Self-Adaptive Vision Agents Using Evolutionary Strategies

Thomas Bäck[1], Rui Li[1], Jeroen Eggermont[2], Michael Emmerich[1],
Ernst Bovenkamp[2], Jouke Dijkstra[2], Johan Reiber[2]
(*baeck@liacs.nl*)

[1]Natural Computing Group, Leiden Advanced Institute of Computer Science (LIACS),
[2]Leiden University Medical Center, LKEB Group,
Leiden University, The Netherlands

Universiteit Leiden
The Netherlands

LUMC

CITATIONS

- Mixed-Integer Evolution Strategies for Parameter Optimization and Their Applications to Medical Image Analysis. R. Li, PhD Thesis, Leiden University, ISBN: 978-90-9024665-9, October 2009

- User-Agent Cooperation in Multiagent IVUS Image Segmentation, E.G.P. Bovenkamp, J. Dijkstra, J.G. Bosch, J.H.C. Reiber, IEEE Transaction on Medical Imaging, 94-105, 28(1), 2009.

- Optimizing a Medical Image Analysis Using Mixed-Integer Evolution Strategies. R. Li, M.T.M. Emmerich, J. Eggermont, E.G.P. Bovenkamp, T. Bäck, J. Dijkstra, and H. Reiber. Book chapter in Evolutionary Image Analysis and Signal Processing, 91-112, Springer, ISBN: 978-3-642-01635-6, July 2009

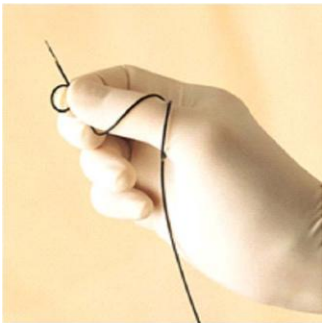
RATIONALE

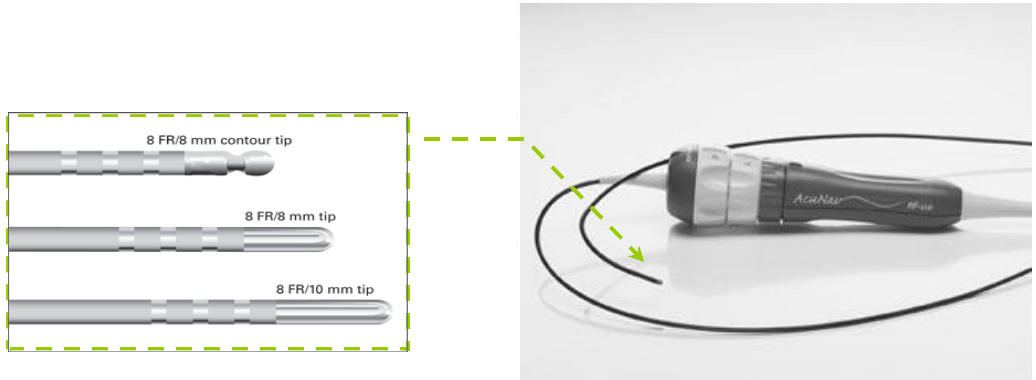
- One of the highest targets in medical image analysis is the realization of intelligent fully automatic image interpretation
  - Cardiovascular disease is recognized as the leading cause of the death (30%) in the world; important to have reliable systems to detect the calcified plaques that cause this disease
  - Intravascular Ultrasound (IVUS), Computed Tomography Angiography (CTA), and Magnetic Resonance Imaging (MRI)
  - Often complex and variable structures, such as calcified plaques in arteries, are to be detected and modeled in image or sequences of images
  - Proven to be very hard due to the complexities of the scenes, poor image quality, variability of objects, artifacts, and occlusion.

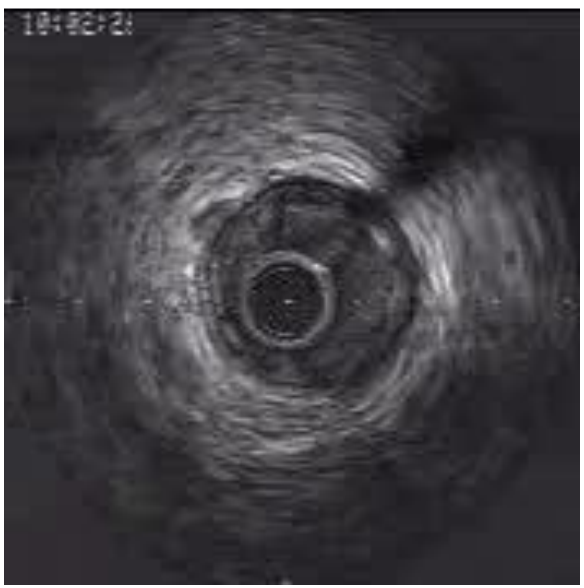
RATIONAL (CONT.)

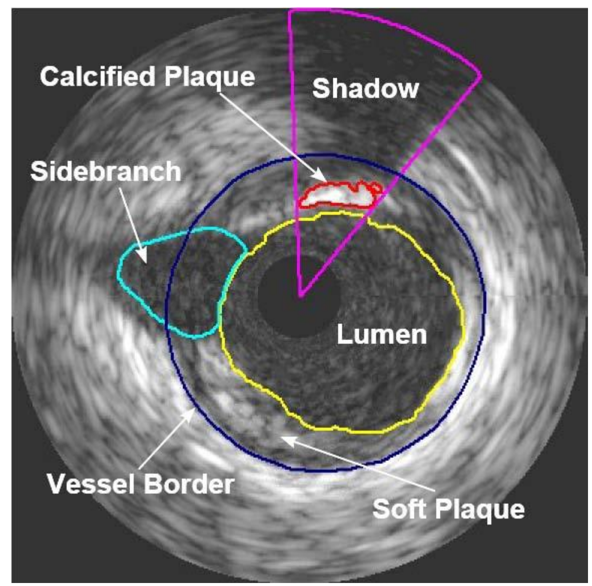
- The performance of most systems still depends on a large number of control parameters
  - The setting of these control-parameters is done by means of an educated guess or manual tuning following a tedious trial and error approach
    - Often leads to suboptimal settings
  - Given the frequent changes in image processing technologies (e.g., IVUS, CTA, and MRI) this manual tuning has to be carried out again and again

Example




8 FR/8 mm contour tip
8 FR/8 mm tip
8 FR/10 mm tip

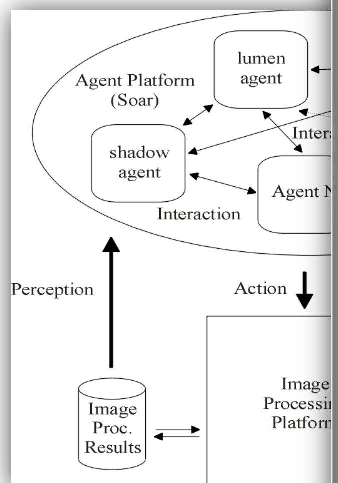


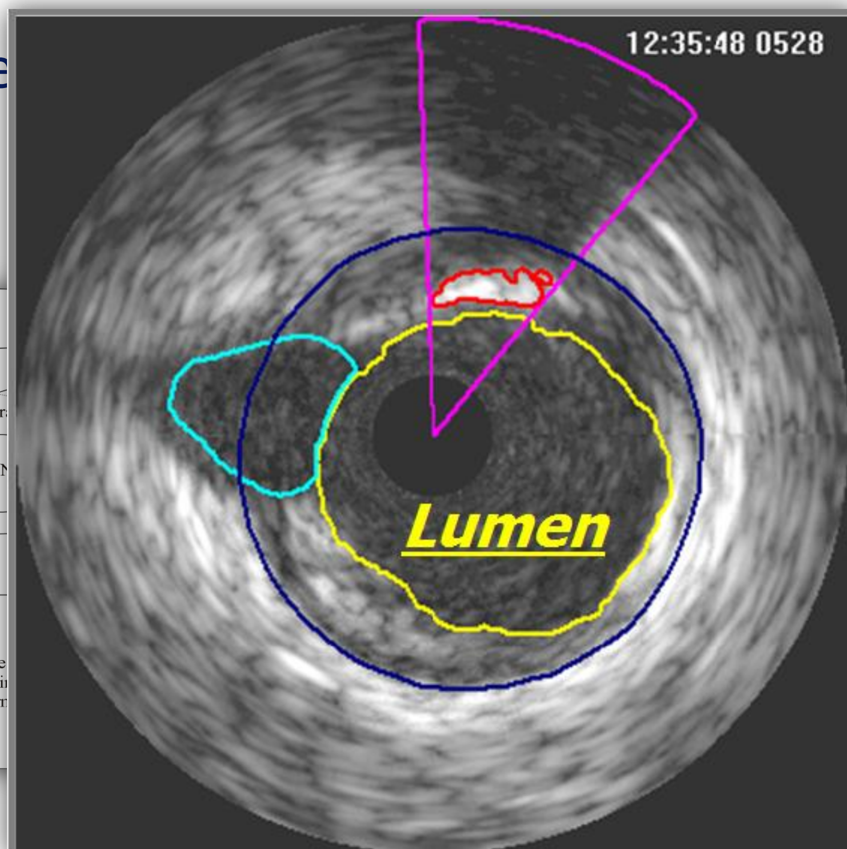

Calcified Plaque
Shadow
Sidebranch
Lumen
Vessel Border
Soft Plaque

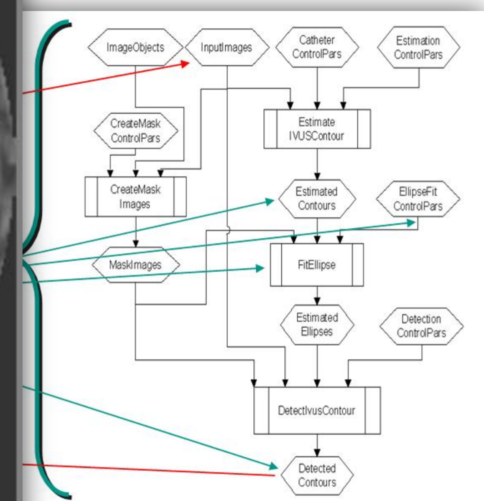
IVUS Image Analysis (cont.)

Multi-Age

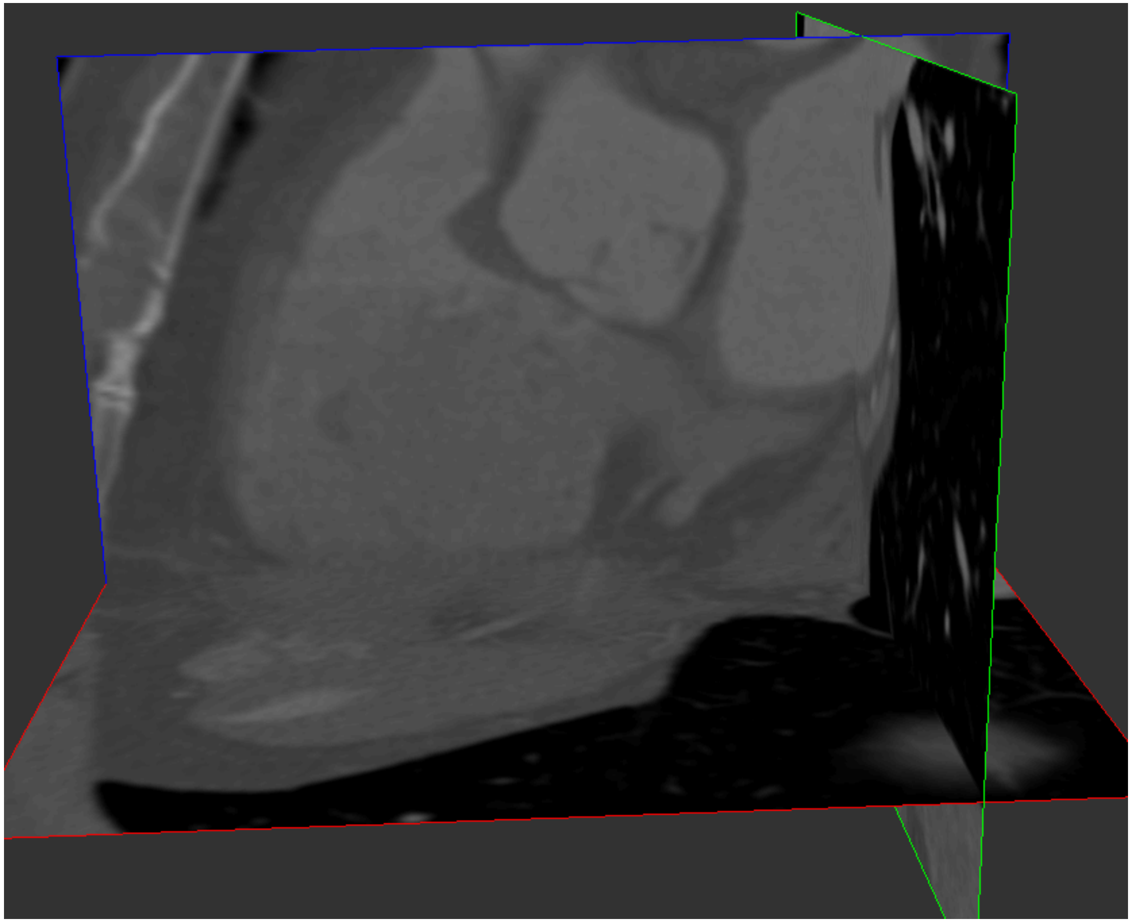
essing Pipeline

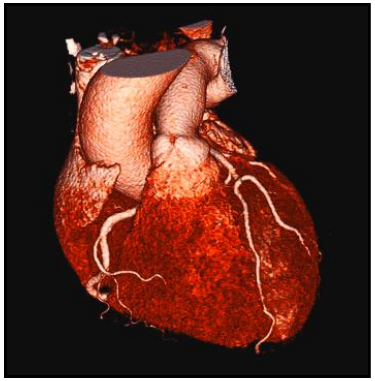




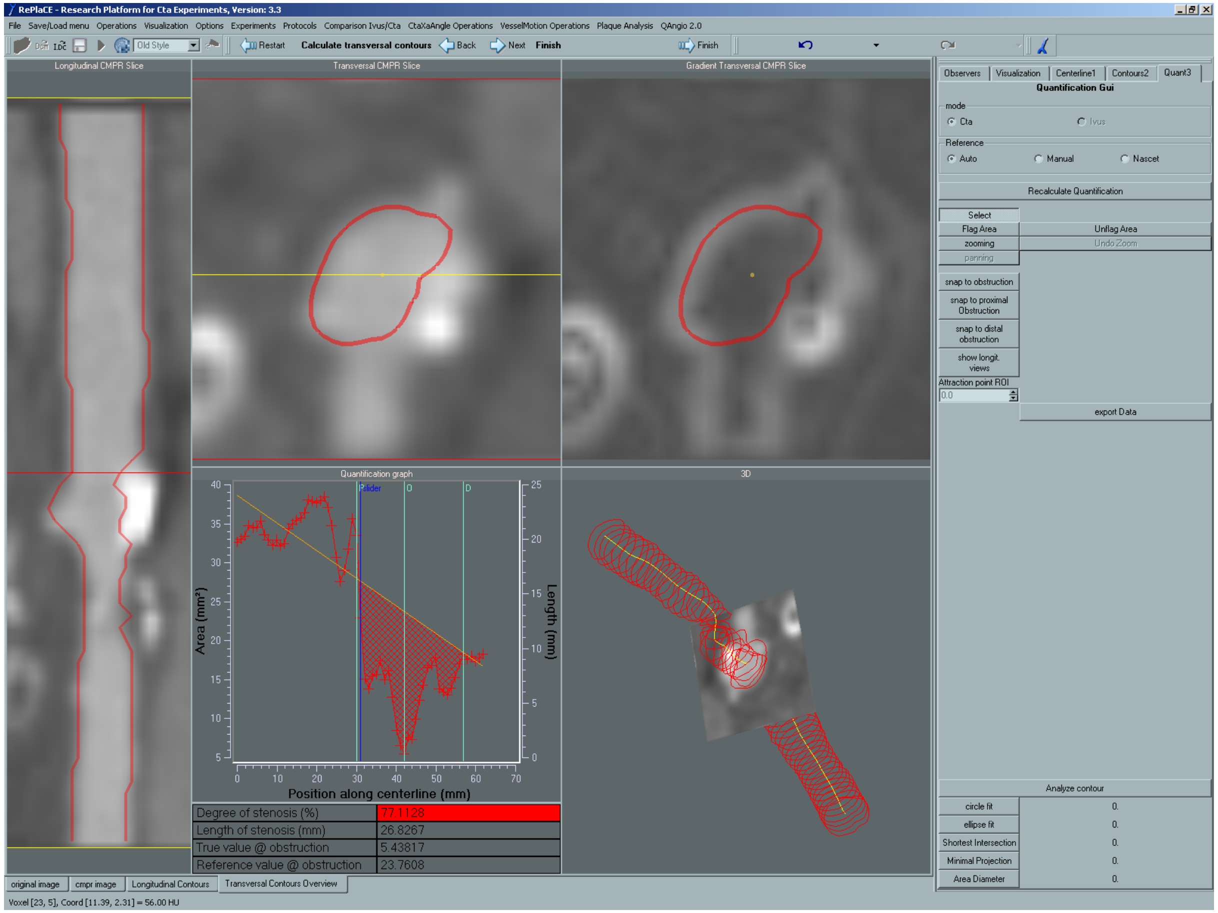


CTA Image Analysis



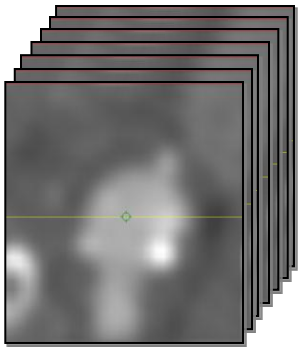


CTA IMAGE ANALYSIS (CONT.)

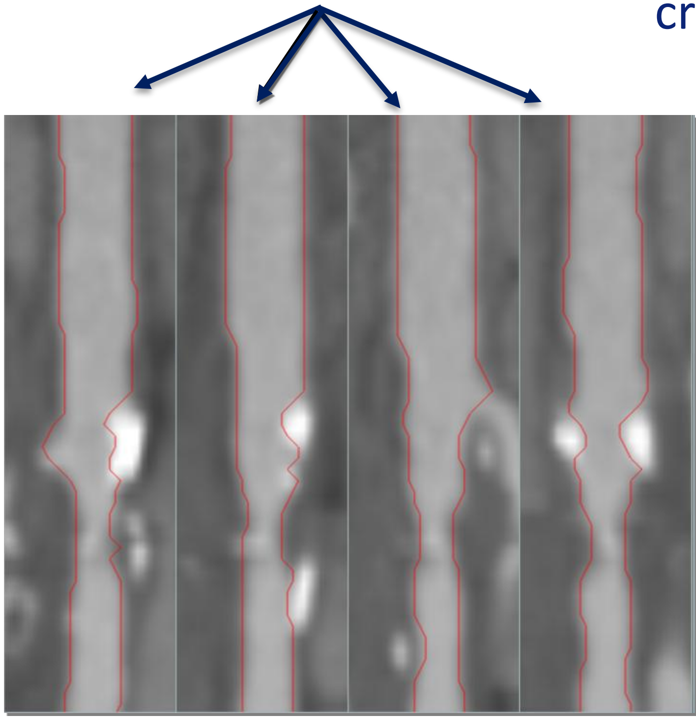


CTA Image Analysis (cont.)

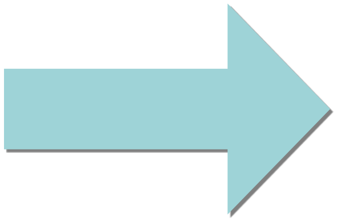
Combination of transversal and longitudinal contour detection for 3D contour detection



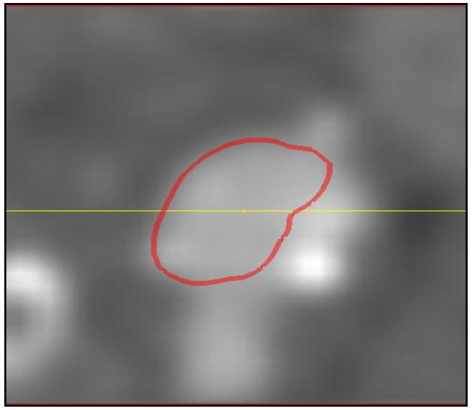
Create longitudinal cross-sectional images



Detect longitudinal lumen contours

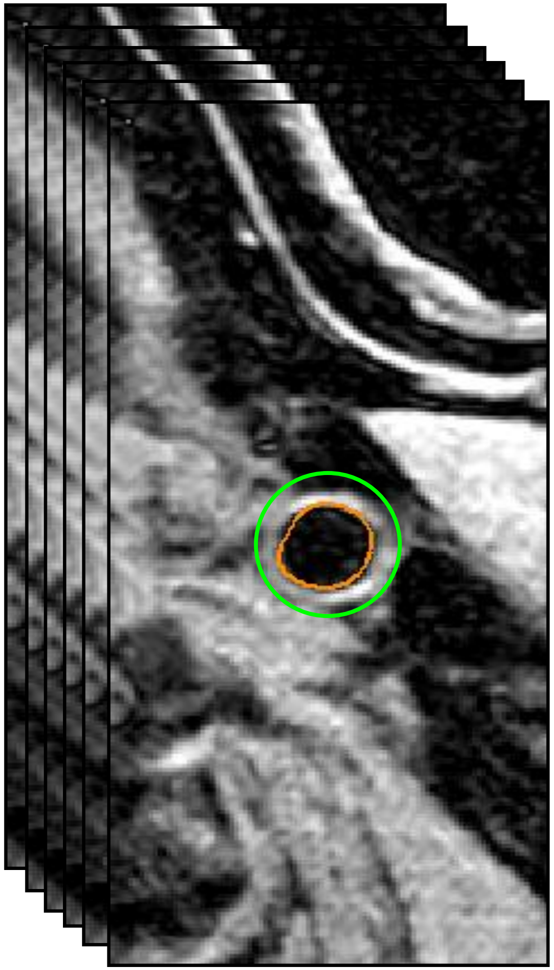


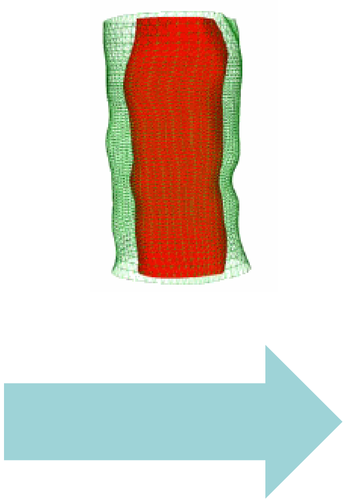
Detect transversal lumen contours

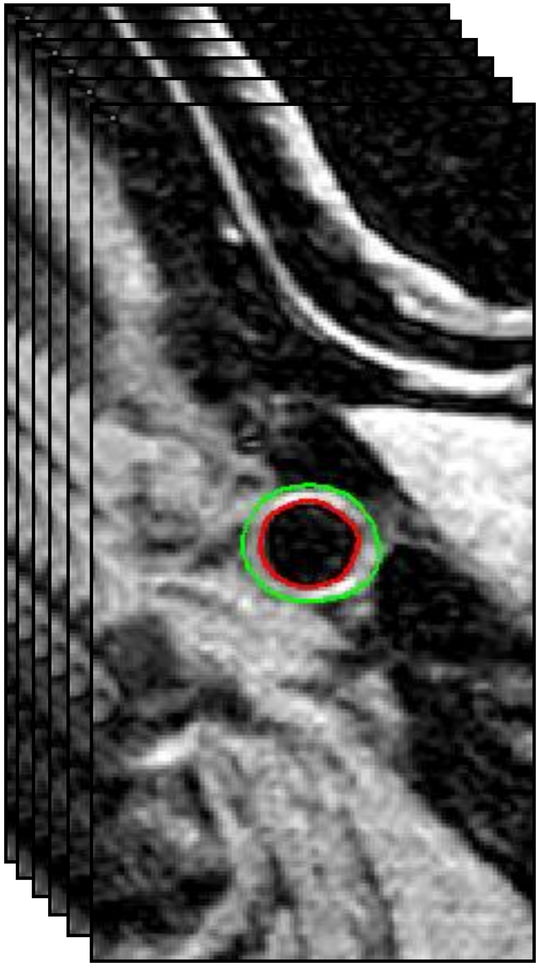


MR IMAGE ANALSYS

- Vessel wall segmentation

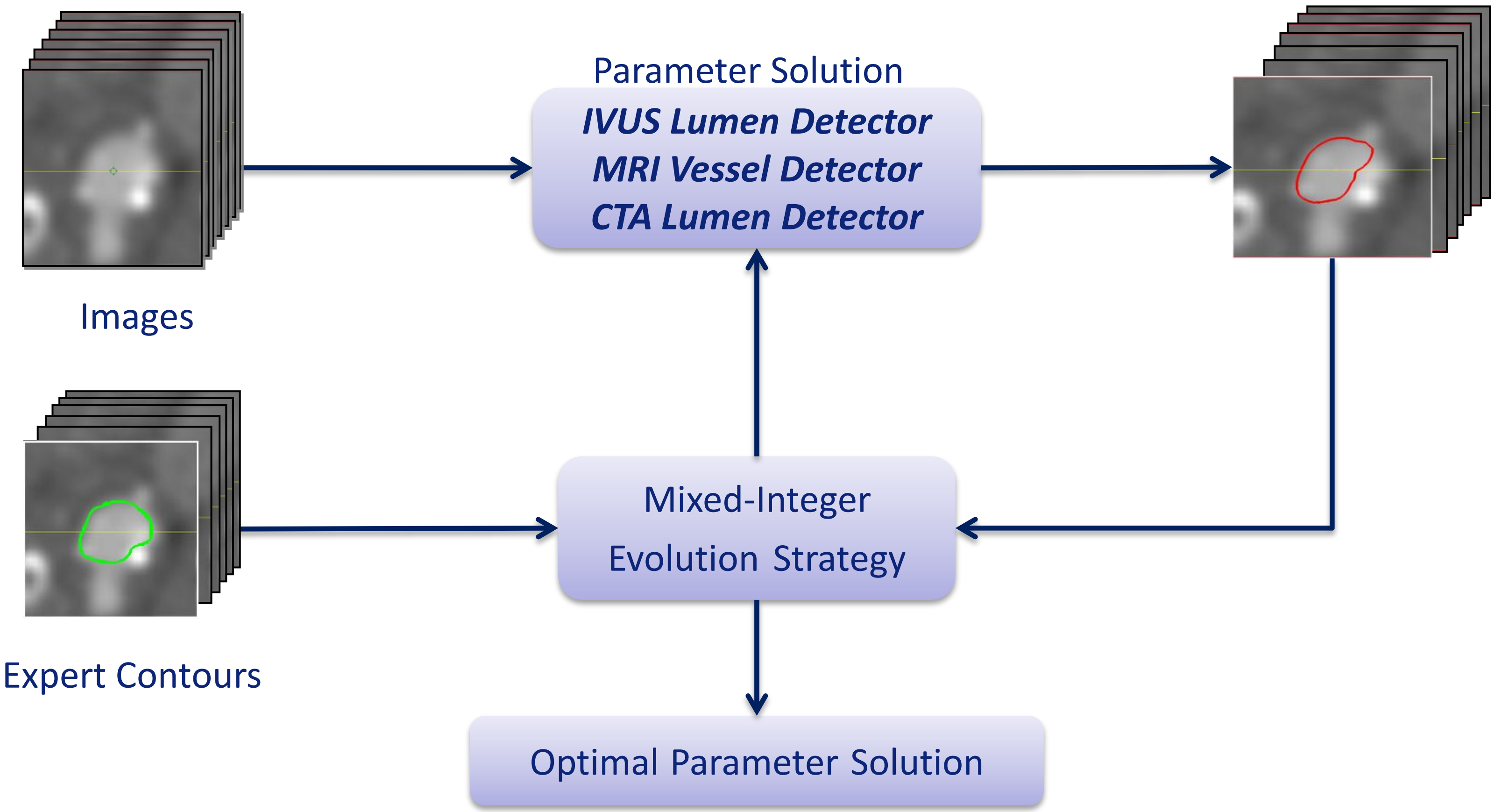






Based on 2D image information and the detected lumen model fit the outer wall using a NURBS Tubular model

Optimizing Medical Image Segmentation



Mixed-Integer Parameters

name	type	range	dependencies	default
maxgray	integer	[2, 150]	> mingray	35
mingray	integer	[1, 149]	< maxgray	1
connectivity	discrete	{4,6,8}		6
relativeopenings	discrete	{false,true}		true
nrofcloses	integer	[0, 100]	used if not relativeopenings	5
nrofopenings	integer	[0, 100]	used if not relativeopenings	45
scanlinedir	discrete	{0,1,2}		1
scanindexleft	integer	[-100, 100]	< scanindexright	-55
scanindexright	integer	[-100, 100]	> scanindexleft	7
centermethod	discrete	{0,1}		1
fitmodel	discrete	{ellipse, circel}		ellipse
sigma	continuous	[0.5 10.0]		0.8
scantype	discrete	{0,1,2}		0
sidestep	integer	[0, 20]		3
sidecost	continuous	[0.0, 100]		5
nroflines	integer	[32, 256]		128

MIXED-INTEGER EVOLUTION STRATEGIES

- A special variant of an Evolution Strategies (ES)
- Designed for the *simultaneous* optimization of continuous, integer, and nominal discrete parameters
  - Combines mutation operators of ES in the different search domain, e.g., geometrical distribution
- Focus on *black-box* optimization problem
  - Assisted by some advanced constraints handling techniques, MIES can also be applied to some classical MINLP problems
- Enriched by introducing some advanced technologies
  - Niching
  - Metamodeling, e.g., Radial basis function network (RBFN)
  - Dynamic fitness partitioning

Mixed-Integer ES: Mutation

Learning rates (global)

Learning rates (local)

for $i = 1, \ldots, n_r$ do
  $s_i' \leftarrow s_i \exp(\tau_g \mathrm{N}_g + \tau_l \mathrm{N}(0,1))$
  $r_i' = r_i + N(0, s_i')$
end for
for $i = 1, \ldots, n_z$ do
  $q_i' \leftarrow q_i \exp(\tau_g \mathrm{N}_g + \tau_l \mathrm{N}(0,1))$
  $z_i' \leftarrow z_i + \mathrm{G}(0, q_i')$
end for
$p_i' := 1/[1 + \frac{1-p_i}{p_i} * \exp(-\tau_l * \mathrm{N}(0,1))]$
for $i \in \{1, \ldots, n_d\}$ do
  if $\mathrm{U}(0,1) < p_i'$ then
    $d_i' \leftarrow$ uniformly randomly value from D_i
  end if
end for

Geometrical distribution

Mutation Probabilities

Results on IVUS Images

- IVUS Images
- Fitness: Dissimilarity measure → min

	Dataset 1		Dataset 2		Dataset 3		Dataset 4		Dataset 5	
	Fitness	**S.D.**	**Fitness**	**S.D.**	**Fitness**	**S.D.**	**Fitness**	**S.D.**	**Fitness**	**S.D.**
Expert	395.2	86.2	400.2	109.2	344.8	66.4	483.1	110.6	444.2	90.6
MI-ES 1	151.3	39.2	183.6	59.0	201.0	67.1	280.9	91.9	365.5	105.9
MI-ES 2	160.3	45.9	181.4	58.7	206.7	70.3	273.6	74.5	372.5	99.2
MI-ES 3	173.8	42.1	202.9	69.1	165.6	47.2	250.7	80.2	446.4	372.8
MI-ES 4	154.0	51.7	243.7	67.7	198.8	80.1	186.4	59.0	171.3	57.8
MI-ES 5	275.7	75.6	358.4	76.9	327.7	56.7	329.1	82.0	171.8	54.5

Table 2. Performance of the best found MI-ES parameter solutions when trained on one of the five datasets (MI-ES solution i was trained on dataset i). All parameter solutions and the (default) expert parameters are applied to all datasets. Average difference (fitness) and standard deviation w.r.t. expert drawn contours are given with $\tau = 2.24$ and $nrofpoints = 128$.

Results on IVUS Images (cont.)

MIES:

Experts:

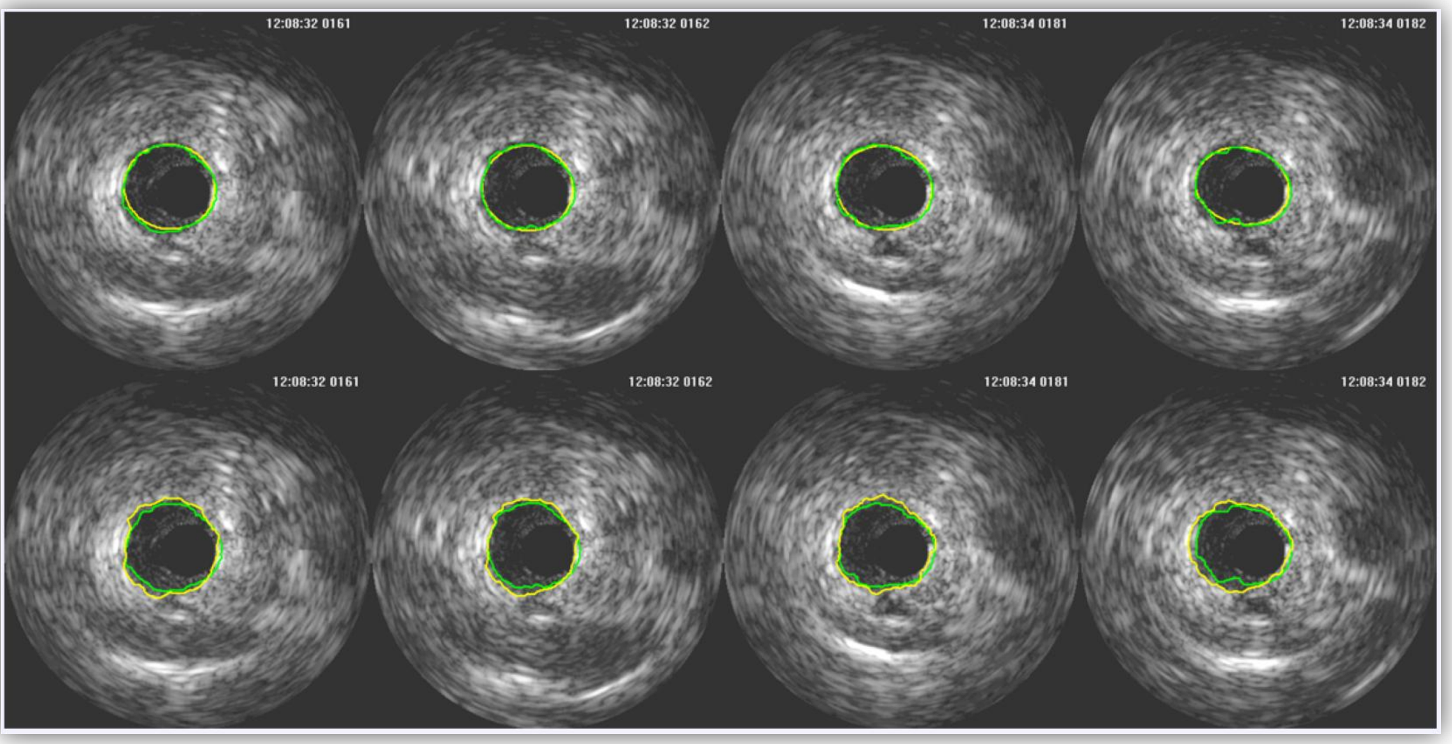


Figure: Expert-drawn lumen contours (green) compared with expert-set parameter solution (yellow, bottom row) and MI-ES parameter solution (top row, yellow). The contours which are detected by using the MIES parameter are more smooth than those by using the default parameter settings.

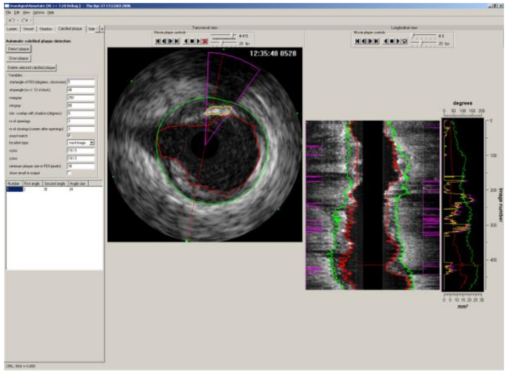
RESULTS ON CTA IMAGES

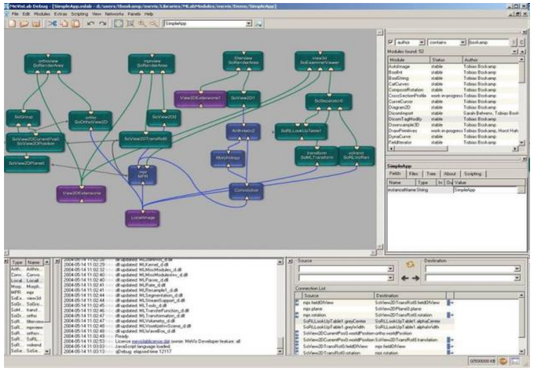
CT data set	Default parameters	MI-ES			
		avg	s.d.	min	max
1	0.295	0.242	0.004	0.236	0.248
2	0.255	0.152	0.003	0.148	0.159
3	0.189	0.176	0.004	0.169	0.182
4	0.211	0.186	0.006	0.175	0.193
5	0.675	0.327	0.016	0.297	0.364
6	0.360	0.320	0.026	0.275	0.343
7	0.324	0.307	0.011	0.276	0.313
8	0.181	0.169	0.001	0.167	0.170
9	0.244	0.199	0.011	0.185	0.219

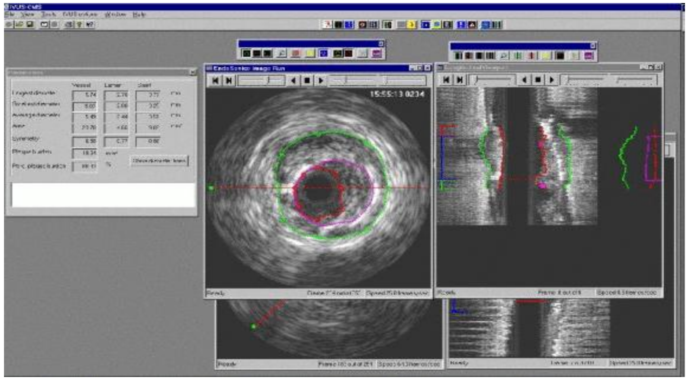
Table: Performance of the best found MI-ES parameter solutions when trained on one of the nine datasets. All parameter solutions and the (default) expert parameters are applied to all datasets

There is no one solution for all images

IVUS Image Analysis: Commercial Software







IVUS Library Interface

IVUS Library Interface

IVUS Library Interface

LKEB

MeVisLab

Medis

IVUS Library Implementation

Satisfied Criterion

- (E) The result is equal to or better than the most recent human-created solution to a long-standing problem for which there has been a succession of increasingly better human-created solutions.

- (F) The result is equal to or better than a result that was considered an achievement in its field at the time it was first discovered

- (G) The results solves a problem of indisputable difficulty in its field

WHY SHOULD WE WIN THE PRIZE ?

- Average improvement of classification measure:
  30-50% (compared to humans)
- Speed-up of image processing time:
  from several minutes (humans) to seconds
- Automatic software configuration approach for IVUS, CTA, MRI image analysis systems
- Provides better and more reliable results than manual tuning
- Improves quality and speed of medical image diagnosis significantly
- Frees up time of cardiovascular disease experts for other tasks, e.g., patient care
- The number of these experts is also quite limited!