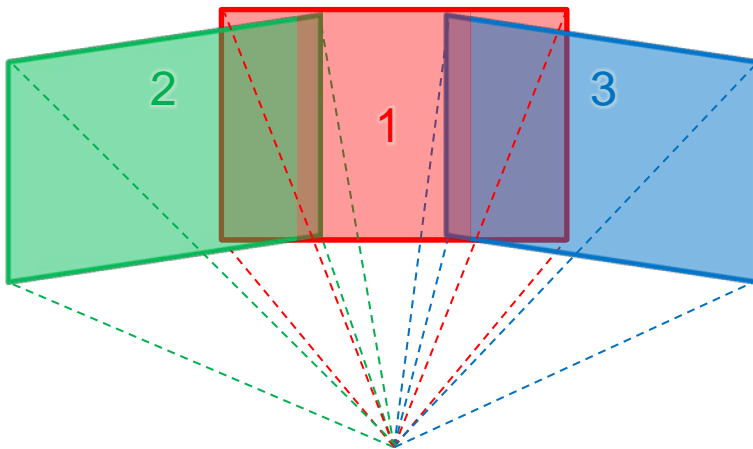
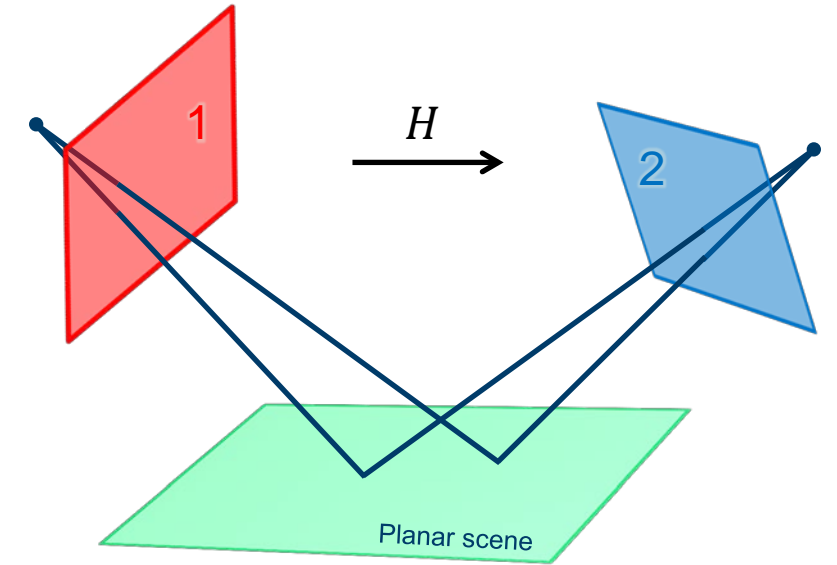
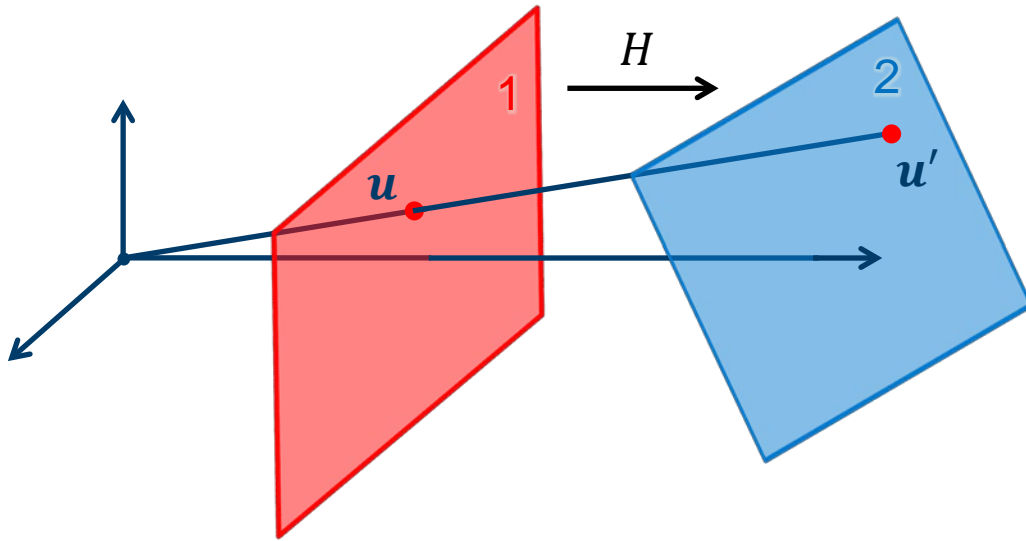


Lecture 4.3

Estimating homographies from feature correspondences

Thomas Opsahl

Homographies induced by central projection

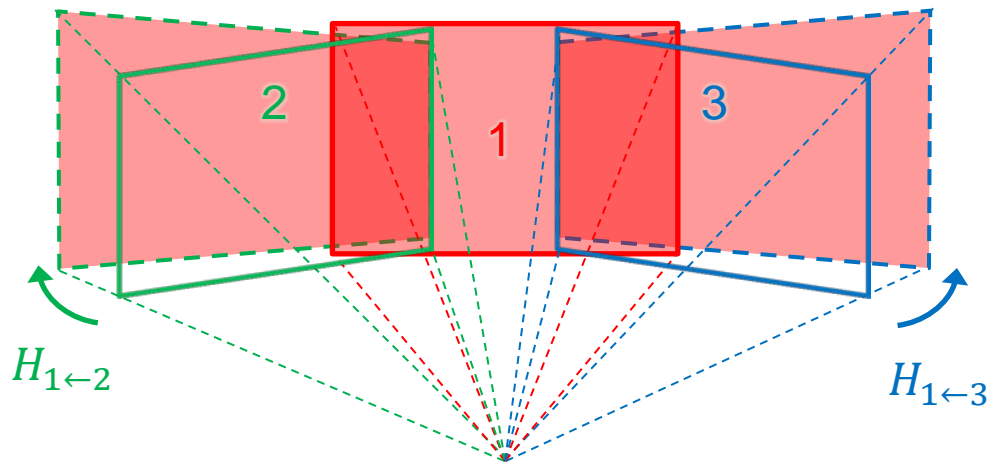
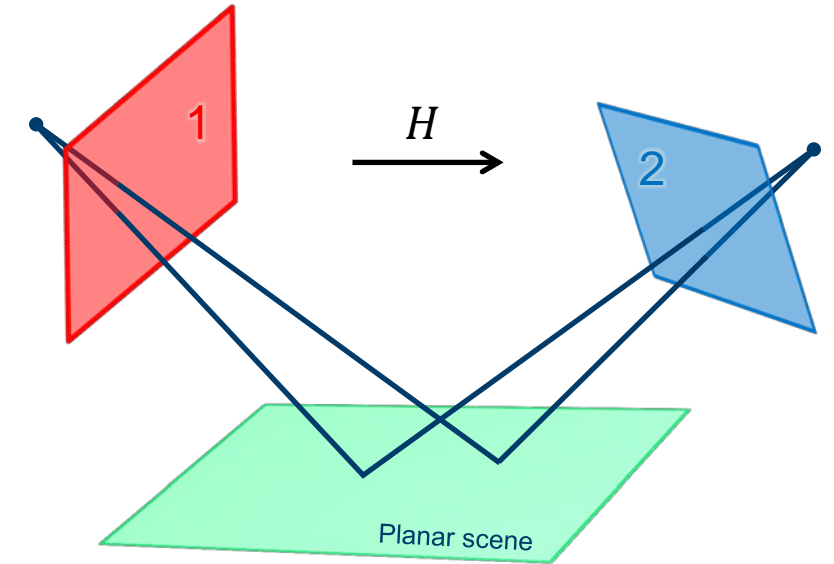
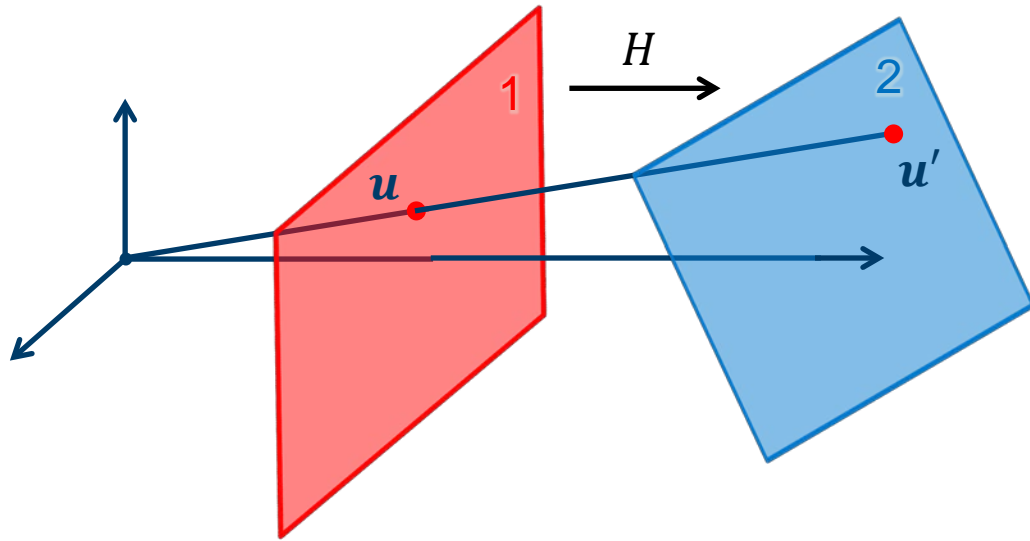


- Homography $H\tilde{u} = \tilde{u}'$

$$H = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$$

- Point-correspondences can be determined automatically
- Erroneous correspondences are common
- Robust estimation is required to find H

Homographies induced by central projection



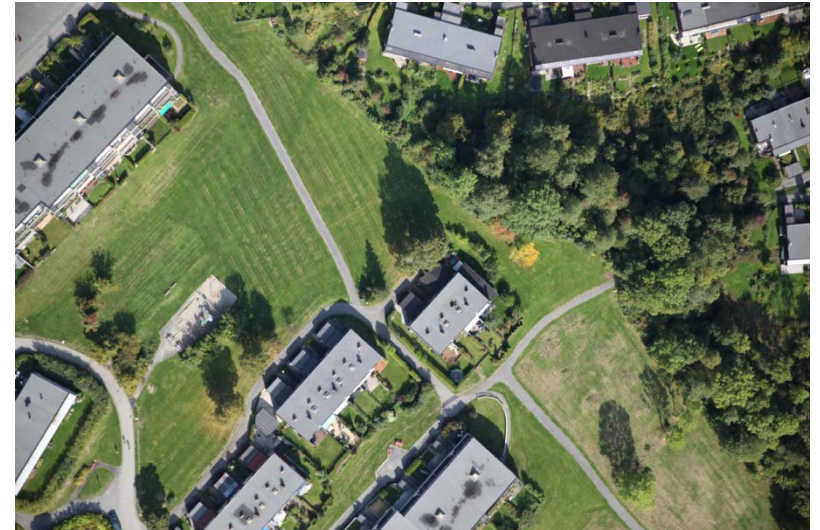
- Homography $H\tilde{u} = \tilde{u}'$

$$H = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$$

- Point-correspondences can be determined automatically
- Erroneous correspondences are common
- Robust estimation is required to find H

Estimating the homography between overlapping images

- Establish point correspondences $\mathbf{u}_i \leftrightarrow \mathbf{u}'_i$
 - Find key points $\{\mathbf{u}_i \in \text{Img1}\}$ and $\{\mathbf{u}'_i \in \text{Img2}\}$
 - Represent key points by suitable descriptors
 - Determine correspondences $\mathbf{u}_i \leftrightarrow \mathbf{u}'_i$ by matching descriptors
 - Some wrong correspondences are to be expected
- Estimate the homography H such that $\mathbf{u}'_i = H\mathbf{u}_i \forall i$
 - Robust estimation with RANSAC
 - Improved estimation based on RANSAC inliers
- This homography enables us to compose the images into a larger image
 - Image mosaicing
 - Panorama



Adaptive RANSAC

Objective

To robustly fit a model $y = f(x; \alpha)$ to a data set S containing outliers

Algorithm

1. Let $N = \infty$, $S_{IN} = \emptyset$ and $\#iterations = 0$
2. while $N > \#iterations$ repeat 3-5
3. Estimate parameters α_{tst} from a random n -tuple from S
4. Determine inlier set S_{tst} , i.e. data points within a distance t of the model $y = f(x; \alpha_{tst})$
5. If $|S_{tst}| > |S_{IN}|$, set $S_{IN} = S_{tst}$, $\alpha = \alpha_{tst}$, $\omega = \frac{|S_{IN}|}{|S|}$ and $N = \frac{\log(1-p)}{\log(1-\omega^n)}$ with $p = 0.99$
Increase $\#iterations$ by 1

Estimating the homography

- Estimating the homography in a RANSAC scheme requires
 1. A basic homography estimation method for n point-correspondences
 2. A way to determine the inlier set of point-correspondences for a given homography

Estimating the homography

- Estimating the homography in a RANSAC scheme requires
 1. **A basic homography estimation method for n point-correspondences**
 2. A way to determine the inlier set of point-correspondences for a given homography
- The homography has 8 degrees of freedom, but it is custom to treat all 9 entries of the matrix as unknowns instead of setting one of the entries to 1 which excludes all potential solutions where this entry is 0
- Let us solve the equation $H\tilde{\mathbf{u}} = \tilde{\mathbf{u}}'$ for the entries of the homography matrix

$$H\tilde{\mathbf{u}} = \tilde{\mathbf{u}}'$$
$$\begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix}$$

Basic homography estimation

$$\begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} \Leftrightarrow \begin{cases} uh_1 + vh_2 + h_3 = u' \\ uh_4 + vh_5 + h_6 = v' \\ uh_7 + vh_8 + h_9 = 1 \end{cases} \Leftrightarrow \begin{bmatrix} 0 & 0 & 0 & -u & -v & -1 & v'u & v'v & v' \\ u & v & 1 & 0 & 0 & 0 & -u'u & -u'v & -u' \\ -v'u & -v'v & -v' & u'u & u'v & u' & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ h_5 \\ h_6 \\ h_7 \\ h_8 \\ h_9 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Leftrightarrow A\mathbf{h} = \mathbf{0}$$

Basic homography estimation

$$\begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} \Leftrightarrow \begin{cases} uh_1 + vh_2 + h_3 = u' \\ uh_4 + vh_5 + h_6 = v' \\ uh_7 + vh_8 + h_9 = 1 \end{cases} \Leftrightarrow \begin{bmatrix} 0 & 0 & 0 & -u & -v & -1 & v'u & v'v & v' \\ u & v & 1 & 0 & 0 & 0 & -u'u & -u'v & -u' \\ -v'u & -v'v & -v' & u'u & u'v & u' & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ h_5 \\ h_6 \\ h_7 \\ h_8 \\ h_9 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Leftrightarrow A\mathbf{h} = \mathbf{0}$$

Observe that the third row in A is a linear combination of the first and second row

$$row_3 = -u' \cdot row_1 - v' \cdot row_2$$

Hence every correspondence $\mathbf{u}_i \leftrightarrow \mathbf{u}'_i$ contribute with 2 equations in the 9 unknown entries

Basic homography estimation

- Since H (and thus \mathbf{h}) is homogeneous, we only need the matrix A to have rank 8 in order to determine \mathbf{h} up to scale
- It is sufficient with 4 point correspondences where no 3 points are collinear
- We can calculate the non-trivial solution to the equation $A\mathbf{h} = \mathbf{0}$ by SVD

$$\text{svd}(A) = USV^T$$
- The solution is given by the right singular vector without a singular value which is the last column of V , i.e. $\mathbf{h} = \mathbf{v}_9$

$$\begin{bmatrix} 0 & 0 & 0 & -u_1 & -v_1 & -1 & v'_1 u_1 & v'_1 v_1 & v'_1 \\ u_1 & v_1 & 1 & 0 & 0 & 0 & -u'_1 u_1 & -u'_1 v_1 & -u'_1 \\ 0 & 0 & 0 & -u_2 & -v_2 & -1 & v'_2 u_2 & v'_2 v_2 & v'_2 \\ u_2 & v_2 & 1 & 0 & 0 & 0 & -u'_2 u_2 & -u'_2 v_2 & -u'_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ h_5 \\ h_6 \\ h_7 \\ h_8 \\ h_9 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \end{bmatrix}$$

$A\mathbf{h} = \mathbf{0}$

Basic homography estimation

- Estimating the homography in a RANSAC scheme requires
 1. **A basic homography estimation method for n point-correspondences**
 2. A way to determine which of the point correspondences that are inliers for a given homography

Direct Linear Transform

$$A = \begin{bmatrix} 0 & 0 & 0 & -u_1 & -v_1 & -1 & v'_1 u_1 & v'_1 v_1 & v'_1 \\ u_1 & v_1 & 1 & 0 & 0 & 0 & -u'_1 u_1 & -u'_1 v_1 & -u'_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

1. Build the matrix A from at least 4 point-correspondences $(u_i, v_i) \leftrightarrow (u'_i, v'_i)$
2. Obtain the SVD of A : $A = USV^T$
3. If S is diagonal with positive values in descending order along the main diagonal, then \mathbf{h} equals the last column of V
4. Reconstruct H from \mathbf{h}

Basic homography estimation

- The basic DLT algorithm is never used with more than 4 point-correspondences
- This is because the algorithm performs better when all the terms of A has a similar scale
 - Note that some of the terms will always be of scale 1
- To achieve this, it is common to extend the algorithm with a normalization and a denormalization step

Normalized Direct Linear Transform

1. Normalize the set of points $\mathbf{u}_i = [u_i, v_i]^T$ by computing a similarity transform T that translates the centroid to the origin and scales such that the average distance from the origin is $\sqrt{2}$
2. In the same way normalize the set of points $\mathbf{u}'_i = [u'_i, v'_i]^T$ by computing a similarity transform T'
3. Apply the basic DLT algorithm on the normalized points to obtain a homography \hat{H}
4. Denormalize to get the homography: $H = T'^{-1}\hat{H}T$

Basic homography estimation

- Estimating the homography in a RANSAC scheme requires
 1. A basic homography estimation method for n point-correspondences
 2. **A way to determine the inlier set of point-correspondences for a given homography**
- For a point correspondence $(u_i, v_i) \leftrightarrow (u'_i, v'_i)$ and homography H , we can choose from several errors
 - Algebraic error: $\varepsilon_i = \|A_i \mathbf{h}\|$ where

$$A_i = \begin{bmatrix} 0 & 0 & 0 & -u_i & -v_i & -1 & v'_i u_i & v'_i v_i & v'_i \\ u_i & v_i & 1 & 0 & 0 & 0 & -u'_i u_i & -u'_i v_i & -u'_i \end{bmatrix}$$

- Geometric errors:
 1. $\varepsilon_i = d(H\mathbf{u}_i, \mathbf{u}'_i) + d(\mathbf{u}_i, H^{-1}\mathbf{u}'_i)$ (**Reprojection error**)
 2. $\varepsilon_i = d(\mathbf{u}_i, H^{-1}\mathbf{u}'_i)$
 3. $\varepsilon_i = d(H\mathbf{u}_i, \mathbf{u}'_i)$

Notation	
Euclidean distance	$d(\cdot, \cdot)$
Inhomogenous $H\tilde{\mathbf{u}}_i$	$H\mathbf{u}_i$
Inhomogeneous $H^{-1}\tilde{\mathbf{u}}'_i$	$H^{-1}\mathbf{u}'_i$

Robust homography estimation

RANSAC estimation of homography

For a set of point-correspondences $S = \{\mathbf{u}_i \mapsto \mathbf{u}'_i\}$, perform N iterations, where N is determined adaptively

1. Estimate H_{tst} from 4 random correspondences $\mathbf{u}_i \mapsto \mathbf{u}'_i$ using the basic DLT algorithm
2. Determine the set of inlier-correspondences $S_{tst} = \{\mathbf{u}_i \mapsto \mathbf{u}'_i \text{ such that } \epsilon_i < t\}$
Here one can choose $\epsilon_i = d(H\mathbf{u}_i, \mathbf{u}'_i) + d(\mathbf{u}_i, H^{-1}\mathbf{u}'_i)$ and $t = \sqrt{5.99}\sigma$ where σ is the expected uncertainty in key-point positions
3. If $|S_{tst}| > |S_{IN}|$ update N , homography and inlier set: $H = H_{tst}$, $S_{IN} = S_{tst}$

- Finally we would typically re-estimate H from all correspondences in S_{IN}
 - Normalized DLT
 - Minimize $\epsilon = \sum \epsilon_i$ in an iterative optimization method like Levenberg Marquardt

Image mosaicing



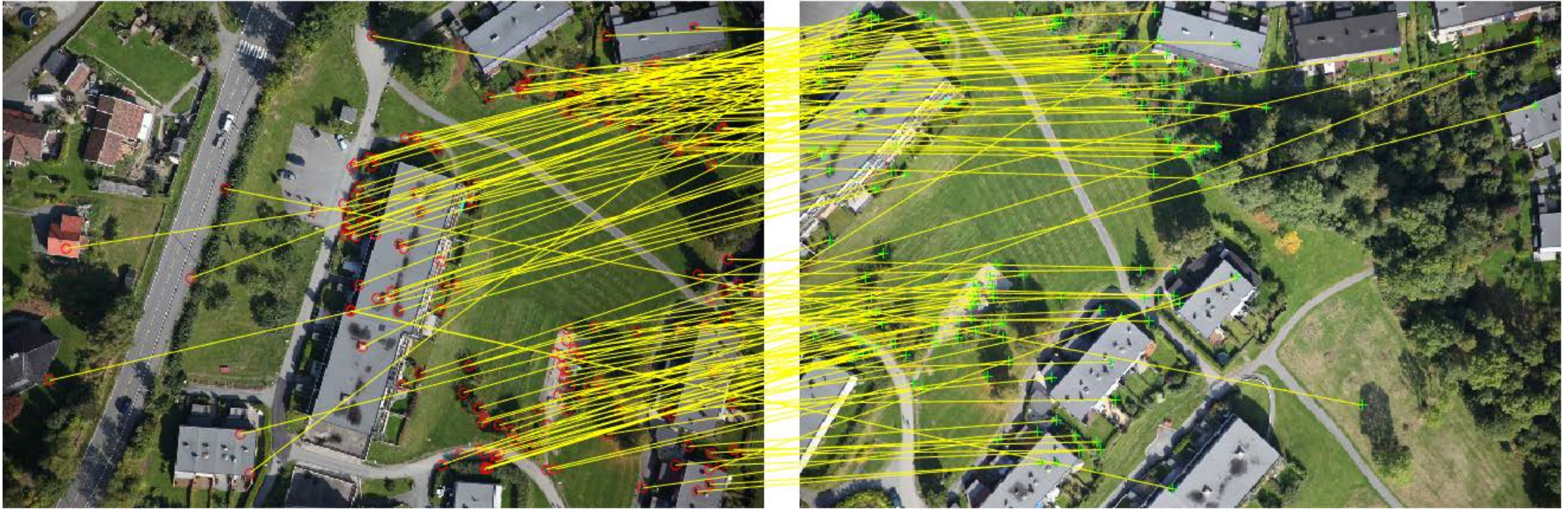
- Let us compose these two images into a larger image

Image mosaicing



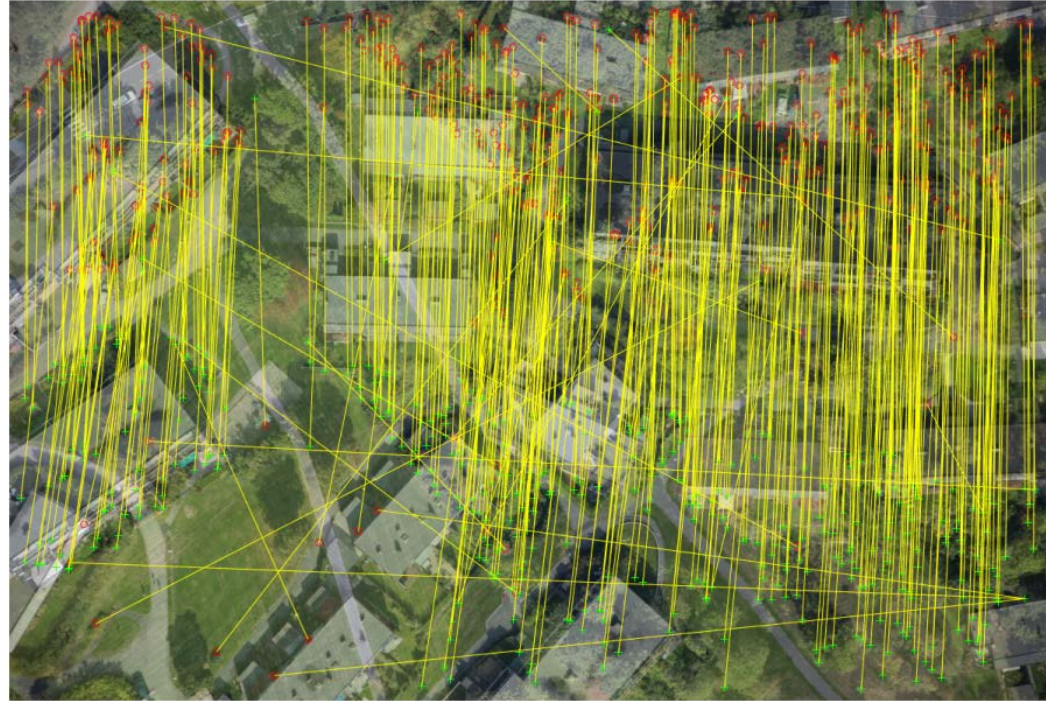
- Find key points and represent by descriptors

Image mosaicing



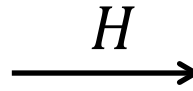
- Establish point-correspondences by matching descriptors
- Several wrong correspondences

Image mosaicing



- Establish point-correspondences by matching descriptors
- Several wrong correspondences

Image mosaicing

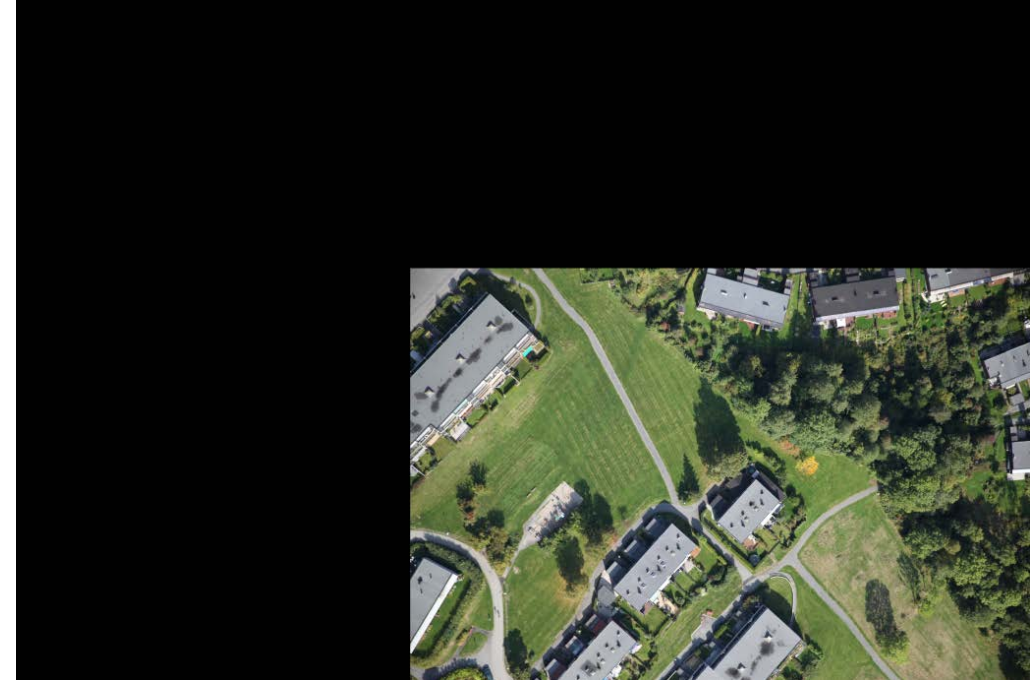
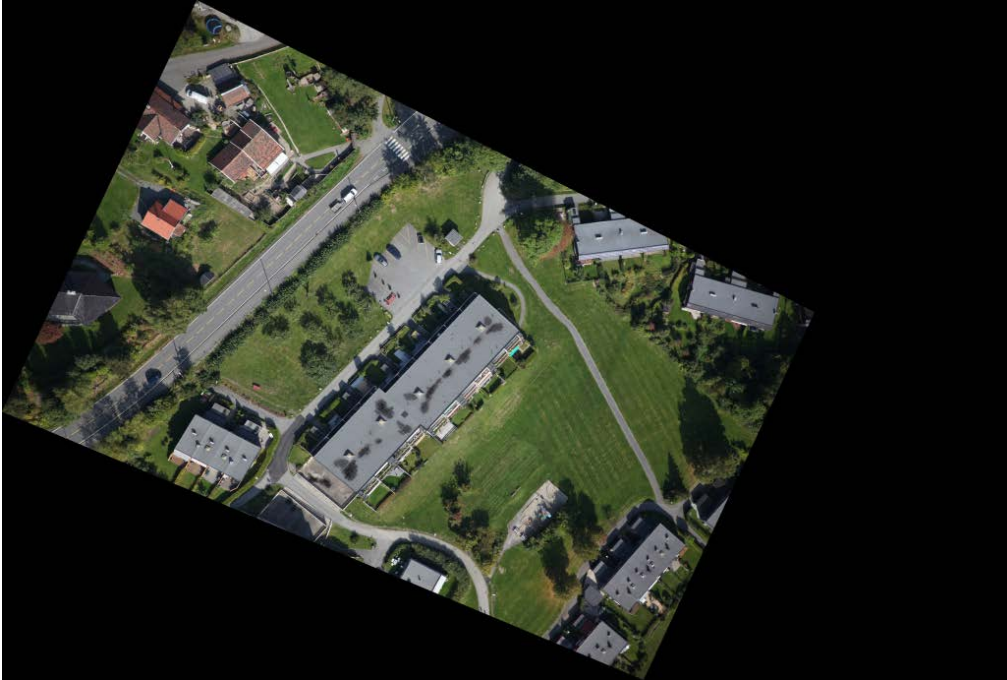


- Estimate homography $H\tilde{u} = \tilde{u}'$
 - OpenCV

```
#include "opencv2/calib3d.hpp"
cv::findHomography(srcPoints, dstPoints, CV_RANSAC);
```
 - Matlab

```
tform = estimateGeometricTransform(srcPoints,dstPoints,'projective');
```


Image mosaicing

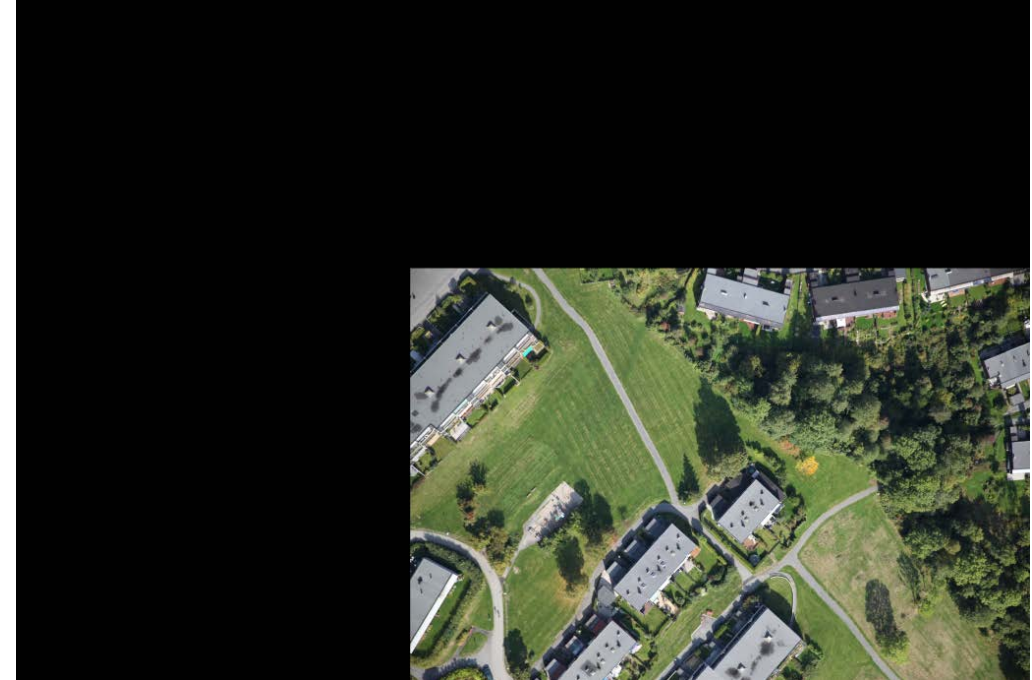
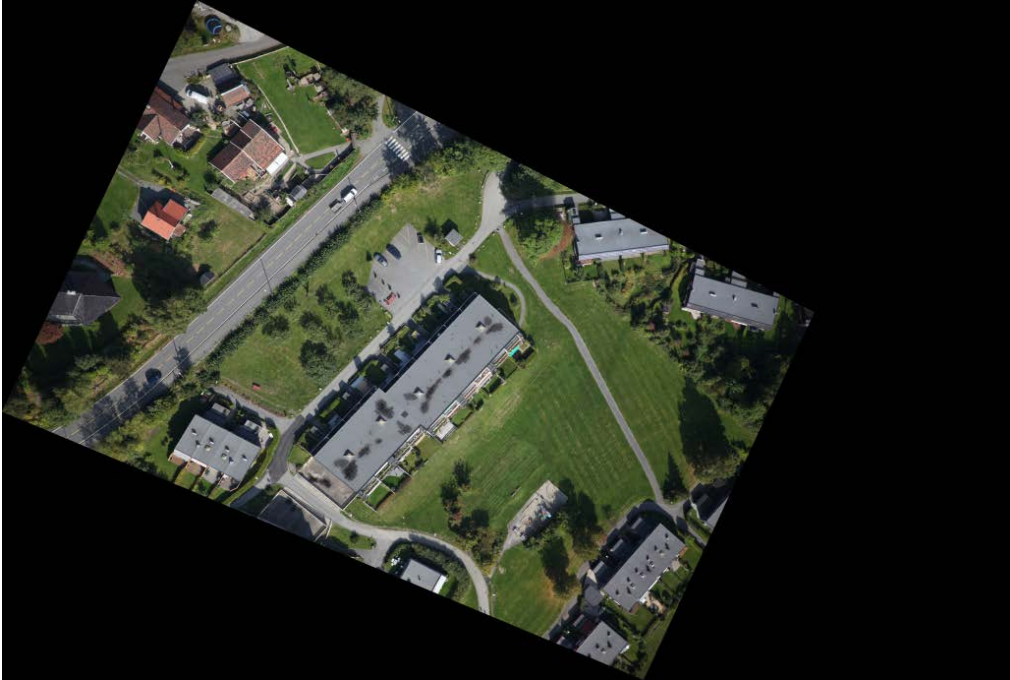


- Represent the images in common coordinates (Note the additional translation!)
 - OpenCV

```
#include "opencv2/calib3d.hpp"
cv::warpPerspective(img1, img2, H, output_size);
```
 - Matlab

```
img2 = imwarp(img1,tform);
```

Image mosaicing



- Now we can compose the images

Overwriting



Blending with a ramp



Blending with a ramp
+ histogram
equalization



SVD

Singular Value Decomposition

The singular value decomposition of a real $m \times n$ matrix A is a factorization $A = USV^T$

Here U is a orthogonal $m \times m$ matrix, V is a orthogonal $n \times n$ matrix and S is a real positive diagonal $m \times n$ matrix

The diagonal entries of $S = \text{diag}(s_1, \dots, s_{\min(m,n)})$ are known as the singular values of A and the columns of $U = [\mathbf{u}_1, \dots, \mathbf{u}_m]$ and $V = [\mathbf{v}_1, \dots, \mathbf{v}_n]$ are known as the left and right singular vectors of A respectively

The nullspace of A is the span of the right singular vectors \mathbf{v}_i that corresponds to a zero singular value s_i (or does not have a corresponding singular value)

How to use

- Matlab
`[U,S,V] = svd(A);`
Right singular vectors are **columns** in V
- OpenCV
`cv::SVD::compute(A, S, U, Vtranspose, cv::SVD::FULL_UV);`
Right singular vectors are **rows** in V^T
- Eigen
`Eigen::JacobiSVD<Eigen::MatrixXd> svd(A, Eigen::ComputeFullU | Eigen::ComputeFullV);`
Right singular vectors are **columns** in `svd.matrixV()`

SVD

Singular Value Decomposition

The singular value decomposition of a real $m \times n$ matrix A is a factorization $A = USV^T$

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The nullspace of A is the span of the right singular vectors \mathbf{v}_i that corresponds to a zero singular value s_i (or does not have a corresponding singular value)

Applications of SVD

Solving homogeneous linear equations like

$$A\mathbf{h} = \mathbf{0}$$

Method

For theoretical problems, $\mathbf{h} \in \text{null}(A)$ so \mathbf{h} is a linear combination of the right singular vectors \mathbf{v}_i that correspond to a zero singular value s_i

$$\mathbf{h} = \sum k_i \mathbf{v}_i; \quad k_i \in \mathbb{R}, s_i = 0 \text{ (or missing)}$$

For practical problems, the presence of noise force us to expand the solution by including those right singular vectors that correspond to small singular values $s_i \approx 0$

$$\mathbf{h} = \sum k_i \mathbf{v}_i; \quad k_i \in \mathbb{R}, s_i \approx 0 \text{ (or missing)}$$

SVD

Example

$$A\mathbf{x} = \mathbf{0}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

From $[U, S, V] = \text{svd}(A)$; we get

$$U = \begin{bmatrix} -0.3863 & -0.9224 \\ -0.9224 & 0.3863 \end{bmatrix} \quad S = \begin{bmatrix} 9.5080 & 0 & 0 \\ 0 & 0.7729 & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} -0.4287 & 0.8060 & 0.4082 \\ -0.5663 & 0.1124 & -0.8165 \\ -0.7039 & -0.5812 & 0.4082 \end{bmatrix}$$

From this we see that A has:

- 2 left singular vectors

$$\mathbf{u}_1 = \begin{bmatrix} -0.3863 \\ -0.9224 \end{bmatrix} \quad \mathbf{u}_2 = \begin{bmatrix} -0.9224 \\ 0.3863 \end{bmatrix}$$

- 2 nonzero singular values

$$s_1 = 9.5080 \quad s_2 = 0.7729$$

- 3 right singular vectors

$$\mathbf{v}_1 = \begin{bmatrix} -0.4287 \\ -0.5663 \\ -0.7039 \end{bmatrix} \quad \mathbf{v}_2 = \begin{bmatrix} 0.8060 \\ 0.1124 \\ -0.5812 \end{bmatrix} \quad \mathbf{v}_3 = \begin{bmatrix} 0.4082 \\ -0.8165 \\ 0.4082 \end{bmatrix}$$

Since \mathbf{v}_3 does not have a corresponding singular value, $\mathbf{x} = \mathbf{v}_3$ is a non-trivial solution to $A\mathbf{x} = \mathbf{0}$ and $\mathbf{x} = k \cdot \mathbf{v}_3$; $k \in \mathbb{R} \setminus \{0\}$ is the family of all non-trivial solutions

SVD

Example

$$A\mathbf{x} = \mathbf{0}$$
$$\begin{bmatrix} 1.0792 & 2.0656 & 3.0849 \\ 4.0959 & 5.0036 & 6.0934 \\ 1.0679 & 2.0743 & 3.0655 \\ 4.0758 & 5.0392 & 6.0171 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

This time singular value decomposition give us the following singular values and right singular vectors:

$$s_1 = 13.6295 \quad s_2 = 1.0849 \quad s_3 = 0.0506$$

$$\mathbf{v}_1 = \begin{bmatrix} -0.4336 \\ -0.5635 \\ -0.7032 \end{bmatrix} \quad \mathbf{v}_2 = \begin{bmatrix} -0.8103 \\ -0.0975 \\ 0.5778 \end{bmatrix} \quad \mathbf{v}_3 = \begin{bmatrix} 0.3942 \\ -0.8203 \\ 0.4143 \end{bmatrix}$$

This time all right singular vectors correspond to a non-zero singular value, so the equation does not have any non-trivial solutions!

If this equation came from a practical problem, instead of looking for solutions to $A\mathbf{x} = \mathbf{0}$, we might be looking for the \mathbf{x} that minimize $\|A\mathbf{x}\|$

Since $s_1 \approx 0, s_2 \approx 0, s_3 \approx 0$, we would conclude that $\mathbf{x} = \mathbf{v}_3$ solves the equation in a least-squares sense

Check:

$$A\mathbf{v}_3 = \begin{bmatrix} 0.0091 \\ 0.4288 \\ -0.0105 \\ -0.0341 \end{bmatrix}$$

Summary

- Homography $H\tilde{\mathbf{u}} = \tilde{\mathbf{u}}'$
$$H = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$$
- Automatic point-correspondences
- Wrong correspondences are common
- RANSAC estimation
 - Basic DLT (Direct Linear Transform) on 4 random correspondences
 - Inliers determined from the reprojection error $\epsilon_i = d(H\mathbf{u}_i, \mathbf{u}'_i) + d(\mathbf{u}_i, H^{-1}\mathbf{u}'_i)$
- Improve estimate by normalized DLT on inliers or iterative methods for an even better estimate
- Additional reading
 - Szeliski: 6.1.1 – 6.1.3