AUTOMATIC SEGMENTATION OF ANATOMICAL STRUCTURES USING DEFORMABLE MODELS AND BIO-INSPIRED/SOFT COMPUTING

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- Motivation
- Theoretical Background
  - Deformable Models
  - Metaheuristics
- Method 1: Active Shape Models and Random Forest
- Method 2: Level Set method and Eigen Shapes
- Method 3: Three terms (region, shape prior, boundaries) and automatic tuning
- Conclusions

Motivation (1)

- Study medical image segmentation algorithms
  - Detection of lesions
  - Measurement of organ size/volume
  - Quantitative tissue analysis
  - Computer-integrated surgery

- Collaboration with the Molecular Biotechnology Center of Torino
  - Tool for performing genome-wide experiments
    - Automatically localizing the hippocampus and analizing its visual features in neuro-genomic images of the mouse brain.

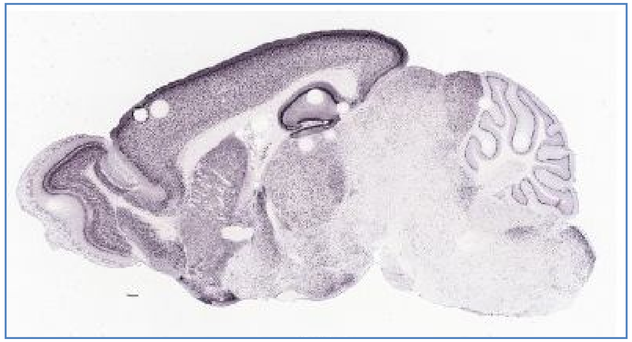
Motivation (and 2)

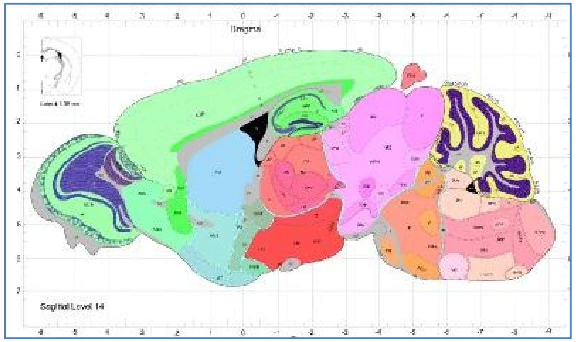
- European Marie Curie Project "MIBISOC"
  - Explore hybridizations betweeen Soft Computing (SC) and Computer Vision (CV) in Medical Imaging

- Methodological objectives
  - Completely **automatic** methods
    - Not initialized/supervised by user
  - Avoid extremely **ad-hoc and poorly tested** algorithms
  - Focus on important, but traditionally ignored, **biomedical image modalities** (like histological imaging)
    - The vast majority of works deal with MRI, CT or US.

Main Dataset

- Histological Images (Allen Mouse Brain Atlas)
  - Used in many of our experiments
  - Public database of high resolution **histological** brain images
    - Expression patterns of about 20,000 genes in the adult mouse brain (In Situ Hybridization). ISH: technique that allows for precise localization of a specific segment of nucleic acid within a histologic section
    - Spatial map of the expression patterns of almost every mouse gene (genomics vs neuroanatomy)





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Deformable Models

- Curves or surfaces defined within an image domain, that move under the influence of
  - "internal forces" - related with the curve features
  - "external forces" – related with the surrounding image
- Parametric DM – Active Shape Models (ASM):
  - represents curves and surfaces explicitly in their parametric forms during deformation,
  - allowing direct interaction with the model and leading to a compact representation for fast real-time implementation
- Geometric DM - Level Set Method (LS):
  - Able to handle topological changes naturally.
  - Based on the theory of curve evolution; it represents curves and surfaces implicitly as a level set of a higher-dimensional scalar function.

Metaheuristics (MHs)

- General-purpose optimization techniques:
  - Approximation and non-deterministic algorithms
  - No requirement for a differentiable or continuous objective function
    - Discontinuous, noisy, high-dimensional, multimodal search spaces
  - No need of specific information about the problem to solve
  - Many of them, implicit parallelism (like GA)
  - Examples: Genetic Algorithms, Tabu Search, Particle Swarm Optimization, Differential Evolution, Ant Colony Optimization,…

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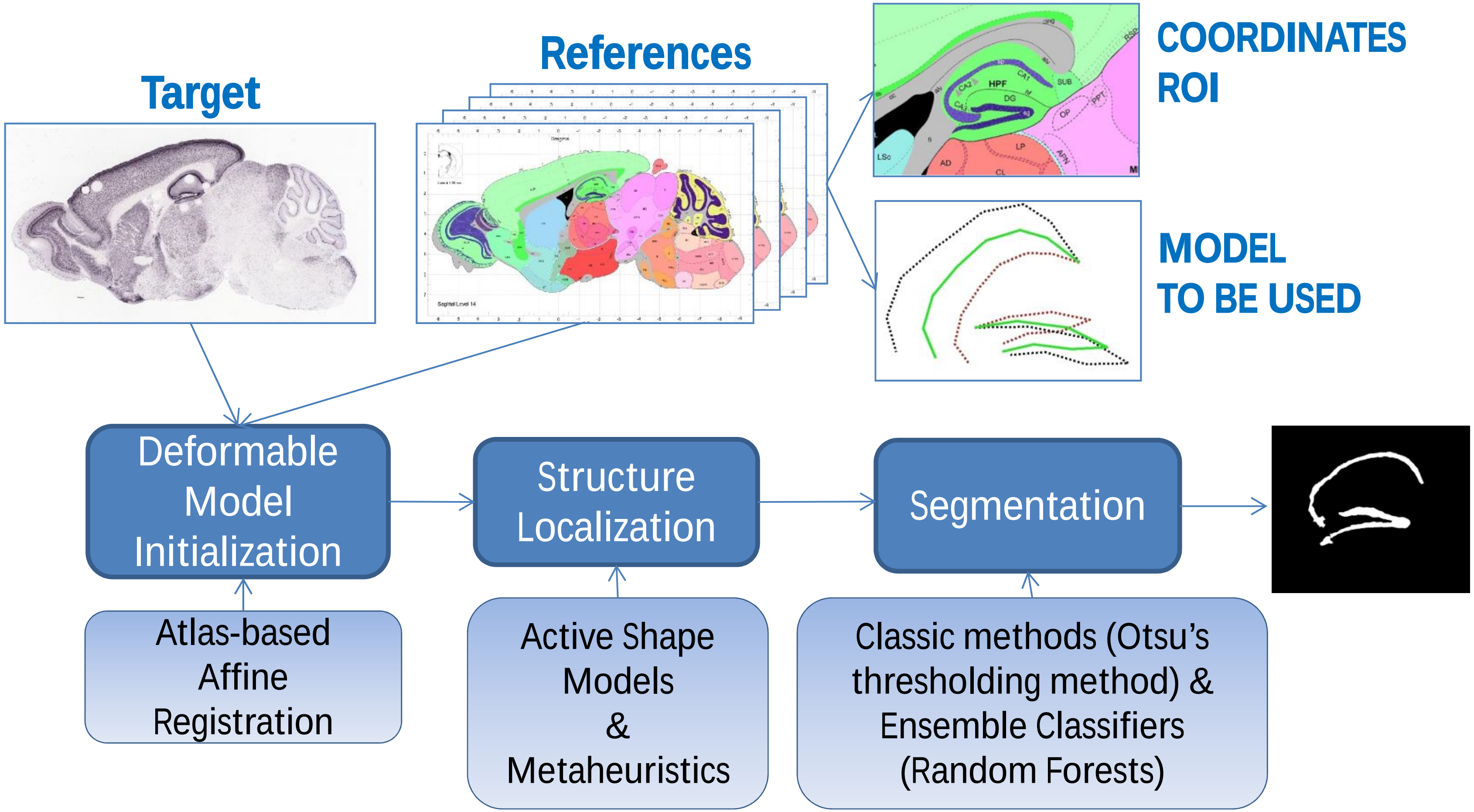
Active Shape Models and Random Forests



Mesejo, P., Ugolotti, R., Di Cunto, F., Giacobini, M., and Cagnoni, S., **"Automatic Hippocampus Localization in Histological Images using Differential Evolution-Based Deformable Models"**, Pattern Recognition Letters, 34, 299-307, 2013 (IF2011: 1.034, COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE)

Experimental Results

comparison of optimizers

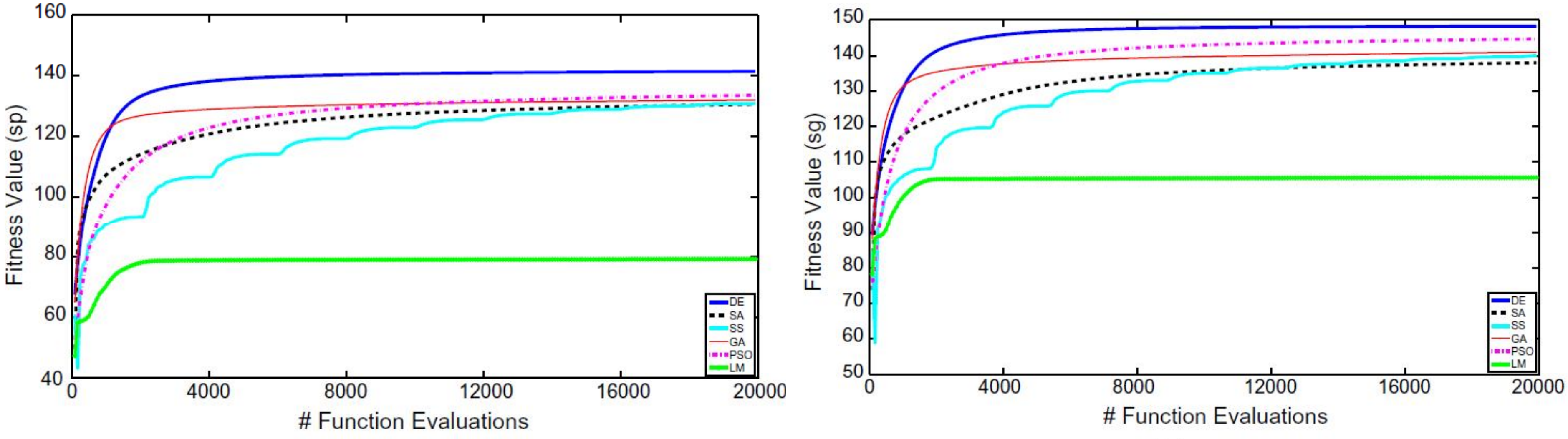
- 250 images | 6 methods | 10 tests/image | 250 iterations

GENETIC ALGORITHM	Pc = 0.6 | Pm = 0.09 | Pop = 80 | Uniform Crossover
SCATTER SEARCH*	Local Search: localized random search | Solution combination method: BLX-α crossover with α=0.5 | |B|=7 | |D|=8
SIMULATED ANNEALING	T_{start} = 1.5 | T_{end} = 1E-9
MODIFIED PSO**	w_{min} = 0.2 | w_{max} = 1.0 | $c_1 = c_2$ = 2.05 | Swarm = 80 particles
DIFFERENTIAL EVOLUTION	Cr = 0.9 | F = 0.7 |Uniform Crossover |Mutation DE/target-to-best/1

* O. Cordon, S. Damas, J. Santamaria, *A fast and accurate approach for 3D image registration using the scatter search evolutionary algorithm*. Pattern Recognition Letters 27, 1191-1200, 2006.

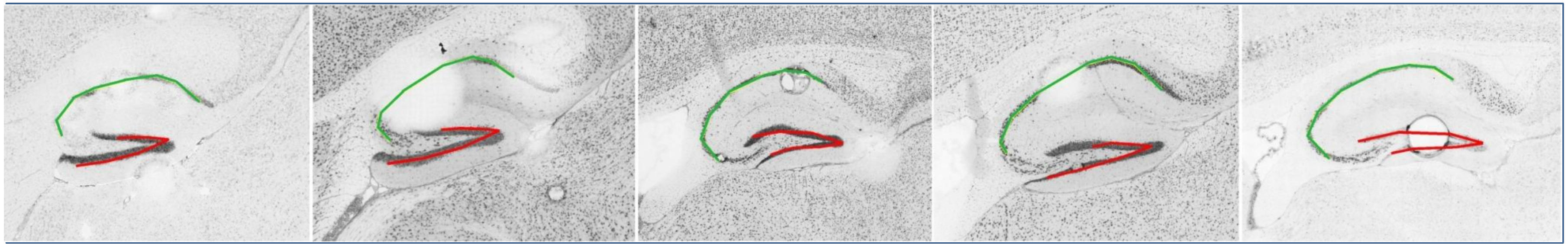
** B. Liu, L. Wang, Y.-H. Jin, F. Tang, D.-X. Huang, *Improved particle swarm optimization combined with chaos*, Chaos Solitons & Fractals, 19, 1261–1271, 2005.

Localization Results:
comparison of optimizers



(a) *sp* (b) *sg*

- Perfect or good localization in 90.9% of cases (250 genes)
- Noise Tolerance



7 Methods Tested

- Parametric Deformable Models (ASM+RF) [Mesejo 2013]

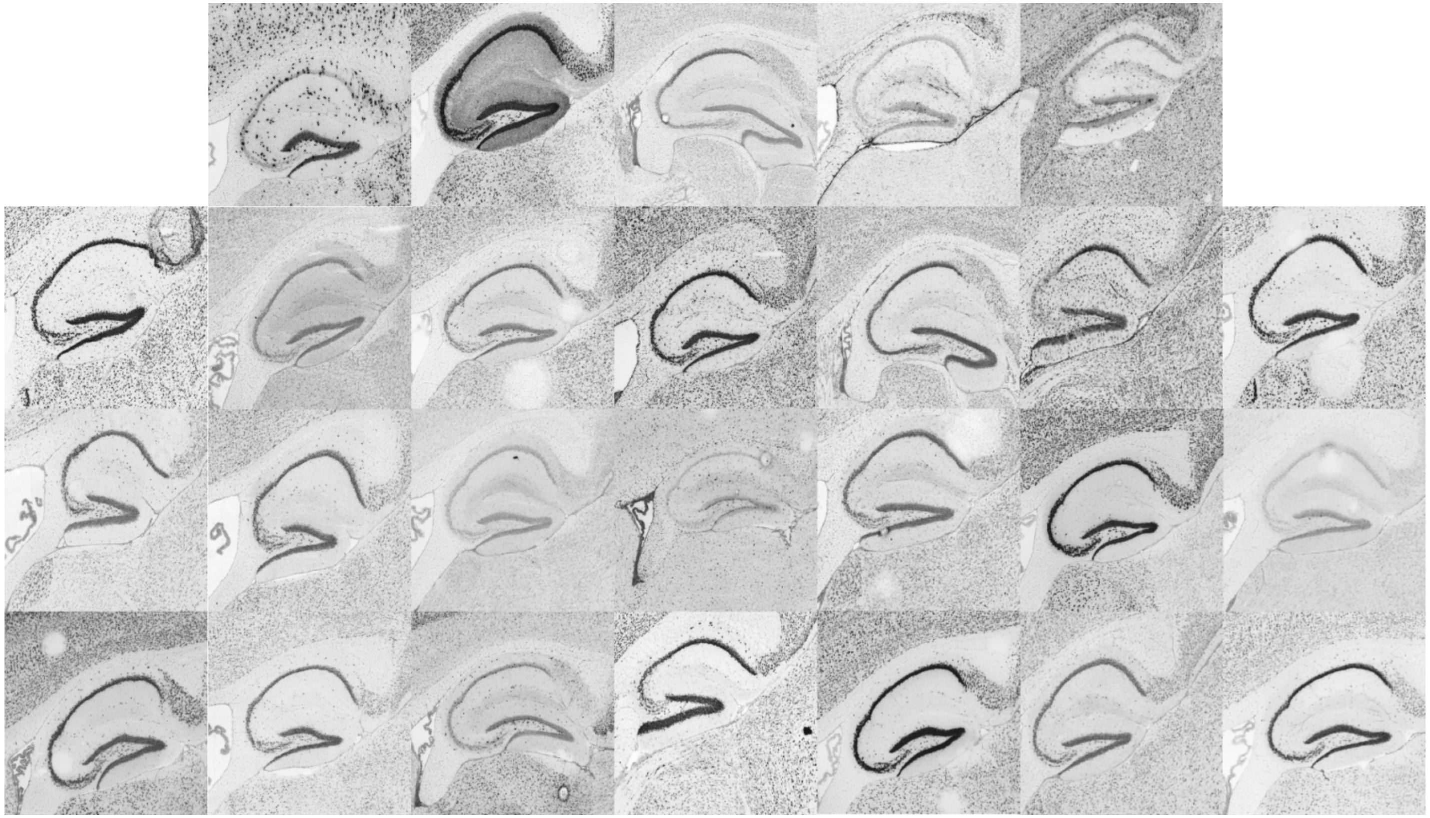
- Histogram-based methods
  - ST [Aja 2010]
    - Successfully applied to CT, MRI and ultrasound imaging
  - Otsu [Otsu 1979]
    - Classic technique
    - ASM+RF uses Otsu's → In this way, we can compare the improvement obtained by the whole pipeline of ASM+RF

- Geometric Deformable Models
  - Region-based: Chan&Vese model (CV and CV+ASM) [Chan 2001]
  - Edge-based: Geodesic Active Contour (GAC, GAC+ASM) [Caselles 1997]

Mesejo, P. and Cagnoni, S., **"An experimental study on the automatic segmentation of in situ hybridization-derived images",** Procs. of the 1st International Conference on Medical Imaging using Bio-Inspired and Soft Computing (MIBISOC'13), 153-160, Brussels, May -2013

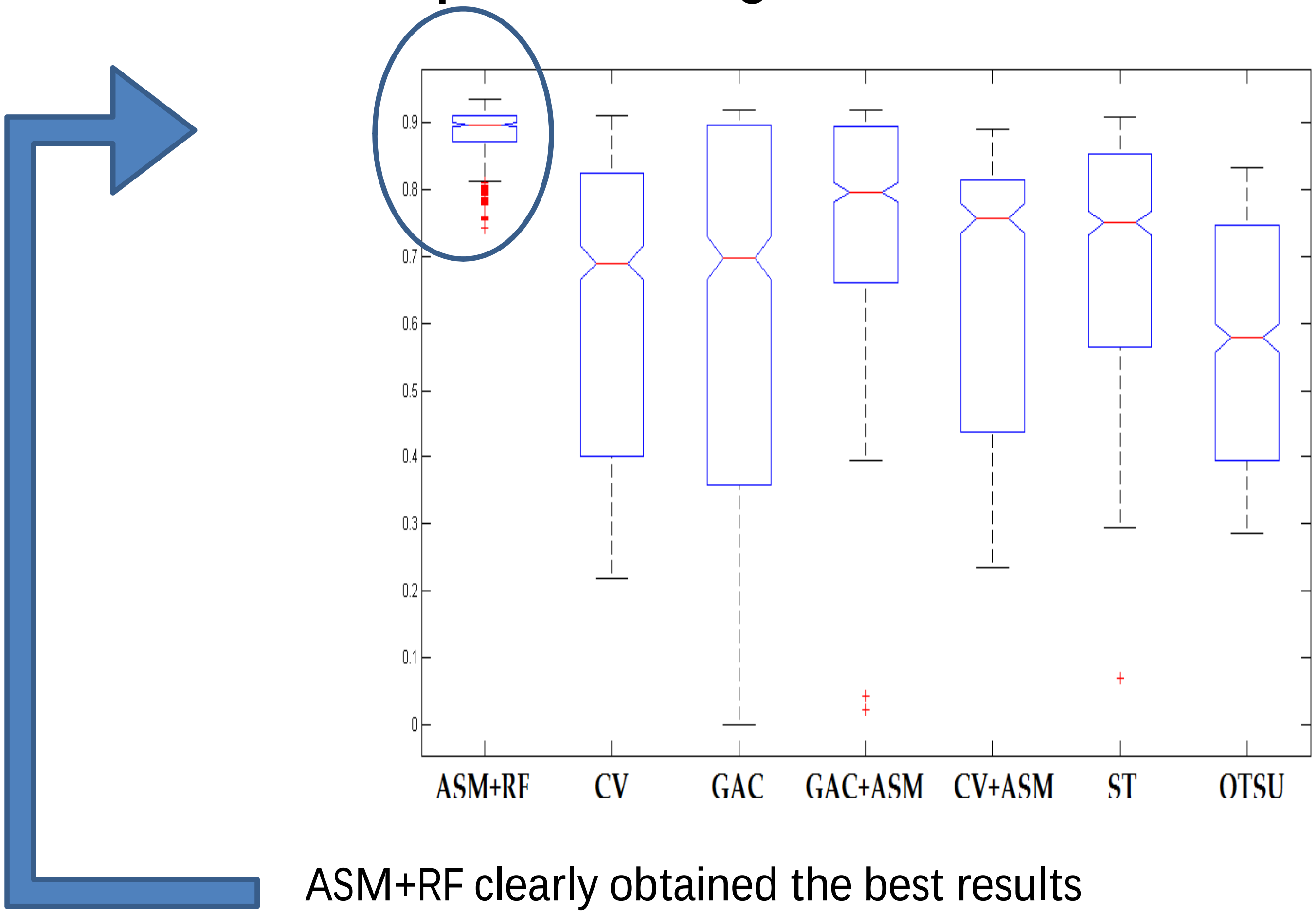
Complete Dataset

- 30 real images with ground truth, representing very different scenarios
- 25 runs per image for non-deterministic methods
- Ground truth: consensus image of 5 manual segmentations



Experimental Results

comparison segmentation methods



ASM+RF clearly obtained the best results

Kruskal-Wallis statistical test confirmed the existence of statistically significant differences p-value << 0.01

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Method 2

- Objectives:
  - Use the Level Set method to manage topological changes
  - Study other uses of the training set of shapes and textures

- Possible Solution based on “A Genetic Algorithm-based Level Set Curve Evolution for Prostate Segmentation on Pelvic CT and MRI Images” [Ghosh 2010]:
  - Use a LS representation (signed distance function)
  - Derive texture, mean shape and shape variability from the training set
  - Texture-based fitness function

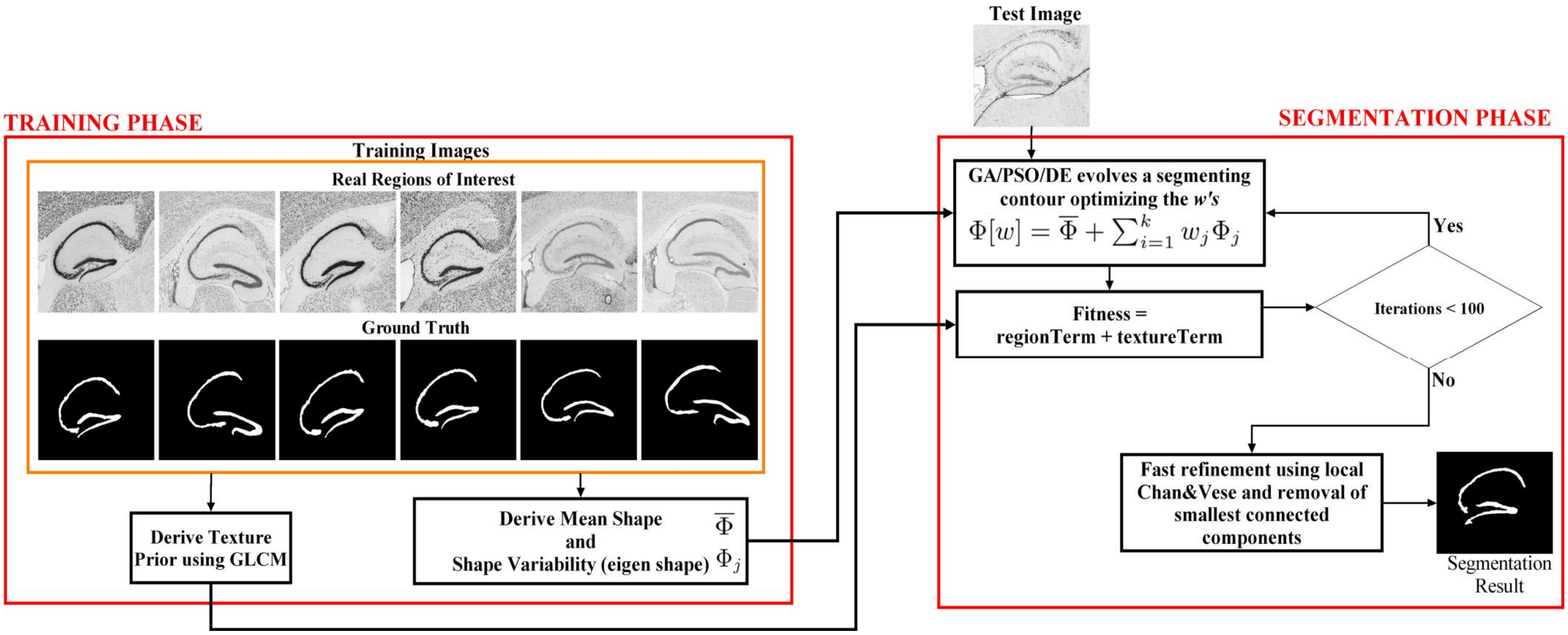
$$\Phi[\boldsymbol{w}, \boldsymbol{p}](x, y) = \overline{\Phi}(\bar{x}, \bar{y}) + \sum_{j=1}^{k} w_j \Phi_j(\bar{x}, \bar{y}).$$

Method 2

- Main differences with the original work [Ghosh et al., 2006 & 2010]
  - an **intensity-based term** has been included in the fitness function (region-based approach + prior knowledge about texture and shape);
  - not use Laws' textural measures or Gabor wavelet transform-based features but **Gray Level Co-occurrence Matrix** (GLCM) features;
  - the single-point **crossover** used has been replaced by a **real-coded** one like the BLX-alpha, due to the nature of the GA chromosomes;
  - the comparison has been extended to **PSO and DE**

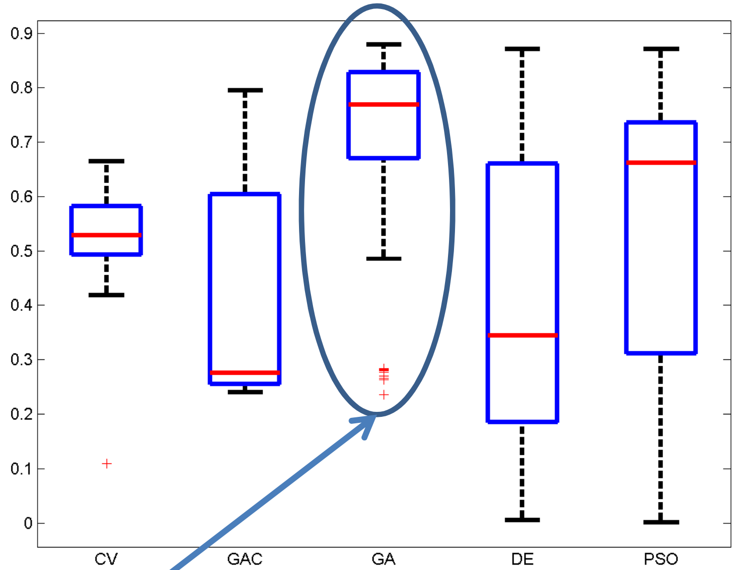
⇒ Intermediate approach dedicated to optimize an existing method and to study another uses of a training set of shapes (using SC). This will lead us to Method 3.

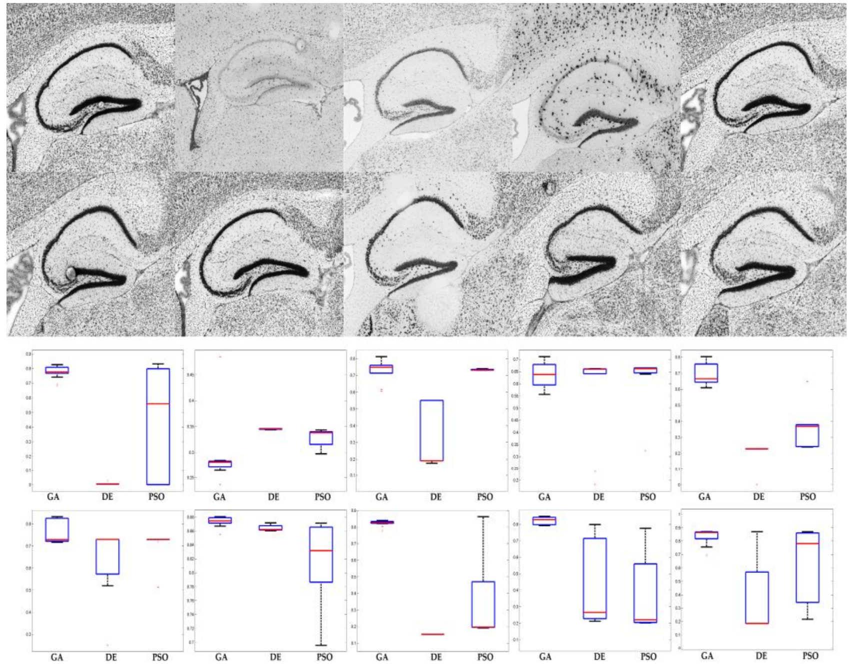
General Pipeline



Mesejo, P., Cagnoni, S., Costalunga, A., and Valeriani, D., "Segmentation of Histological Images using a Metaheuristic-based Level Set Approach", 9th GECCO Workshop on Medical Applications of Genetic and Evolutionary Computation (GECCO'13). Amsterdam. 2013

Comparative Study





- LS-GA obtained the best results, but far from the performance obtained by ASM+RF
- Friedman test with the Tukey-Kramer correction → LS-GA best performing method

- Every iteration/individual: evolve contour, calculate textural features, and evaluate fitness
- Region and texture terms are global → refine fitness function

Contents

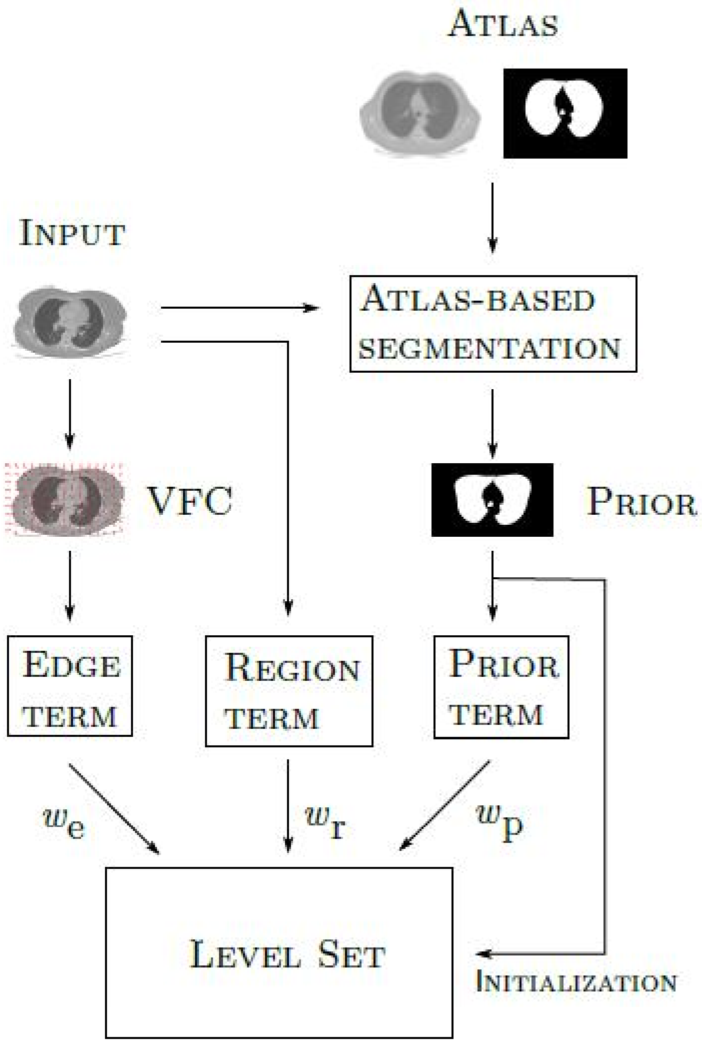
Method 3

- Objectives:
  - Use the Level Set method to manage topological changes
  - Create a more integrated method
    - Instead of 4 sequential phases: initialization + localization + segmentation + expansion/refinement
  - Reduce the need of training examples
- Possible Solution:
  - Use a LS with 3 terms:
    - Prior Shape (using the result of Deformable Registration with the ground truth of the Atlas) → we need only one reference slice, not a whole training set
    - Edge-based term: VFC or GAC
    - Region-based term: local CV

General Pipeline

- Registration Algorithm SS+
  - Affine Registration using SS
  - Deformable B-Spline-based registration
- Edge Term: Vector Field Convolution
- Region Term: Chan and Vese method

$$F = w_e E + w_r R + w_p P$$



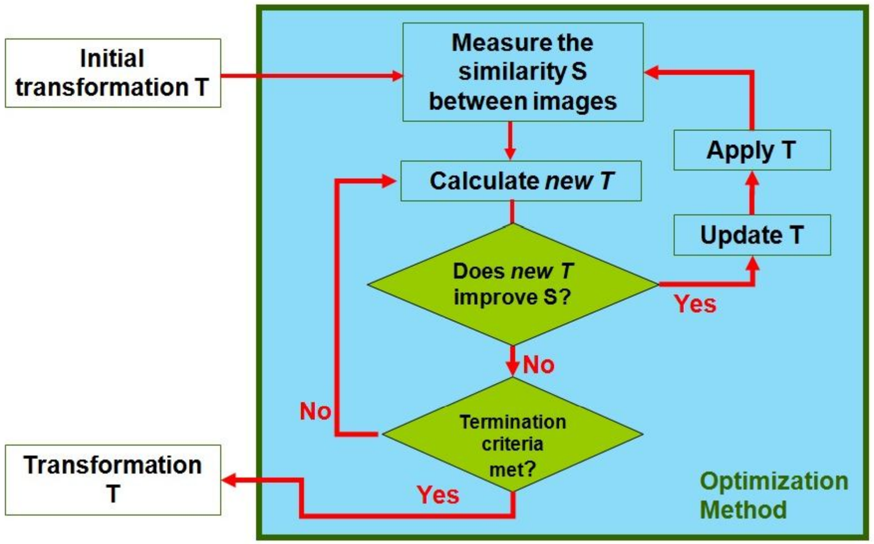
- Microscopy (hippocampus): 26 images
- MRI (caudate, putamen, globus pallidus, and thalamus): 17 images
- CT (lung and knees): 10 images

Mesejo, P., Valsecchi, A., Marrakchi-Kacem, L., Cagnoni, S., and Damas, S., **"Biomedical Image Segmentation using Geometric Deformable Models and Metaheuristics"**, Computerized Medical Imaging and Graphics (IF2011: 1.467, BIOMEDICAL ENGINEERING and RADIOLOGY, NUCLEAR MEDICINE & MEDICAL IMAGING)

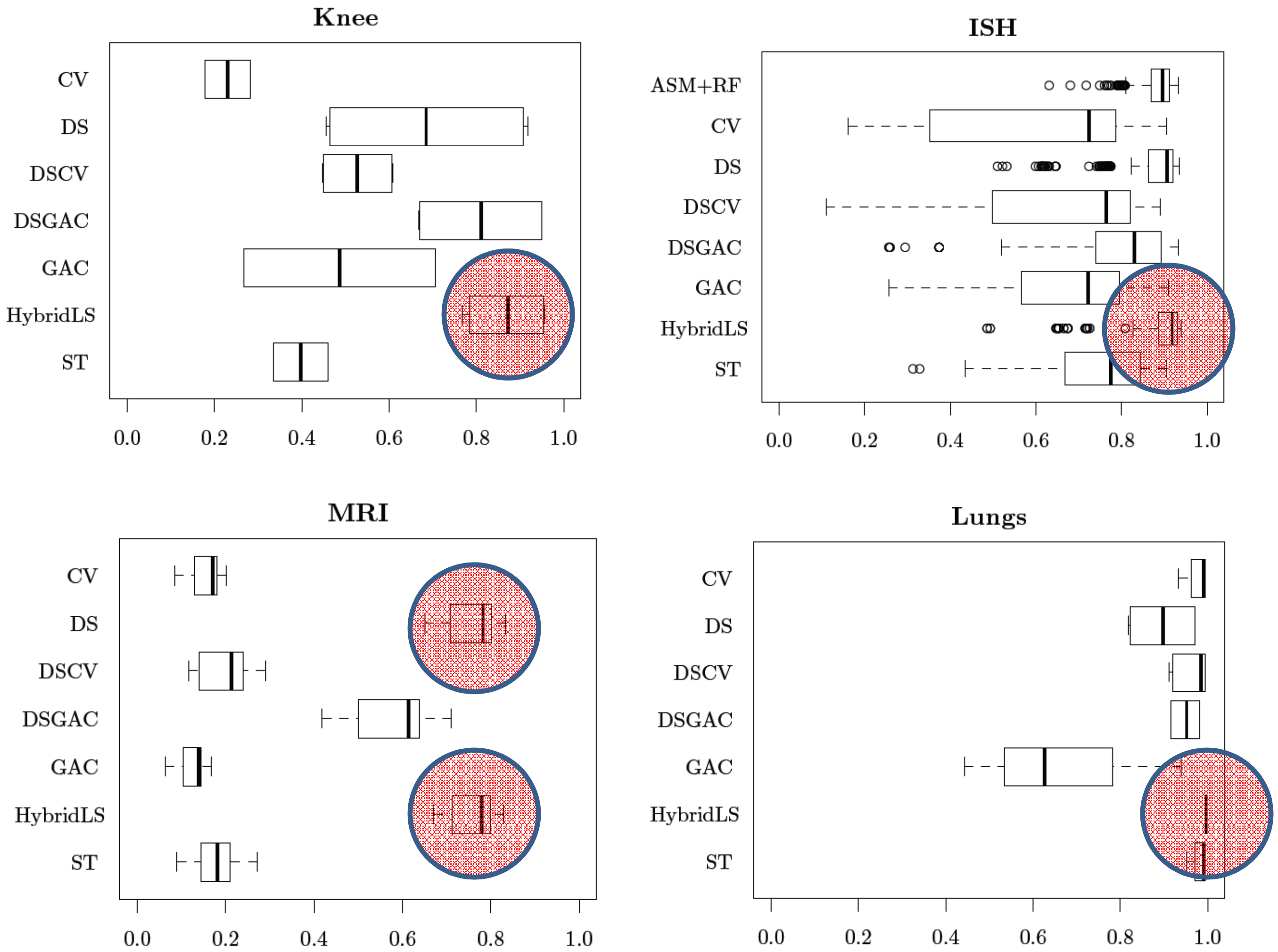
Optimization

- **GA** used for automatically tuning the parameters of the new approach (weights + internal parameters of the terms)
  - Manual tuning: time-consuming, error-prone, tedious, biased.
  - Fitness value: average DSC using a set of parameters
  - Training set of already segmented images: ISH (4), CT (2), MRI (3)
  - Better performance than grid and random search

- **Scatter Search** in the registration process



Comparison



Knee
CV
DS
DSCV
DSGAC
GAC
HybridLS
ST
0.0
0.2
0.4
0.6
0.8
1.0
ISH
ASM+RF
CV
DS
DSCV
DSGAC
GAC
HybridLS
ST
0.0
0.2
0.4
0.6
0.8
1.0
MRI
CV
DS
DSCV
DSGAC
GAC
HybridLS
ST
0.0
0.2
0.4
0.6
0.8
1.0
Lungs
CV
DS
DSCV
DSGAC
GAC
HybridLS
ST
0.0
0.2
0.4
0.6
0.8
1.0

HybridLS main features

- **Accurate and also general** segmentation method (average DSC 0.875);
- Overall standard deviation is the lowest among the different methods
  - the developed approach is **consistent and stable in terms of performance**;
- No need of a training set of textures or shapes to segment the object of interest (it needs **only one reference image to obtain the shape prior**);
- **Self-adaptation of its own parameters** depending on the medical image modality to segment (it adapts the importance of every term);
- It uses **metaheuristics** to generate the shape prior and to perform the previously mentioned learning of parameters.

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Main Contributions

- We have effectively solved a real-world problem
  - Fast and accurate localization of the hippocampus
  - We compare favourably with the State-of-the-Art
    - 6 optimizers in localization phase
    - 7 segmentation algorithms

- We have improved our own method
  - More general (ISH, CT and MRI; topology) and more accurate,
  - automatic tuning using few sample images,
  - only 1 image necessary for getting prior shape knowledge

- Very few examples of:
  - Segmentation of histological images using DMs (let alone SC)
  - Use of Standard Metrics + Statistical Tests

Main Contributions (and 2)

- We have showed how SC can help in:
  - Optimization of noisy and highly-multimodal functions
  - Automatic parameter tuning
  - Refinement of results using classifiers

- Main Scientific Milestones (2010 - 2013)
  - 5 ISI-JCR papers
    - 1st Quartile: 2 PLoS ONE, 1 Applied Soft Computing
    - 3rd Quartile: 1 Pattern Recognition Letters, 1 Computerized Medical Imaging and Graphics
  - 12 International Conference papers
    - 5 GECCO, 1 PPSN, 1 MAEB, 1 CBMS, among others.

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