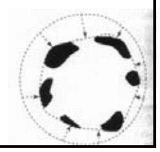
Fitting: Deformable contours

Thursday, Sept 24
Kristen Grauman
UT-Austin

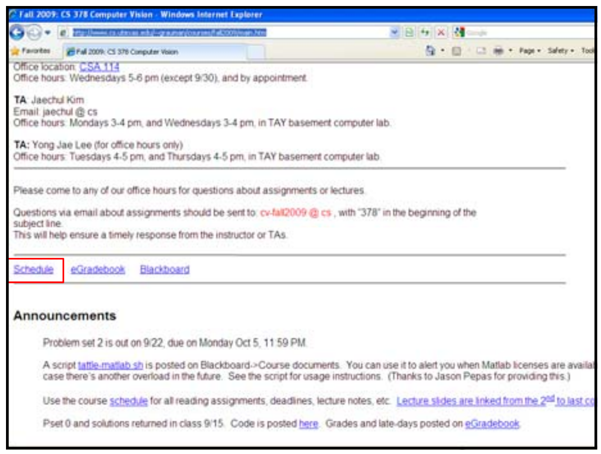


Announcements

- Next week : guest lectures
  - Tuesday : Background modeling
  - Thursday : Image formation
- Yong Jae and I are not available for office hours next week. Jaechul is available as usual.

Announcements

- Matlab issues: ask us about Matlab coding problems.
  - e.g., "How do I remove a different pixel from each row? When I try to delete them this way (XYZ), I get a size error…"
  - (but not: "What does the function imfilter do?")
- Check the functions listed in the psets
  - help <function name>



Fall 2009: CS 378 Computer Vision - Windows Internet Explorer

Office location: CSA 114
Office hours: Wednesdays 5-6 pm (except 9/30), and by appointment

TA: Jaechul Kim
Email: jaechul @ cs
Office hours: Mondays 3-4 pm, and Wednesdays 3-4 pm, in TAY basement computer lab.

TA: Yong Jae Lee (for office hours only)
Office hours: Tuesdays 4-5 pm, and Thursdays 4-5 pm, in TAY basement computer lab.

Please come to any of our office hours for questions about assignments or lectures.

Questions via email about assignments should be sent to: cv-fall2009 @ cs , with "378" in the beginning of the subject line.
This will help ensure a timely response from the instructor or TAs.

Schedule eGradebook Blackboard

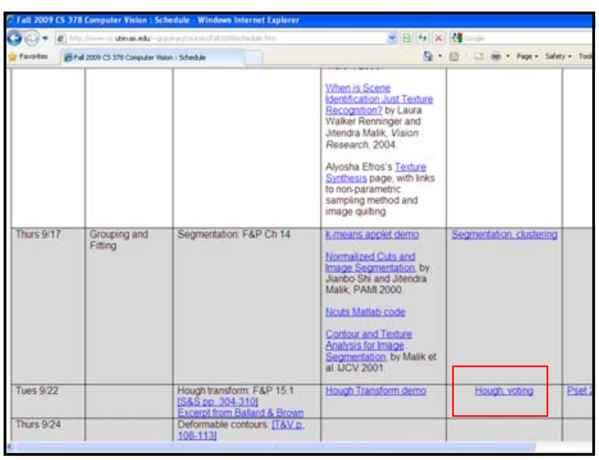
Announcements

Problem set 2 is out on 9/22, due on Monday Oct 5, 11:59 PM.

A script tattle-matlab.sh is posted on Blackboard->Course documents. You can use it to alert you when Matlab licenses are availal case there's another overload in the future. See the script for usage instructions. (Thanks to Jason Pepas for providing this.)

Use the course schedule for all reading assignments, deadlines, lecture notes, etc. Lecture slides are linked from the 2nd to last co

Pset 0 and solutions returned in class 9/15. Code is posted here. Grades and late-days posted on eGradebook.



Fall 2009 CS 378 Computer Vision : Schedule - Windows Internet Explorer

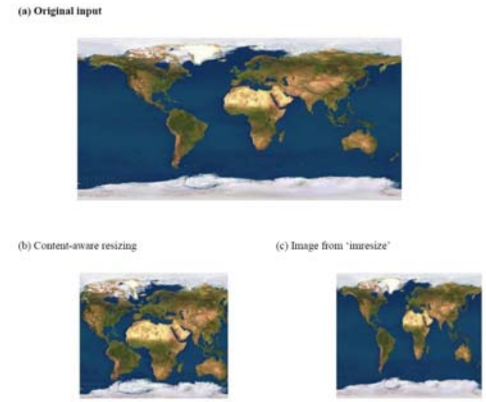
			When is Scene Identification Just Texture Recognition? by Laura Walker Renninger and Jitendra Malik, *Vision Research*, 2004. Alyosha Efros's Texture Synthesis page, with links to non-parametric sampling method and image quilting		
Thurs 9/17	Grouping and Fitting	Segmentation: F&P Ch 14	k-means applet demo Normalized Cuts and Image Segmentation, by Jianbo Shi and Jitendra Malik, PAMI 2000. Ncuts Matlab code Contour and Texture Analysis for Image Segmentation, by Malik et al. IJCV 2001	Segmentation, clustering	
Tues 9/22		Hough transform: F&P 15.1 [S&S pp. 304-310] Excerpt from Ballard & Brown	Hough Transform demo	Hough, voting	Pset 2
Thurs 9/24		Deformable contours: [T&V p. 108-113]			

Some seam carving results from Pset 1

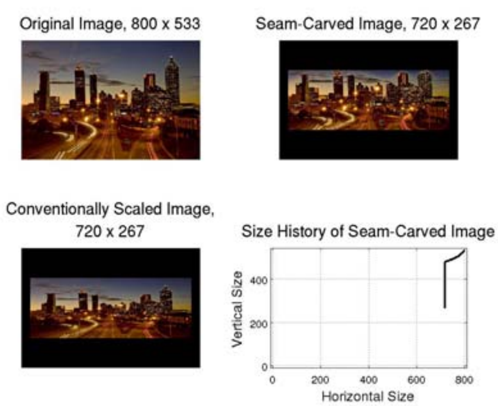
Results from Michael Yao

- Left, “chinese_opera.jpg” (768x600), Original
- Top Right, “chinese_opera-dumb-resize.jpg”(400x768), Regular Resize
- Bottom Right, “chinese_opera-seamcarving-resize.jpg”(400x768), Content Aware Resize

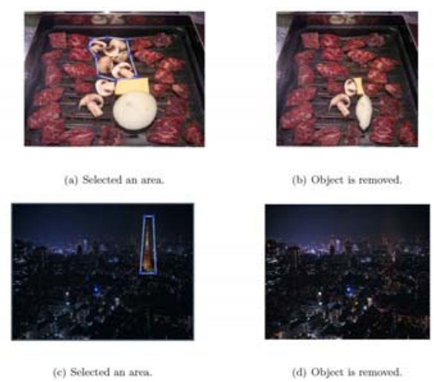
Results from Eunho Yang



Results from Larry Lindsey



Results from Donghyuk Shin



Removal of a marked object

Results from Donghyuk Shin

Original image (500 by 368)

Seam carving using HSV (300 by 268)

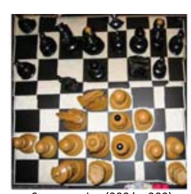
Convention resize(300 by 268)

Seam carving using a gradient energy (300 by 268)

This example shows a hue-based skin detector works well to preserve the face in seam carving. However, we can see the body is largely removed, producing a undesirable artifact in the proportion between face and body.

Results from Michael Fairley

Original image (500 by 500)

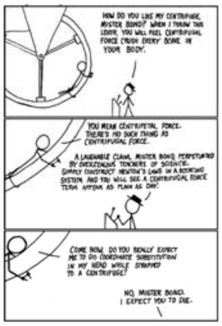


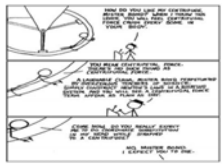
Seam carving (300 by 300)

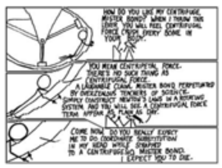
Conventional resize (300 by 300)

***This example shows a failure case of seam carving in an image with a regular texture pattern.**

Results from Dustin Ho


Original image


Conventional resize


Seam carving

Results from Jay Hennig

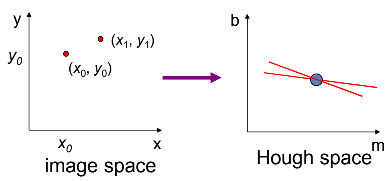

Original image (599 by 799)

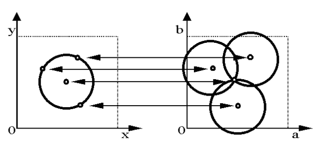

Conventional resize (399 by 599)


Seam carving (399 by 599)

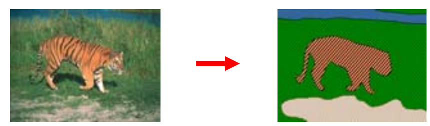
Last time: Fitting with "voting"

- Hough transform for fitting lines, circles





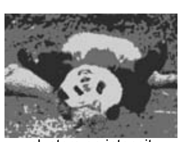
Grouping and Fitting



Goal: move from array of pixel values (or filter outputs) to a collection of regions, objects, and shapes.

Pixels vs. regions


image


clusters on intensity


image


clusters on color

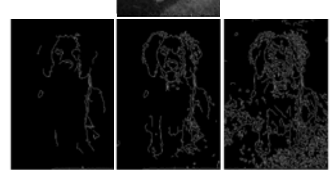
By grouping pixels based on Gestalt-inspired attributes, we can map the pixels into a set of regions.

Each region is consistent according to the features and similarity metric we used to do the **clustering**.

Edges vs. boundaries

Edges useful signal to indicate occluding boundaries, shape.

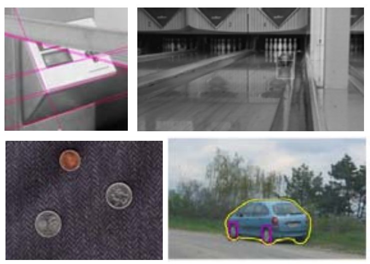
Here the raw edge output is not so bad…



…but quite often boundaries of interest are fragmented, and we have extra "clutter" edge points.

Images from D. Jacobs

Edges vs. boundaries



Given a model of interest, we can overcome some of the missing and noisy edges using **fitting** techniques.

With voting methods like the **Hough transform**, detected points vote on possible model parameters.

Previously, we focused on the case where a line or circle was the model…

Today

- Fitting an arbitrary shape model with Generalized Hough Transform
- Fitting an arbitrary shape with "active" deformable contours

Generalized Hough transform

- What if want to detect arbitrary shapes defined by boundary points and a reference point?

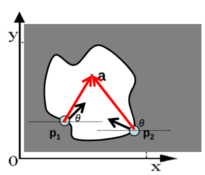


Image space

At each boundary point, compute displacement vector: $\mathbf{r} = \mathbf{a} - \mathbf{p}_i$.

For a given model shape: store these vectors in a table indexed by gradient orientation θ.

[Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980]

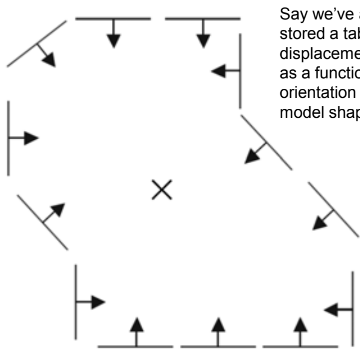
Generalized Hough transform

To *detect* the model shape in a new image:

- For each edge point
  - Index into table with its gradient orientation *θ*
  - Use retrieved **r** vectors to vote for position of reference point
- Peak in this Hough space is reference point with most supporting edges

Assuming translation is the only transformation here, i.e., orientation and scale are fixed.

Example

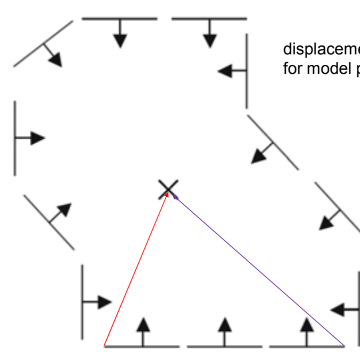


Say we've already stored a table of displacement vectors as a function of edge orientation for this model shape.

model shape

Adapted from Lana Lazebnik

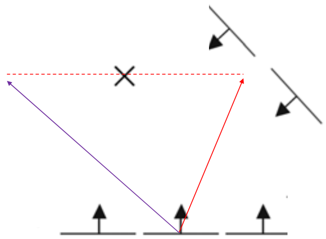
Example



displacement vectors for model points

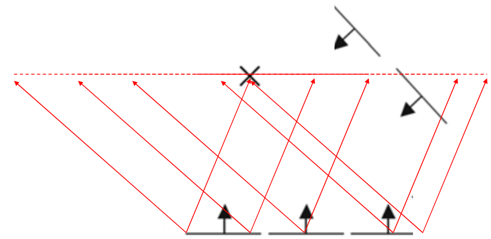
Example

Now we want to look at some edge points detected in a *new* image, and vote on the position of that shape.



range of voting locations for test point

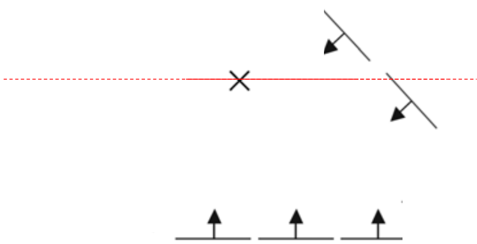
Example



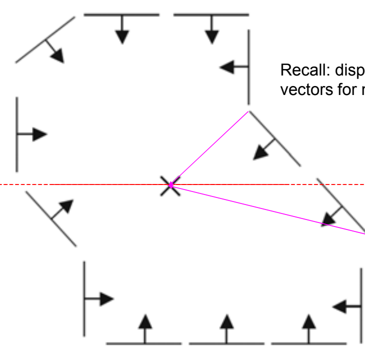
range of voting locations for test point

Example

votes for points with $\theta = \uparrow$

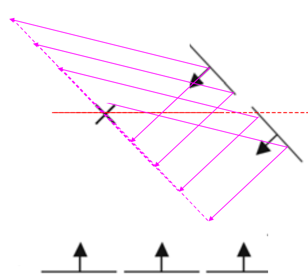


Example



Recall: displacement vectors for model points

Example

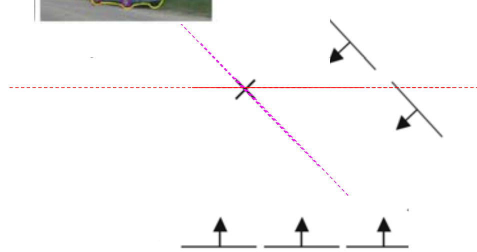


range of voting locations for test point

Example

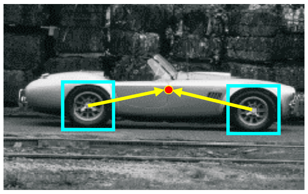
votes for points with $\theta = \swarrow$

votes for points with $\theta = \uparrow$



Application of Generalized Hough for recognition

- Instead of indexing displacements by gradient orientation, index by "visual codeword"



training image

visual codeword with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Slide credit: L. Lazebnik

Application of Generalized Hough for recognition

- Instead of indexing displacements by gradient orientation, index by "visual codeword"

test image

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Slide credit: L. Lazebnik

Today

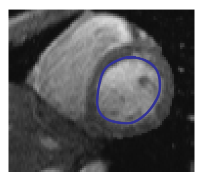
- Fitting an arbitrary shape model with Generalized Hough Transform
- Fitting an arbitrary shape with "active" deformable contours

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

[Snakes: Active contour models, Kass, Witkin, & Terzopoulos, ICCV1987]

Figure credit: Yuri Boykov

Deformable contours: intuition

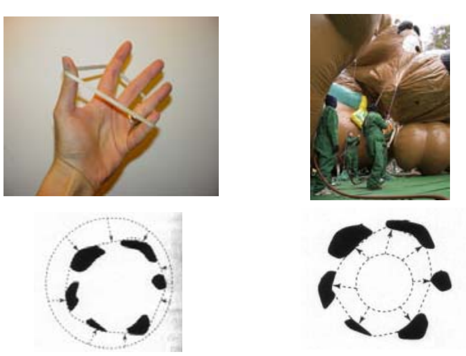
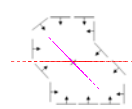
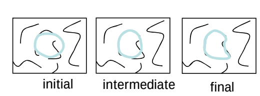


Image from http://www.healthline.com/blogs/exercise_fitness/uploaded_images/HandBand2-795868.JPG

Deformable contours vs. Hough

Like generalized Hough transform, useful for shape fitting; but





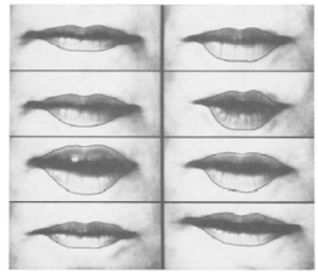
Hough
Rigid model shape
Single voting pass can detect multiple instances

Deformable contours
Prior on shape types, but shape iteratively adjusted (*deforms*)
Requires initialization nearby
One optimization "pass" to fit a single contour

Why do we want to fit deformable shapes?

- Some objects have similar basic form but some variety in the contour shape.

Why do we want to fit deformable shapes?



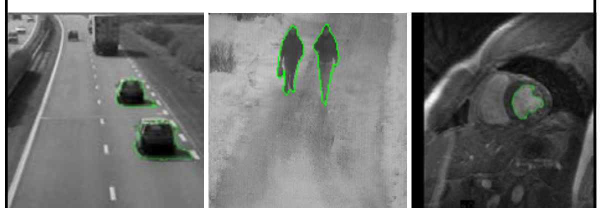
- Non-rigid, deformable objects can change their shape over time, e.g. lips, hands…

Figure from Kass et al. 1987

Why do we want to fit deformable shapes?

- Non-rigid, deformable objects can change their shape over time, e.g. lips, hands…

Why do we want to fit deformable shapes?



- Non-rigid, deformable objects can change their shape over time.

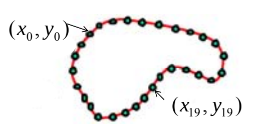
Figure credit: Julien Jomier

Aspects we need to consider

- Representation of the contours
- Defining the energy functions
  - External
  - Internal
- Minimizing the energy function
- Extensions:
  - Tracking
  - Interactive segmentation

Representation

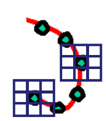
- We'll consider a discrete representation of the contour, consisting of a list of 2d point positions ("vertices").



$$v_i = (x_i, y_i),$$

for $i = 0, 1, \ldots, n-1$

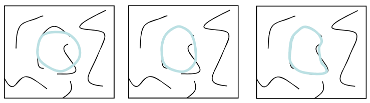
- At each iteration, we'll have the option to move each vertex to another nearby location ("state").



Fitting deformable contours

How should we adjust the current contour to form the new contour at each iteration?

- Define a cost function ("energy" function) that says how good a candidate configuration is.
- Seek next configuration that minimizes that cost function.



initial intermediate final

Energy function

The total energy (cost) of the current snake is defined as:

$$E_{total} = E_{internal} + E_{external}$$

Internal energy: encourage *prior* shape preferences: e.g., smoothness, elasticity, particular known shape.

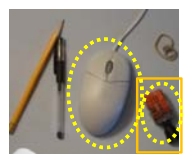
External energy ("image" energy): encourage contour to fit on places where image structures exist, e.g., edges.

A good fit between the current deformable contour and the target shape in the image will yield a **low** value for this cost function.

External energy: intuition

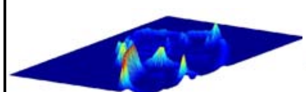
- Measure how well the curve matches the image data
- "Attract" the curve toward different image features
  - Edges, lines, texture gradient, etc.

External image energy



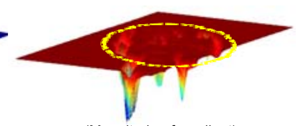
How do edges affect "snap" of rubber band?

Think of external energy from image as gravitational pull towards areas of high contrast



Magnitude of gradient

$$G_x(I)^2 + G_y(I)^2$$

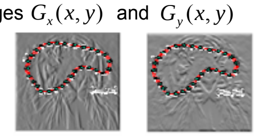


- (Magnitude of gradient)

$$-\left(G_x(I)^2 + G_y(I)^2\right)$$

External image energy

- Gradient images $G_x(x,y)$ and $G_y(x,y)$



- External energy at a point on the curve is:

$$E_{external}(\nu) = -(\,|G_x(\nu)|^2 + |G_y(\nu)|^2\,)$$

- External energy for the whole curve:

$$E_{external} = -\sum_{i=0}^{n-1} |G_x(x_i, y_i)|^2 + |G_y(x_i, y_i)|^2$$

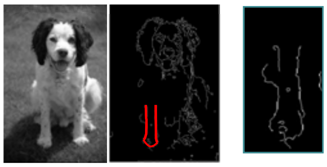
Internal energy: intuition

What are the underlying boundaries in this fragmented edge image?

And in this one?

Internal energy: intuition

A priori, we want to favor **smooth** shapes, contours with **low curvature**, contours similar to a **known shape**, etc. to balance what is actually observed (i.e., in the gradient image).



Internal energy

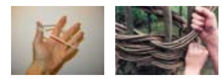
For a *continuous* curve, a common internal energy term is the "bending energy".

At some point *v(s)* on the curve, this is:

$$E_{internal}(\nu(s)) = \alpha \left|\frac{d\nu}{ds}\right|^2 + \beta \left|\frac{d^2\nu}{d^2 s}\right|^2$$

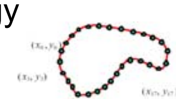
Tension, Elasticity

Stiffness, Curvature



Internal energy

- For our discrete representation,



$$\nu_i = (x_i, y_i) \qquad i = 0 \;....\; n-1$$

$$\frac{d\nu}{ds} \approx \nu_{i+1} - \nu_i \qquad \frac{d^2\nu}{ds^2} \approx (\nu_{i+1} - \nu_i) - (\nu_i - \nu_{i-1}) = \nu_{i+1} - 2\nu_i + \nu_{i-1}$$

- Internal energy for the whole curve:

$$E_{internal} = \sum_{i=0}^{n-1} \alpha \left\|\nu_{i+1} - \nu_i\right\|^2 + \beta \left\|\nu_{i+1} - 2\nu_i + \nu_{i-1}\right\|^2$$

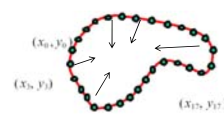
*Why do these reflect **tension** and **curvature**?*

Penalizing elasticity

- Current elastic energy definition uses a discrete estimate of the derivative:

$$E_{elastic} = \sum_{i=0}^{n-1} \alpha \left\|\nu_{i+1} - \nu_i\right\|^2$$

$$= \alpha \cdot \sum_{i=0}^{n-1} (x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2$$



What is the possible problem with this definition?

Penalizing elasticity

- Current elastic energy definition uses a discrete estimate of the derivative:

$$E_{elastic} = \sum_{i=0}^{n-1} \alpha \left\|\nu_{i+1} - \nu_i\right\|^2$$

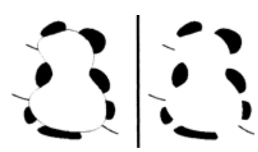
Instead:

$$= \alpha \cdot \sum_{i=0}^{n-1} \left((x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 - \bar{d} \right)^2$$

where *d* is the average distance between pairs of points – updated at each iteration.

Dealing with missing data

- The preferences for low-curvature, smoothness help deal with missing data:

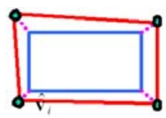


Illusory contours found!

[Figure from Kass et al. 1987]

Extending the internal energy: capture shape prior

- If object is some smooth variation on a known shape, we can use a term that will penalize deviation from that shape:



$$E_{internal} += \alpha \cdot \sum_{i=0}^{n-1} (v_i - \hat{v}_i)^2$$

where $\{\hat{v}_i\}$ are the points of the known shape.

Fig from Y. Boykov

Total energy

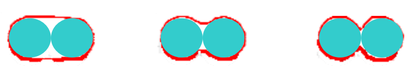
$$E_{total} = E_{internal} + \gamma E_{external}$$

$$E_{external} = -\sum_{i=0}^{n-1} |G_x(x_i, y_i)|^2 + |G_y(x_i, y_i)|^2$$

$$E_{internal} = \sum_{i=0}^{n-1} \alpha \left(\bar{d} - \|v_{i+1} - v_i\|\right)^2 + \beta \|v_{i+1} - 2v_i + v_{i-1}\|^2$$

Function of the weights

- e.g., α weight controls the penalty for internal elasticity

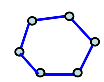


large α medium α small α

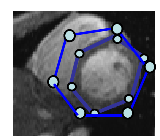
Fig from Y. Boykov

Recap: deformable contour

- A simple elastic snake is defined by:
  - A set of *n* points,
  - An internal energy term (tension, bending, plus optional shape prior)
  - An external energy term (gradient-based)



- To use to segment an object:
  - Initialize in the vicinity of the object
  - Modify the points to minimize the total energy

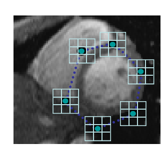


Energy minimization

- Several algorithms have been proposed to fit deformable contours.
- We'll look at two:
  - Greedy search
  - Dynamic programming (for 2d snakes)

Energy minimization: greedy

- For each point, search window around it and move to where energy function is minimal
  - Typical window size, e.g., 5 x 5 pixels

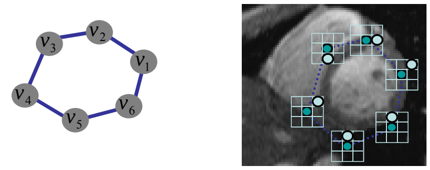


- Stop when predefined number of points have not changed in last iteration, or after max number of iterations
- Note:
  - Convergence not guaranteed
  - Need decent initialization

Energy minimization

- Several algorithms have been proposed to fit deformable contours.
- We'll look at two:
  - Greedy search
  - Dynamic programming (for 2d snakes)

Energy minimization: dynamic programming



With this form of the energy function, we can minimize using dynamic programming, with the *Viterbi* algorithm.

Iterate until optimal position for each point is the center of the box, i.e., the snake is optimal in the local search space constrained by boxes.

Fig from Y. Boykov
[Amini, Weymouth, Jain, 1990]

Energy minimization: dynamic programming

- Possible because snake energy can be rewritten as a sum of pair-wise interaction potentials:

$$E_{total}(v_1,\ldots,v_n) = \sum_{i=1}^{n-1} E_i(v_i, v_{i+1})$$

- Or sum of triple-interaction potentials.

$$E_{total}(v_1,\ldots,v_n) = \sum_{i=1}^{n-1} E_i(v_{i-1}, v_i, v_{i+1})$$

Snake energy: pair-wise interactions

$$E_{total}(x_1,\ldots,x_n,y_1,\ldots,y_n) = -\sum_{i=1}^{n-1} |G_x(x_i,y_i)|^2 + |G_y(x_i,y_i)|^2 + \alpha \cdot \sum_{i=1}^{n-1} (x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2$$

Re-writing the above with $v_i = (x_i, y_i)$:

$$E_{total}(v_1,\ldots,v_n) = -\sum_{i=1}^{n-1} \|G(v_i)\|^2 + \alpha \cdot \sum_{i=1}^{n-1} \|v_{i+1}-v_i\|^2$$

$$E_{total}(v_1,\ldots,v_n) = E_1(v_1,v_2) + E_2(v_2,v_3) + \ldots + E_{n-1}(v_{n-1},v_n)$$

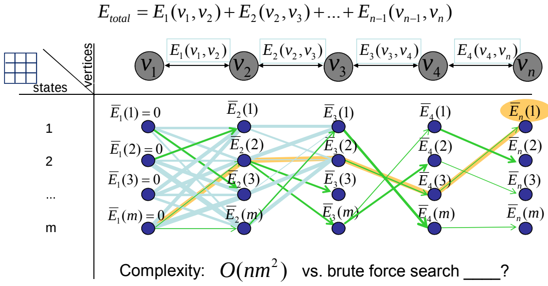
where $E_i(v_i, v_{i+1}) = -\|G(v_i)\|^2 + \alpha \|v_{i+1}-v_i\|^2$

In which terms of this sum will a vertex v_i show up?

Viterbi algorithm

Main idea: determine optimal position (state) of predecessor, for each possible position of self. Then backtrack from best state for last vertex.

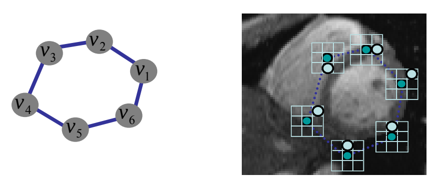
$$E_{total} = E_1(v_1,v_2) + E_2(v_2,v_3) + \ldots + E_{n-1}(v_{n-1},v_n)$$



Complexity: $O(nm^2)$ vs. brute force search ____?

Example adapted from Y. Boykov

Energy minimization: dynamic programming



With this form of the energy function, we can minimize using dynamic programming, with the *Viterbi* algorithm.

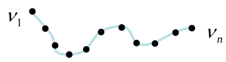
Iterate until optimal position for each point is the center of the box, i.e., the snake is optimal in the local search space constrained by boxes.

Fig from Y. Boykov
[Amini, Weymouth, Jain, 1990]

Energy minimization: dynamic programming

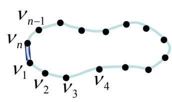
DP can be applied to optimize an open ended snake

$$E_1(v_1,v_2)+E_2(v_2,v_3)+\ldots+E_{n-1}(v_{n-1},v_n)$$



For a closed snake, a "loop" is introduced into the total energy.

$$E_1(v_1,v_2)+E_2(v_2,v_3)+\ldots+E_{n-1}(v_{n-1},v_n)+\boxed{E_n(v_n,v_1)}$$



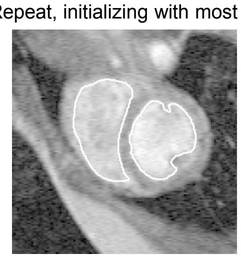
Work around:
1) Fix v_1 and solve for rest .
2) Fix an intermediate node at its position found in (1), solve for rest.

Aspects we need to consider

- Representation of the contours
- Defining the energy functions
  - External
  - Internal
- Minimizing the energy function
- Extensions:
  - Tracking
  - Interactive segmentation

Tracking via deformable contours

1. Use final contour/model extracted at frame *t* as an initial solution for frame *t+1*
2. Evolve initial contour to fit exact object boundary at frame *t+1*
3. Repeat, initializing with most recent frame.



Tracking Heart Ventricles (multiple frames)

Tracking via deformable contours

Visual Dynamics Group, Dept. Engineering Science, University of Oxford.

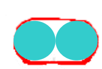
Applications: Traffic monitoring
Human-computer interaction
Animation
Surveillance
Computer assisted diagnosis in medical imaging

3D active contours

Jorgen Ahlberg
http://www.cvl.isy.liu.se/ScOut/Masters/Papers/Ex1708.pdf

Limitations

- May over-smooth the boundary



- Cannot follow topological changes of objects

Limitations

- External energy: snake does not really "see" object boundaries in the image unless it gets very close to it.

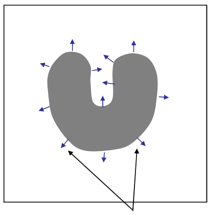


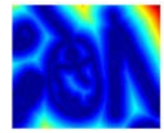
image gradients ∇I
are large only directly on the boundary

Distance transform

- External image can instead be taken from the **distance transform** of the edge image.

original

-gradient



distance transform

edges

Value at (x,y) tells how far that position is from the nearest edge point (or other binary mage structure)

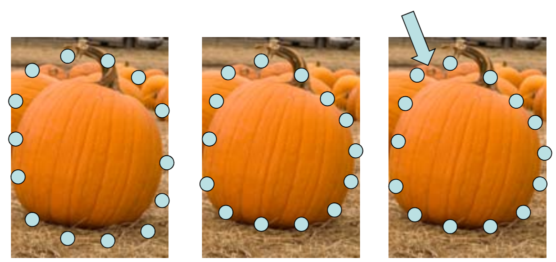
```
>> help bwdist
```

Deformable contours: pros and cons

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.

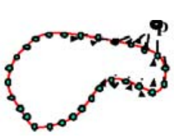
Cons:
- Must have decent initialization near true boundary, may get stuck in local minimum
- Parameters of energy function must be set well based on prior information

Interactive forces



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:



$$E_{push} = \sum_{i=0}^{n-1} \frac{r^2}{|\nu_i - p|^2}$$

Nearby points get pushed hardest

What expression could we use to pull points towards the cursor position?

Intelligent scissors

Another form of interactive segmentation:

Use dynamic programming to compute optimal paths from every point to the seed based on edge-related costs.

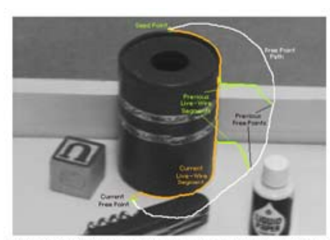
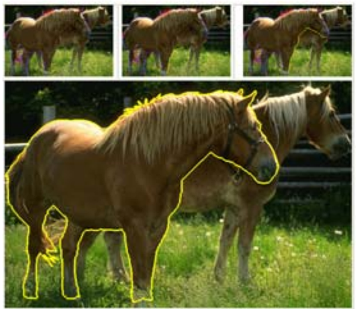


Figure 2: *Image demonstrating how the live-wire segment adapts and snaps to an object boundary as the free point moves (via cursor movement). The path of the free point is shown in white. Live-wire segments from previous free point positions (t_0, t_1, and t_2) are shown in green.*

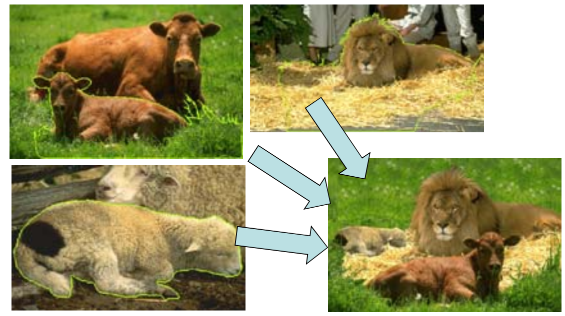
[Mortensen & Barrett, SIGGRAPH 1995, CVPR 1999]

Intelligent scissors



- http://rivit.cs.byu.edu/Eric/Eric.html

Intelligent scissors



- http://rivit.cs.byu.edu/Eric/Eric.html

Summary

- Deformable shapes and active contours are useful for
  - Segmentation: fit or “snap” to boundary in image
  - Tracking: previous frame’s estimate serves to initialize the next
- Fitting active contours:
  - Define terms to encourage certain shapes, smoothness, low curvature, push/pulls, …
  - Use weights to control relative influence of each component cost
  - Can optimize 2d snakes with Viterbi algorithm.
- Image structure (esp. gradients) can act as attraction force for *interactive* segmentation methods.

Recap: mid-level vision Features → regions, shapes, boundaries

- **Segment regions** (last Thursday)
  - cluster pixel-level features, like color, texture, position
  - leverage Gestalt properties
- **Fitting models** (Tuesday)
  - explicit rigid parametric models such as lines and circles, or arbitrary shapes defined by boundary points and reference point
  - voting methods useful to combine grouping of tokens and fitting of parameters; e.g. Hough transform
- **Detection of *deformable* contours, and *interactive* segmentation** (today)
  - provide rough initialization nearby true boundary, or
  - interactive, iterative process where user guides the boundary placement

Coming up

- Tues: Background modeling
  - Read F&P 14.3
  - Stauffer & Grimson paper
- Thurs: Image formation
  - Read F&P Chapter 1
- Pset 1 due Mon 10/5