## CS4670/5760: Computer Vision

 Noah SnavelyLecture 11: Image alignment, Part 2


## Announcements

- Project 2 due Monday at 11:59pm
- Project 1 voting open, closing Thursday night
- No class Friday
- Please work on your projects!


## Reading

- Szeliski: Chapter 6.1


## Image Warping

- Given a coordinate xform $\left(x^{\prime}, \boldsymbol{y}^{\prime}\right)=\boldsymbol{T}(x, y)$ and a source image $f(x, y)$, how do we compute an xformed image $g\left(x^{\prime}, y^{\prime}\right)=f(T(x, y))$ ?



## Computing transformations

- Given a set of matches between images $A$ and $B$
- How can we compute the transform $T$ from $A$ to $B$ ?

- Find transform T that best "agrees" with the matches


## Computing transformations

- Can also think of as fitting a "model" to our data
- The model is the transformation of a given type, e.g. a translation, affine xform, homography etc.
- Fitting the model means solving for the parameters that best explain the observed data
- Usually involves minimizing some objective / cost function


## Solving for translations

- Using least squares - one type of cost function

$$
\begin{aligned}
& {\left[\begin{array}{cc}
1 & 0 \\
0 & 1 \\
1 & 0 \\
0 & 1 \\
\vdots \\
1 & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{c}
x_{t} \\
y_{t}
\end{array}\right]=\left[\begin{array}{c}
x_{1}^{\prime}-x_{1} \\
y_{1}^{\prime}-y_{1} \\
x_{2}^{\prime}-x_{2} \\
y_{2}^{\prime}-y_{2} \\
\vdots \\
x_{n}^{\prime}-x_{n} \\
y_{n}^{\prime}-y_{n}
\end{array}\right]} \\
& \underset{2 k 2}{\mathbf{A}} \underset{2 x}{\mathbf{t}}=\underset{2 k}{\mathbf{b}}
\end{aligned}
$$

## Least squares: <br> generalized linear regression



## Linear regression


$\operatorname{Cost}(m, b)=\sum_{i=1}^{n}\left|y_{i}-\left(m x_{i}+b\right)\right|^{2}$

## Linear regression

$$
\left[\begin{array}{cc}
x_{1} & 1 \\
x_{2} & 1 \\
\vdots & \\
x_{n} & 1
\end{array}\right]\left[\begin{array}{c}
m \\
b
\end{array}\right]=\left[\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
y_{n}
\end{array}\right]
$$

## Affine transformations

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{lll}
a & b & c \\
d & e & f \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]
$$



- How many unknowns?
- How many equations per match?
- How many matches do we need?


## Affine transformations

- Residuals:

$$
\begin{aligned}
r_{x_{i}}(a, b, c, d, e, f) & =\left(a x_{i}+b y_{i}+c\right)-x_{i}^{\prime} \\
r_{y_{i}}(a, b, c, d, e, f) & =\left(d x_{i}+e y_{i}+f\right)-y_{i}^{\prime}
\end{aligned}
$$

- Cost function:

$$
\begin{aligned}
& C(a, b, c, d, e, f)= \\
& \quad \sum_{i=1}^{n}\left(r_{x_{i}}(a, b, c, d, e, f)^{2}+r_{y_{i}}(a, b, c, d, e, f)^{2}\right)
\end{aligned}
$$

## Affine transformations

- Matrix form

$$
\begin{aligned}
& {\left[\begin{array}{cccccc}
x_{1} & y_{1} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{1} & y_{1} & 1 \\
x_{2} & y_{2} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{2} & y_{2} & 1 \\
& & & & & \\
& & & & & \\
x_{n} & y_{n} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{n} & y_{n} & 1
\end{array}\right]\left[\begin{array}{l}
a \\
b \\
c \\
d \\
e \\
f
\end{array}\right]=\left[\begin{array}{c}
x_{1}^{\prime} \\
y_{1}^{\prime} \\
x_{2}^{\prime} \\
y_{2}^{\prime} \\
\vdots \\
x_{n}^{\prime} \\
y_{n}^{\prime}
\end{array}\right]} \\
& \text { A } \\
& \mathbf{t}_{61}=\mathbf{b}_{2 \times 1}
\end{aligned}
$$

## Homographies



To unwarp (rectify) an image

- solve for homography $\mathbf{H}$ given $\mathbf{p}$ and $\mathbf{p}^{\prime}$
- solve equations of the form: wp' = Hp
- linear in unknowns: w and coefficients of $\mathbf{H}$
- H is defined up to an arbitrary scale factor
- how many points are necessary to solve for $\mathbf{H}$ ?


## Solving for homographies

$$
\begin{gathered}
{\left[\begin{array}{c}
x_{i}^{\prime} \\
y_{i} \\
1
\end{array}\right] \cong\left[\begin{array}{lll}
h_{00} & h_{01} & h_{02} \\
h_{10} & h_{11} & h_{12} \\
h_{20} & h_{21} & h_{22}
\end{array}\right]\left[\begin{array}{c}
x_{i} \\
y_{i} \\
1
\end{array}\right]} \\
x_{i}^{\prime}=\frac{h_{00} x_{i}+h_{01} y_{i}+h_{02}}{h_{20} x_{i}+h_{21} y_{i}+h_{22}} \\
y_{i}^{\prime}=\frac{h_{10} x_{i}+h_{11} y_{i}+h_{12}}{h_{20} x_{i}+h_{21} y_{i}+h_{22}}
\end{gathered} \text { Not linea } \quad \begin{gathered}
\\
x_{i}^{\prime}\left(h_{20} x_{i}+h_{21} y_{i}+h_{22}\right)=h_{00} x_{i}+h_{01} y_{i}+h_{02} \\
y_{i}^{\prime}\left(h_{20} x_{i}+h_{21} y_{i}+h_{22}\right)=h_{10} x_{i}+h_{11} y_{i}+h_{12}
\end{gathered}
$$

## Solving for homographies

$$
\begin{aligned}
x_{i}^{\prime}\left(h_{20} x_{i}+h_{21} y_{i}+h_{22}\right) & =h_{00} x_{i}+h_{01} y_{i}+h_{02} \\
y_{i}^{\prime}\left(h_{20} x_{i}+h_{21} y_{i}+h_{22}\right) & =h_{10} x_{i}+h_{11} y_{i}+h_{12}
\end{aligned}
$$

$$
\left[\begin{array}{ccccccccc}
x_{i} & y_{i} & 1 & 0 & 0 & 0 & -x_{i}^{\prime} x_{i} & -x_{i}^{\prime} y_{i} & -x_{i}^{\prime} \\
0 & 0 & 0 & x_{i} & y_{i} & 1 & -y_{i}^{\prime} x_{i} & -y_{i}^{\prime} y_{i} & -y_{i}^{\prime}
\end{array}\right]\left[\begin{array}{l}
h_{00} \\
h_{01} \\
h_{02} \\
h_{10} \\
h_{11} \\
h_{12} \\
h_{20} \\
h_{21} \\
h_{22}
\end{array}\right]=\left[\begin{array}{l}
0 \\
0
\end{array}\right]
$$

## Solving for homographies

$$
\left[\begin{array}{ccccccccc}
x_{1} & y_{1} & 1 & 0 & 0 & 0 & -x_{1}^{\prime} x_{1} & -x_{1}^{\prime} y_{1} & -x_{1}^{\prime} \\
0 & 0 & 0 & x_{1} & y_{1} & 1 & -y_{1}^{\prime} x_{1} & -y_{1}^{\prime} y_{1} & -y_{1}^{\prime} \\
x_{n} & y_{n} & 1 & 0 & 0 & \vdots & 0 & -x_{n}^{\prime} x_{n} & -x_{n}^{\prime} y_{n} \\
0 & 0 & 0 & x_{n} & y_{n} & 1 & -x_{n}^{\prime} \\
0 & -y_{n}^{\prime} x_{n} & -y_{n}^{\prime} y_{n} & -y_{n}^{\prime}
\end{array}\right]\left[\begin{array}{c}
h_{00} \\
h_{01} \\
h_{02} \\
h_{10} \\
h_{11} \\
h_{12} \\
h_{20} \\
h_{21} \\
h_{22}
\end{array}\right]=\left[\begin{array}{c}
0 \\
\mathbf{n}_{\mathbf{2 n} \times \mathbf{9}}
\end{array}=\left[\begin{array}{ll}
\mathbf{n} \\
\vdots \\
0 \\
0
\end{array}\right]\right.
$$

Defines a least squares problem: minimize $\|A h-0\|^{2}$

- Since $\mathbf{h}$ is only defined up to scale, solve for unit vector $\hat{\mathbf{h}}$
- Solution: $\hat{\mathbf{h}}=$ eigenvector of $\mathbf{A}^{T} \mathbf{A}$ with smallest eigenvalue
- Works with 4 or more points


## Questions?

## Image Alignment Algorithm

Given images $A$ and $B$

1. Compute image features for $A$ and $B$
2. Match features between $A$ and $B$
3. Compute homography between $A$ and $B$ using least squares on set of matches

What could go wrong?


## Robustness

- Let's consider a simpler example... linear regression


Problem: Fit a line to these datapoints


Least squares fit

- How can we fix this?


## We need a better cost function...

- Suggestions?


## Idea

- Given a hypothesized line
- Count the number of points that "agree" with the line
- "Agree" = within a small distance of the line
- I.e., the inliers to that line
- For all possible lines, select the one with the largest number of inliers


## Counting inliers



## Counting inliers



Inliers: 3

## Counting inliers



## How do we find the best line?

- Unlike least-squares, no simple closed-form solution
- Hypothesize-and-test
- Try out many lines, keep the best one
- Which lines?

