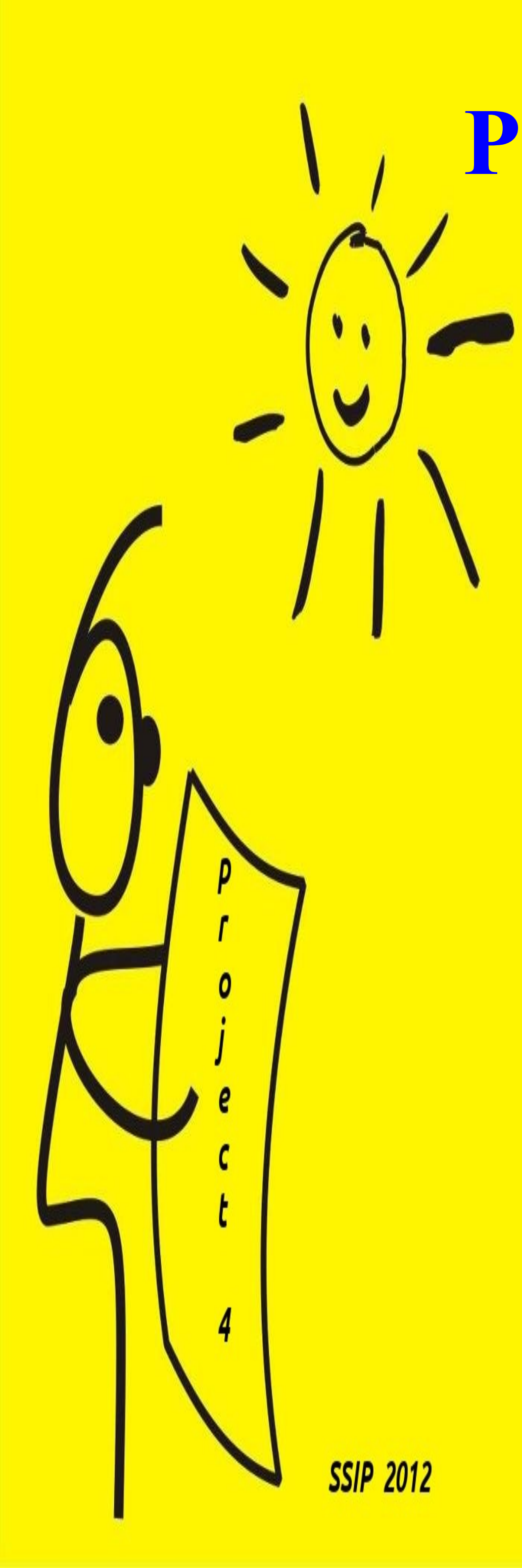


Particle Filter Segmentation

Vienna, Austria, July 2012

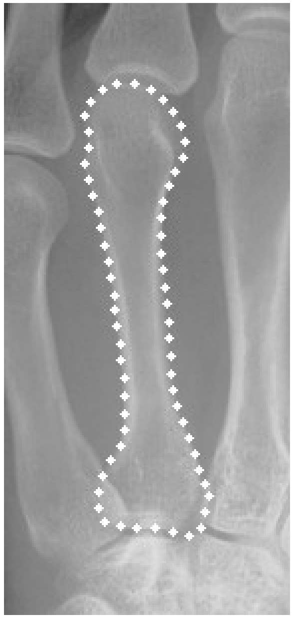
Zoltán Bárdosi

Donatella Granata

Gabor Lugos

Ahmad Pahlavan Tafti

Sanjay Saxena

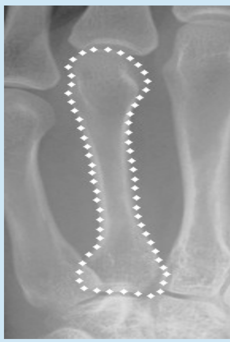


Outline

- Introduction
- Model
  - Generative Shape model
- Training
  - Random forest
- Fitting
  - Cost Function
- Results

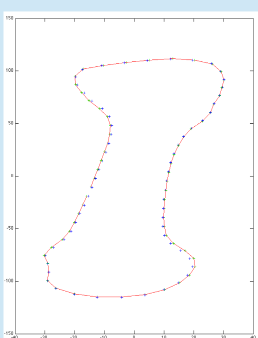
Introduction

Shape model



Annotated Shape Contour

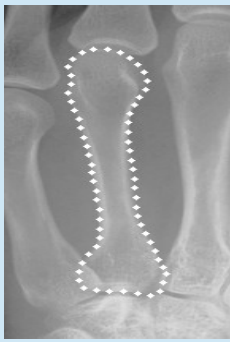
PCA



Generative shape model

Introduction

S h a p e m o d e l



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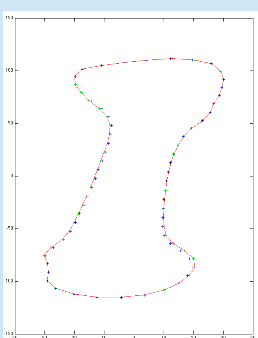
Shape Contour



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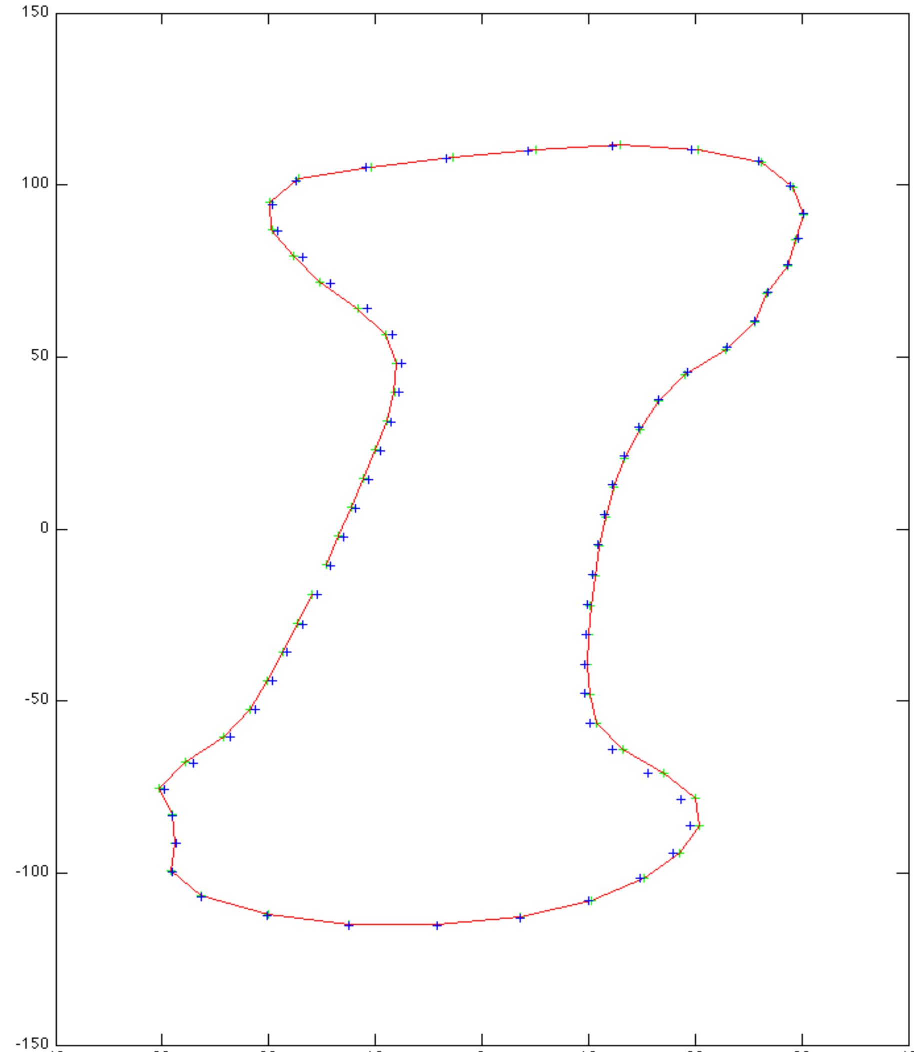

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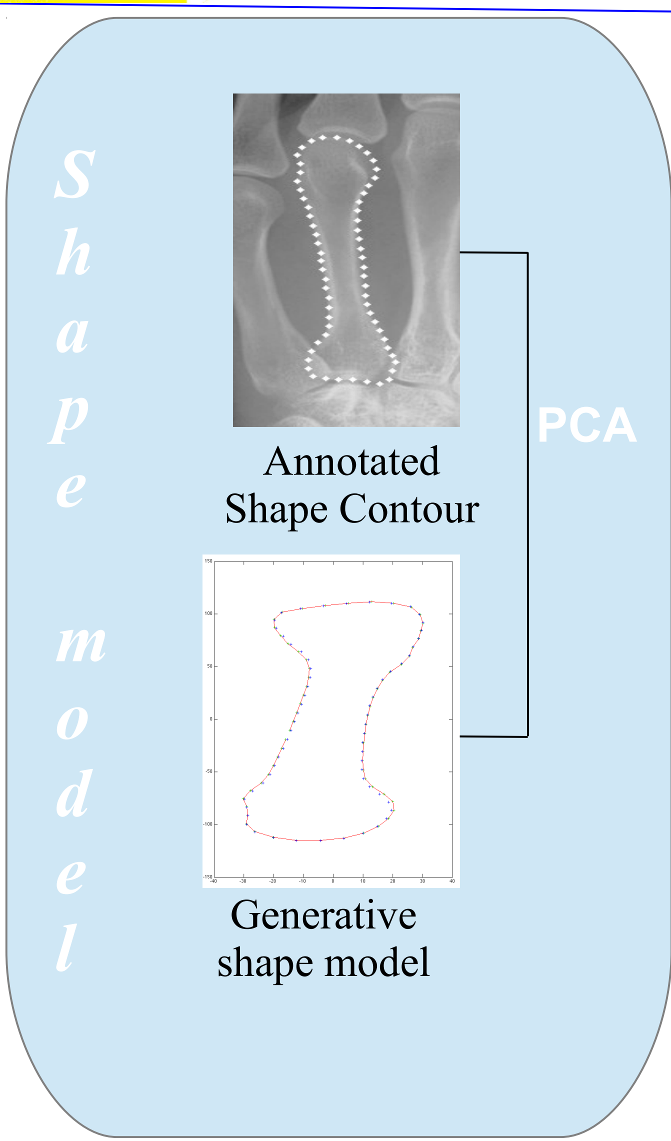
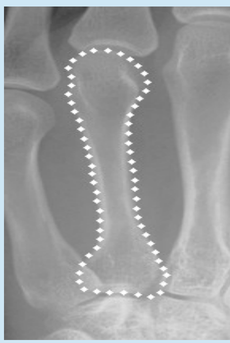


Introduction

Shape model



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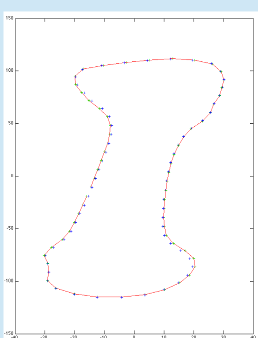
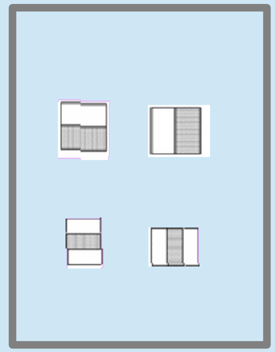


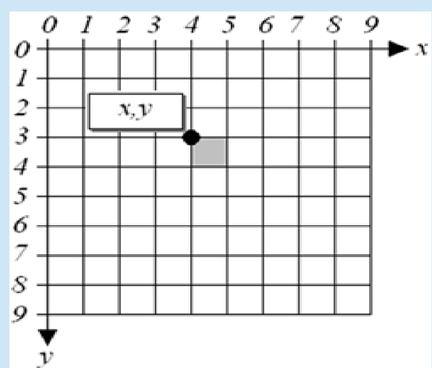
Generative shape model

PCA

Boundary features

Haar-like Features





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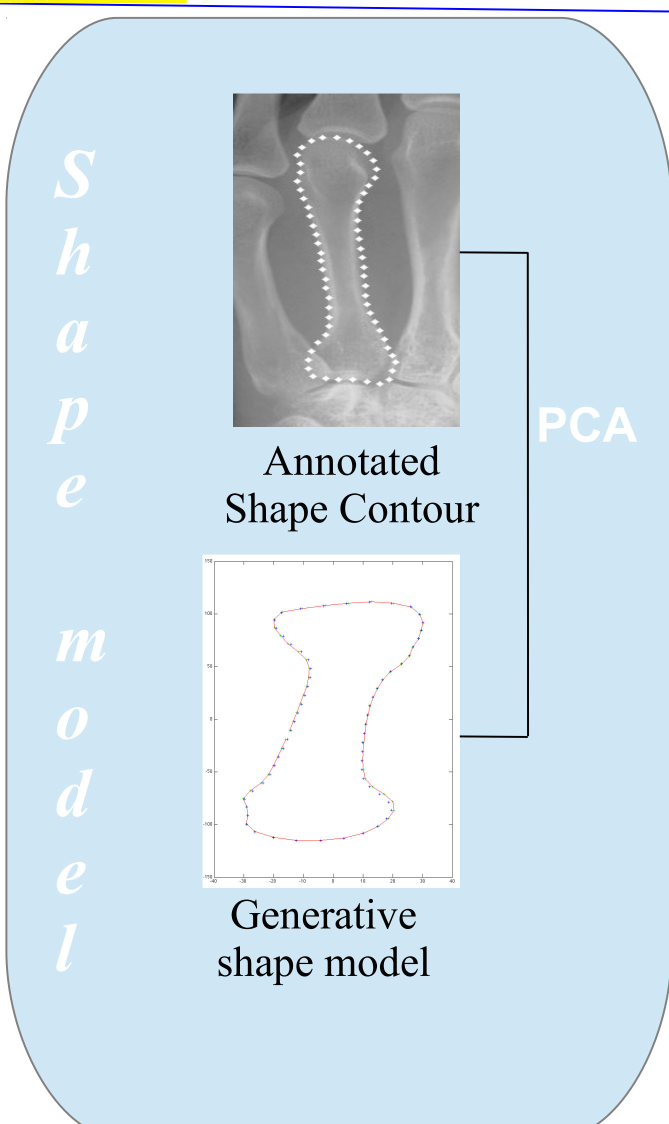
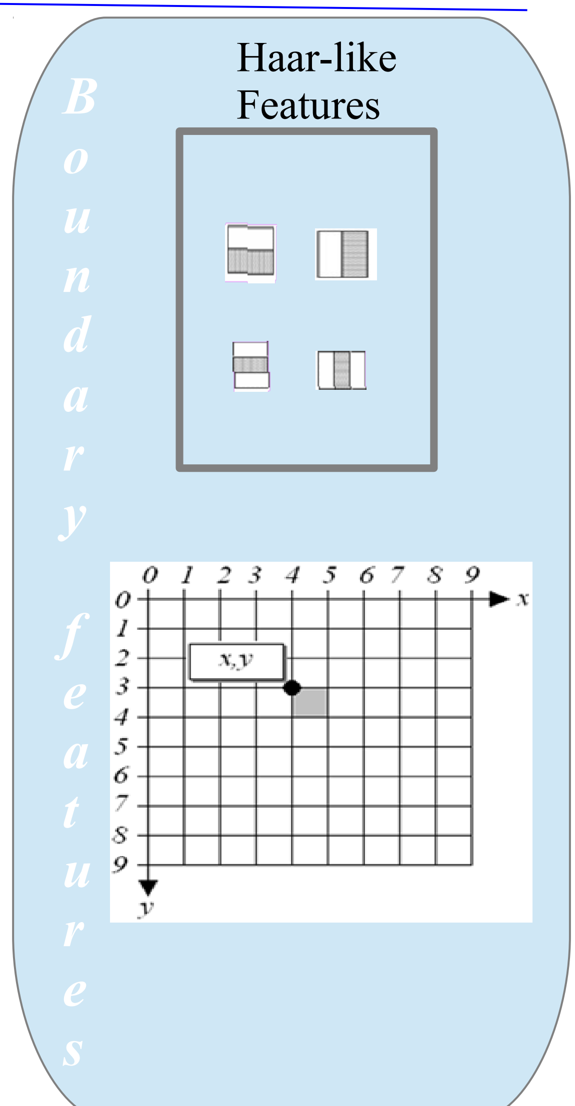
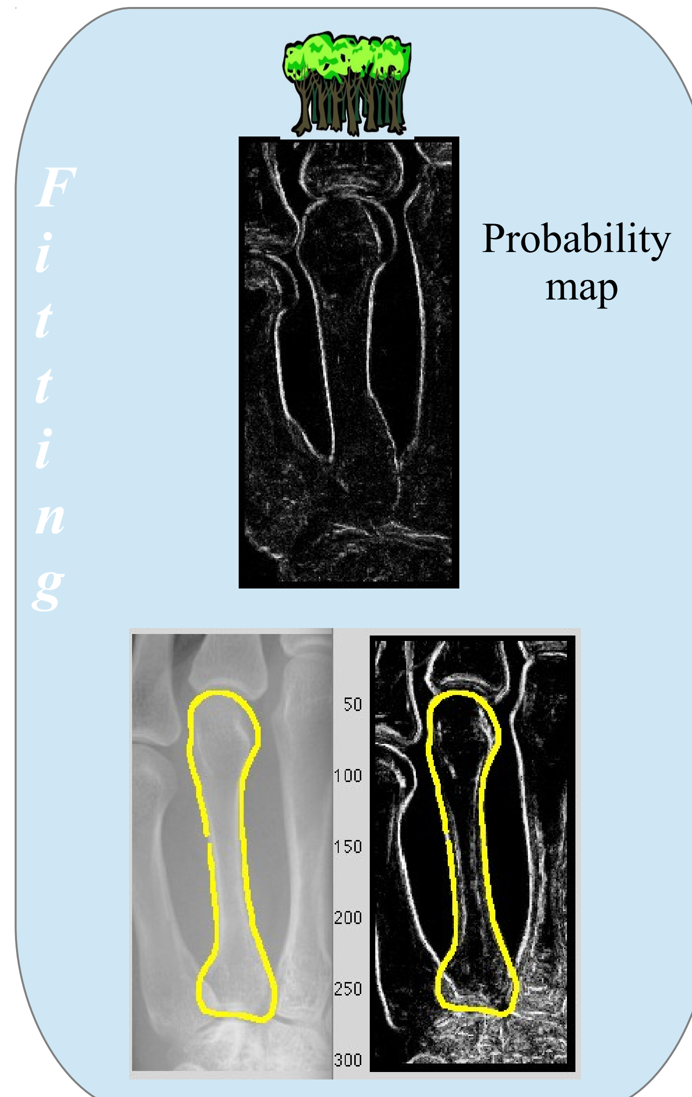
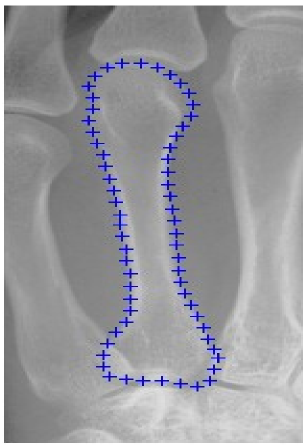






Shape Model



Landmarks are derived from this manually annotated image contours.

$\forall\, i \in \{1, \ldots, N_s\}$ annotated shapes

for d-dimensional landmarks

$$vi = \begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1d} \\ l_{21} & & & l_{2n} \\ \vdots & & & \vdots \\ l_{n1} & l_{n2} & \cdots & l_{nd} \end{bmatrix}$$

The training set is then aligned using Procrustes Analysis, which minimizes

$\sum \left(v_i - \bar{v}\right)^2$ where $\bar{v}$ is the mean of all vectors, i. e. the mean of the shape

Principal Component Analysis

$$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_m \end{bmatrix} = \overbrace{\begin{bmatrix} A_{11} & A_{12} & \cdots & A_{nd} \\ A_{21} & & & A_{nd} \\ \vdots & & & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{m(nd)} \end{bmatrix}}^{\text{A}}$$

m=number of samples (i.e 50)

nd=nd denotes the number of landmarks
(i.e. n=64 and d=2)

$\forall\, i \in \{1, \ldots nd\}$ normalized data set (with zero mean)

$A_i = A_i - \bar{A}_i$ where $\bar{A}_i$ is the mean of each dimension or column

Principal Component Analysis

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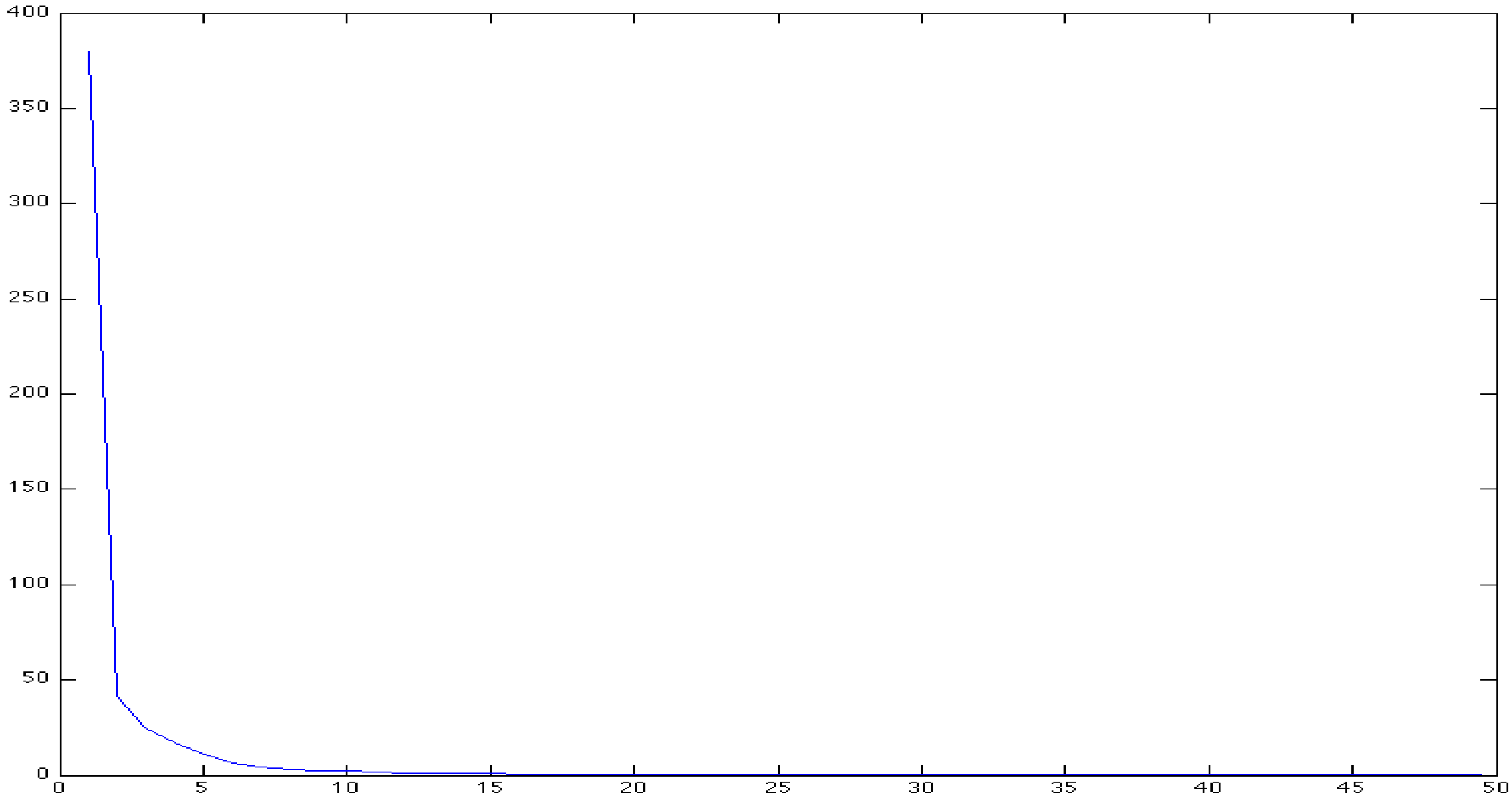
Normalization is crucial for PCA
to assure that the data is centered
around the origin, otherwise
a wrong direction for the eigenvectors
is calculated.

$\forall\, i \in \{1, \ldots nd\}$ normalized data set (with zero mean)

$A_i = A_i - \bar{A}_i$ where $\bar{A}_i$ is the mean of each dimension or column

Principal Component Analysis

The eigenvector with the largest eigenvalue of the covariance matrix of the data is the data set's principle component.



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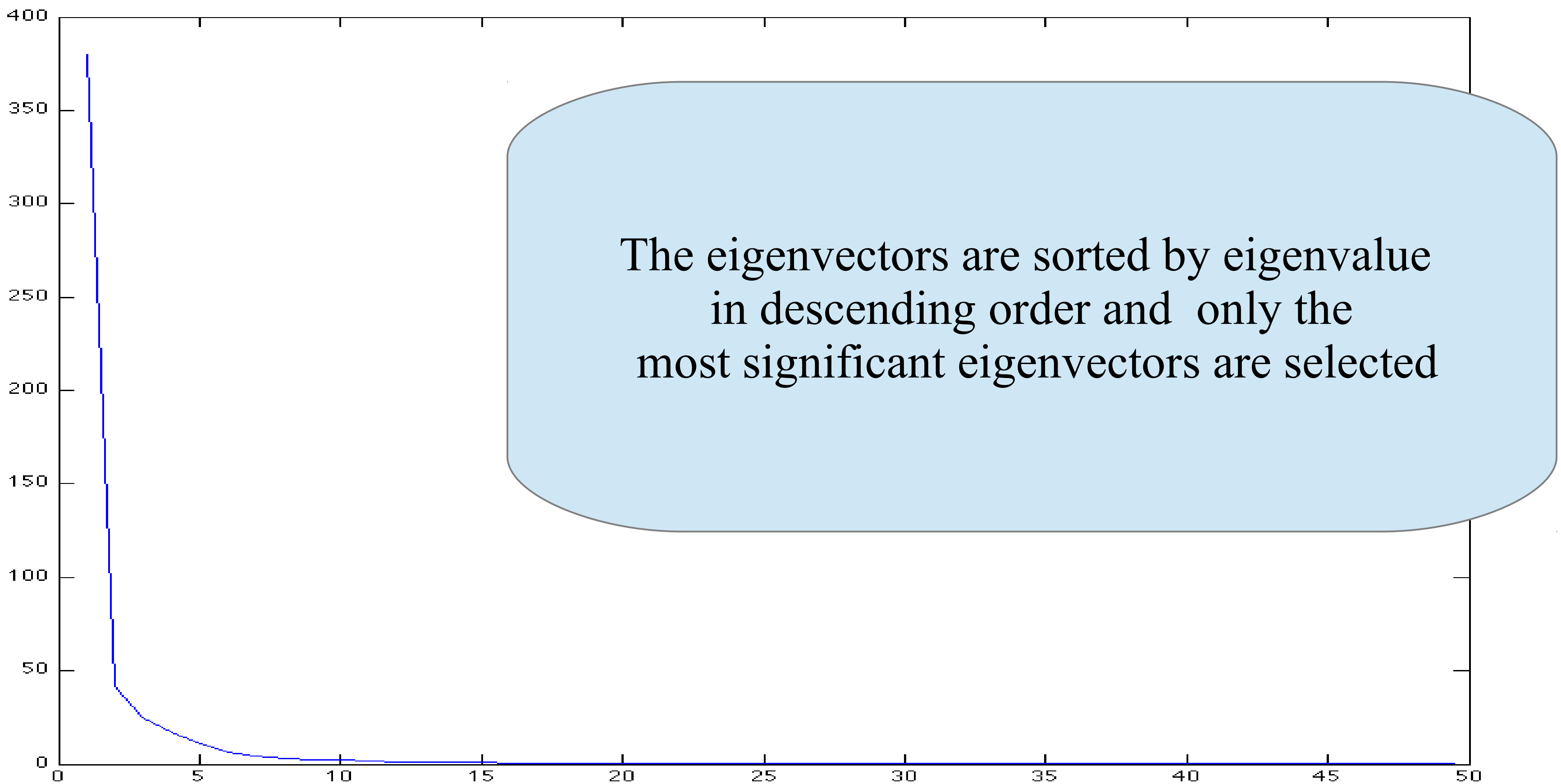
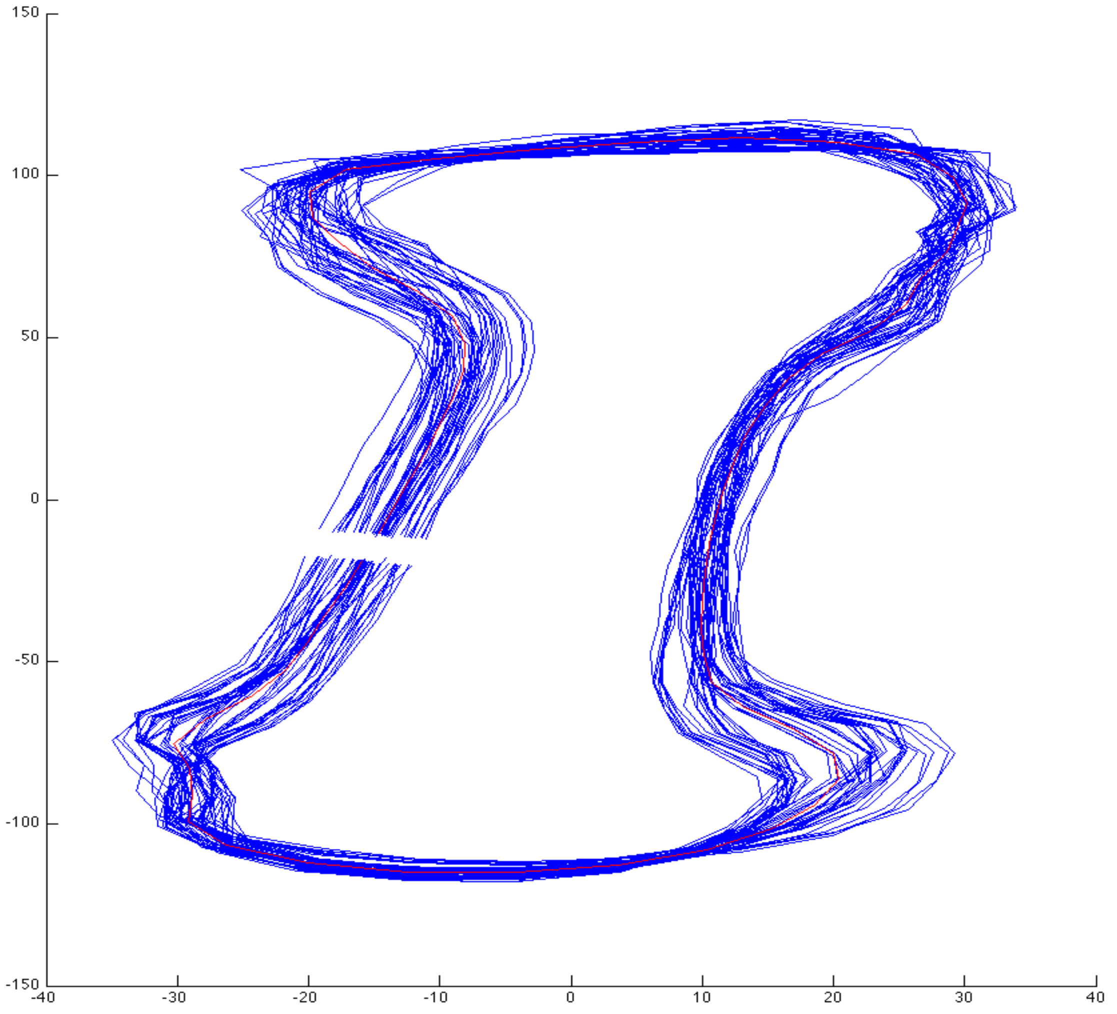


Input and mean shapes



Generative Shape Model

To generate new shapes v.

The actual point distribution model is built by applying PCA.

on $V=(V_{1,}\dots,V_{N_s})$ yielding eigenvectors $e_{1,}\dots,e_{\hat{e}}$ with $e_{\hat{e}}=min(nd,N_s)$

Excluding the modes with small variance $e<\hat{e}$

Any shape v within the subspace spanned by the training set can be represented by:

$$v\approx\bar{v}+Eb$$

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shape within subspace

basis of the eigenspace

defines the parameters for the deformable model

Generative Shape Model

To generate new shapes v.

The actual point distribution model

Each element of b controls
one mode of shape variation, the first
modes being responsible for the highest variation,
in descending order

on $V=(V_{1,}\dots,V_{N_s})$ yielding $N_s)$

Excluding the modes with small

Any shape v within the subspace spanne training set can be represented by:

$$v \approx \bar{v} + Eb$$

shape within subspace

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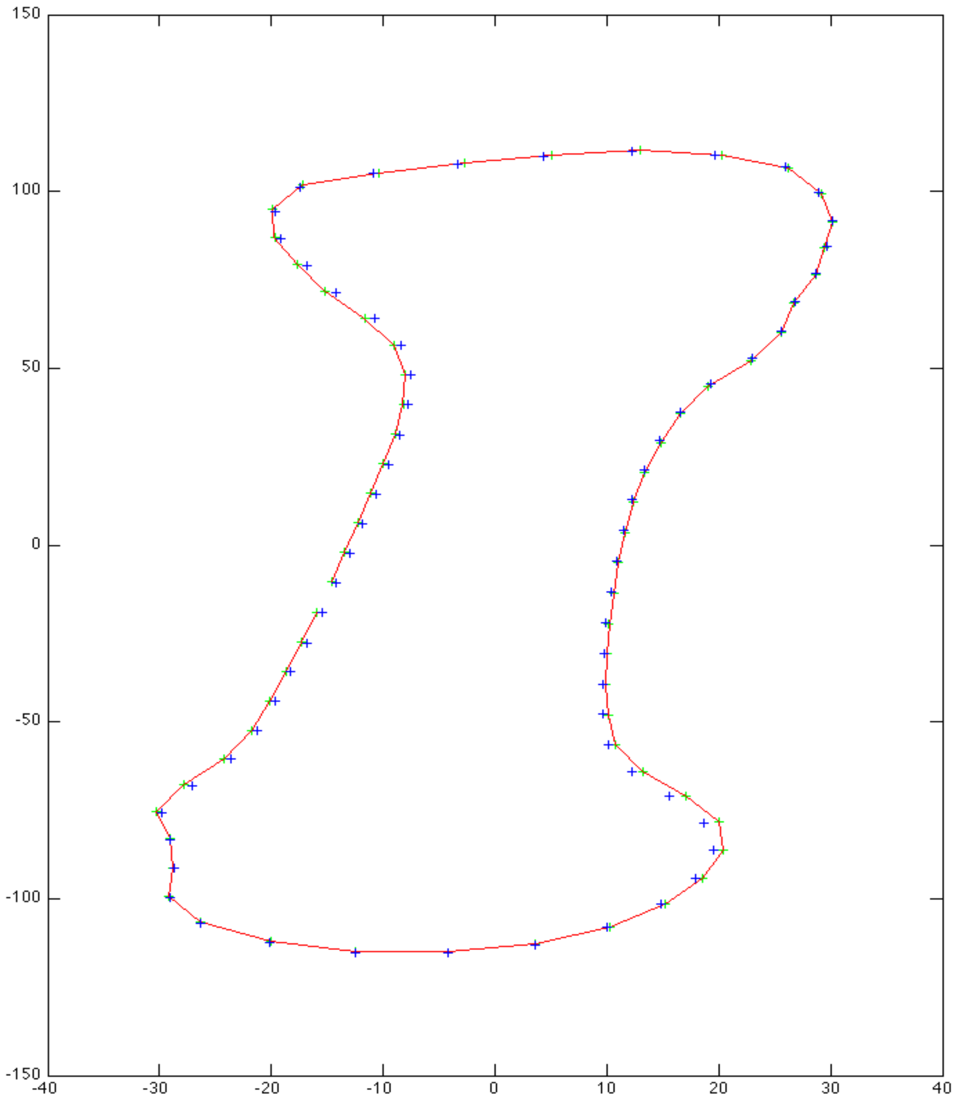
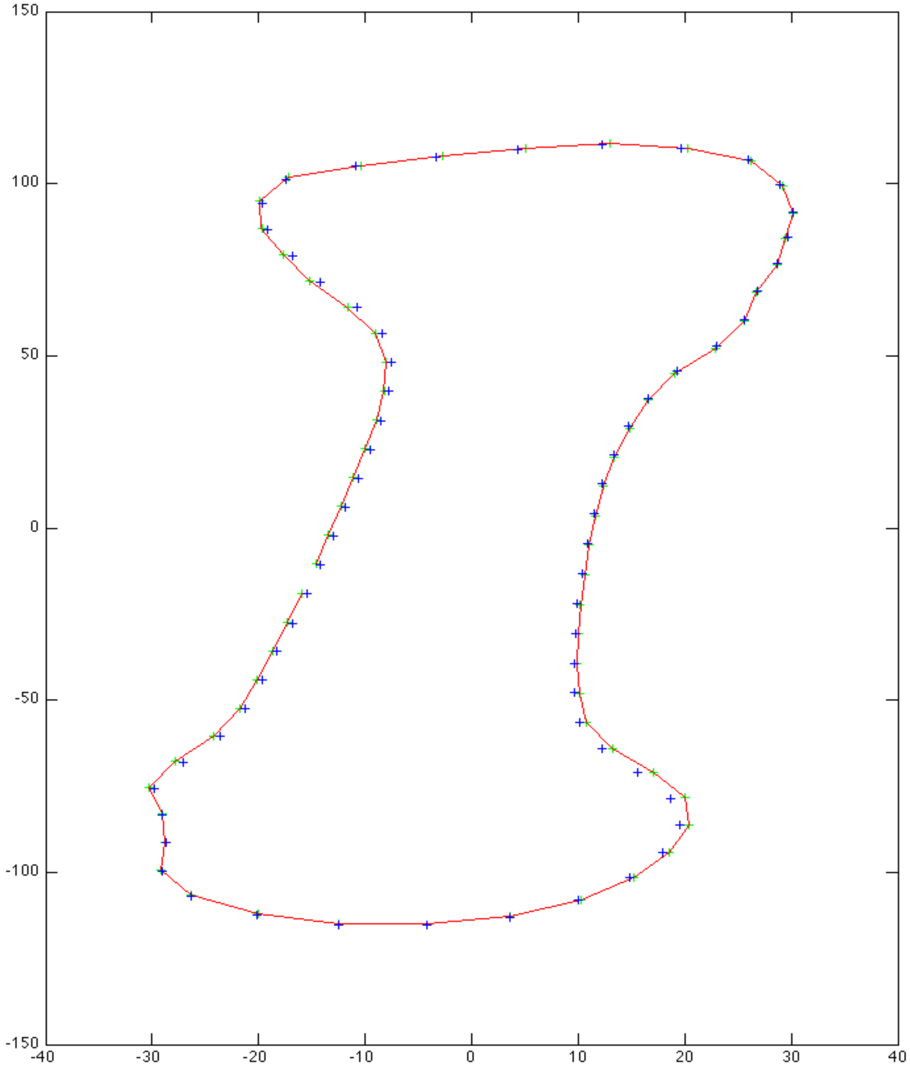
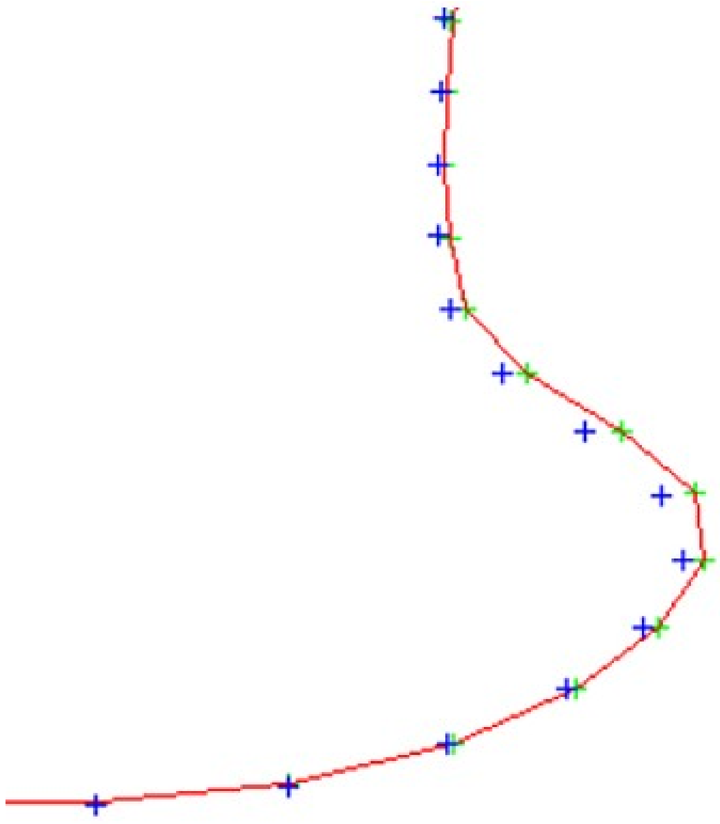
New shape example

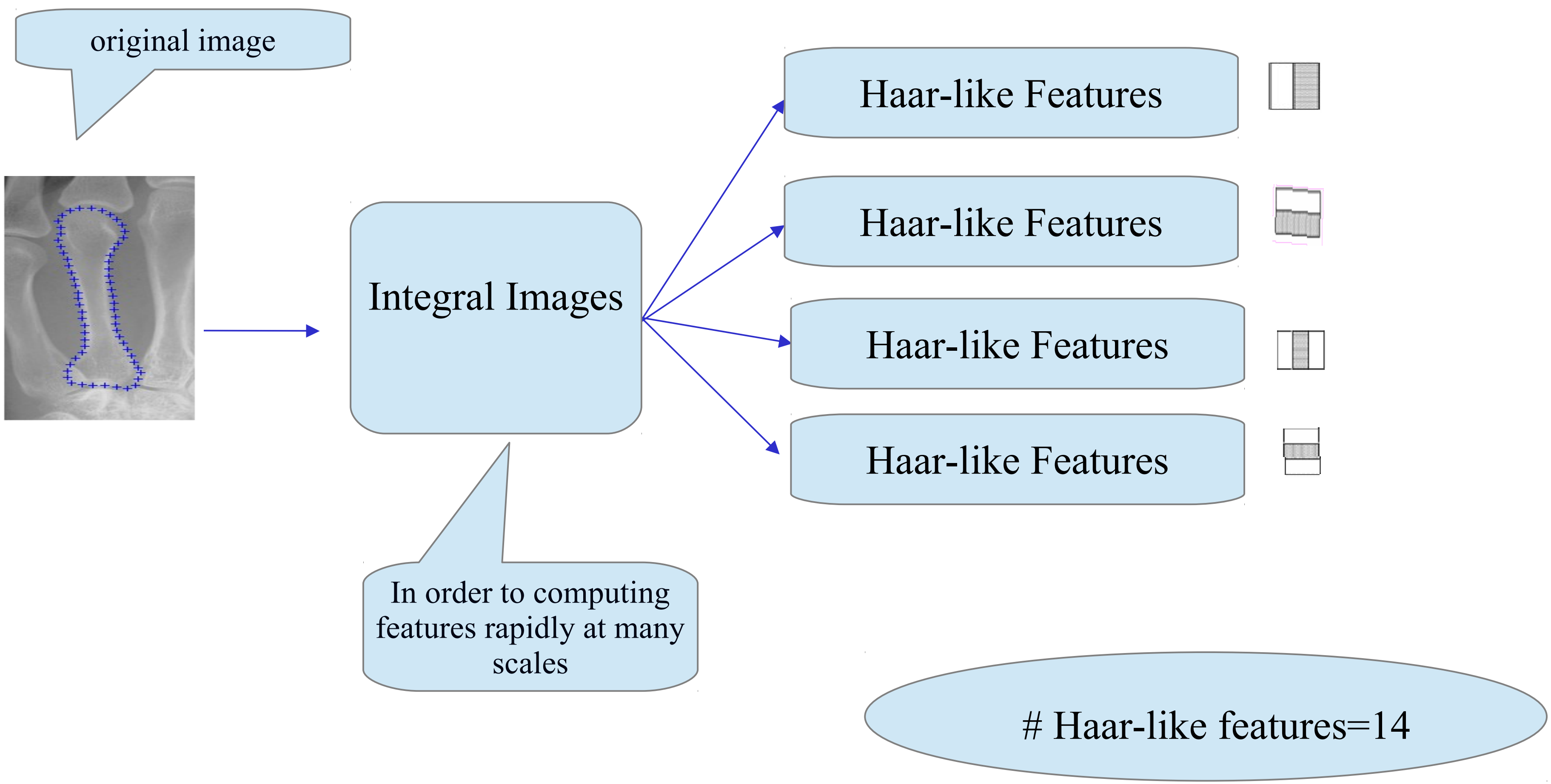


New shape example



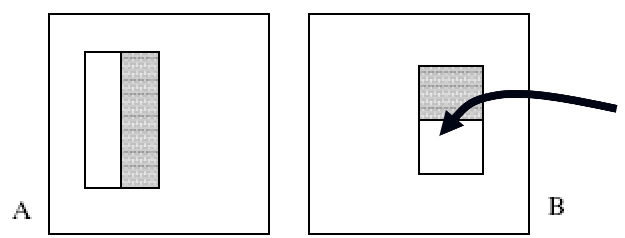


Haar-like features



Haar-like features: two rectangle

The difference between the sum of pixels within two rectangular regions



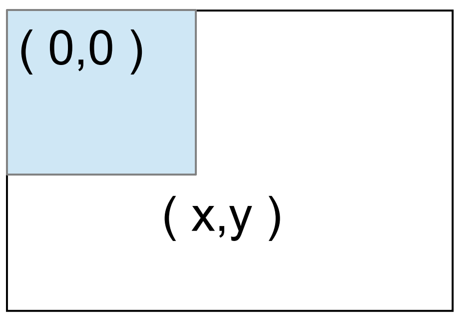
The region have the same size and shape
And are horizontally or vertically adjacent

Integral Image

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x', y'),$$

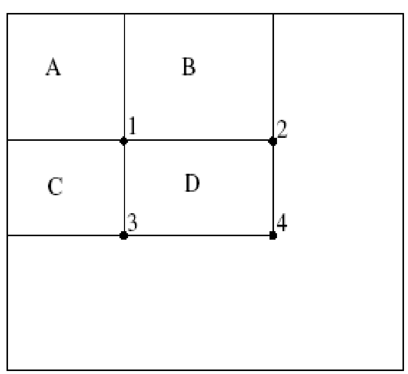
original image

integral image



$$\begin{aligned} s(x,y) &= s(x,y-1) + i(x,y) \\ ii(x,y) &= ii(x-1,y) + s(x,y) \end{aligned}$$

Calculating any rectangle sum with integral image



1 ➡ A
2 ➡ A + B
3 ➡ A + C
4 ➡ A + B + C + D

Rectangle Sum
D = 4 - 3 - 2 + 1

Random Forest Classification

- Build many decision trees
- Train each tree on a different subset of training data (bagging)
- At each tree node, split the data based on a different subset of features.
- Evaluate each tree using “out-of-bag” data (i.e., data not used to train tree).
- Aggregate results over all trees

Random Forest Classification

```
>> t= treBagger(32, X, Y);
```

predictors

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ \vdots \\ P_{12} \\ P_{13} \\ P_{14} \\ \vdots \\ P_{30} \\ P_{31} \\ P_{32} \end{bmatrix}$$

```
>>[Y_pred, allpred]=predict(t,X_new);
```

response

$\overline{p}$

Cost function

2 translation coeffs

2 scaling coeffs

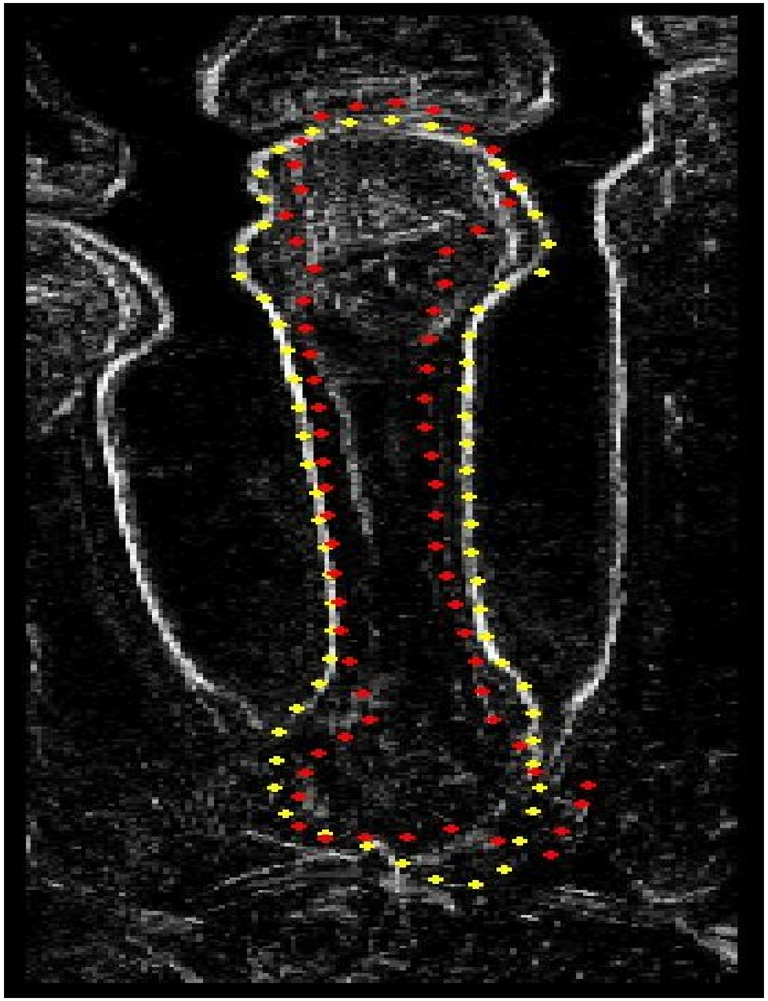
$$x = \left[b_{1,} \dots b_{8,} t_x, t_y, r, s_{1,} s_2 \right] \quad x \in R^{13}$$

8 PCA comps

1 rotation param

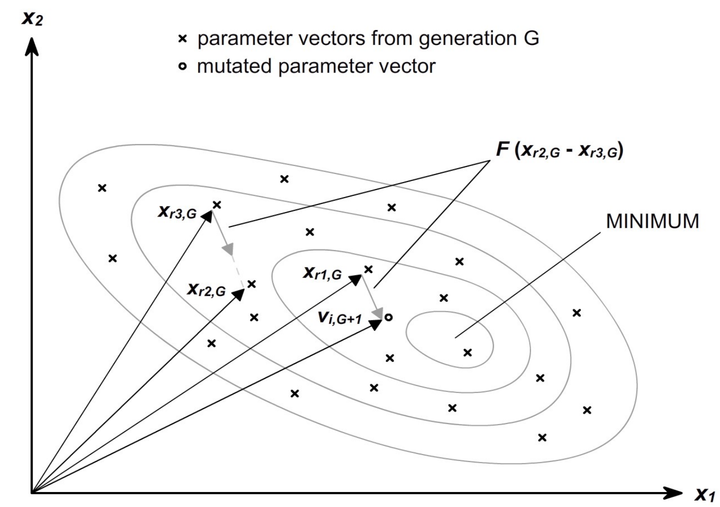
$$f(x) = 1 - \frac{\sum_{p_i \in shape(x)}^{n} p_i}{n}$$

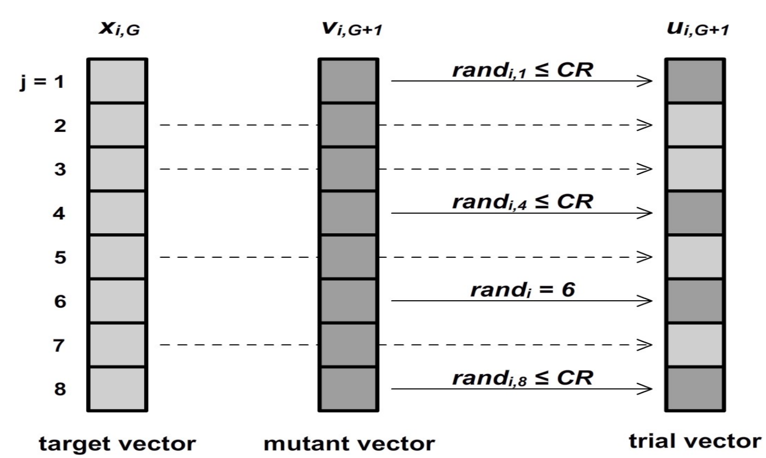
$$\min f(x)$$
$$x \in R^{13}$$



Differential Evolution

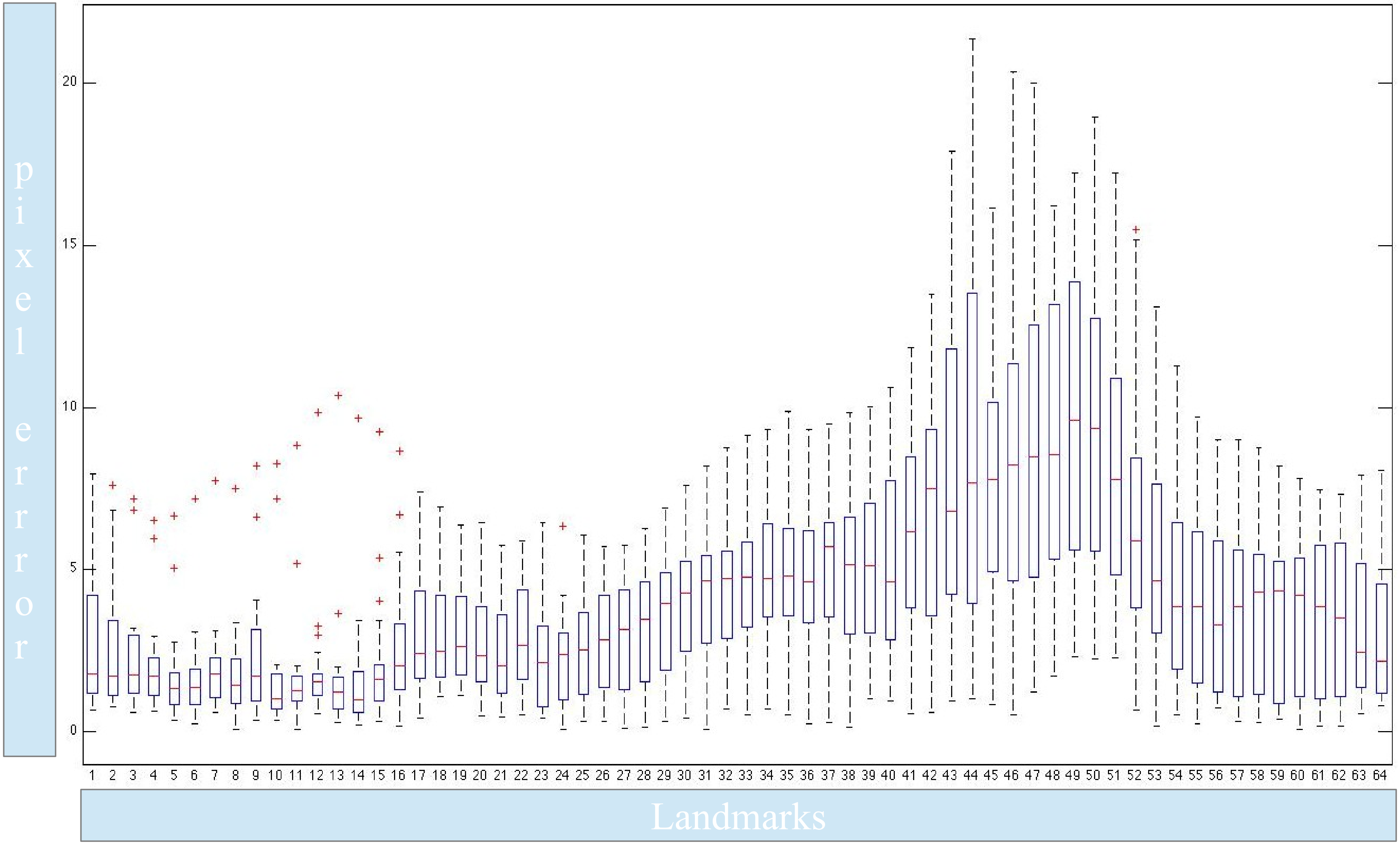
- DE is an extention of classical
  GA algorithms
- It works with a set of candidate solutions (population).
- It uses a nature inspired search operator.
  - -Mutation
  - -Crossover
  - -Selection
- It is dependent on the problem that we need to solve.





Results:

Results: Landmarks MSE



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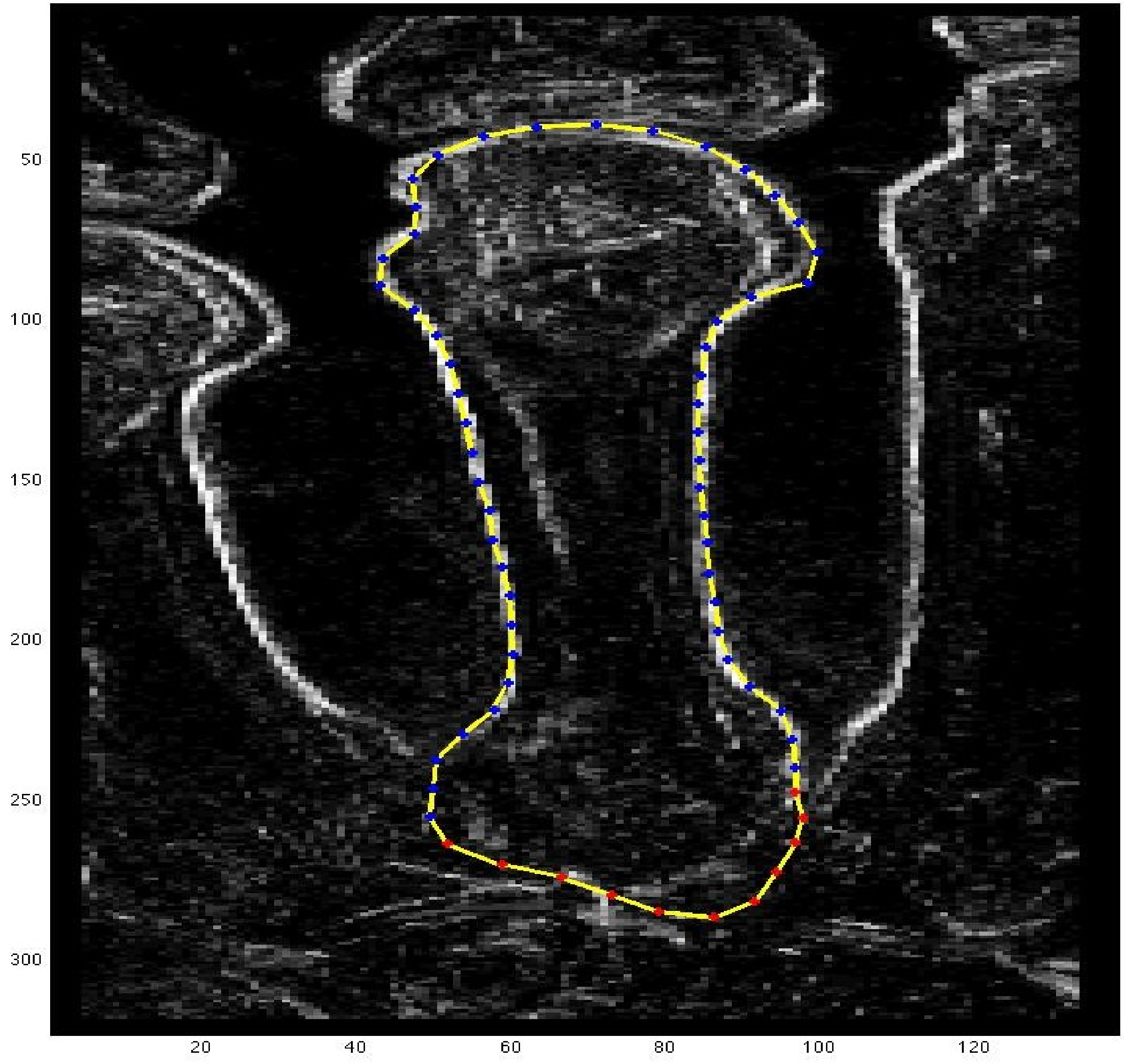

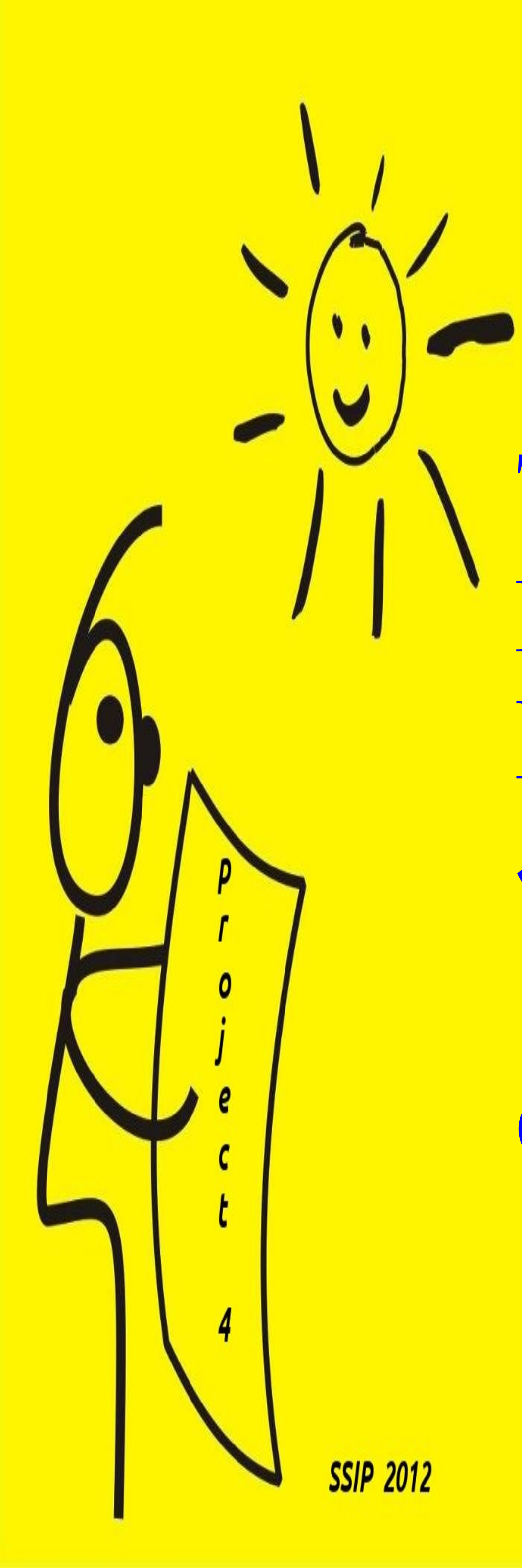

Thanks for your attention!!

Danke für Ihre Aufmerksamkeit!!

Köszönjük a figyelmet!!

आपका ध्यान के लिए धन्यवाद !!

با تشکر از توجه شما !!

Grazie per l'attenzione !!