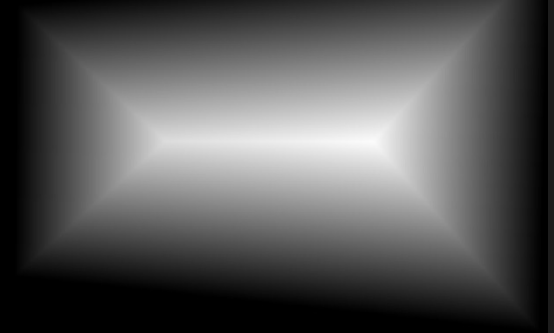
Image 3



Weight  $w_1$



Weight  $w_2$



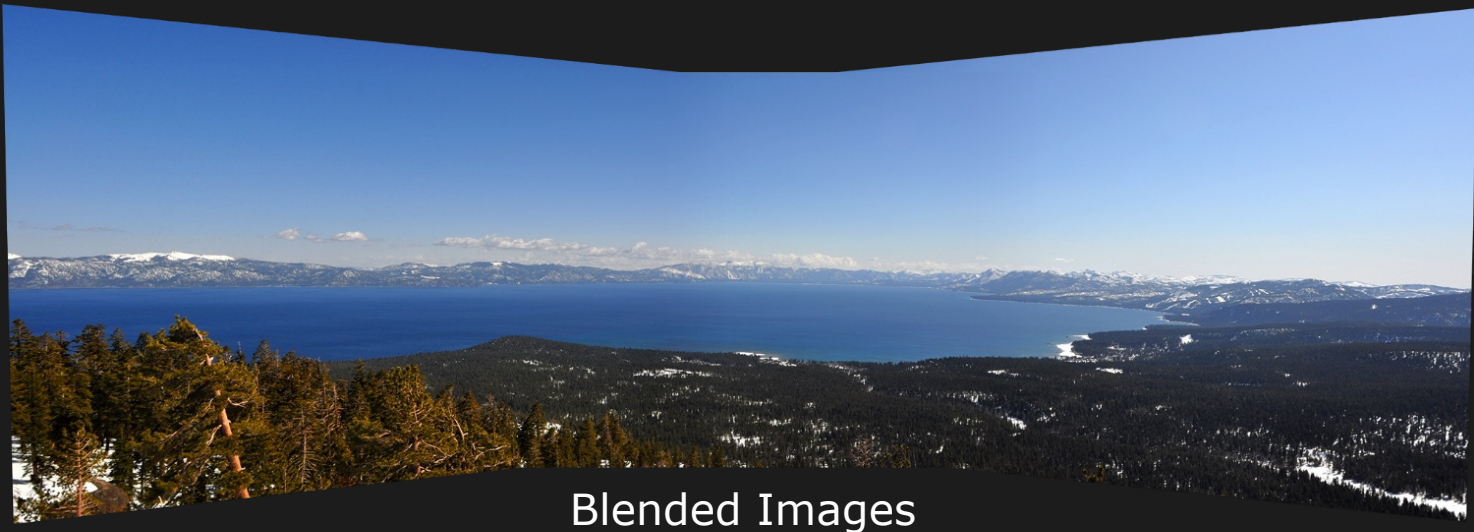
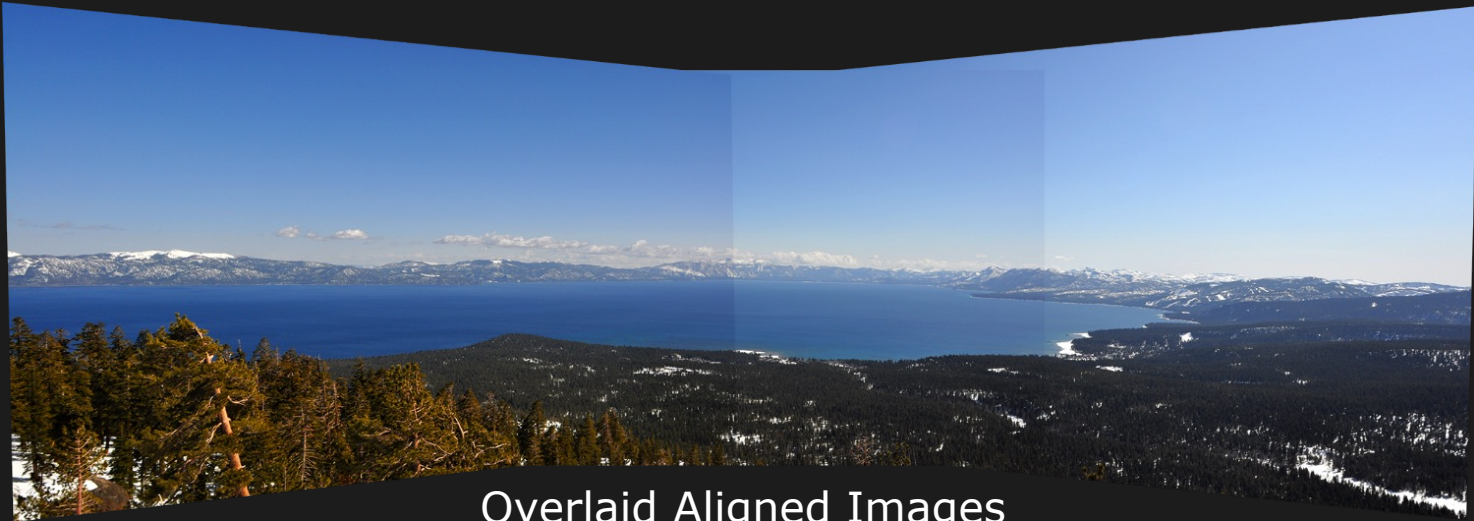
Weight  $w_3$

Pixels closer to the edge get a lower weight.

Python: `scipy.ndimage.distance_transform_edt`

# Weighted Blending

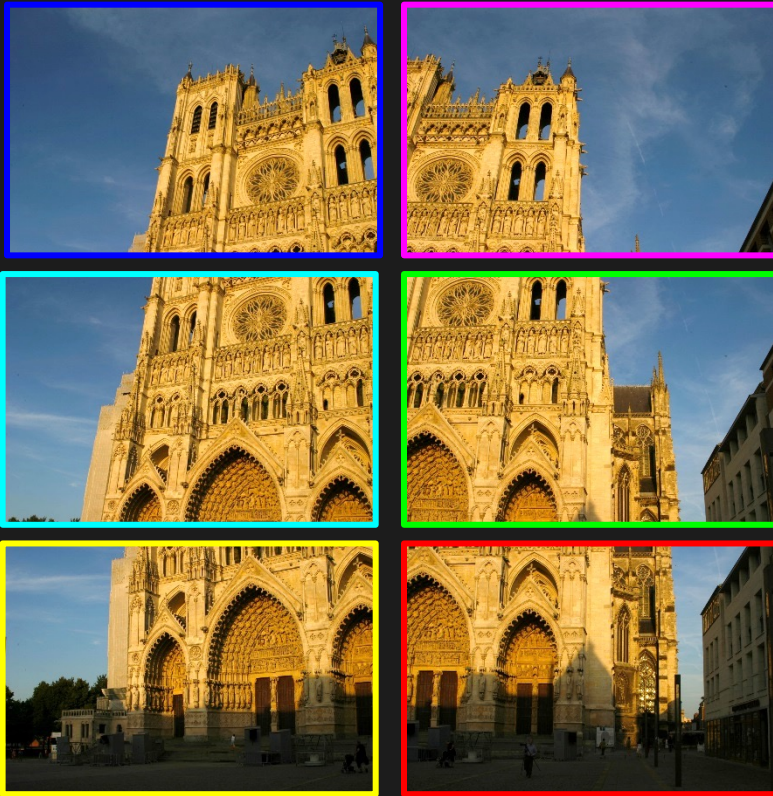
---



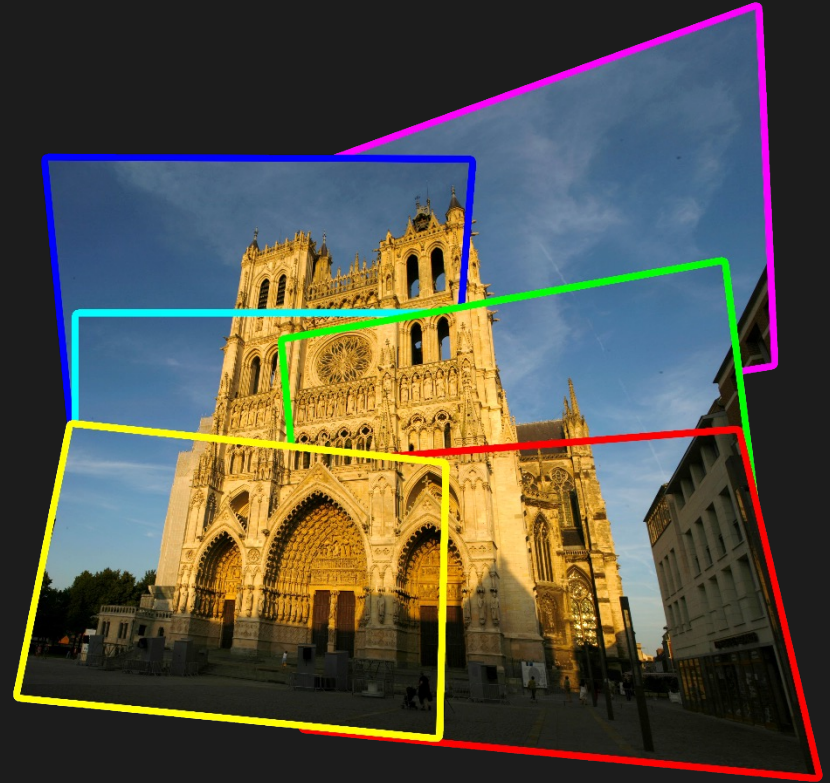


# Image Stitching Example

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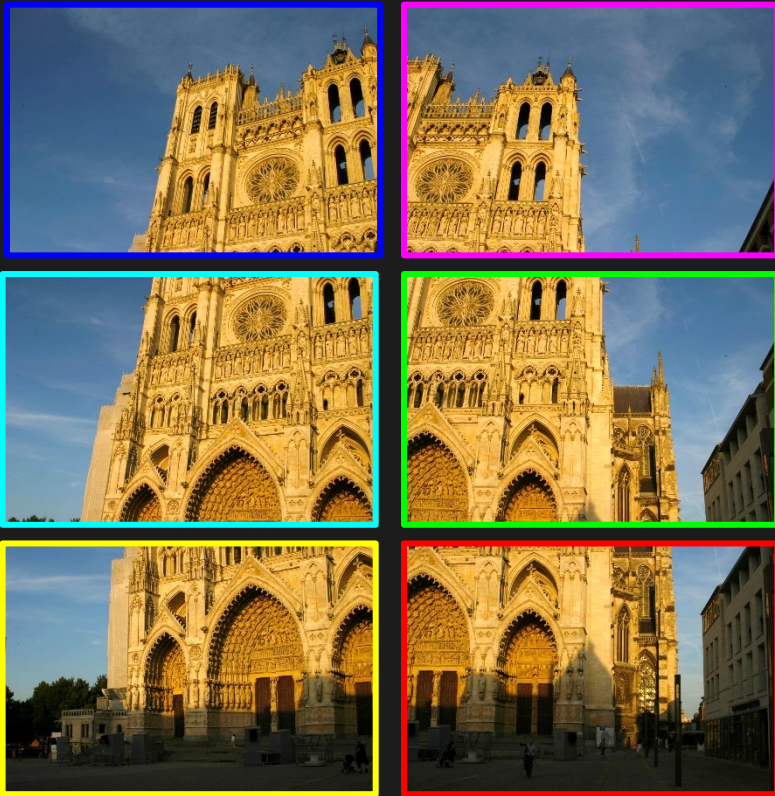
Source Images



Aligned Images

# Image Stitching Example

---



Source Images



Blended Images

# References: Textbooks

---

Computer Vision: Algorithms and Applications (Chapter 2, 9)

Szeliski, R., Springer

# References: Papers

---

[Fischler 1981] Fischler M. A. and Bolles R. C. "Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography", 1981.

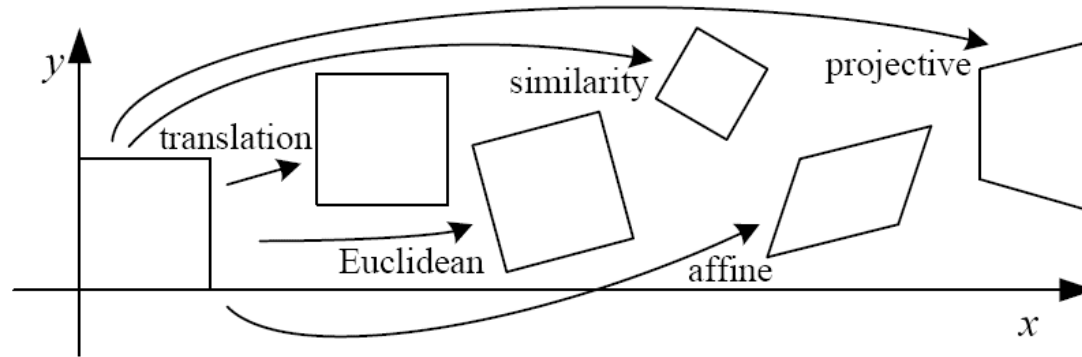







# Image Credits

---

- I.1 <http://www.flickr.com/photos/byspice/4577634277>
- I.2 <http://www.ptgui.com/examples/quicktour5/>
- I.3 Figure 2.4, Table 2.1, Computer Vision: Algorithms and Applications, Szeliski, R., Springer

# Appendix A: Linear Transformations



Name	Matrix	# D.O.F.	Preserves:	Icon
translation	$\begin{bmatrix} \mathbf{I} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	2	orientation + ...	
rigid (Euclidean)	$\begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	3	lengths + ...	
similarity	$\begin{bmatrix} s\mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	4	angles + ...	
affine	$\begin{bmatrix} \mathbf{A} \end{bmatrix}_{2 \times 3}$	6	parallelism + ...	
projective	$\begin{bmatrix} \tilde{\mathbf{H}} \end{bmatrix}_{3 \times 3}$	8	straight lines	

# Appendix B: RANSAC

---

How many iterations?

Suppose,

- $p$ : probability or confidence with which we need the correct fit.
- $\alpha$ : probability of choosing an inlier while selecting the  $s$  samples.

If the  $s$  points are selected **independently**. Then,

Minimum number of iterations required:

$$N = \frac{\log(1 - p)}{\log(1 - \alpha^s)}$$

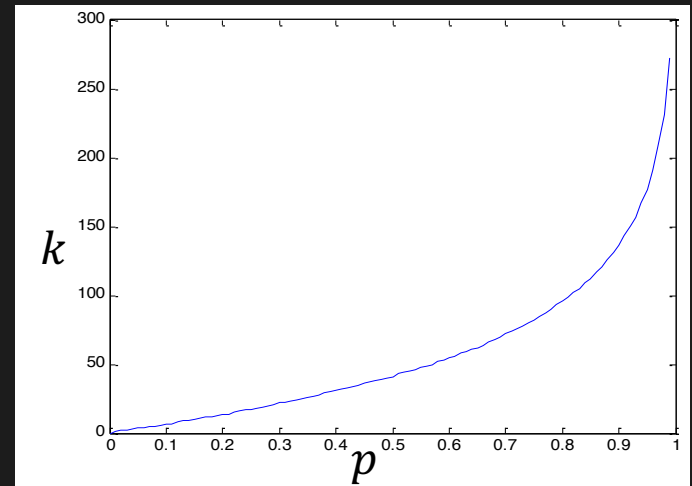
# Appendix B: RANSAC

Minimum number of iterations required:

$$k = \frac{\log(1 - p)}{\log(1 - \alpha^s)}$$

	Proportion of inliers $\alpha$						
s	95%	90%	80%	75%	70%	60%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

Minimum number of iterations ( $p = 0.99$ )



$s = 8, \alpha = 60\%$