Computational Intelligence for Abdominal Aortic Aneurysm Imaging Analysis

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Outline

Motivation I

- The motivation comes from the high prevalence of Abdominal Aortic Aneurysm (AAA) in western population.
  - AAA is a dilation of the aorta that occurs between the renal and iliac arteries.
  - Treatment options involve the implantation of the Endovascular Aneurysm Repair (EVAR).
  - The patient needs to be monitored imaging the abdominal region along the follow up period.

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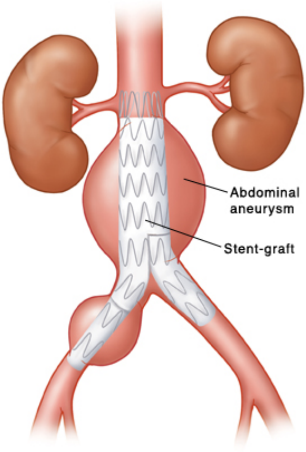
EVAR Treatment



Motivation II

- This Thesis is concerned with tools for image based EVAR monitoring.
- This Thesis has grown along two main lines of work:
  - First, the segmentation of challenging structures in the abdominal Computed Tomography Angiography (CTA) images applying an Active Learning approach.
  - Second, the idea of predicting the evolution of patients who underwent (EVAR).

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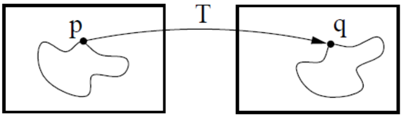
Image Registration

Image registration is the process of determining the **spatial transform** that maps points from one image to homologous points in the second image.



We can asses the registration quality by means of similarity measures.

Pipeline

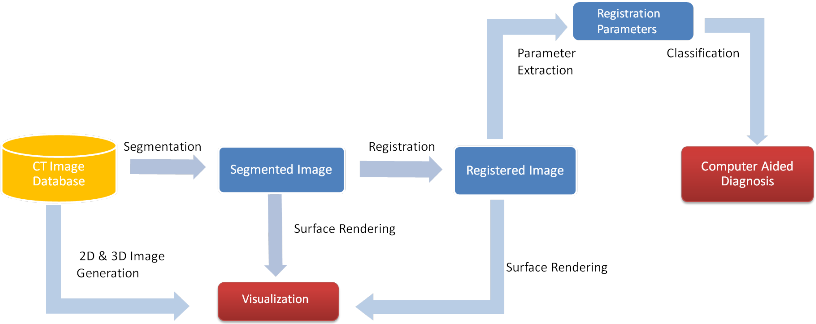


Figure : Pipeline of the processes involved in the works performed in this Thesis

Contributions I

- A state-of-the-art **review** covering visualization techniques, AAA segmentation, registration, and Machine Learning for medical image analysis.
- **Feature selection procedure** for Random Forests based on the sensitivity of the out-of-bag error as a measure of feature importance.
- **Active Learning strategy** based on the variance of the individual classifier Random Forest outputs, as a measure of classification uncertainty.
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- **Visual assessment** of AAA's thrombus evolution, avoiding artifacts due to image registration.
- Feature extraction for a Computer Aided Diagnosis (CAD) system devoted to **EVAR prognosis** based in registration quality measures.
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Computed Tomography Angiography

- Modality for non-invasive medical imaging that has been established as the gold standard in many areas.

3D Image Processing

- Starting from 2D slices, using image processing, anatomical structures can be segmented and three-dimensional images can be created.
  - Multiplanar reformatting → 2D orthogonal planes
  - 3D rendering (surface and volume)

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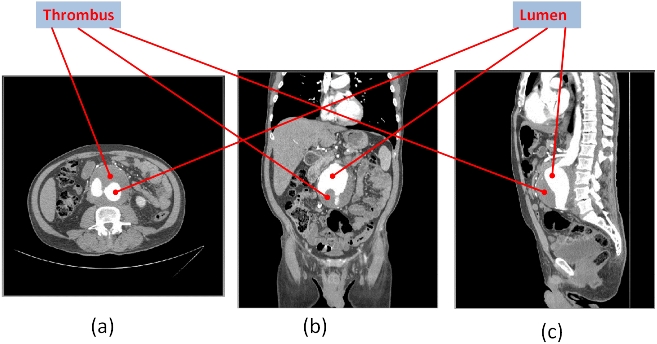
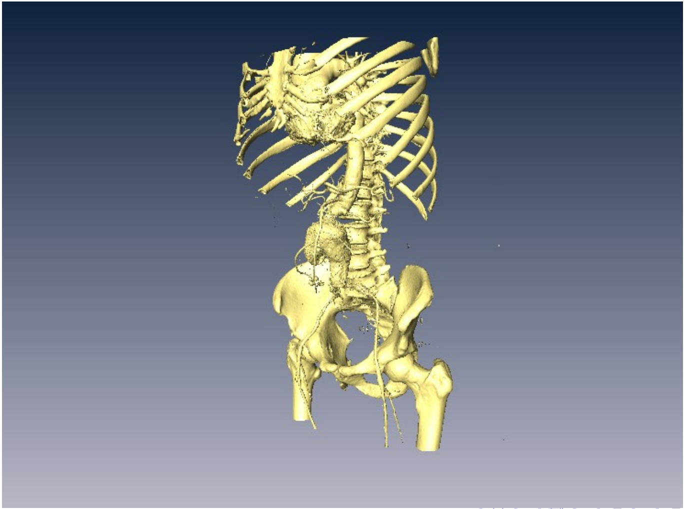
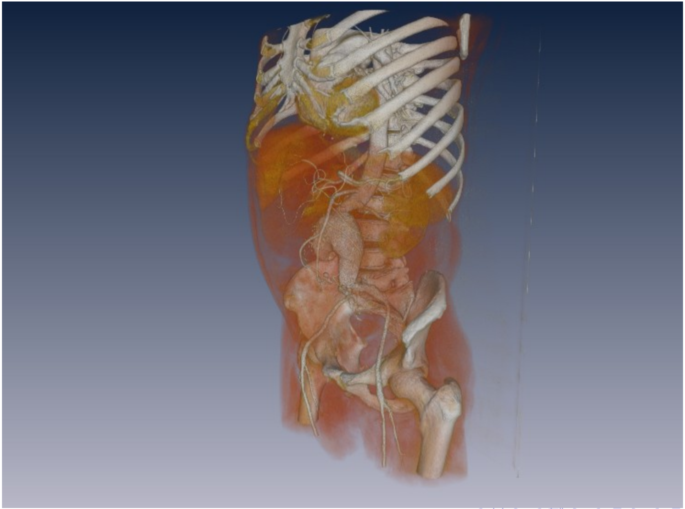
Multiplanar reformatting of a 3-D CT volume image: (a) axial, (b) coronal and (c) sagittal view



Surface Rendering



Volume Rendering



Segmentation of AAA

- Segmentation of AAA thrombus and lumen in the CTA volume image is still a challenging task.
  - AAA CTA data may have strong variability
  - Surrounding tissue with similar gray values
- We have followed the Active Learning strategy to train specific classifiers for the detection of the thrombus.

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Computer Aided Diagnosis

We are aiming to offer a Machine Learning approach to provide a CAD system for EVAR prognosis in two ways:

1. The visual inspection of the **evolution of the thrombus** in the aneurysm sac provides a direct way to perform the desired assessment.
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- Because RF is an ensemble, we can follow the **committee approach** to the prediction of the unlabeled sample uncertainty.
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Feature extraction

- Aims to attach additional information to each pixel computed from the **spatial distribution** of intensity values so that more discriminant information is obtained.
- Computed intensity functions of the neighboring pixels:
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Feature selection based on variable importance I

- Feature selection is done on the basis of the variable importance.
- For each tree $h(\mathbf{x};\psi_t)$ of the RF, consider the associated out-of-bag OOB_t dataset.
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Feature selection based on variable importance II

- The Variable Importance of feature X^j is computed as follows:

$$VI(X^j) = \frac{1}{T}\sum_t (err\widetilde{OOB_t}^{j} - errOOB_t)$$

where T denotes the number of trees of the RF

Datasets

- We have performed computational experiments over 8 datasets
- Each dataset consists in real human contrast-enhanced datasets between 216 and 560 slices of the abdominal area with 512x512 pixel resolution on each slice.
- The datasets show diverse sizes and locations of the thrombus.
- Ground truth segmentations manually performed by a clinical radiologist.

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Selected Features

Image Feature (Filter radius)	Importance
Maximum (16)	1.277
Maximum (4)	0.9533
Maximum (8)	0.9531
Median (8)	0.8037
Maximum (2)	0.7623
Maximum (1)	0.7594
Median (1)	0.7415
Median (4)	0.7406
Median (16)	0.7328
Gaussian Blur (4)	0.725

Table : Features selected according to the variable importance ranking

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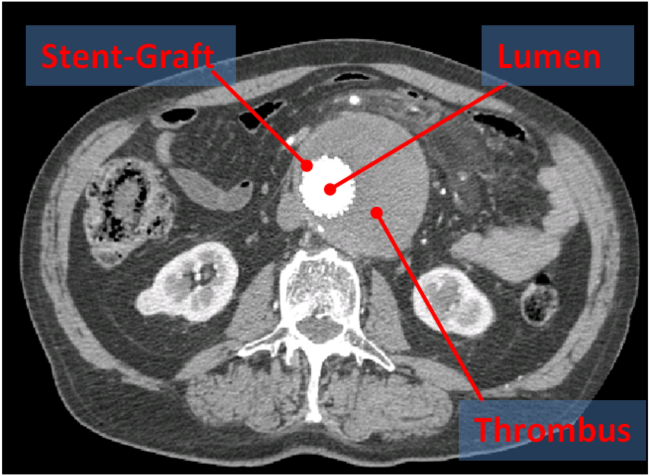
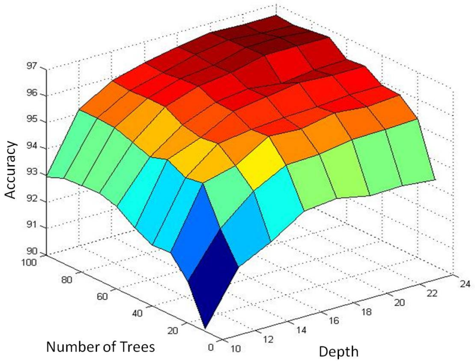
2D CT Slice

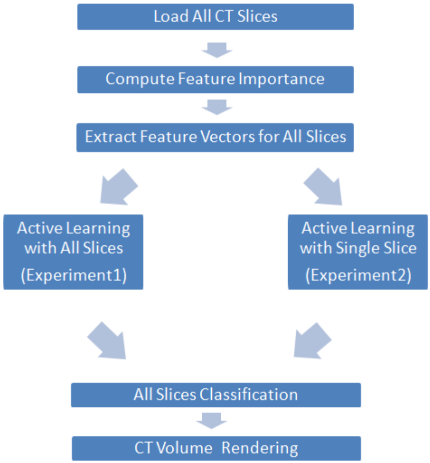


Parameter Sensitivity

- We train the RF classifier with a single slice to test the sensitivity of the forest parameters.



Experimental Design



Experiments

- We have designed two different experiments:
  - Independent slice classifier: we build a separate RF classifier for each slice of the volume and we test it with the corresponding slice.
  - Generalization of a single slice classifier: we build only one RF classifier from the data of the central slice of the aneurysm and we apply it to every slice of the CT volume.

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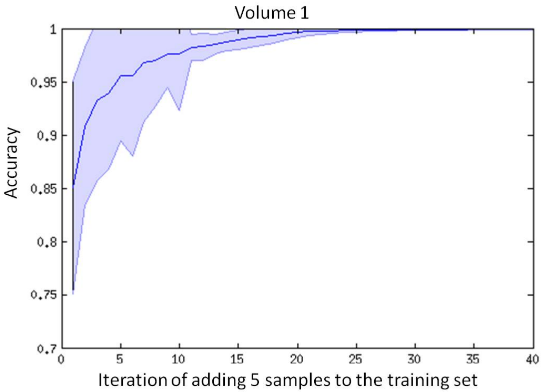
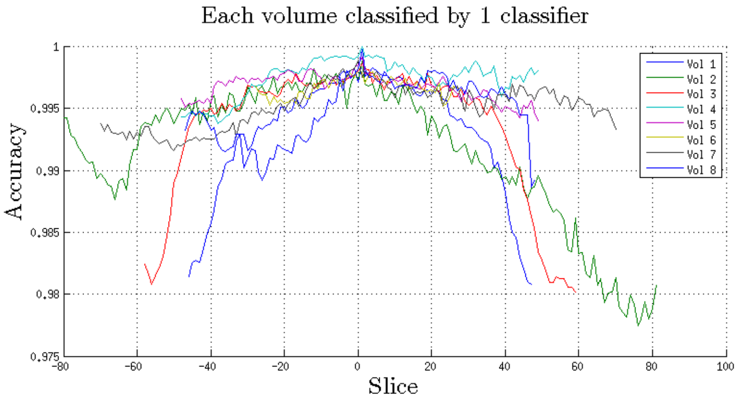
Results

- Experiment 1 in which we test each slice with the classifier built on that slice.



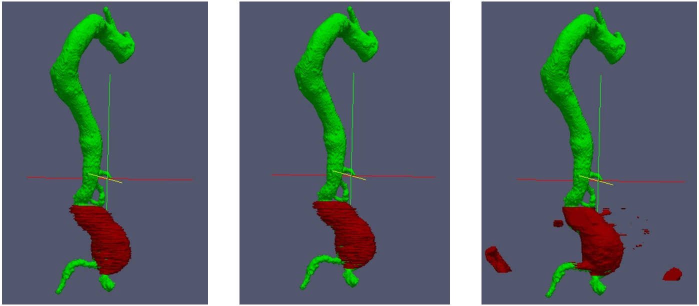
Results

- Experiment 2 in which we test all the slices with the classifier built on the image features of one single slice.



Results

Volume rendering of aortic lumen (green) and thrombus (red). (a) manual segmentation of the ground truth, (b) result of classifiers detecting the thrombus in each slice, (c) result of generalization of the classifier on the central slice to the remaining slices.



(a) (b) (c)

Conclusions

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- A great **reduction of human segmentation effort** is obtained preserving a high accuracy.
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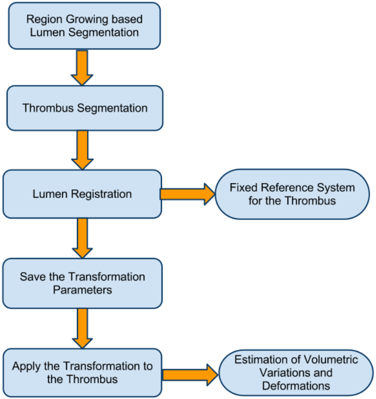
Thrombus Evolution Visualization Pipeline



Thrombus Evolution Visualization

- The approach followed consists in the **co-registration** of the thrombus according to the rigid, affine and elastic registration transformation computed on the Aorta's lumen.
- The complete procedure is as follows:
  - Segment aortic lumen and thrombus in fixed and moving CTA volumes
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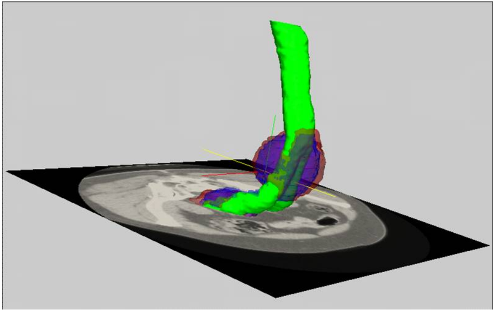
Co-registration of the thrombus

Thrombus extracted for two points in time (blue for the first one, semi-transparent red the second one), both referenced to lumen of the first point in time. It can be seen an increase in thrombus volume.



EVAR Prognosis

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- Specifically, this data consists in the measurements of the deformation of the lumen between two different time instants obtained as the image registration quality measures.

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Quantitative Measurement of the Lumen Deformations

- The quantitative features for the classification systems are the values of similarity metrics obtained after rigid, affine and deformable registration of the aortic lumen.
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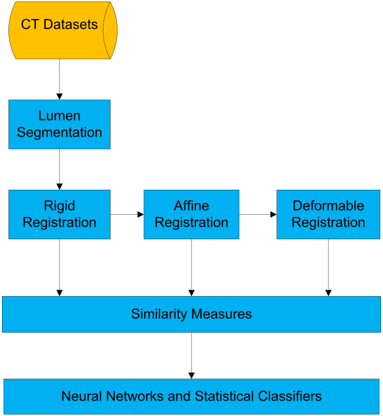
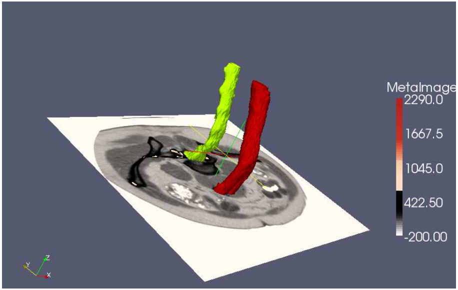
Computational Pipeline



Lumen Segmentation

- Aorta's lumen segmentation is performed applying User-Guided Level Set Segmentation.[1]



[1] Paul A. Yushkevich, Joseph Piven, Heather Cody Hazlett, Rachel Gimpel Smith, Sean Ho, James C. Gee, and Guido Gerig. User-guided 3D active contour segmentation of anatomical structures: Significantly improved efficiency and reliability. Neuroimage 2006 Jul 1;31(3):1116-28.

Registration of the Aortic Lumen after EVAR

- A sequence of rigid, affine and deformable registration is performed.
- The segmented lumen of the first study is considered as the fixed image and the others are registered relative to it.
- A linear interpolator, Mutual Information (MI) metric, and Regular Step Gradient Descent Optimizer are used.
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Experimental Results

- We deal with a two class classification problem, given a collection of training/testing input feature vectors $X = \{\mathbf{x}_i \in \mathbb{R}^n, \, i = 1, \ldots, l\}$ and the corresponding labels $\{y_i \in \{-1, 1\}, \, i = 1, \ldots, l\}$, our aim is to classify the patients as those who have a favorable or unfavorable evolution.
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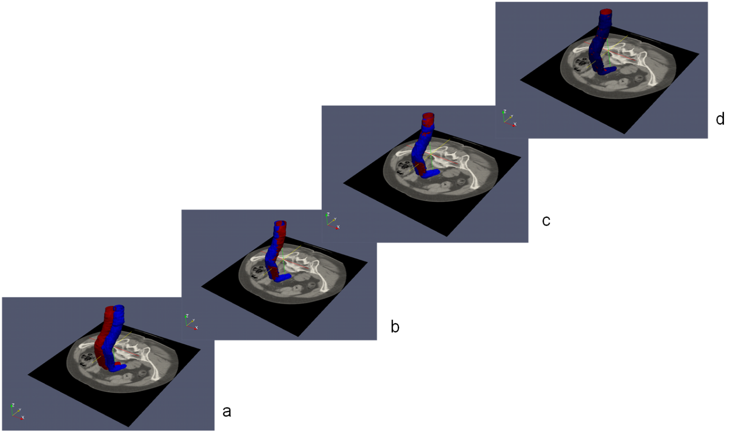
Registration Visualization



Visualization of fixed and moving images of the lumen (a) before registration, (b)after rigid, (c) affine, and (d) deformable registration.

Results

- We train over the set of features different classifiers and we show the results for accuracy, sensitivity, specificity, and area under the ROC (AUC).

Classifier	Accuracy	Sensitivity	Specificity	AUC
Linear SVM	0.72	0.75	0.67	0.97
RBF SVM	0.77	0.80	0.70	0.98
LVQ	0.80	0.86	0.72	0.76
BP- MLP	0.73	0.71	0.80	0.97
Random-Forest	0.91	0.99	0.73	0.99

Figure : Leave-one-out cross-validation results of EVAR evolution classification performed over the similarity metric features computed from the available CT datasets.

Conclusions

- We have built a CAD system for the prognosis of EVAR treated patients.
- Co-registration of the thrombus of the aneurysm sac of the patients provide a powerful visualization tool that may allow early detection of negative evolution of the EVAR treatment.
- Features for the CAD classifier are the similarity measures of the segmented lumen after rigid, affine and deformable registration.
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1. Introduction
2. Active Learning for Thrombus Segmentation
3. Computer Aided Diagnosis (CAD)
4. Summary and Further Work

Summary I

- The Thesis is focused in a specific application of medical imaging to a disease and treatment: the Abdominal Aortic Aneurysm (AAA) and its Endovascular Aneurysm Repair (EVAR).
- The motivation comes from the high prevalence of AAA in western population and the need to perform accurate follow-up of the treatment to prevent the associated risks.
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Thanks

Thank you very much for your attention.