# Front-End Processing Research on Shape Analysis

MURI Annual Review

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with contributions from
Ayres Fan, John Fisher, Alan Willsky, W. Clem Karl

November 3, 2008

# List of Topics

- Looking for Shapes in Clutter: Connecting the Dots
- Bayesian Shape Extraction
  - MCMC sampling from posterior (level set)
  - MAP estimation, prior using distribution differences
  - MAP estimation using active contours (contours)
- Facial Biometrics
- Predicting Novel Shapes

# Looking for Shapes in Clutter: "Connecting the Dots"

Bayesian Fusion of Features in Images for Shape Classification

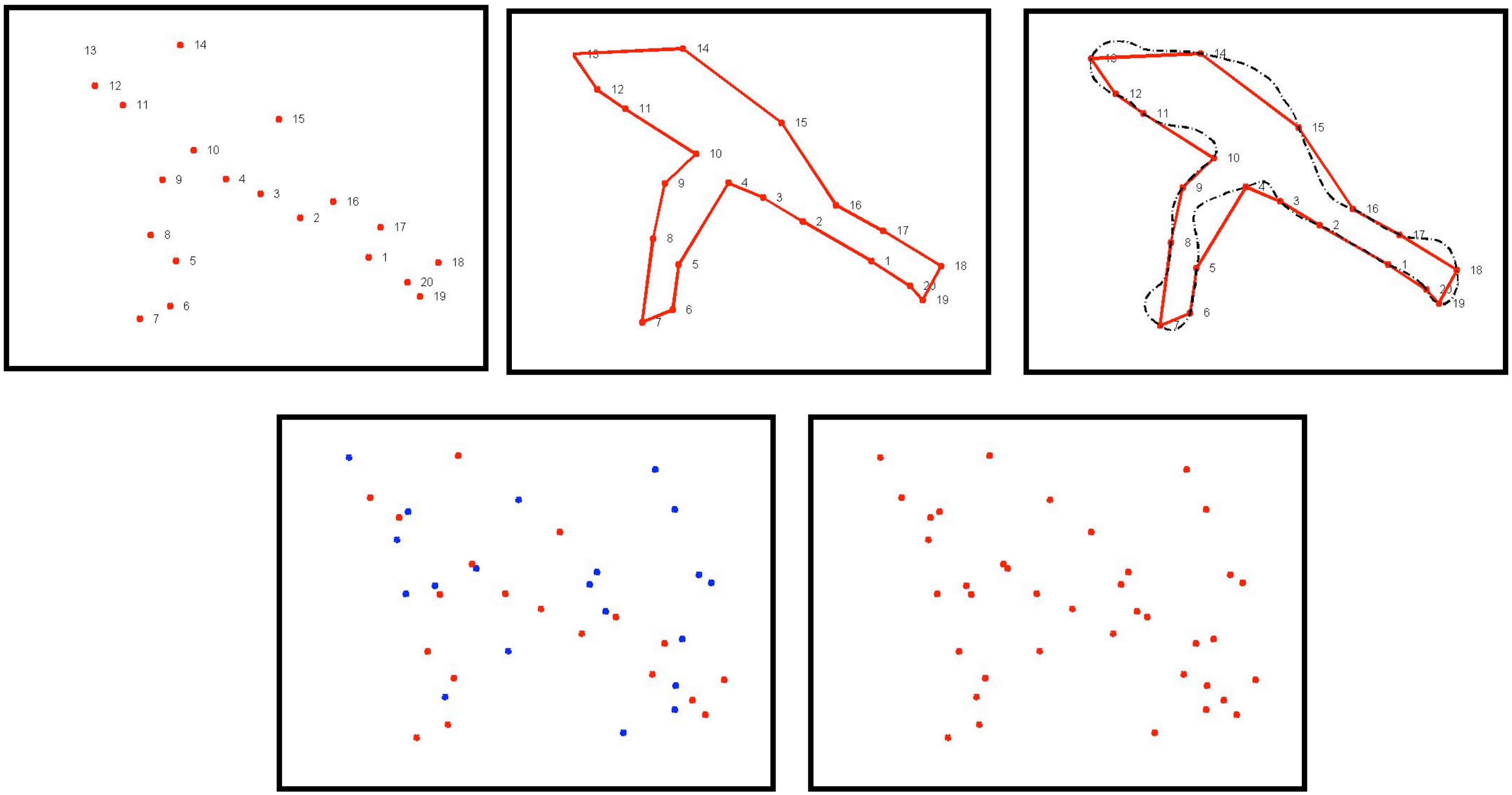
# Problem Motivation

Data    Front-End Processing: Feature Detection

An important problem is:

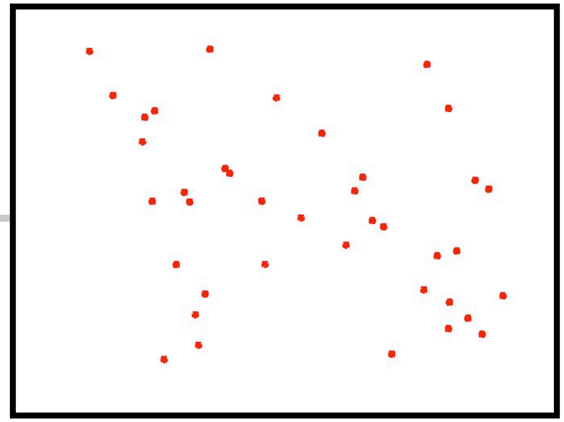
HOW TO COMBINE FEATURES INTO HYPOTHESES OF INTEREST?

# Problem Motivation



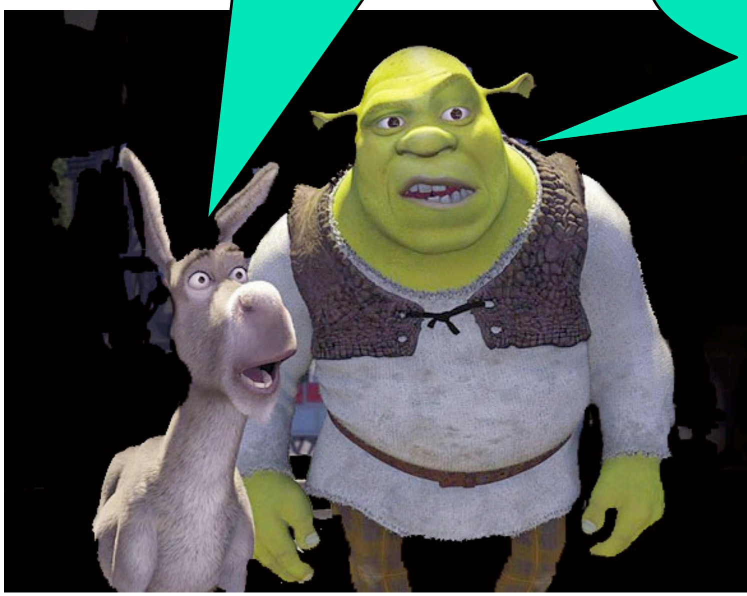
Two-Dimensional Point Cloud

# Shrek Wisdom

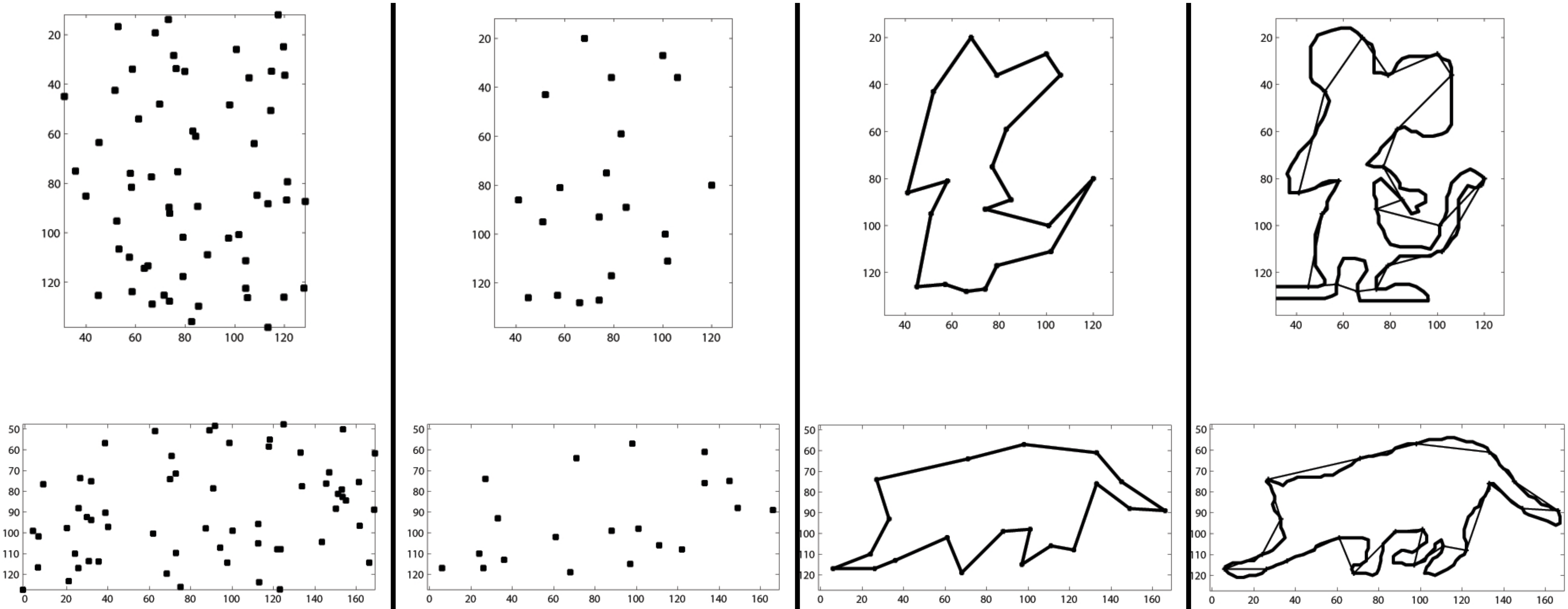


Man, that ain't nothing but a bunch of little dots

You know, donkey, sometimes things are more than they appear

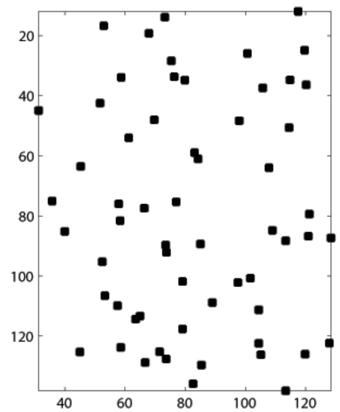


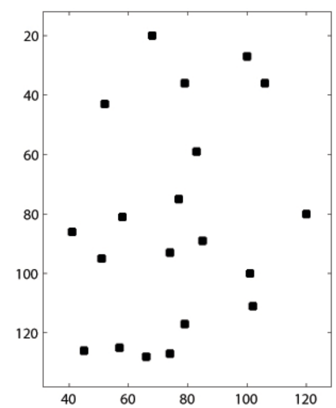
# Problem Challenges

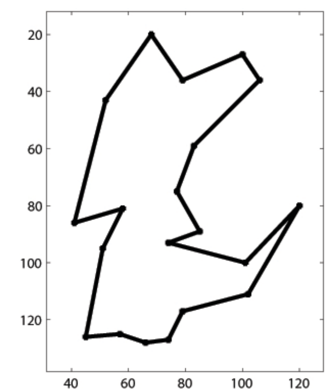


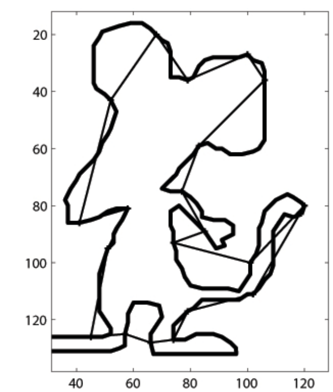
Clutter Rejection | Ordering | Classification

# Problem Challenges




Clutter Rejection

Ordering

Classification

m=40

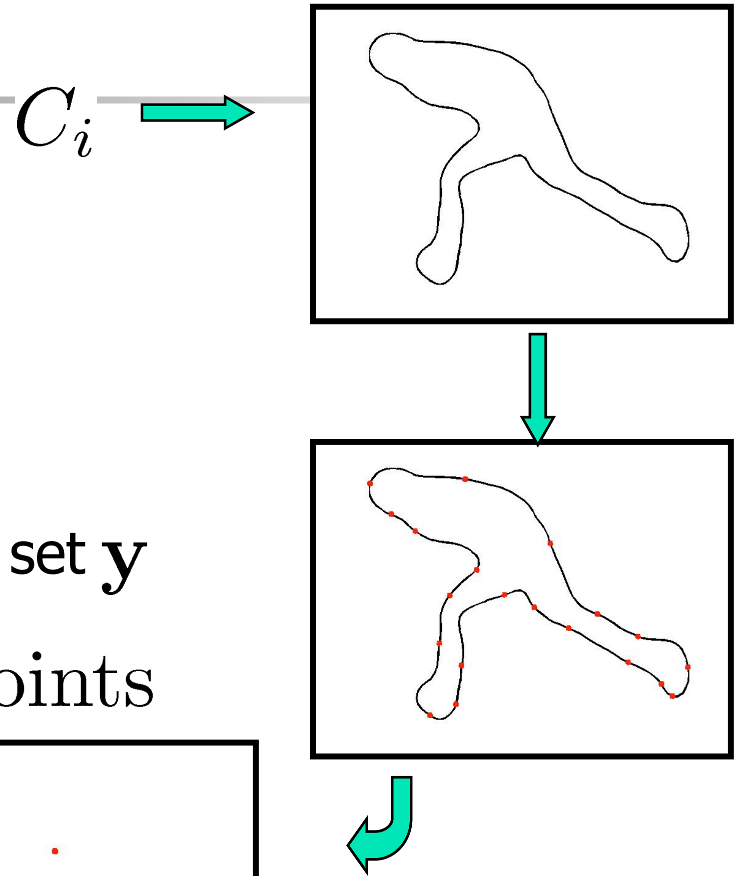
n=20

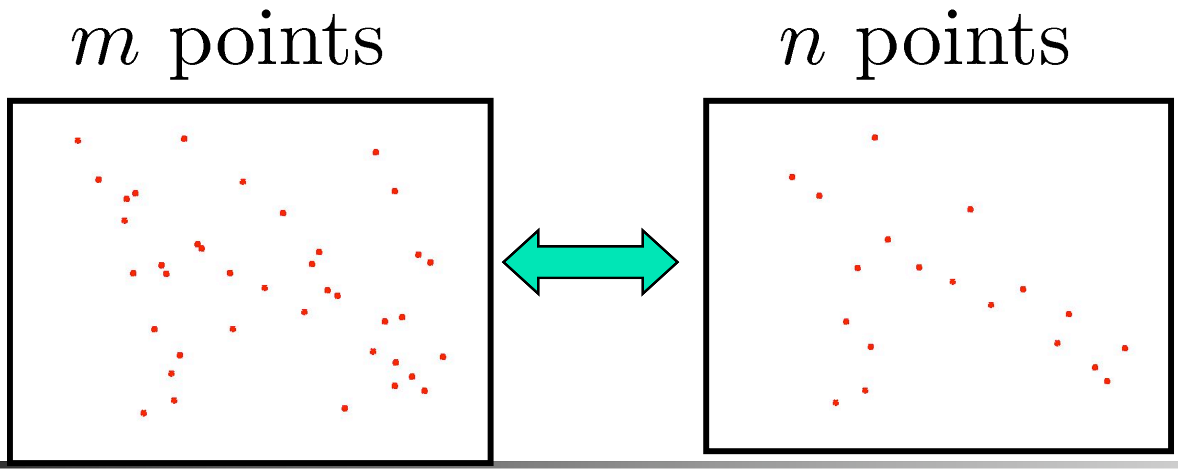
$10^{11}$ possibilities

$10^{18}$ possibilities

# Our Approach

- Select a shape class $C_i$
- Generate a shape $q$ in that class
- Sample that shape using $n$ points
- Match this point set with the data set $\mathbf{y}$



# Bayesian Classification

MAP Estimation of Shape Class

$$\hat{C} = \text{argmax}_{C_i} P(C_i|\mathbf{y})$$

Posterior Probability

$$P(C_i|\mathbf{y}) = \frac{P_0(C_i)}{P(\mathbf{y})} \int\int\int P(\mathbf{y}|q,x,\gamma)P(q|C_i)P(\gamma|C_i)P(x|C_i)dq\, d\gamma\, dx$$

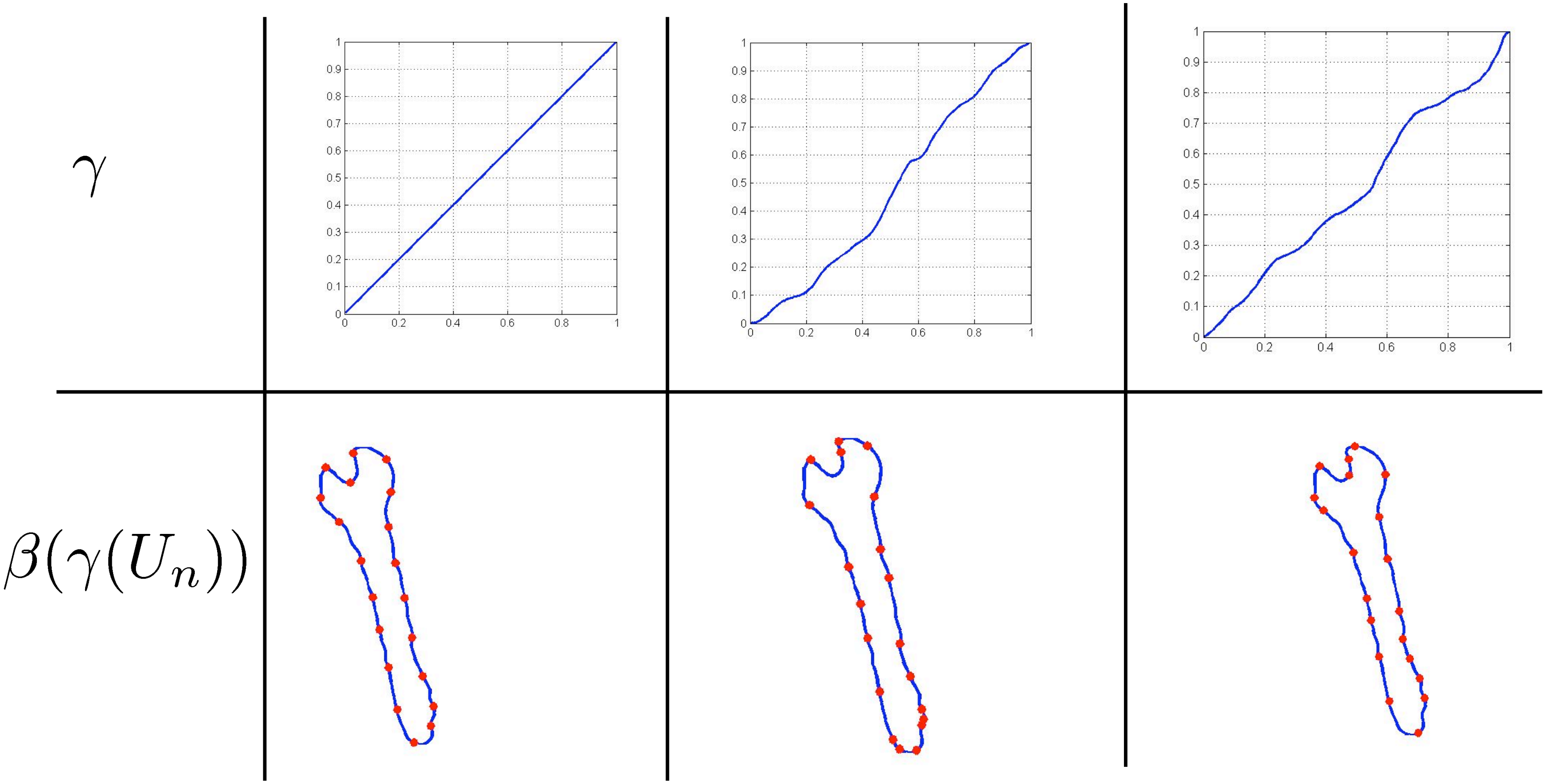
where

$q$ is the shape of the curve

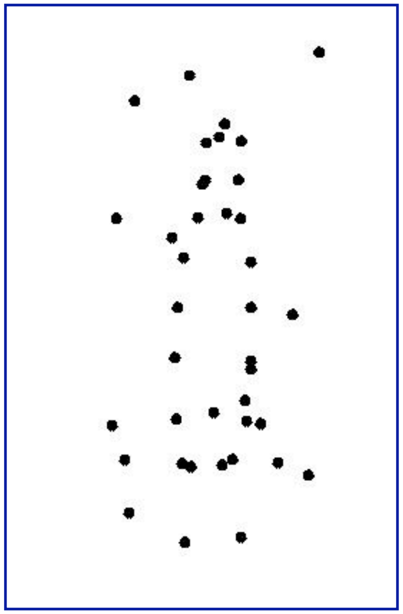
$x$ is the placement of the curve

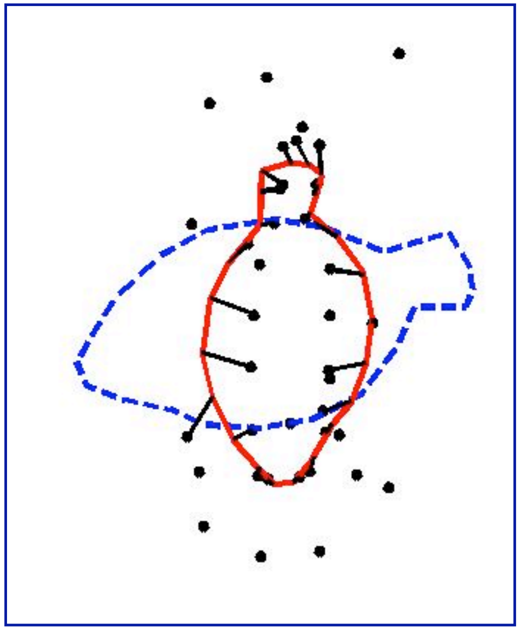
$\gamma$ is the sampling function

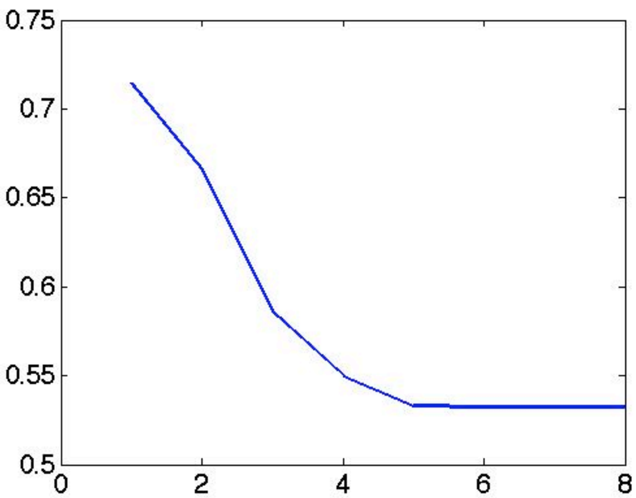
# Sampling Variability $\gamma : [0,1] \rightarrow [0,1]$



# Joint Matching & Transformation



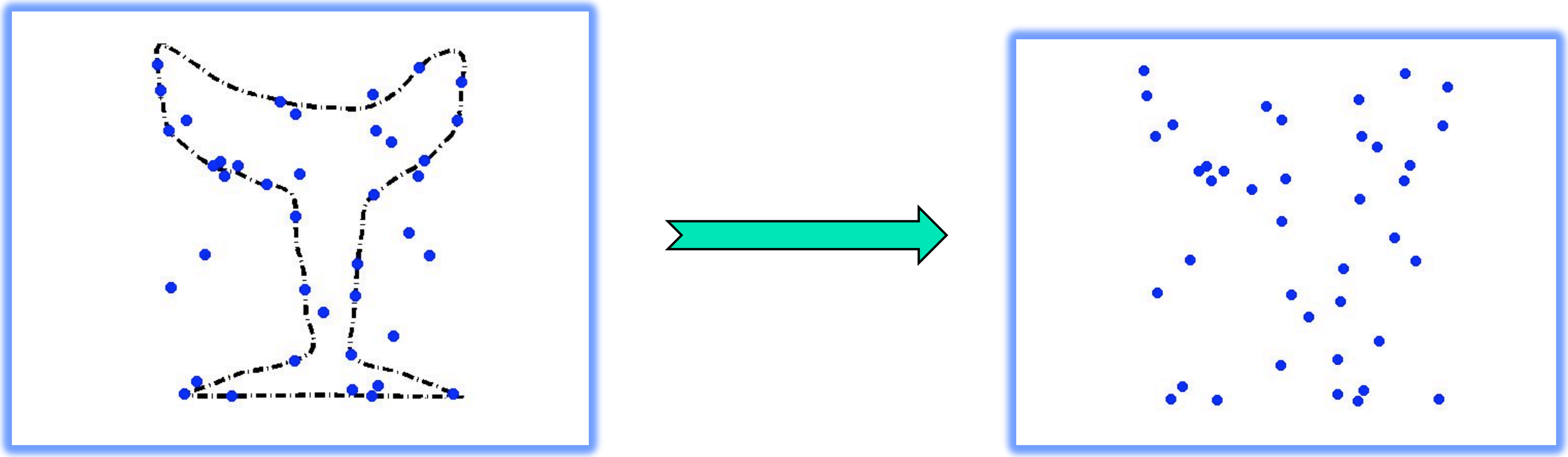





- Iterative optimization:
- Fix transformation and register points using Hungarian algorithm
- Fix registration and transform points using Procrustes method

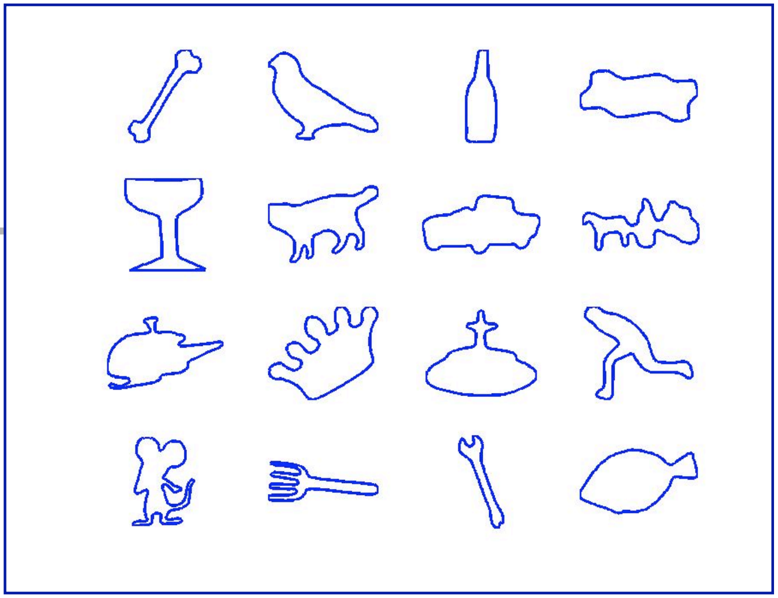
# Experimental Results

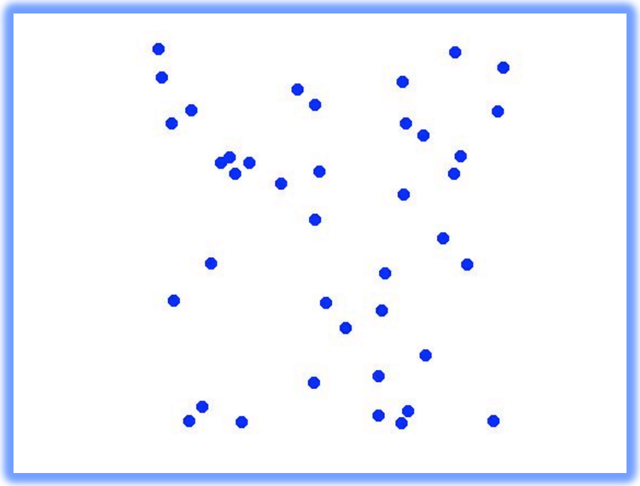
Simulated Data



$\mathbf{y}$

# Experimental Results





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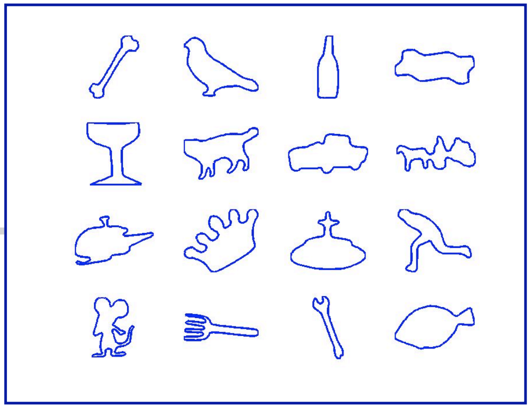

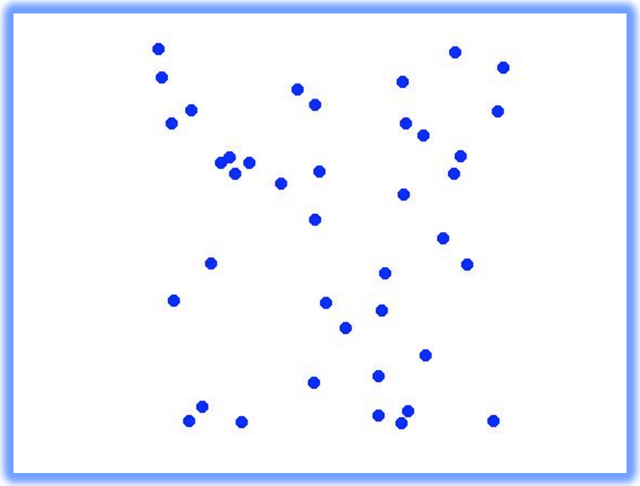

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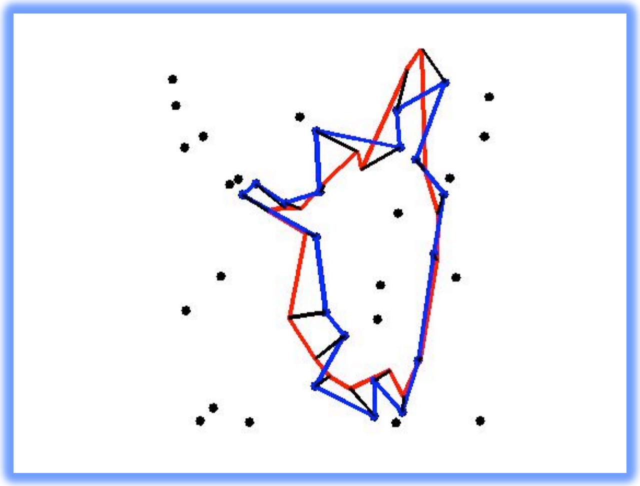
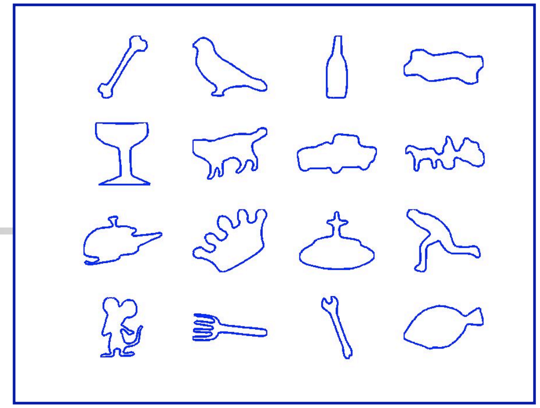
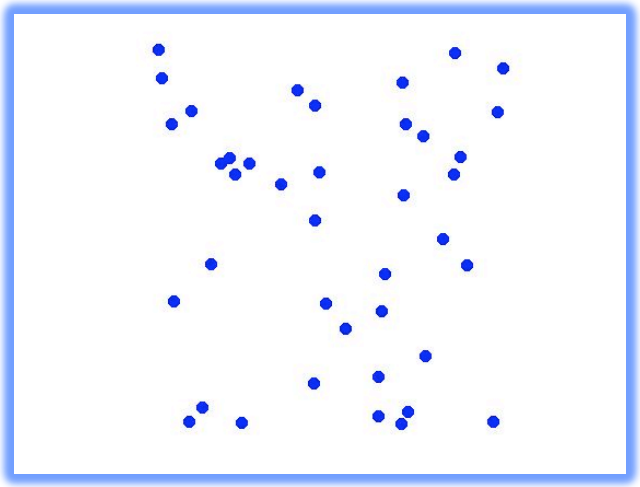


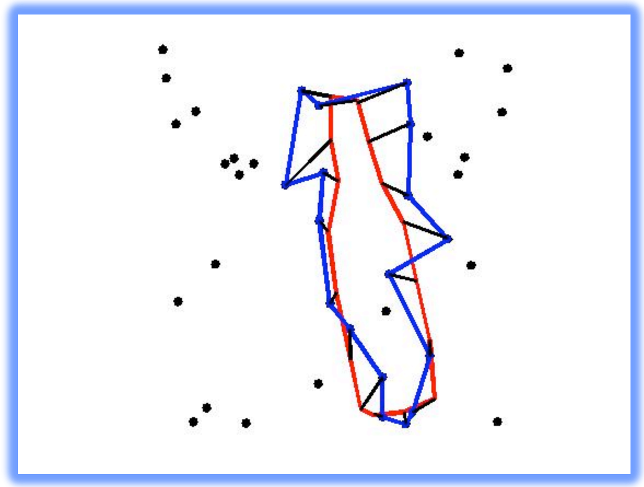
$\mathbf{x}$ (chopper)

# Experimental Results



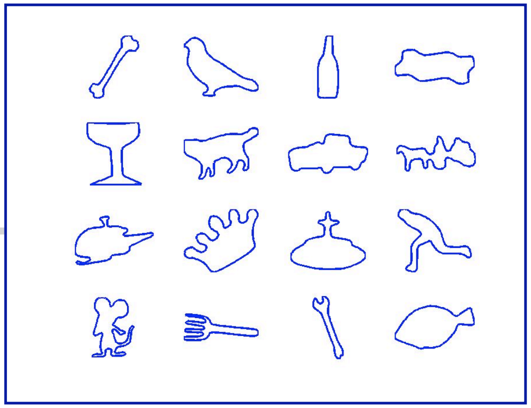


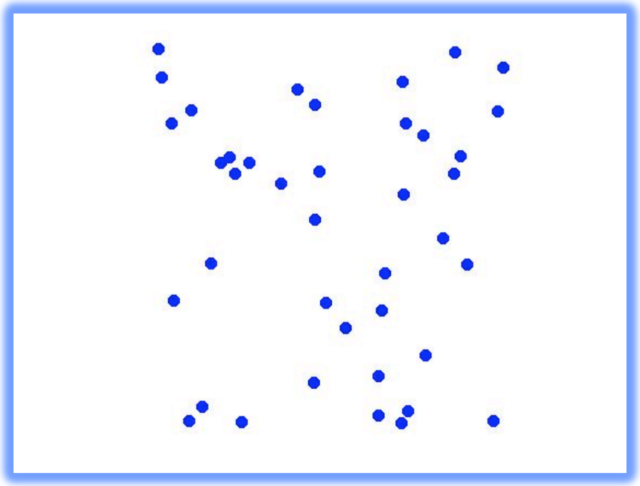
$\mathbf{y}$



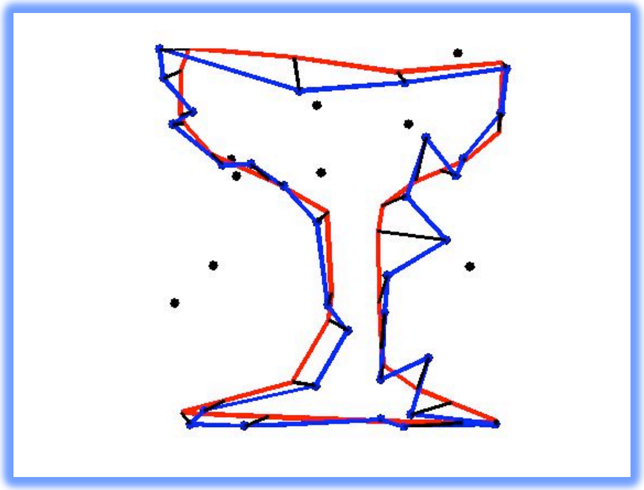
$\mathbf{x}$ (bottle)

# Experimental Results



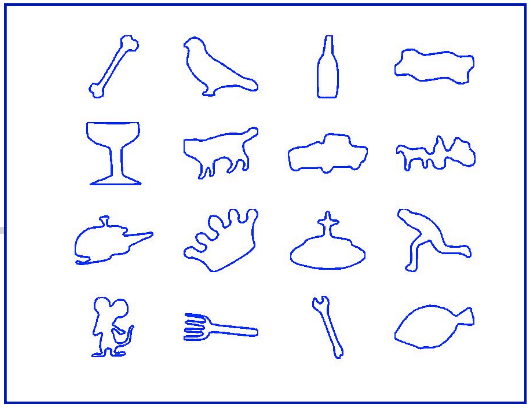


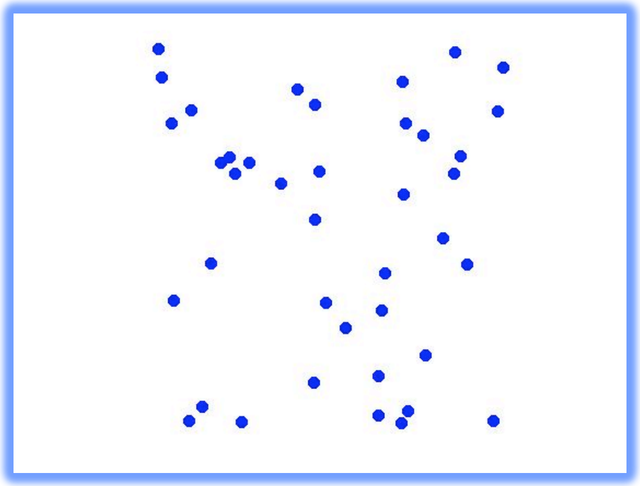
$\mathbf{y}$



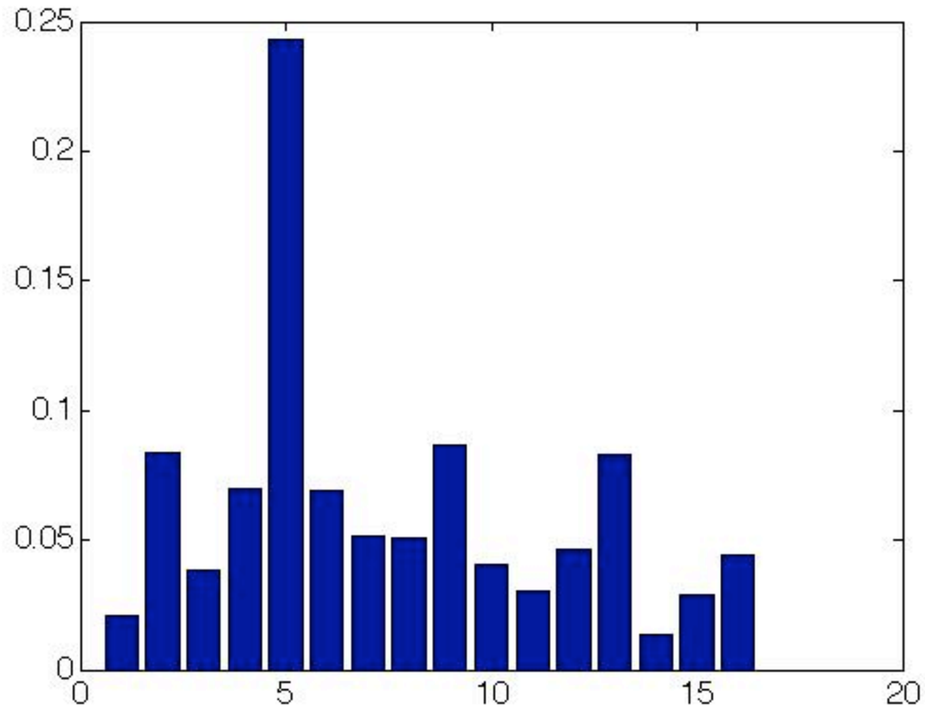
$\mathbf{x}$ (glass)

# Experimental Results





$\mathbf{y}$



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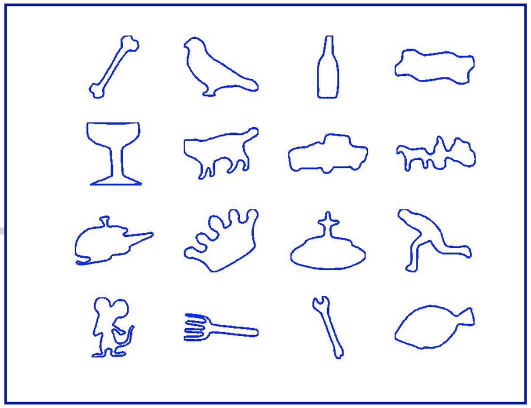

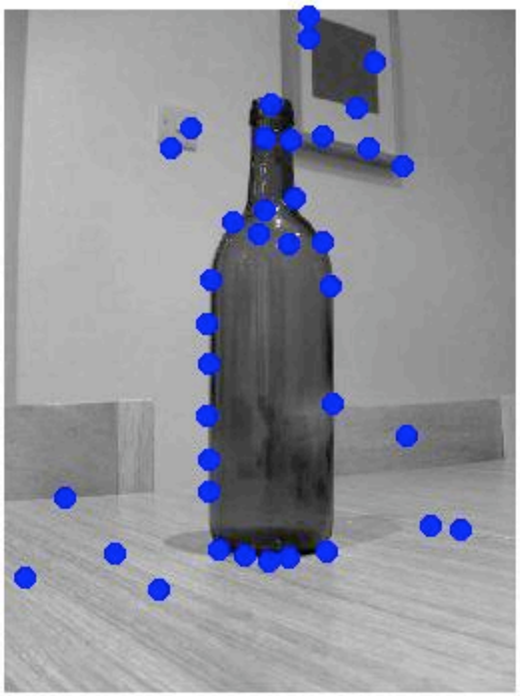

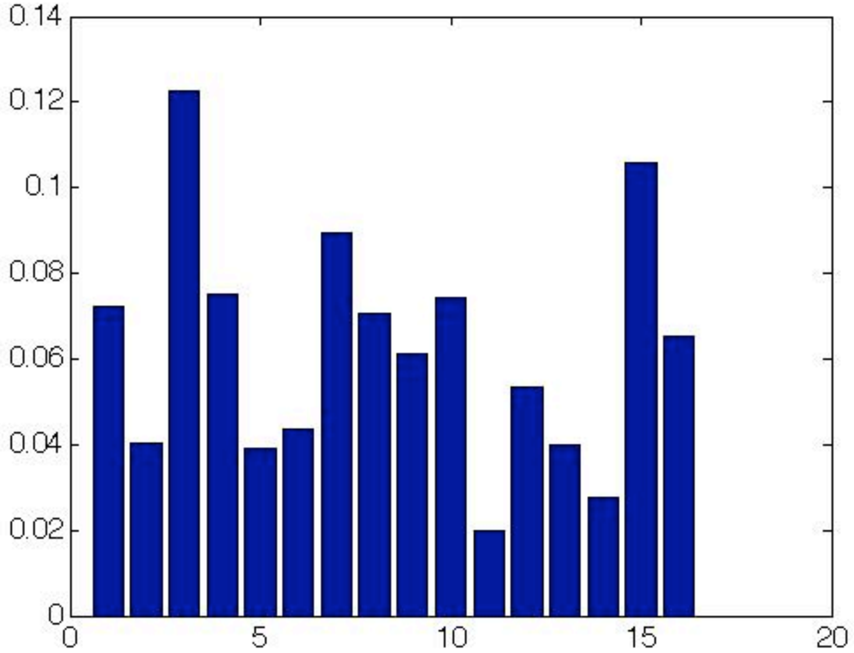

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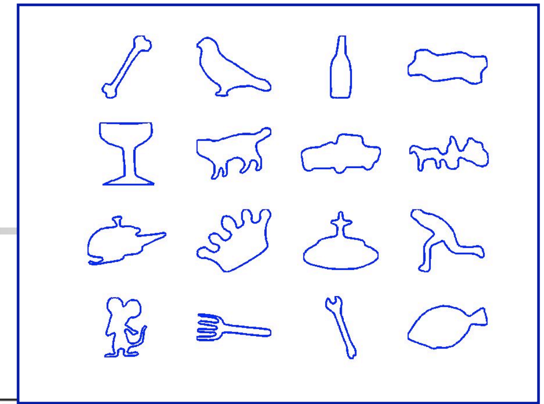
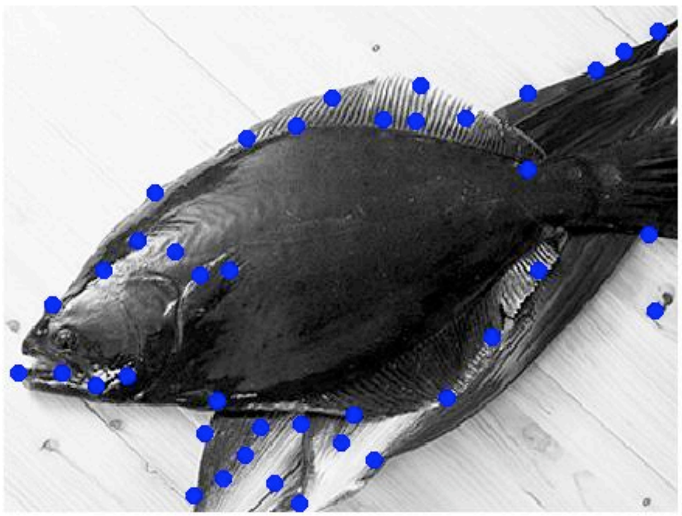
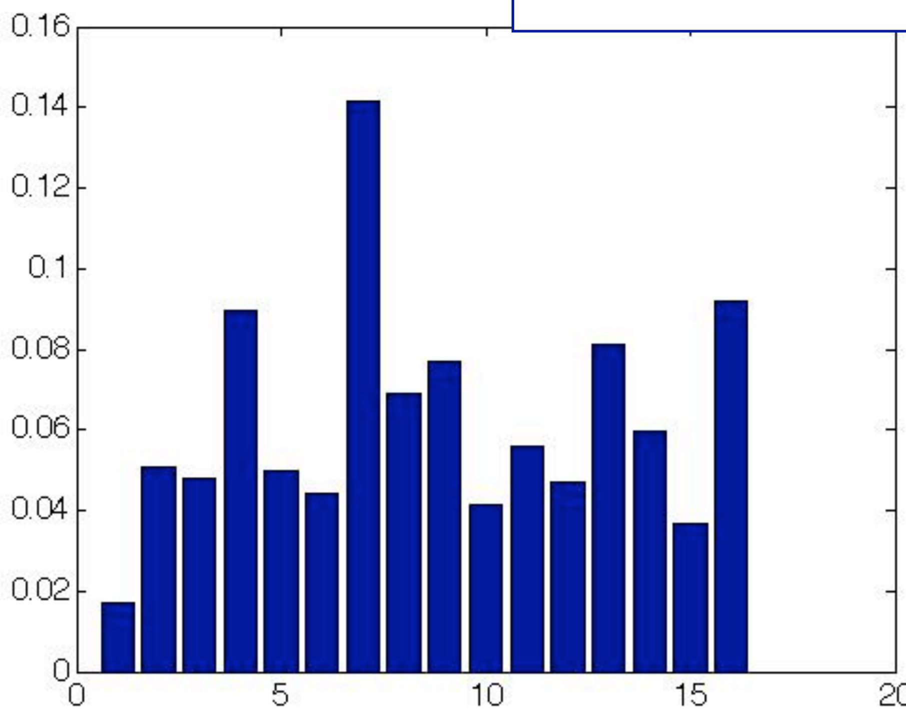






# Publications

- *Looking for Shapes in Two-Dimensional, Cluttered Point Cloud*

  Srivastava and Jermyn,

  9th DSP Workshop Special Session (Moses Organizer)

  IEEE Transactions on Pattern Analysis and Machine Intelligence, accepted, August 2008.

# List of Topics

- Looking for Shapes in Clutter: Connecting the Dots
- Bayesian Shape Extraction
  - MCMC sampling from posterior (level set)
  - MAP estimation, prior using distribution differences
  - MAP estimation using active contours (contours)
- Facial Biometrics
- Predicting Novel Shapes

# Bayesian Shape Extraction

Bayesian framework allows:

1. Inference: estimation of unknown variables
2. Performance Prediction: posterior errors, error bounds

# MCMC Approach (Fan, Fisher, Willsky)

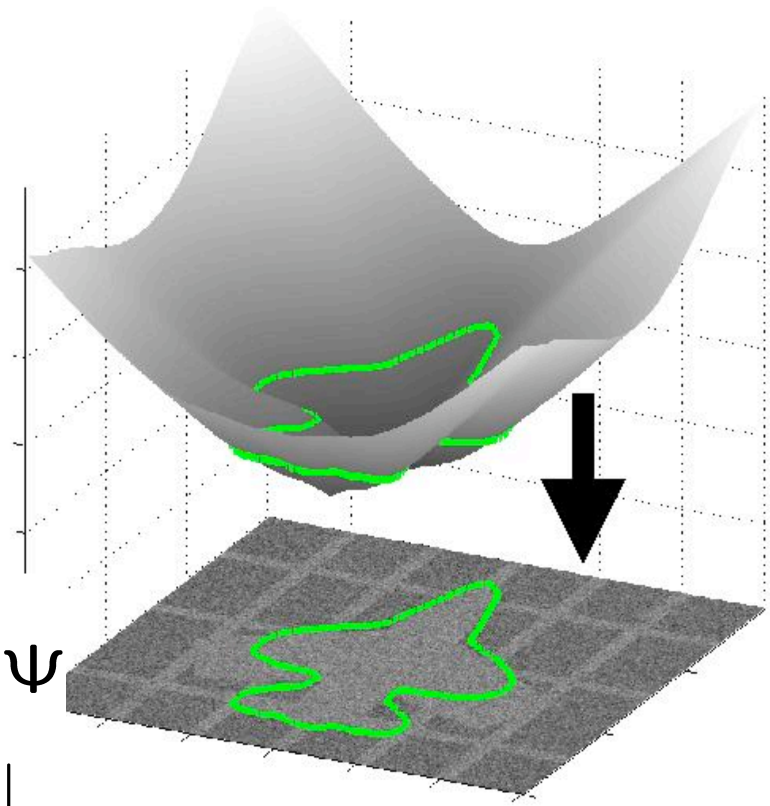
- Force level set to be zero on the curve

  $$\Psi(\vec{C}(p)) = 0$$

  $$\forall p \in [0, 1]$$

- Chain rule gives us

  $$\begin{aligned} \frac{\mathrm{d}\Psi}{\mathrm{d}t} &= -\frac{\mathrm{d}\vec{C}}{\mathrm{d}t} \cdot \nabla\Psi \\ &= -\mathrm{f}||\nabla\Psi|| \end{aligned}$$



# Markov Chain Monte Carlo

- C is a curve, y is the observed image (can be vector), S is a shape model
  - Typically model data as iid given the curve
- We wish to sample from p(x|y;S), but cannot do so directly
- Instead, iteratively sample from a proposal distribution q and keep samples according to an acceptance rule a. Goal is to form a Markov chain with stationary distribution p
- Examples include Gibbs sampling, Metropolis-Hastings

$$\mathrm{p}(\vec{C}|y;S) \propto \mathrm{p}(y|\vec{C};S)\mathrm{p}(\vec{C};S)$$

# Metropolis-Hastings

- Metropolis-Hastings algorithm:
  1. Start with x0
  2. At time t, sample candidate $f_t$ from q given $x_{t-1}$
  3. Calculate Hastings ratio:

$$r^t = \frac{\mathrm{p}(\phi^t)}{\mathrm{p}(x^{t-1})} \cdot \frac{\mathrm{q}(x^{t-1}|\phi^t)}{\mathrm{q}(\phi^t|x^{t-1})}$$

     1. Set $x_t = f_t$ with probability $\min(1, r_t)$, otherwise $x_t = x_{t-1}$
     2. Go back to 2

# MCMC Curve Sampling

- Generate perturbation on the curve:
  $$\vec{C}'(s) = \vec{C}(s) + f(s)\vec{N}(s)\mathrm{d}t$$
- Sample by adding smooth random fields:
  $$f \sim \mathrm{N}(-\kappa + \gamma, \Sigma)$$
- $\Sigma$ controls the degree of smoothness in field, $\kappa$ term is a curve smoothing term, $\gamma$ is an inflation term
- Mean term to move average behavior towards higher-probability areas of p

# Synthetic noisy image

- Piecewise-constant observation model:

$$y(x) = \mu(x) + n(x)$$

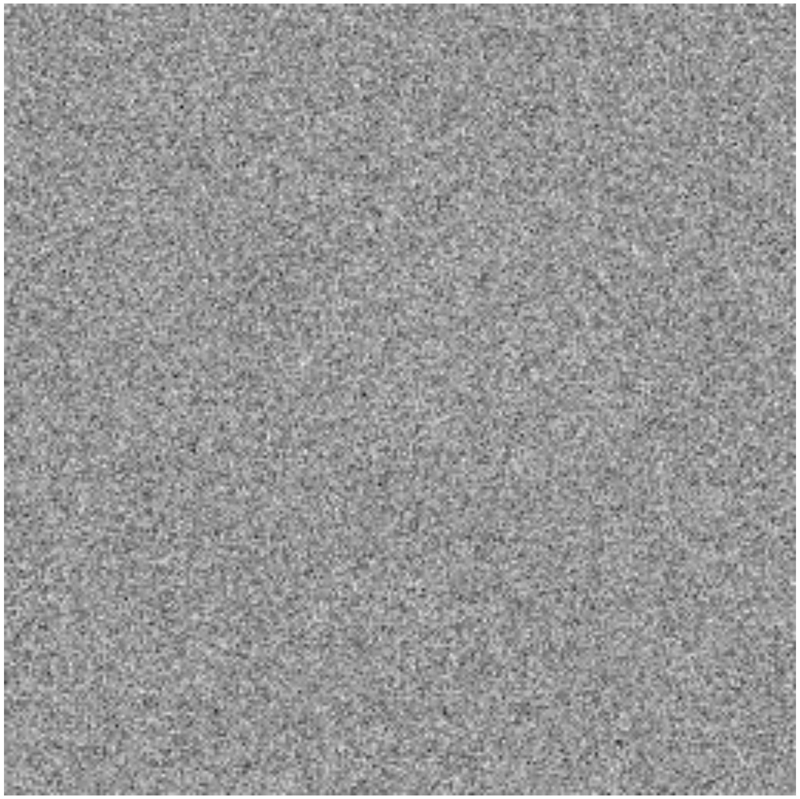
- Chan-Vese energy functional:

$$E(\vec{C}) = \iint_{R_0} (y-\mu_0)^2 dx + \iint_{R_1} (y-\mu_1)^2 dx + \alpha \oint_{\vec{C}} ds$$

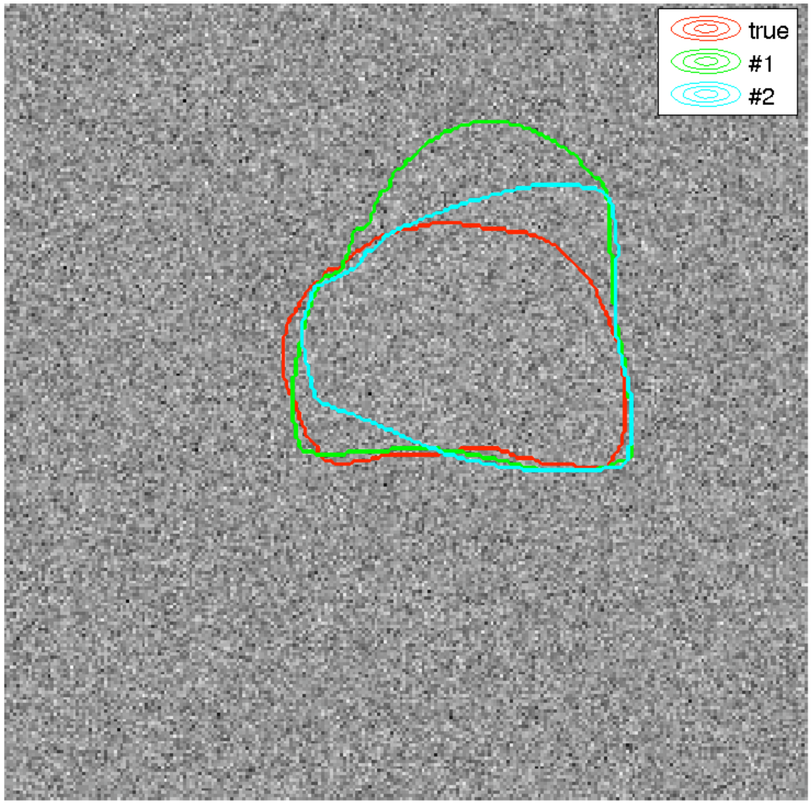
- Probability distribution ($T=2s^2$):

$$\mathrm{p}(\vec{C}) = \frac{1}{Z} \exp(-\mathrm{E}(\vec{C})/T)$$

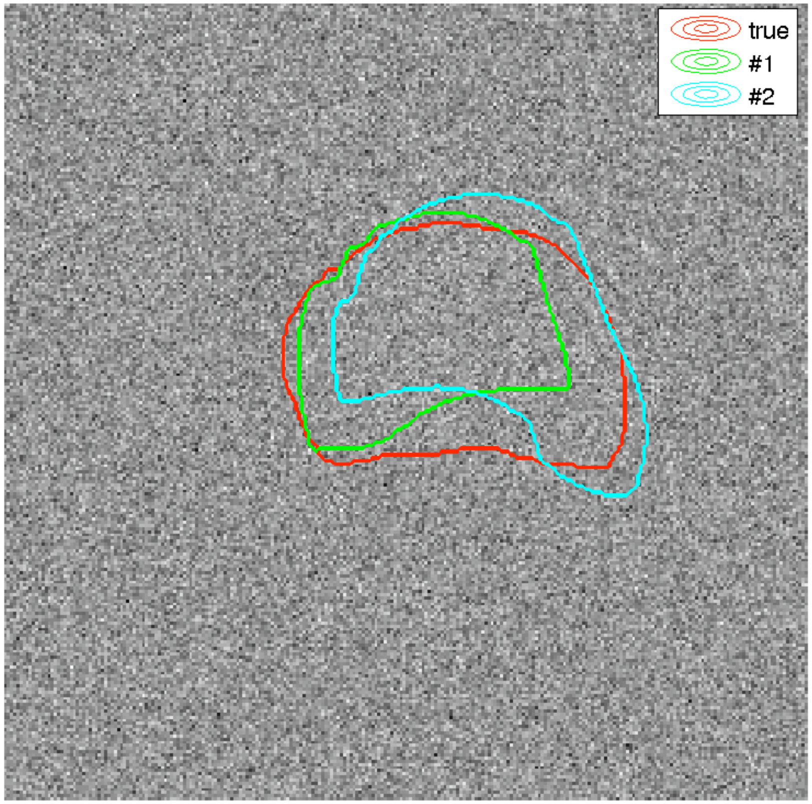
# Needle in the Haystack



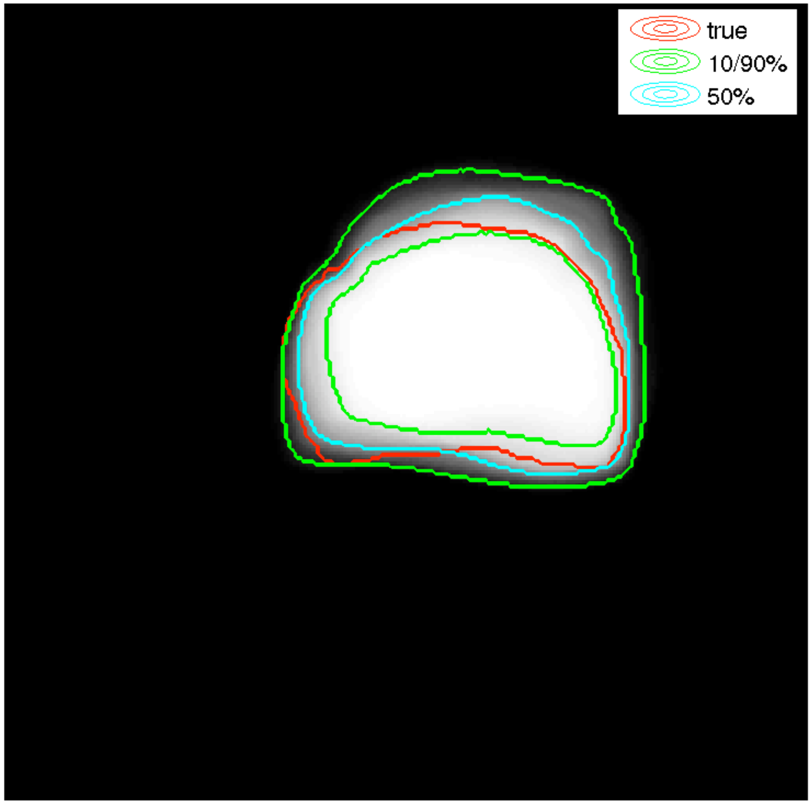
# Most likely samples



# Least likely samples



# Confidence intervals



# When "best" is not best

- In this example, the most likely samples under the model are not the most accurate according to the underlying truth
- 10%/90% "confidence" bands do a good job of enclosing the true answer
- Histogram image tells us more uncertainty in upper-right corner
- "Median" curve is quite close to the true curve
- Optimization would result in subpar results

# Distribution-based Representation (Karl)

- Use *feature distributions* to represent object
  - Shape
  - Appearance
- Construct priors through *distribution differences*
- Couple priors with *curve evolution* methods
  - Evolve curve to match feature distributions

# Curve evolution formulation

- Curve evolution

$$C^* = \arg\min_{C} E(C) = \arg\min_{C} E_{\text{data}} + \alpha E_{\text{shape}}$$

- New distribution-based shape prior

$$E_{\text{shape}}(C) = \sum_{i=1}^{M} w_i \int_{\lambda} \left[ H_i^*(\lambda) - H_i(C,\lambda) \right]^2 d\lambda$$

$M$ Feature functions

**Target distributions**

**Distributions for the curve C**

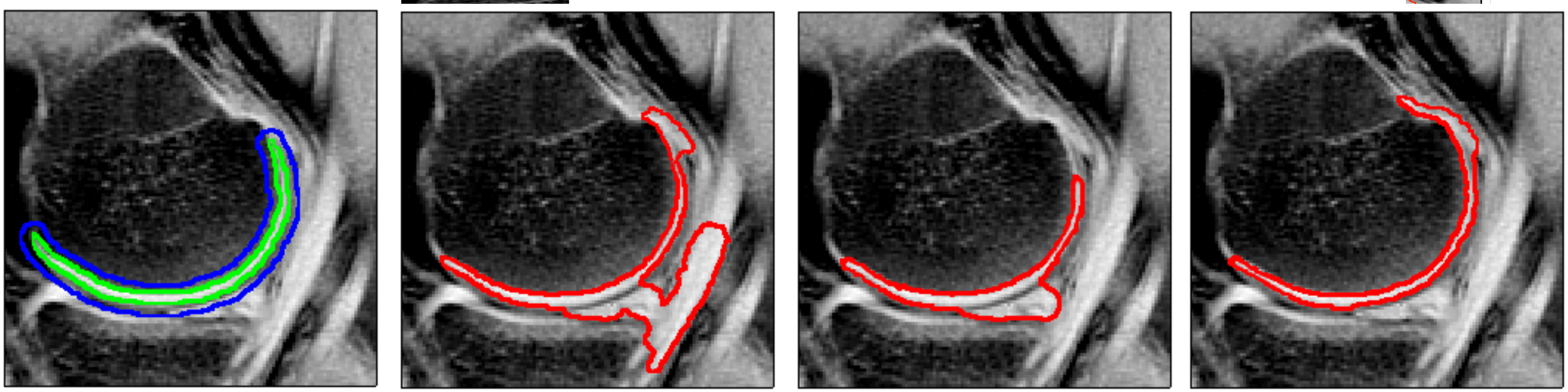
# Knee segmentation example

- Knee cartilage segmentation for thickness assessment in osteoarthritis treatment
- Many competing nearby edges
- Even local intensity is insufficient

Initial

Ground truth

Curve length | Leventon prior | Our prior



MRI knee images: courtesy Paul Debevec, ICT Graphics lab

# Bayesian Active Contours (Joshi, Srivastava)

- Shapes are represented by contours

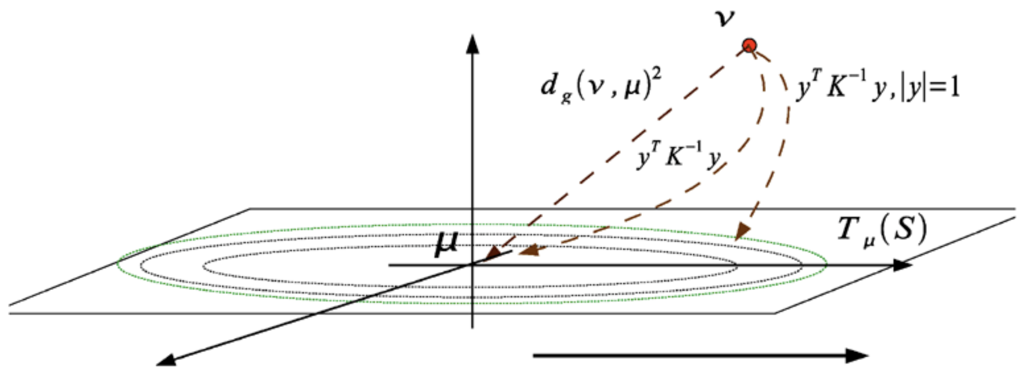
- Posterior Energy:

$$E_{total}(\beta) = \lambda_1 E_{image}(\beta) + \lambda_2 E_{smooth}(\beta) + \lambda_3 E_{prior}(\beta)$$

- Gradient: Each term provides a vector field on the curve

# Bayesian Active Contours

Illustration of shape evolution under different $E_{prior}$ in $S$

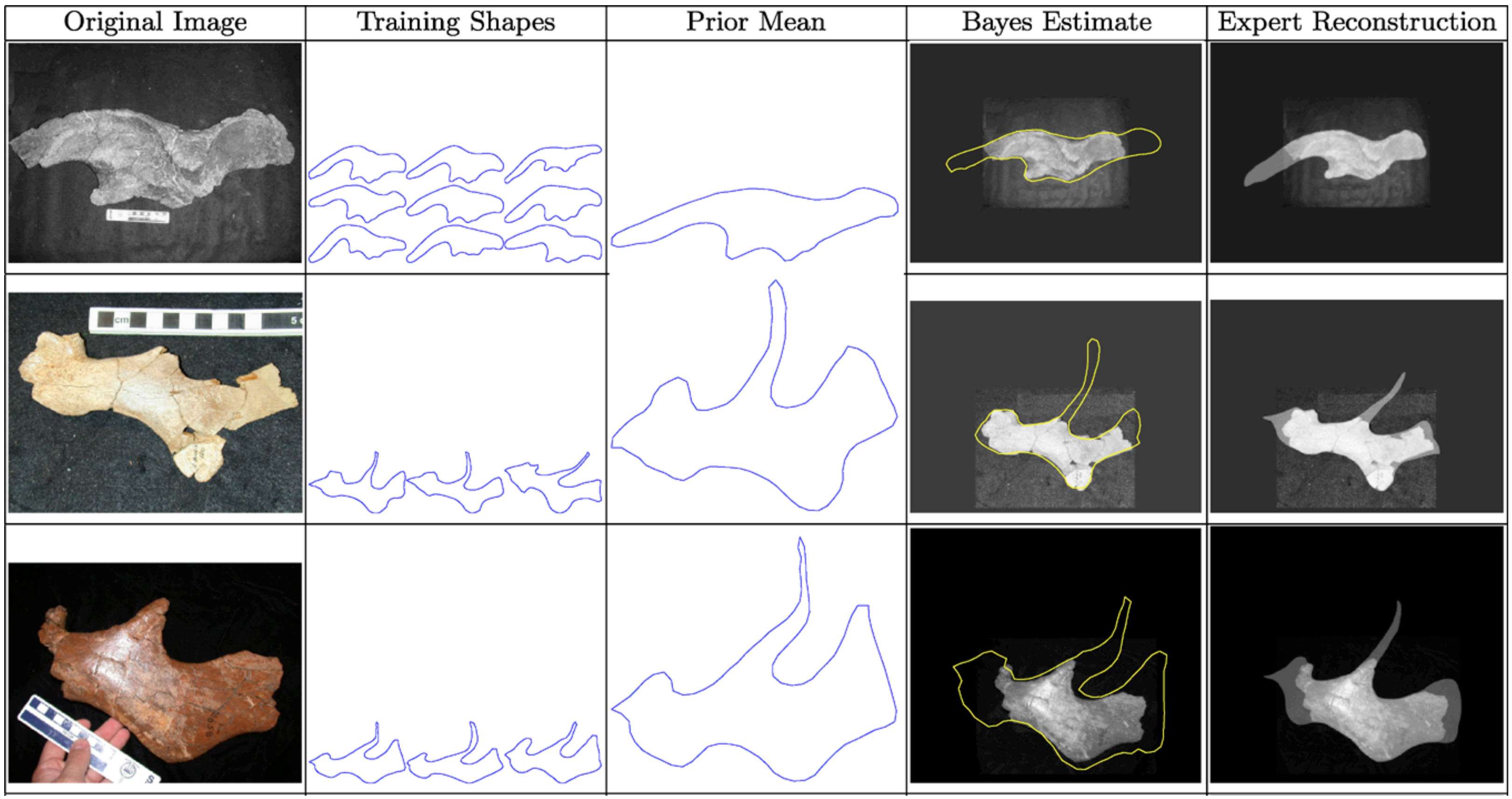



(a)

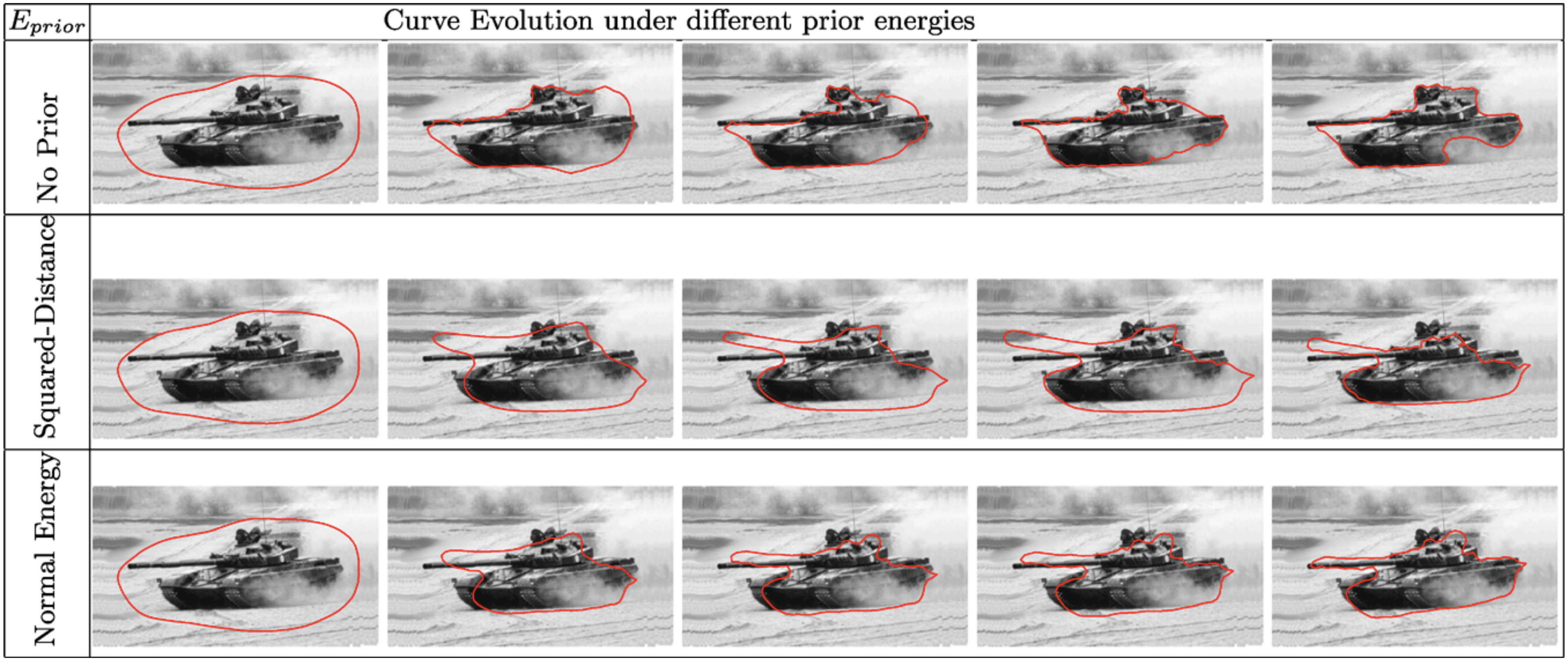
| Energy | Expression | Shape evolution |
|---|---|---|
| Squared-Distance | $d(\nu,\mu)^2$ |  |
| Normal Energy | $y^T K^{-1} y$ |  |
| Rayleigh's Quotient | $\frac{y^T K^{-1} y}{y^T y}$ |  |

(b)

# Bayesian Active Contours



# Bayesian Active Contours



# Publications

- *MCMC Shape Sampling*

  Fan, Fisher, and Willsky,

  MICCAI 2007 and

  Special Issue of IEEE Transactions on Pattern Analysis and Maching Intelligence, to be submitted, 2008
- *Distribution-Based Shape Prior*

  Litvin and Karl

  Special Issue of IEEE Transactions on Pattern Analysis and Maching Intelligence, submitted, 2008
- *Intrinsic Bayesian Active Contours for Extraction of Object Contours in Images*

  Joshi and Srivastava,

  International Journal of Computer Vision, accepted, July 2008.

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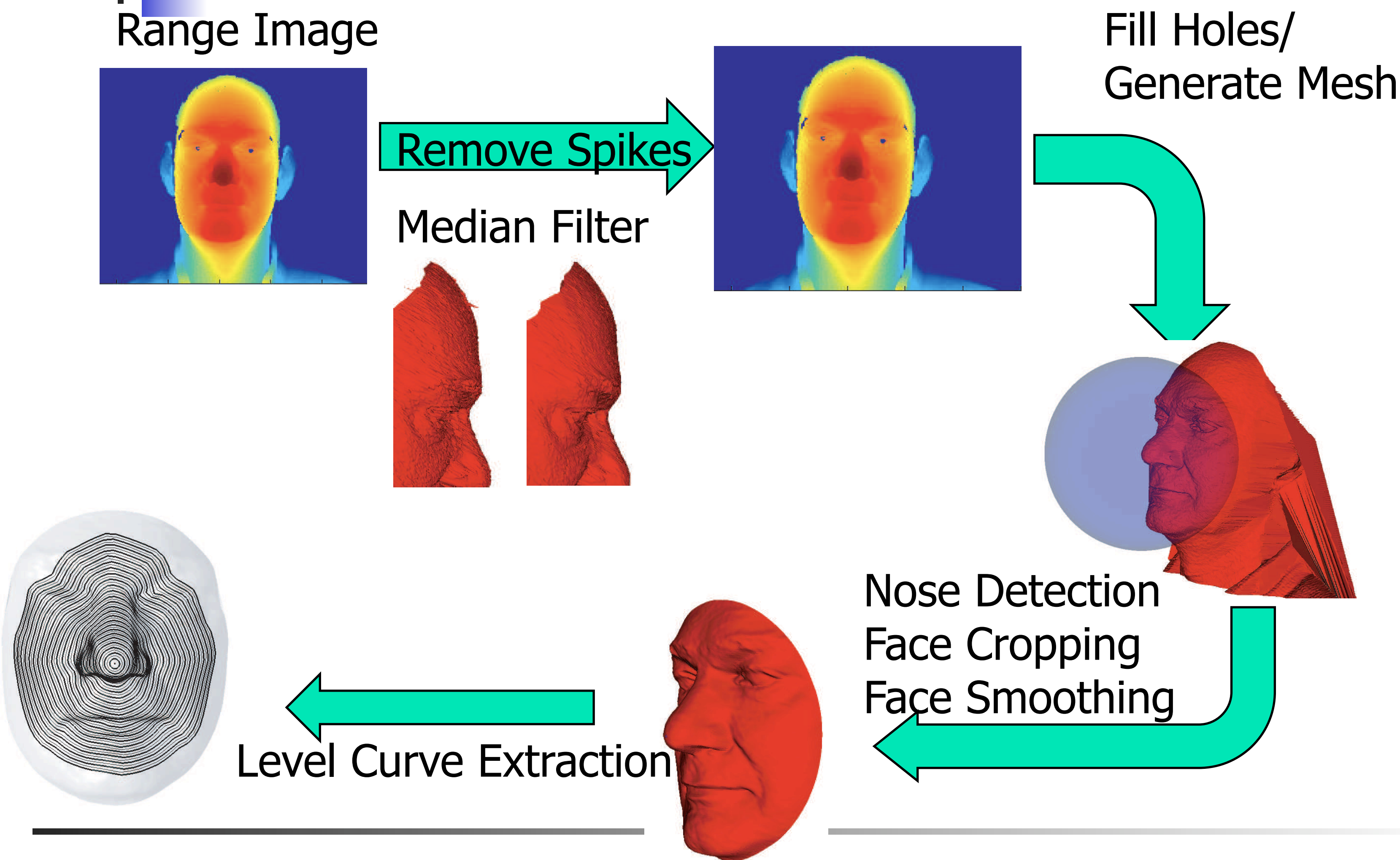
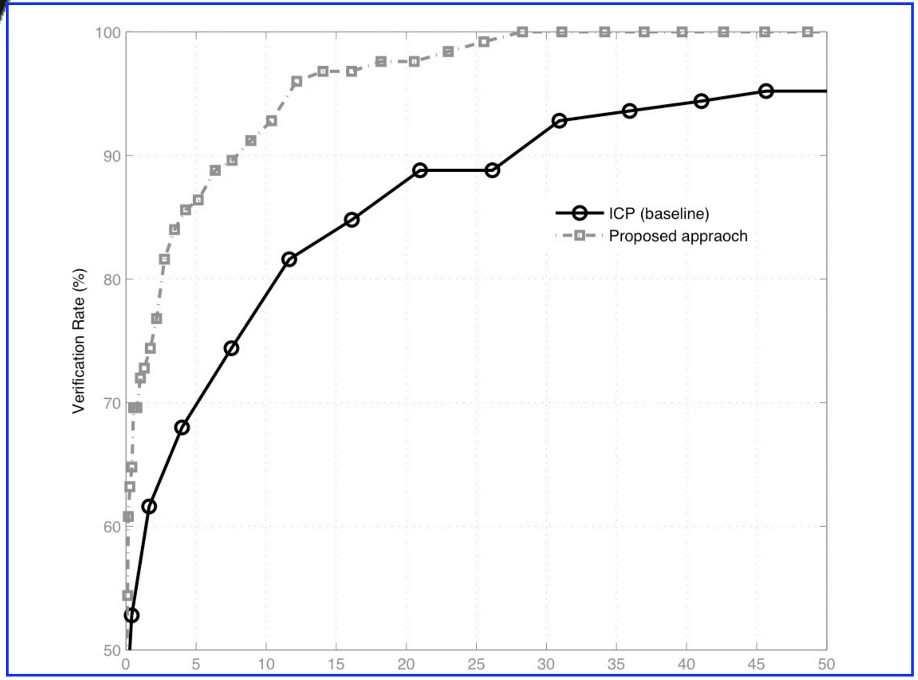
# Facial Biometrics: Shapes of Face Parts

Collaboration with Prof. Daoudi, University of Lille, France.

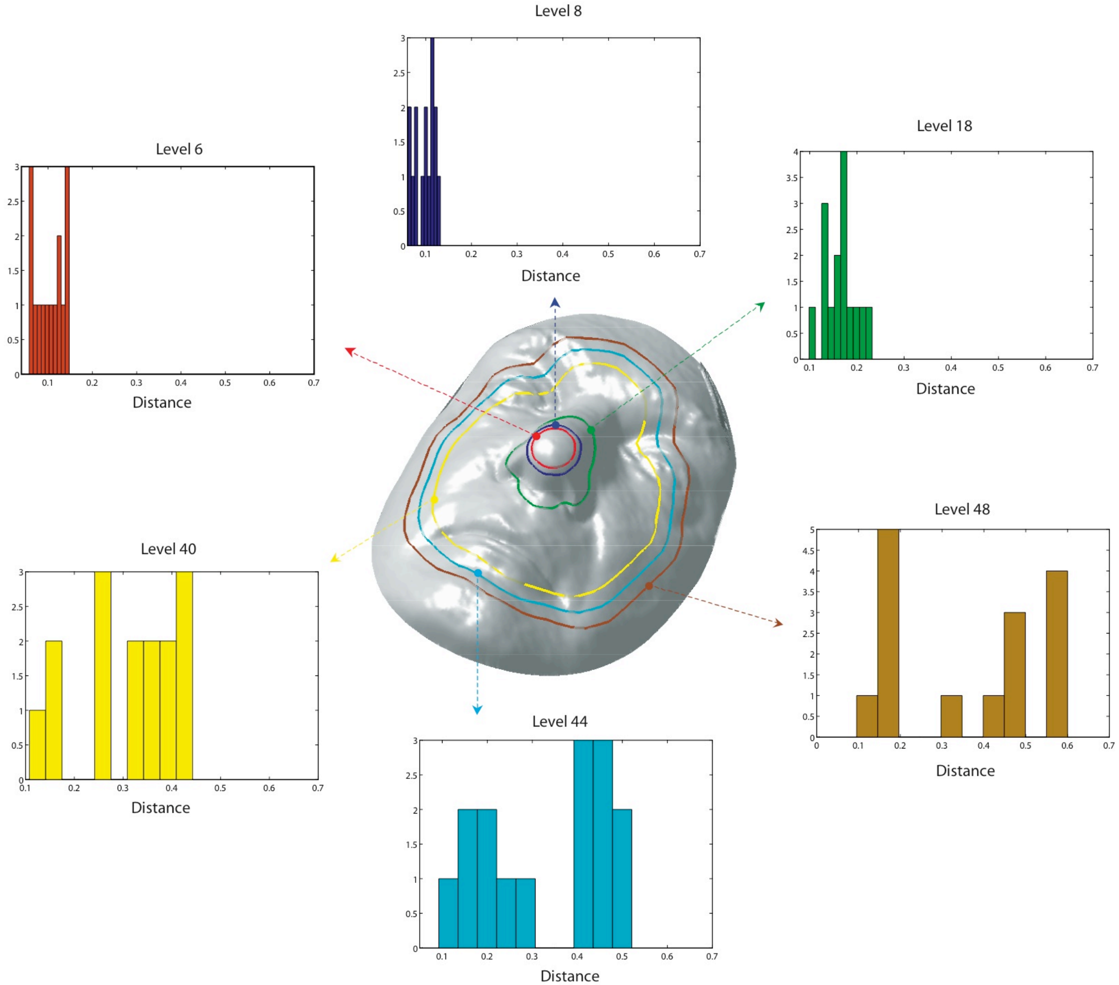
# Face Biometrics: Pre-Processing



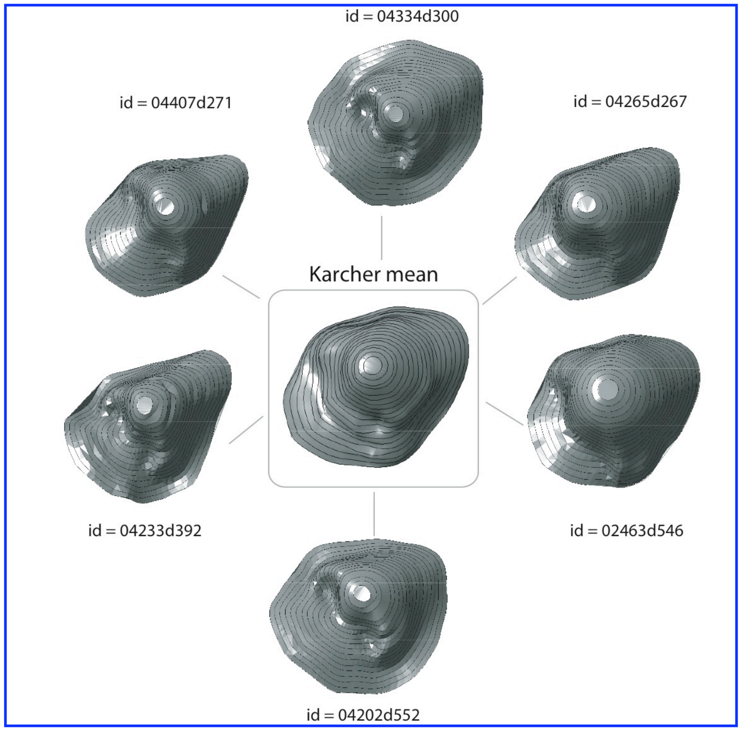
# Shape of Facial Surfaces Using Curves

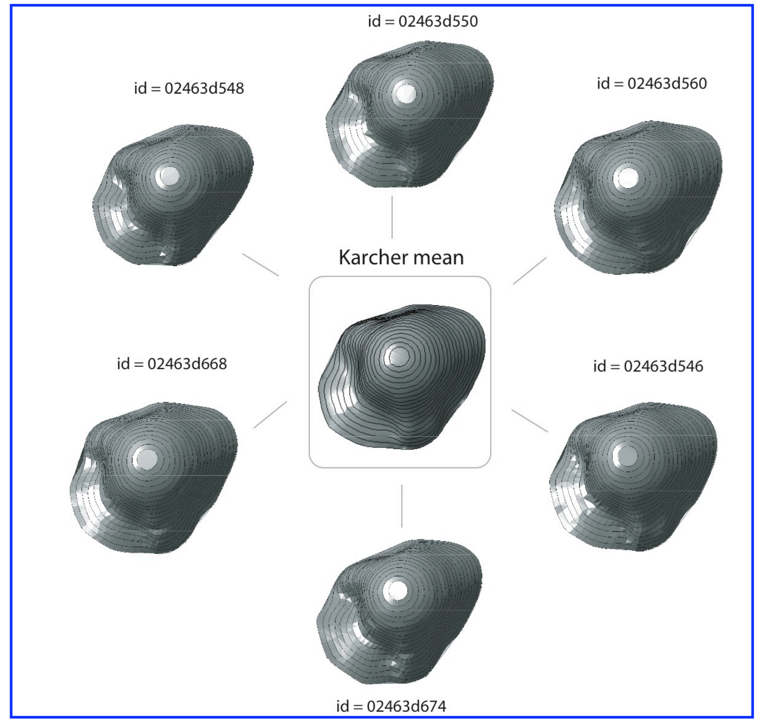


# Shape of Nose Region

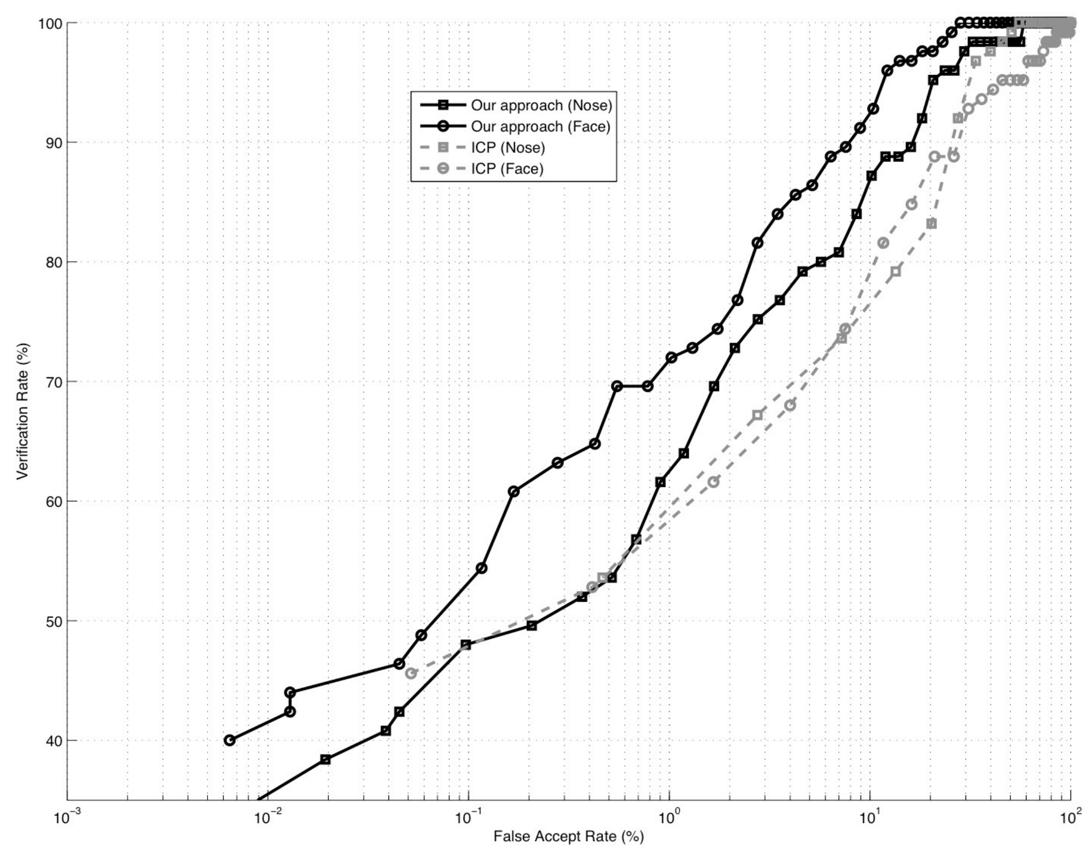


# Statistical Shape Averaging



# Recognition Performance: Face Vs Nose



# Publications

- *Elastic Shape Models for Face Analysis Using Curvilinear Coordinates,* Srivastava et al., Journal of Mathematical Imaging & Vision, accepted, 2008
- *Intrinsic Framework for Shape Analysis of Facial Surfaces*
  Samir et al., International Journal of Computer Vision, accepted, 2008
- *Face Recognition in Presence of Facial Expressions*
  Ben Amor et al., Annals of Telecommunications, accepted, 2008
- *Biometrics Using Shapes of Nose Region*
  Drari et al., European Journal on Signal Processing, submitted, 2008

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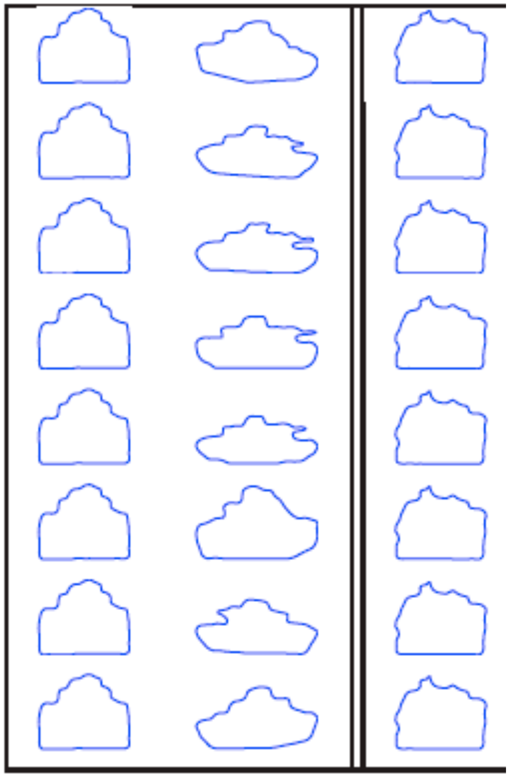
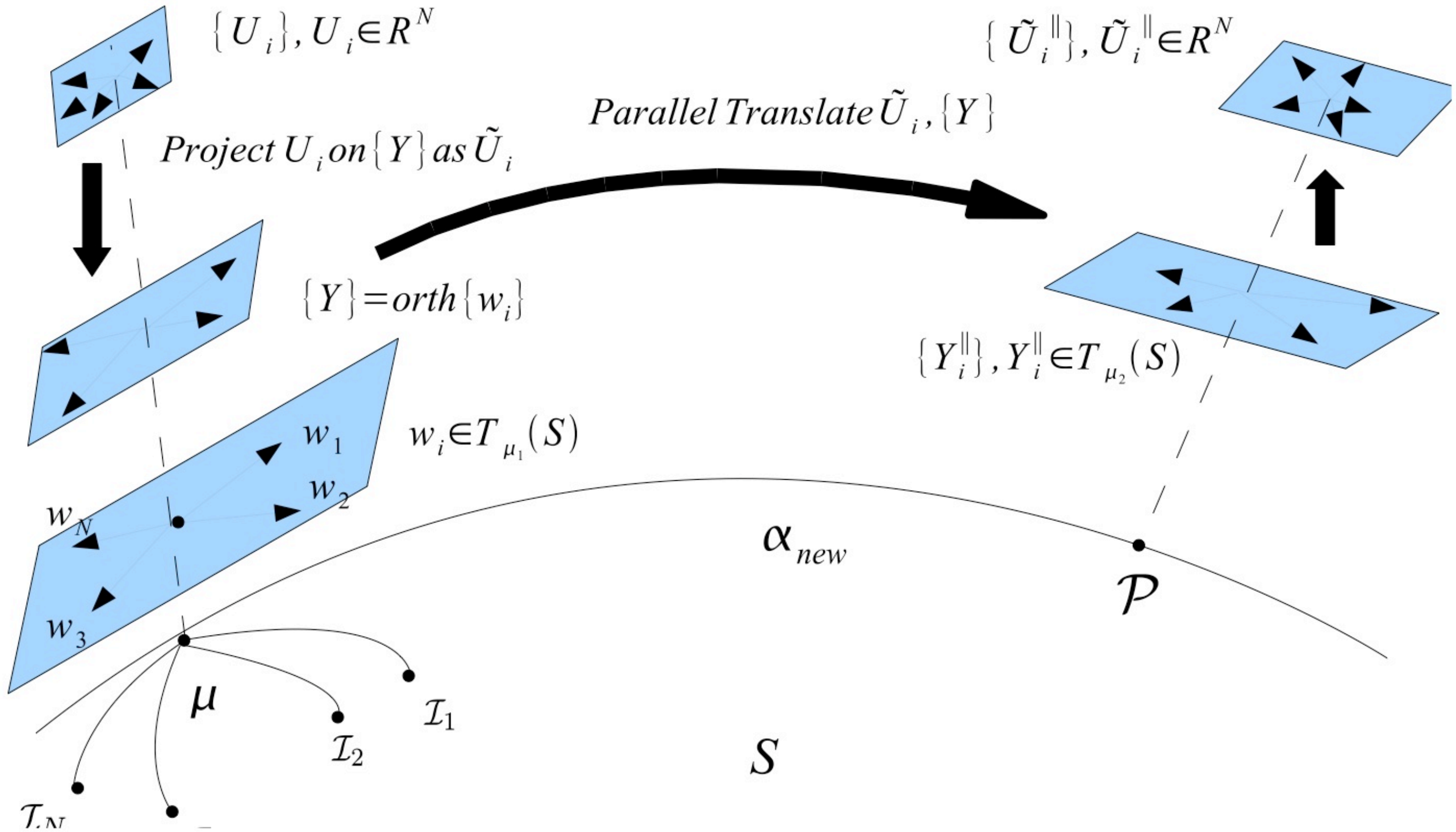
# Prediction of Novel Shapes

Given: Stochastic models for shape variability of a known object or a known view.

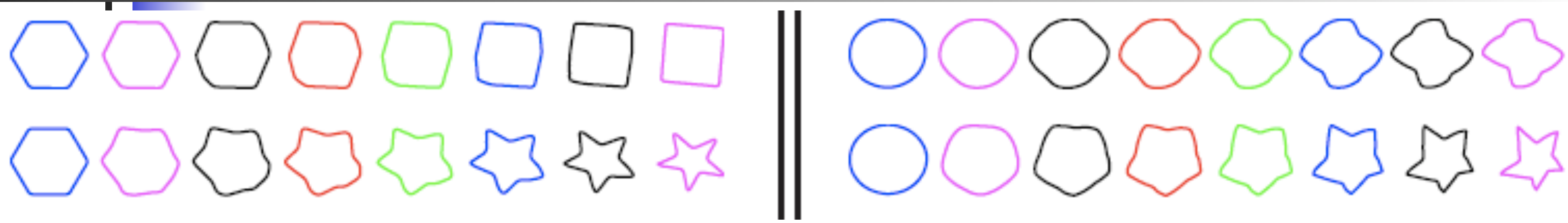
Problem: Predict shape variability of a new (similar) object or the same object from a novel view.

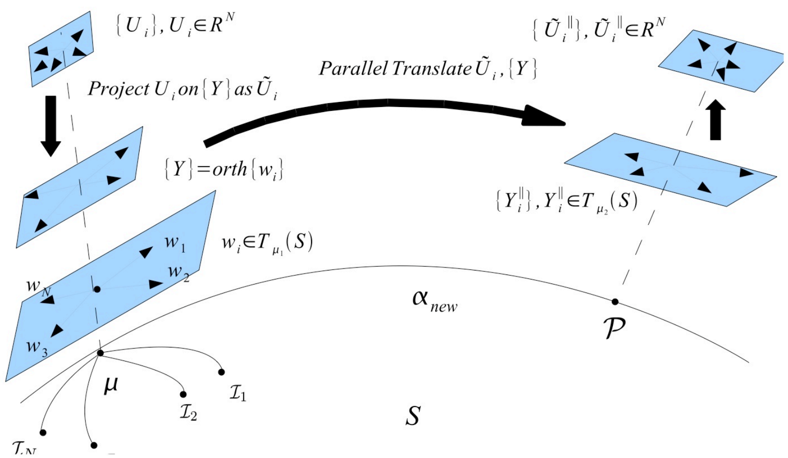


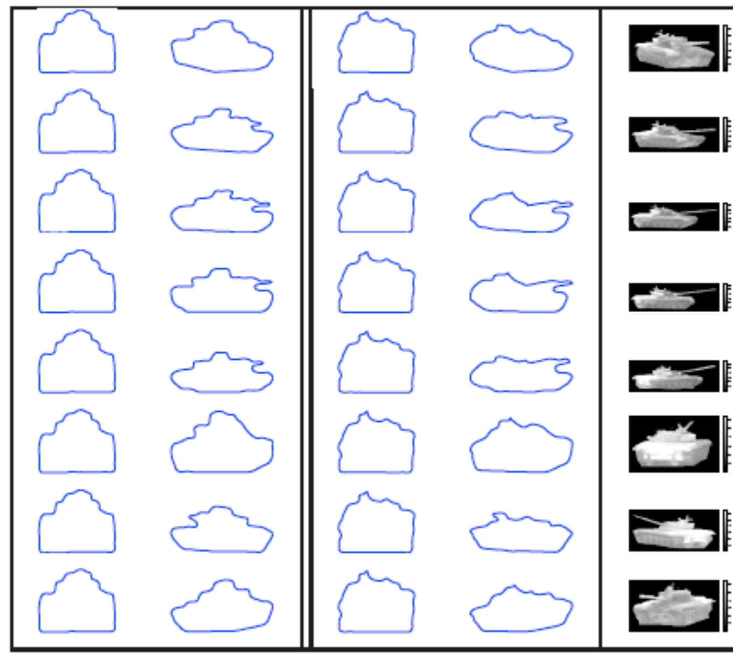
# Parallel Transport of Models on Manifolds



# Prediction of Novel Shapes





# Publications

- *Shape Analysis of Elastic Curves in Euclidean Spaces*
  Joshi, Klassen, Srivastava and Jermyn,
  IEEE Transactions on Pattern Analysis and Machine Intelligence, to be submitted, 2008.

# Additional Shape Efforts

- *Rate-Invariant Recognition of Humans and Their Activities*
  Veeraraghavan, Srivastava, Roy-Chowdhury, Chellappa (UMD)
  IEEE Transactions on Image Analysis, accepted, 2008.

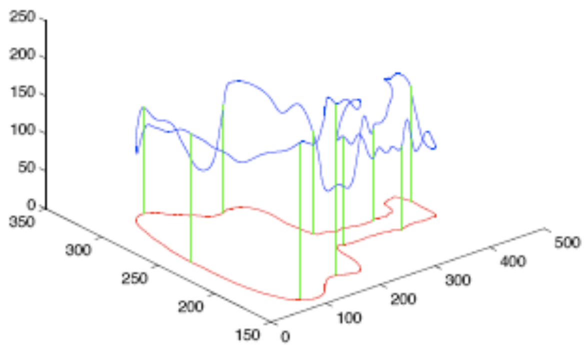
- *Labelling of Cortical Sulci using Multidimensional Scaling*
  Mani, Srivastava, Barillot (IRISA, Rennes, France)
  MICCAI Workshop on Manifolds in Medical Imaging, 2008

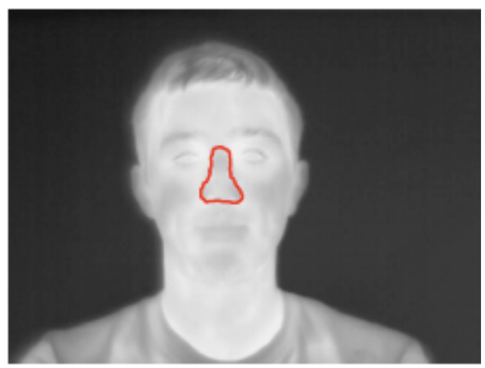
- *Genetics of Brain Fiber Architecture and Intellectual Performance*
  M.-C. Chiang et al. (UCLA)
  Journal of Neuroscience, accepted, 2008.

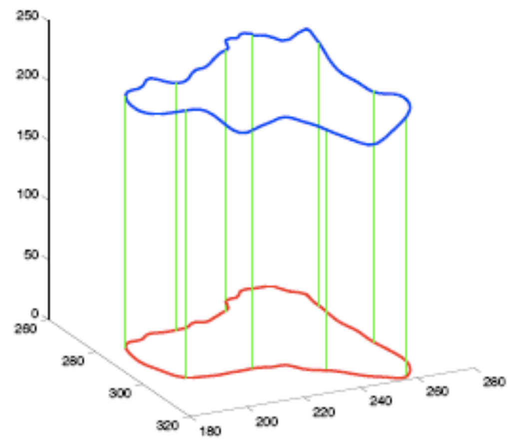
- *Modelling Spatial Patterns of Shapes*
  Srivastava, Liu, and Joshi, ICIP, 2008.

# Looking Ahead

Joint Shape and Texture Analysis of Objects in Images







# Joint Shape-Texture Geodesics