

Fitting a transformation: feature-based alignment

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Last time: Deformable contours


## Last time: Deformable contours

a.k.a. active contours, snakes

Given: initial contour (model) near desired object
Goal: evolve the contour to fit exact object boundary


Main idea: elastic band is iteratively adjusted so as to

- be near image positions with high gradients, and
- satisfy shape "preferences" or contour priors


## Announcements

- Reminder: Pset 2 due Wed March 2
- Midterm exam is Wed March 9
(2 weeks from now)


## Last time: Deformable contours

## Pros:

- Useful to track and fit non-rigid shapes
- Contour remains connected
- Possible to fill in "subjective" contours
- Flexibility in how energy function is defined, weighted

Cons:

- Must have decent initialization near true boundary, may get stuck in local minimum
- Parameters of energy function must be set well based on prior information


## Today

- Interactive segmentation
- Feature-based alignment
- 2D transformations
- Affine fit
- RANSAC


How can we implement such an interactive force with deformable contours?

## Interactive forces

- An energy function can be altered online based on user input - use the cursor to push or pull the initial snake away from a point.
- Modify external energy term to include:

$E_{\text {push }}=\sum_{i=0}^{n-1} \frac{r^{2}}{\left|v_{i}-p\right|^{2}}$
Nearby points get pushed hardest


Beyond boundary snapping...

- Another form of interactive guidance: specify regions
- Usually taken to suggest foreground/background color distributions


User Input


Result
How to use this information?

Recall: Images as graphs


Fully-connected graph


- node for every pixel
- link between every pair of pixels, p,q
- similarity $\mathrm{w}_{\mathrm{pq}}$ for each link
" similarity is inversely proportional to difference in color and position

Recall: Segmentation by Graph Cuts


Link Cut

- set of links whose removal makes a graph disconnected
- cost of a cut:

$$
\operatorname{cut}(A, B)=\sum_{p \in A, q \in B} w_{p, q}
$$

Find minimum cut

- gives you a segmentation
- fast algorithms exist for doing this

Recall: Segmentation by Graph Cuts


Break graph into segments


- Delete links that cross between segments
- Easiest to break links that have low similarity - similar pixels should be in the same segments
- dissimilar pixels should be in different segments


Add two additional nodes, object and background "terminals"
Link each pixel

- To both terminals
- To its neighboring pixels

Yuri Boykov



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## Parametric (global) warping

Examples of parametric warps:


In alignment, we will fit the parameters of some
transformation according to a set of matching feature pairs ("correspondences").


Parametric (global) warping



## Scaling

Scaling operation:

$$
\begin{aligned}
& x^{\prime}=a x \\
& y^{\prime}=b y
\end{aligned}
$$

Or, in matrix form:

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\underbrace{\left[\begin{array}{ll}
a & 0 \\
0 & b
\end{array}\right]}_{\text {cratina matriv }}\left[\begin{array}{l}
x \\
y
\end{array}\right]
$$

What transformations can be represented with a $2 \times 2$ matrix?

2D Scaling?
$x^{\prime}=\boldsymbol{s}_{x} * \boldsymbol{x}$
$y^{\prime}=s_{y} * y$

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
s_{x} & 0 \\
0 & s_{y}
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]
$$

2D Rotate around $(0,0)$ ?

$$
\begin{aligned}
& x^{\prime}=\cos \Theta^{*} x-\sin \Theta * y \\
& y^{\prime}=\sin \Theta * x+\cos \Theta * y
\end{aligned} \quad\left[\begin{array}{l}
\boldsymbol{x}^{\prime} \\
\boldsymbol{y}^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
\cos \Theta & -\sin \Theta \\
\sin \Theta & \cos \Theta
\end{array}\right]\left[\begin{array}{l}
\boldsymbol{x} \\
\boldsymbol{y}
\end{array}\right]
$$

2D Shear?
$x^{\prime}=x+\boldsymbol{s h}_{x} * y$
$y^{\prime}=s h_{y}{ }^{*} x+y$
$\left[\begin{array}{l}x^{\prime} \\ y^{\prime}\end{array}\right]=\left[\begin{array}{cc}1 & s h_{x} \\ s h_{y} & 1\end{array}\right]\left[\begin{array}{l}x \\ y\end{array}\right]$

What transformations can be represented with a $2 \times 2$ matrix?

2D Mirror about $Y$ axis?

$$
\begin{aligned}
& x^{\prime}=-x \\
& y^{\prime}=y
\end{aligned} \quad\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
-1 & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]
$$

2D Mirror over ( 0,0 )?

$$
\begin{aligned}
& x^{\prime}=-x \\
& y^{\prime}=-y
\end{aligned} \quad\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
-1 & 0 \\
0 & -1
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]
$$

2D Translation?
$x^{\prime}=x+t_{x}$
$y^{\prime}=y+t_{y}$$\quad$ NO!

## Homogeneous coordinates

To convert to homogeneous coordinates:

$$
\begin{gathered}
(x, y) \Rightarrow\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right] \\
\text { homogeneous image } \\
\text { coordinates }
\end{gathered}
$$

Converting from homogeneous coordinates

$$
\left[\begin{array}{l}
x \\
y \\
w
\end{array}\right] \Rightarrow(x / w, y / w)
$$

$\left[\begin{array}{c}x \\ y \\ w\end{array}\right] \Rightarrow(x / w, y / w)$

## Homogeneous Coordinates

Q: How can we represent 2d translation as a 3x3 matrix using homogeneous coordinates?
$x^{\prime}=x+t_{x}$
$y^{\prime}=y+t_{y}$
A: Using the rightmost column:
Translation $=\left[\begin{array}{ccc}1 & 0 & \boldsymbol{t}_{x} \\ 0 & 1 & \boldsymbol{t}_{y} \\ 0 & 0 & 1\end{array}\right]$

## Translation

Homogeneous Coordinates
!
$\left[\begin{array}{c}x^{\prime} \\ y^{\prime} \\ 1\end{array}\right]=\left[\begin{array}{lll}1 & 0 & t_{x} \\ 0 & 1 & t_{y} \\ 0 & 0 & 1\end{array}\right]\left[\begin{array}{c}x \\ y \\ 1\end{array}\right]=\left[\begin{array}{c}x+t_{x} \\ y+t_{y} \\ 1\end{array}\right]$



Source: Alyosha Efros

## 2D Affine Transformations

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

Affine transformations are combinations of ...

- Linear transformations, and
- Translations

Parallel lines remain parallel


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## Alignment problem

- We have previously considered how to fit a model to image evidence
- e.g., a line to edge points, or a snake to a deforming contour
- In alignment, we will fit the parameters of some transformation according to a set of matching feature pairs ("correspondences").



## Image alignment



- Two broad approaches:
- Direct (pixel-based) alignment
- Search for alignment where most pixels agree
- Feature-based alignment
- Search for alignment where extracted features agree
- Can be verified using pixel-based alignment


## Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?

$\left[\begin{array}{l}x_{i}^{\prime} \\ y_{i}^{\prime}\end{array}\right]=\left[\begin{array}{ll}m_{1} & m_{2} \\ m_{3} & m_{4}\end{array}\right]\left[\begin{array}{l}x_{i} \\ y_{i}\end{array}\right]+\left[\begin{array}{l}t_{1} \\ t_{2}\end{array}\right]$

An aside: Least Squares Example
Say we have a set of data points ( $\left.\mathrm{X} 1, \mathrm{X} 1^{\prime}\right)$, ( $\mathrm{X} 2, \mathrm{X} 2^{\prime}$ ),
$(X 3, X 3$ '), etc. (e.g. person's height vs. weight)
We want a nice compact formula (a line) to predict $X$ 's from Xs: $\quad X a+b=X^{\prime}$
We want to find $a$ and $b$
How many ( $\mathrm{X}, \mathrm{X}^{\prime}$ ) pairs do we need?

$$
\begin{aligned}
& X_{1} a+b=X_{1}^{\prime} \\
& X_{2} a+b=X_{2}^{\prime}
\end{aligned} \quad\left[\begin{array}{ll}
X_{1} & 1 \\
X_{2} & 1
\end{array}\right]\left[\begin{array}{l}
a \\
b
\end{array}\right]=\left[\begin{array}{l}
X_{1}^{\prime} \\
X_{2}^{\prime}
\end{array}\right] \quad \mathrm{Ax}=\mathrm{B}
$$

What if the data is noisy?
$\left[\begin{array}{cc}X_{1} & 1 \\ X_{2} & 1 \\ X_{3} & 1 \\ \ldots & \ldots\end{array}\right]\left[\begin{array}{c}a \\ b\end{array}\right]=\left[\begin{array}{c}X_{1}^{\prime} \\ X_{2}^{\prime} \\ X_{3}^{\prime} \\ \ldots\end{array}\right] \quad \min \|A x-B\|^{2}$
overconstrained

Fitting an affine transformation

$$
\left[\begin{array}{cccccc} 
& & \cdots & & & \\
x_{i} & y_{i} & 0 & 0 & 1 & 0 \\
0 & 0 & x_{i} & y_{i} & 0 & 1 \\
& \cdots & & & 1
\end{array}\right]\left[\begin{array}{c}
m_{1} \\
m_{2} \\
m_{3} \\
m_{4} \\
t_{1} \\
t_{2}
\end{array}\right]=\left[\begin{array}{c}
\cdots \\
x_{i}^{\prime} \\
y_{i}^{\prime} \\
\cdots
\end{array}\right]
$$

- How many matches (correspondence pairs) do we need to solve for the transformation parameters?
- Once we have solved for the parameters, how do we compute the coordinates of the corresponding point for $\left(x_{\text {new }}, y_{\text {new }}\right)$ ?
- Where do the matches come from?


## Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?


$$
\left[\begin{array}{l}
x_{i}^{\prime} \\
y_{i}^{\prime}
\end{array}\right]=\left[\begin{array}{ll}
m_{1} & m_{2} \\
m_{3} & m_{4}
\end{array}\right]\left[\begin{array}{l}
x_{i} \\
y_{i}
\end{array}\right]+\left[\begin{array}{l}
t_{1} \\
t_{2}
\end{array}\right]\left[\begin{array}{c}
m_{1} \\
m_{2} \\
m_{3} \\
m_{4} \\
t_{1} \\
t_{2}
\end{array}\right]=[]
$$

## What are the correspondences?



- Compare content in local patches, find best matches. e.g., simplest approach: scan with template, and compute SSD or correlation between list of pixel intensities in the patch
- Later in the course: how to select regions according to the geometric changes, and more robust descriptors.

Fitting an affine transformation


Affine model approximates perspective projection of planar objects.

## Outliers

- Outliers can hurt the quality of our parameter estimates, e.g.,
- an erroneous pair of matching points from two images
- an edge point that is noise, or doesn't belong to the line we are fitting.

Kristen Grauman

Outliers affect least squares fit


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## RANSAC

- RANdom Sample Consensus
- Approach: we want to avoid the impact of outliers, so let's look for "inliers", and use those only.
- Intuition: if an outlier is chosen to compute the current fit, then the resulting line won't have much support from rest of the points.





## RANSAC for line fitting

## Repeat $\boldsymbol{N}$ times:

- Draw $\boldsymbol{s}$ points uniformly at random
- Fit line to these $\boldsymbol{s}$ points
- Find inliers to this line among the remaining points (i.e., points whose distance from the line is less than $t$ )
- If there are $\boldsymbol{d}$ or more inliers, accept the line and refit using all inliers


## RANSAC pros and cons

- Pros
- Simple and general
- Applicable to many different problems
- Often works well in practice
- Cons
- Lots of parameters to tune
- Doesn't work well for low inlier ratios (too many iterations, or can fail completely)
- Can't always get a good initialization of the model based on the minimum number of samples



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