

# Feature-Based Image Alignment

CS 650: Computer Vision

Bryan S. Morse

# Image Registration

One common task is to align two images

- ▶ Different positions
- ▶ Different times
- ▶ Different types of imaging

This is called *image registration*.

# Image Stitching

One common application of image registration is to stitch together or *mosaic* two or more images together.

Here's a link to an example.

# Image Stitching

The key to image stitching is to be able to warp one image to match another, then combine.

Cases:

- ▶ Can't do in general without depth information due to *parallax*
- ▶ Can do if all of the images have the same focal point (pure 3-D rotation, panoramas)
- ▶ Can do if scene is planar (homographies)

## Planar Case

If the scene is planar or approximately so (a wall, objects far away, etc.), you can warp one image to another using a homography:

$$\tilde{\mathbf{x}}' = \tilde{\mathbf{H}}\bar{\mathbf{x}}$$

or

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} \sim \begin{bmatrix} \tilde{x}' \\ \tilde{y}' \\ \tilde{w}' \end{bmatrix} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

If  $\det(\tilde{\mathbf{H}}) \neq 0$ , the homography *uniquely* maps 2-D homogeneous points to other 2-D homogeneous points.

## Finding the Homography Between Two Images?

Common approaches to registration:

- ▶ Area matching (“direct” or “area-based”)
- ▶ Sparse set of feature points (“feature-based”)
- ▶ Segment, represent, then match objects  
—can be very robust for multimodal registration but very domain-specific

## Direct Registration

Basic approach:

- ▶ Define some error metric that measures how well the images match (correlation, L-norms, normalized cross-correlation, etc.)
- ▶ Select the parameters for the homography that optimizes the quality of the match

We'll come back later to ways to do this.

## Feature-Based Registration

Basic approach:

- ▶ Find “interesting” points (Moravec, Harris, SIFT, etc.)
- ▶ Match them somehow (neighborhoods, SIFT descriptors, etc.)
- ▶ Solve for the homography

Can solve for a homography with a minimum of four points, with no three of them colinear (the *4-point algorithm*).

Warning: don't even get close to colinear!!

What about noise? What about mismatches?



# The Four-Point Algorithm

Mapping:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} \sim \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

or

$$x' = \frac{h_{00}x + h_{01}y + h_{02}}{h_{20}x + h_{21}y + 1}$$

$$y' = \frac{h_{10}x + h_{11}y + h_{12}}{h_{20}x + h_{21}y + 1}$$

## The Four-Point Algorithm

Using

$$x' = \frac{h_{00}x + h_{01}y + h_{02}}{h_{20}x + h_{21}y + 1} \qquad y' = \frac{h_{10}x + h_{11}y + h_{12}}{h_{20}x + h_{21}y + 1}$$

Let's re-write this:

$$\begin{aligned} h_{00}x + h_{01}y + h_{02} - x'(h_{20}x + h_{21}y + 1) &= 0 \\ h_{10}x + h_{11}y + h_{12} - y'(h_{20}x + h_{21}y + 1) &= 0 \end{aligned}$$

Can we write this in matrix form?

# The Four-Point Algorithm

$$\begin{bmatrix} x & y & 1 & 0 & 0 & 0 & -x'x & -x'y \\ 0 & 0 & 0 & x & y & 1 & -y'x & -y'y \end{bmatrix} \begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \end{bmatrix} = \begin{bmatrix} x' \\ y' \end{bmatrix}$$

# The Four-Point Algorithm

$$\begin{bmatrix}
 x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1 x_1 & -x'_1 y_1 \\
 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1 x_1 & -y'_1 y_1 \\
 x_2 & y_2 & 1 & 0 & 0 & 0 & -x'_2 x_2 & -x'_2 y_2 \\
 0 & 0 & 0 & x_2 & y_2 & 1 & -y'_2 x_2 & -y'_2 y_2 \\
 x_3 & y_3 & 1 & 0 & 0 & 0 & -x'_3 x_3 & -x'_3 y_3 \\
 0 & 0 & 0 & x_3 & y_3 & 1 & -y'_3 x_3 & -y'_3 y_3 \\
 x_4 & y_4 & 1 & 0 & 0 & 0 & -x'_4 x_4 & -x'_4 y_4 \\
 0 & 0 & 0 & x_4 & y_4 & 1 & -y'_4 x_4 & -y'_4 y_4
 \end{bmatrix}
 \begin{bmatrix}
 h_{00} \\
 h_{01} \\
 h_{02} \\
 h_{10} \\
 h_{11} \\
 h_{12} \\
 h_{20} \\
 h_{21}
 \end{bmatrix}
 =
 \begin{bmatrix}
 x'_1 \\
 y'_1 \\
 x'_2 \\
 y'_2 \\
 x'_3 \\
 y'_3 \\
 x'_4 \\
 y'_4
 \end{bmatrix}$$

## Camera Calibration (Revisited)

- ▶ This general approach found in the four-point algorithm can be used in lots of other problems.
- ▶ Keep in mind that *it's the elements of the matrix that are the unknowns* and re-write the equations to make these the “unknown vector” and the other information the “matrix”
- ▶ Example: Camera Calibration

$$\mathbf{p} \sim \mathbf{P} \mathbf{p}_w$$

Write in terms of 11 unknowns of  $\mathbf{P}$  and then use known 3-D points  $\mathbf{p}_w$  and projected points  $\mathbf{p}$

## Dealing with Noise

Deal with noise in estimating any one point by *using more points than needed*—this is an *overconstrained* system of equations

Let  $\mathbf{x}' = (x', y')$  denote the remapped points as before:

$$x' = \frac{h_{00}x + h_{01}y + h_{02}}{h_{20}x + h_{21}y + 1} \qquad y' = \frac{h_{10}x + h_{11}y + h_{12}}{h_{20}x + h_{21}y + 1}$$

and let  $\hat{x}$  denote the correct matching position in the other image, then minimize the sum of the squared error:

$$\sum_i \|x - \hat{x}\|^2$$

and solve using least-squares fitting.

## Least Squares

**Your book has a more detailed discussion in 6.1.1, 6.1.3, A.2.**

General Form:

Let for each point pair  $i$  and a set of transformation parameters  $p$ :

$$\begin{array}{ll} x'_i = f(x_i, p) & \text{predicted (mapped) location} \\ \hat{x}_i & \text{measured location of matching point} \\ r_i = \hat{x}_i - x'_i & \text{error or } \textit{residual} \end{array}$$

Goal: minimize the squared residuals

$$\sum_i \|r_i\|^2 = \sum_i \|x' - \hat{x}\|^2$$

Key piece: if  $x_i$  stays fixed and you change a parameter in  $p$ , how does the predicted matching point  $x'_i$  change?

# Linear Least Squares

The Jacobian is an extension of the gradient for multiple outputs:

$$J = \frac{\partial f}{\partial p}$$

If the relationship between the point motion and the parameters  $p$  is *linear* (e.g., up to affine),

$$\Delta x = x' - x = J(x) p$$

The minimum-error result can then be found by a *pseudoinverse* technique:

$$A p = b$$

where

$$A = \sum_i J^T(x_i) J(x_i)$$

$$b = \sum_i J^T(x_i) \Delta x_i$$



## Nonlinear Least Squares

If the relationship between the point motion and the parameters of the transformation is *not* linear (e.g., homography, lots of other things in vision), you have to use an iterative solver.

- ▶ Basic idea: iteratively adjust parameters until residual reaches minimum — essentially variants on gradient descent
- ▶ The Jacobian is essential to all of these since it tells you how changing each parameter in  $p$  will change the result
- ▶ One popular technique for minimizing squared-error measures is *Levenberg-Marquardt*.
- ▶ Iterative solvers require a good starting point, so how do you get one? Use a linear technique to seed it (e.g., four-point method).

## Dealing with Bad Point Matches

- ▶ Some point matches might be wrong—how do you deal with it?
- ▶ From a least-squares fitting view, these are *outliers*, which throw off the answer.
- ▶ Common approach: Use RANSAC and the four-point algorithm to simultaneously separate outliers and solve for initial estimate for  $\tilde{\mathbf{H}}$ .
- ▶ Throw all the resulting inliers into a least-squares solver.