Shape Analysis

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BIL717, April 2012

Introduction

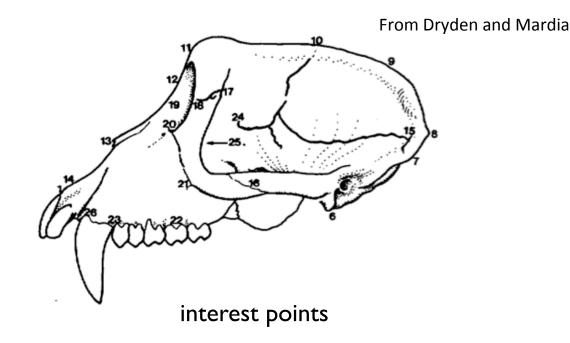
- <u>Shape</u> is the primary source of visual information
 - Objects can be immediately recognized and classified based on their shapes
- Other visual clues are color, texture, spatial and temporal information, etc.



Slide: A. Erdem

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- Common shape representations:
 - Landmarks

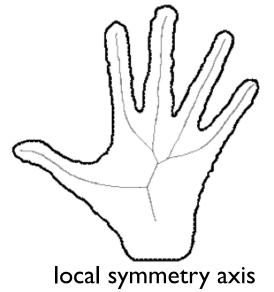


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 - Shape Boundary



points, splines, level sets, etc.

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- Common shape representations:
 - Landmarks
 - Shape Boundary
 - Shape Skeleton

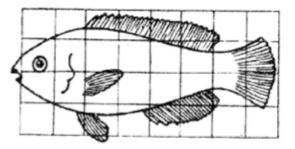


From "Skeletons and segmentation of shapes", Shah, 2005

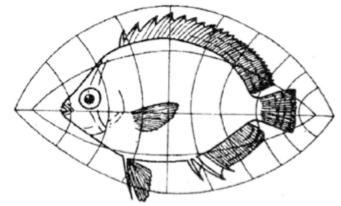
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• Common shape representations:

- Landmarks
- Shape Boundary
- Shape Skeleton
- Transformation models



From D'Arcy Thomson's On Growth and Form



diffeomorphisms

• A general theory of shape does not exist to date.

• Common shape representations:

- Landmarks
- Shape Boundary
- Shape Skeleton
- Transformation models
- Implicit representations
- Each representation has its own strengths and weaknesses

Implicit Shape Representations

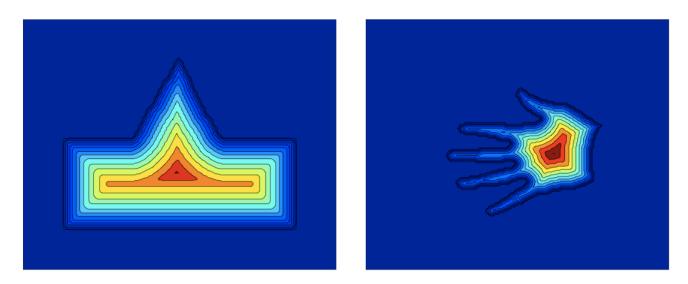
- Distance transform
- TSP Surfaces [Tari, Shah and Pien, 1997]
- Poisson Transform [Gorelick et al., 2006]
- Integral Kernels [Hong et al., 2006]



Distance Transform

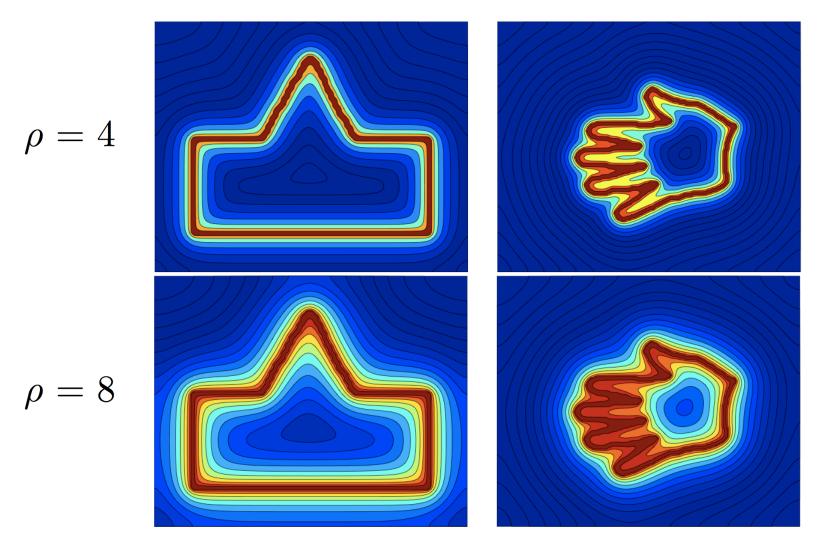
• Estimate a surface whose value at each internal point is the minimum distance of the point to the shape boundary

$$\phi(x) = \min_{y \in \Gamma} dist(x, y) \qquad |\nabla \phi| = 1$$

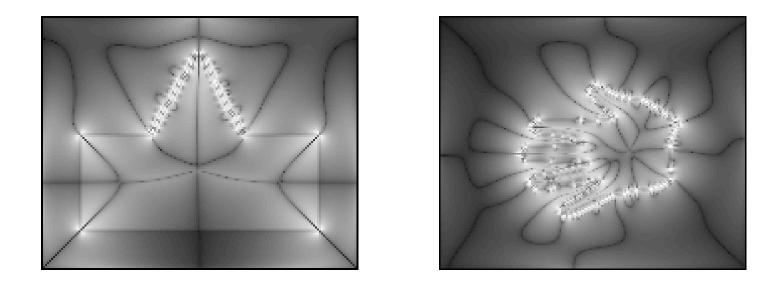


- depends on the Ambrosio-Tortorelli model
- A sufficiently large value of ρ , instead of a small one
- For a binary silhouette, a TSP surface is estimated by solving:

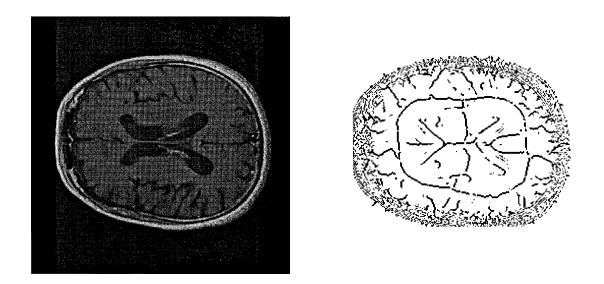
$$\frac{\partial v}{\partial t} = \nabla^2 v - \frac{v}{\rho^2}, \quad v|_{\Gamma} = 1$$



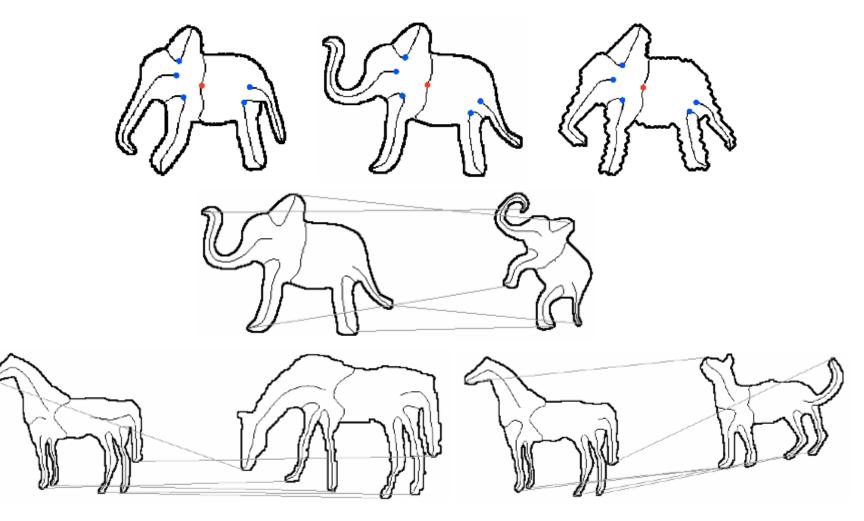
- The TSP method can be easily extended to grayscale images.
- The TSP surfaces encode the skeleton information.



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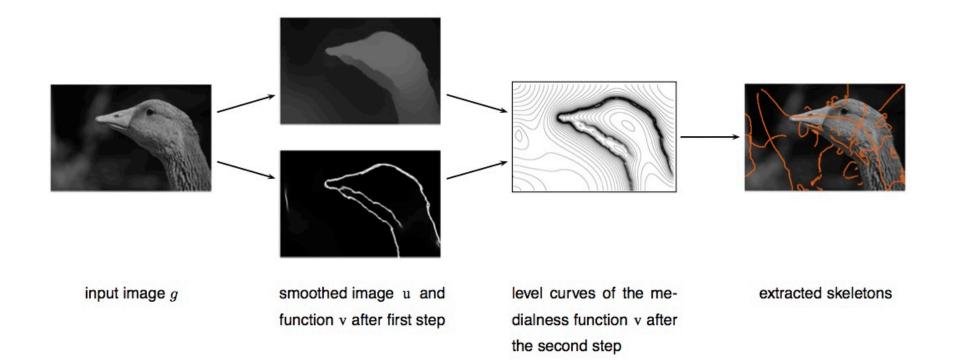


Disconnected Skeleton



C. Aslan and S. Tari, An Axis-Based Representation for Recognition, ICCV, 2005 C. Aslan, A. Erdem, E. Erdem and S. Tari, Disconnected Skeleton: Shape at its Absolute Scale. IEEE Trans. Pattern Anal. Mach. Intel., 2008

Skeleton Extraction from Natural Images



E. Erdem and S. Tari, unpublished work

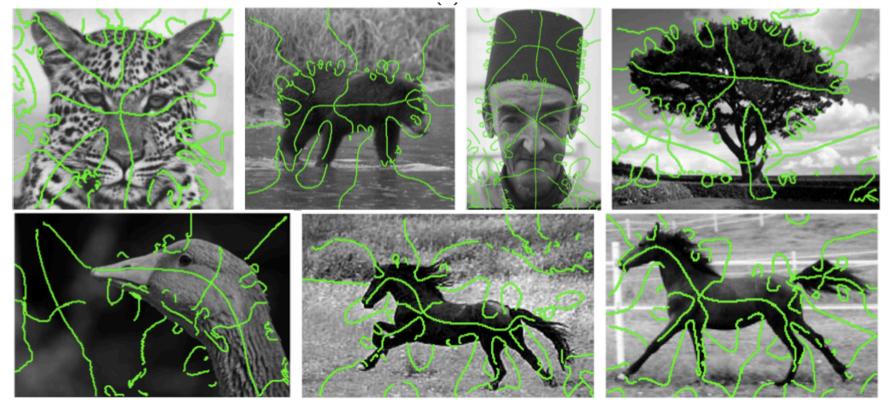
Skeleton Extraction from Natural Images



sample input images

E. Erdem and S. Tari, unpublished work

Skeleton Extraction from Natural Images



proposed method

E. Erdem and S. Tari, unpublished work

Poisson Transform

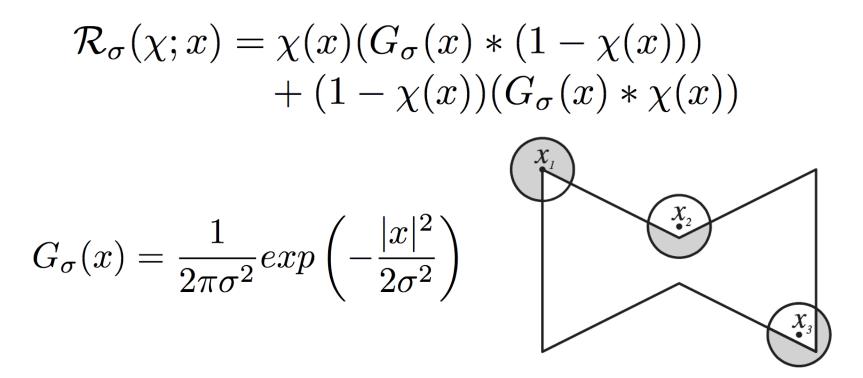
• Estimate a surface from a given silhouette by solving a Poisson equation

$$\nabla^2 U = \frac{\partial^2 U}{\partial x^2} + \frac{\partial^2 U}{\partial y^2} = -1 \qquad U(x,y)\Big|_{\partial S} = 0$$

Gorelick et al., Shape representation and classification using the poisson equation, IEEE TPAMI, 28(12),2006

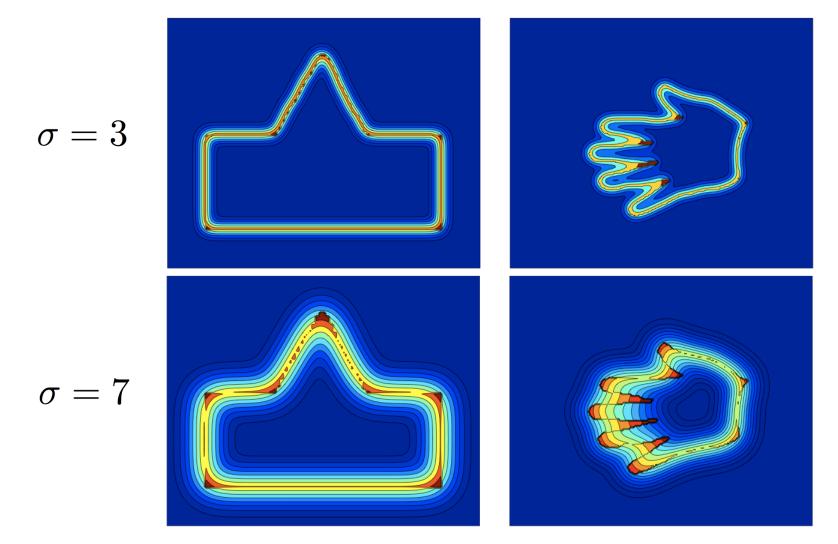
Integral Kernels

 Describe the local structure of a shape by using a kernel representation



Hong et al., Shape representation based on integral kernels: Application to image matching and segmentation, CVPR, 2006

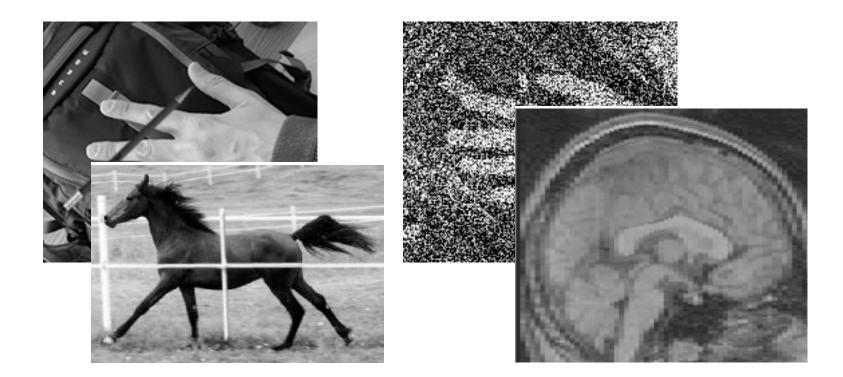
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Hong et al., Shape representation based on integral kernels: Application to image matching and segmentation, CVPR, 2006

Segmentation

• Partition an image into meaningful regions that are likely to correspond to objects exist in the image



Prior-Guided Segmentation

- Incorporate prior shape information into the segmentation process
- Early 2000, -
 - Leventon et al.'00, Rousson and Paragios'02,
 Cremers et al.'02, Tsai et al.'03, Riklin-Raviv et al.'04, Hong et al.'06, …
 - Borenstein and Ullman'02, Leibe et al.'04,
 Shotton et al.'05, Opelt et al.'06, ...

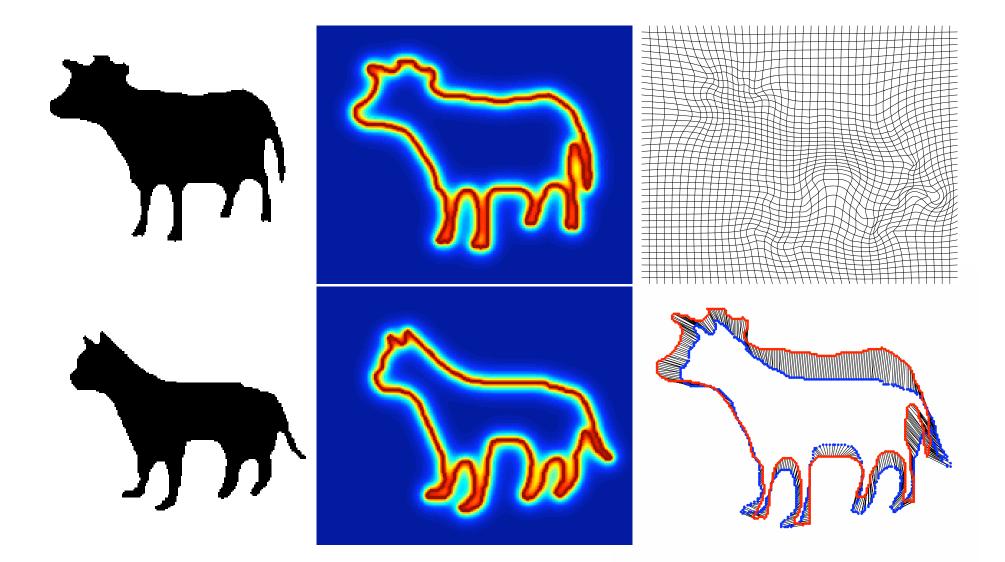
Shape Matching Using A Local Deformation Model

- Determine correspondences between two shapes
- <u>Matching as a registration problem [Hong et al'06]</u>: Estimate a transformation function between two shapes

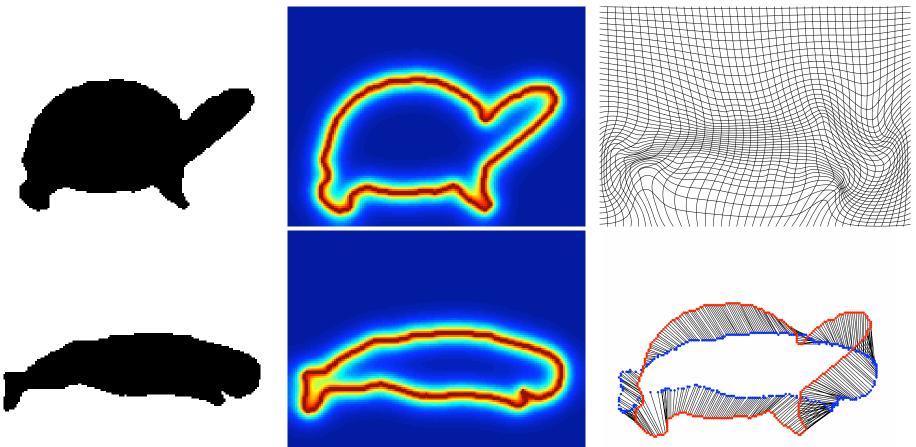
$$E_{match}(h) = E_{fid}(h) + \beta E_{reg}(h)$$

$$E_{fid}(h) = \frac{1}{2} \int_{\Omega} \left(v_2(x+h(x)) - v_1(x) \right)^2 dx$$
$$E_{reg}(h) = \int_{\Omega} \left(\frac{\bar{\mu}}{4} \sum_{i,j=1}^2 \left(\partial_{x_i} h_j + \partial_{x_j} h_i \right)^2 + \frac{\lambda}{2} (\nabla \cdot h)^2 \right) dx$$

Matching Examples



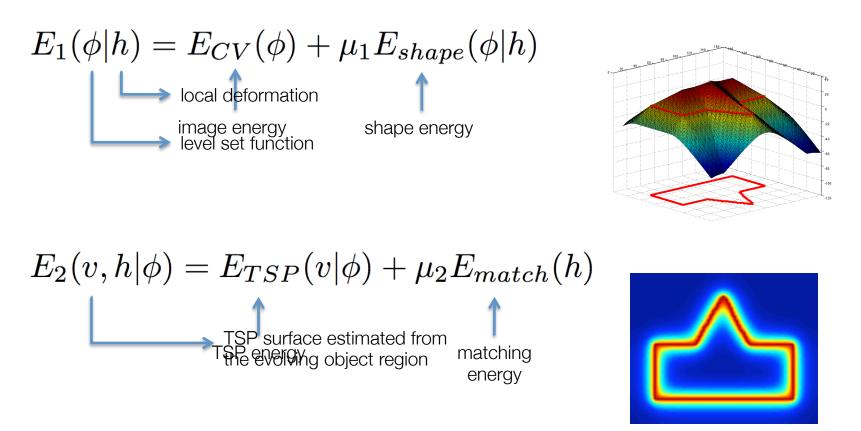
Matching Examples



- Shapes are registered accurately, yet the correspondences are not meaningful
- Shapes to be matched should be locally similar

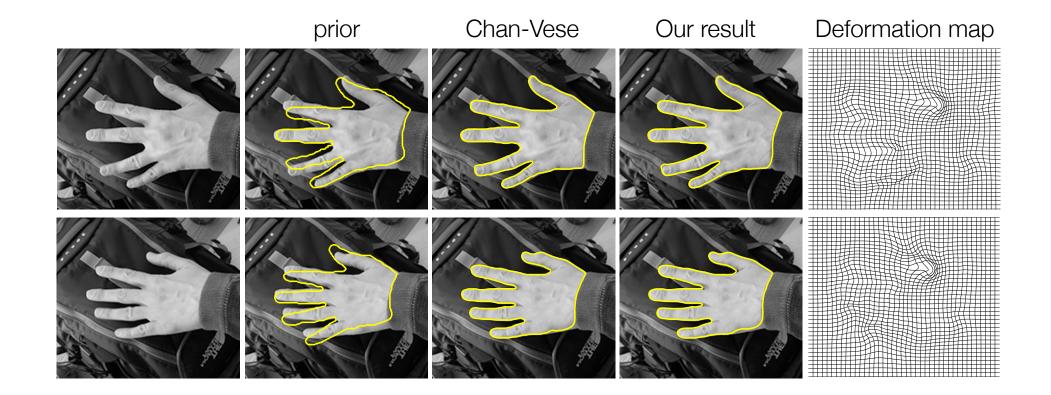
Prior-Guided Segmentation Framework

Segmentation by minimizing coupled energies

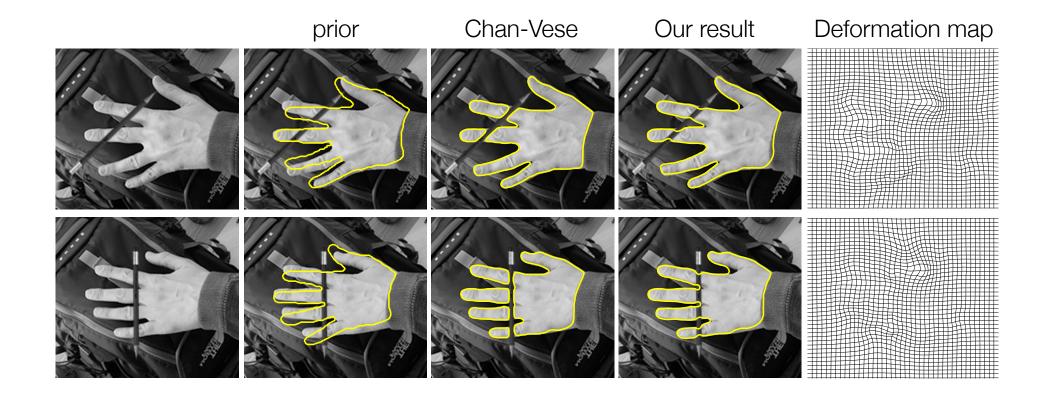


Erdem, Tari and Vese, Segmentation Using the Edge Strength Function as a Shape Prior within a Local Deformation Model, ICIP, 2009

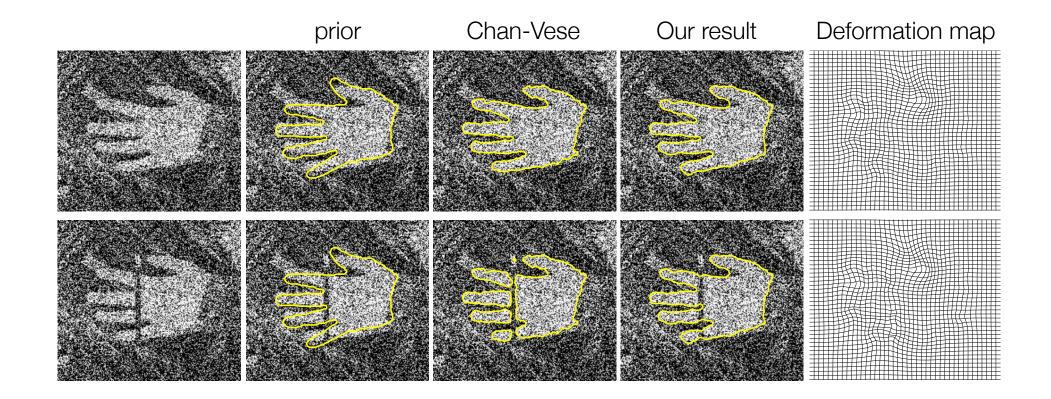
Experimental Results no corrupting influence



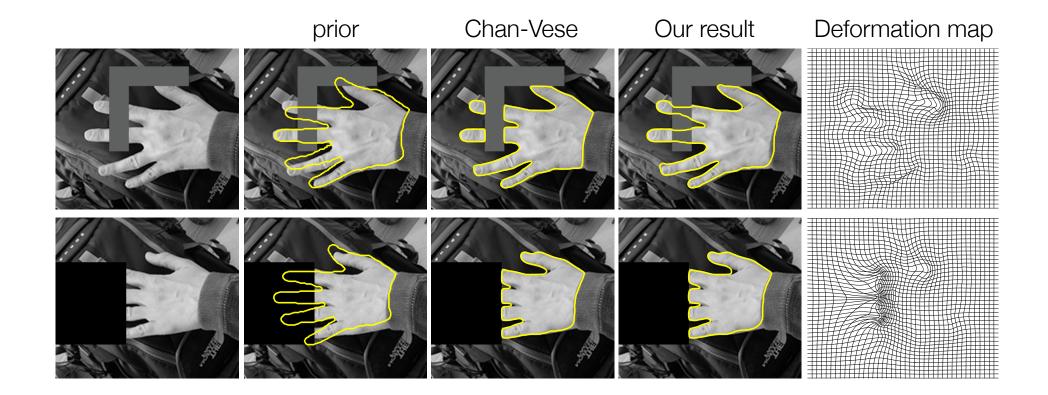
Experimental Results partial occlusion



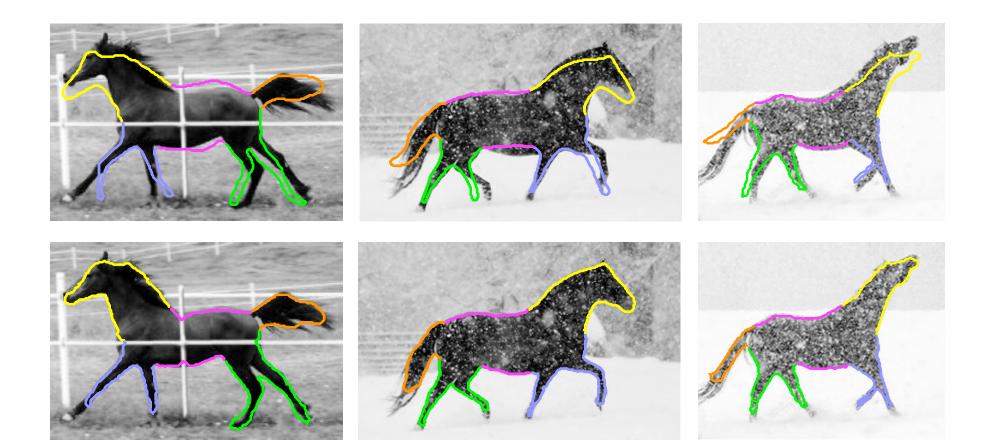
Experimental Results significant amount of noise



Experimental Results heavy occlusion

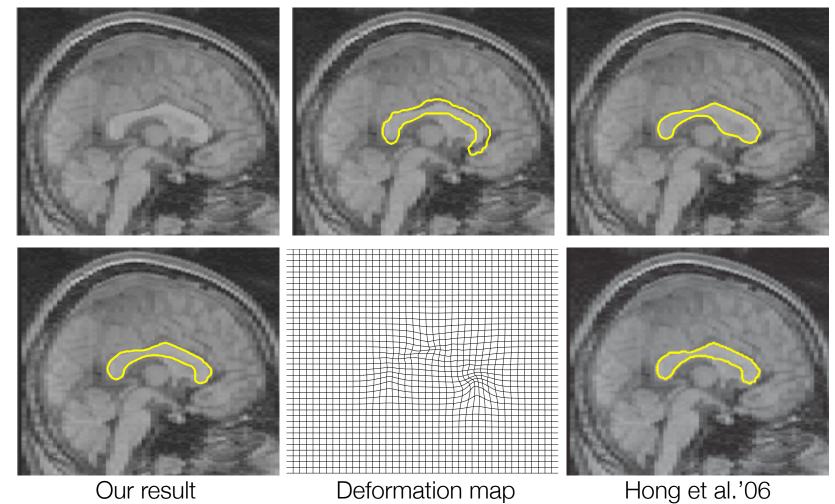


Experimental Results joint segmentation and registration



Experimental Results Comparison with the Method of Hong et al.'06 Chan-Vese

prior



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