Grupo de Inteligencia Computacional

A Hybrid Segmentation of Abdominal CT Images

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Outline

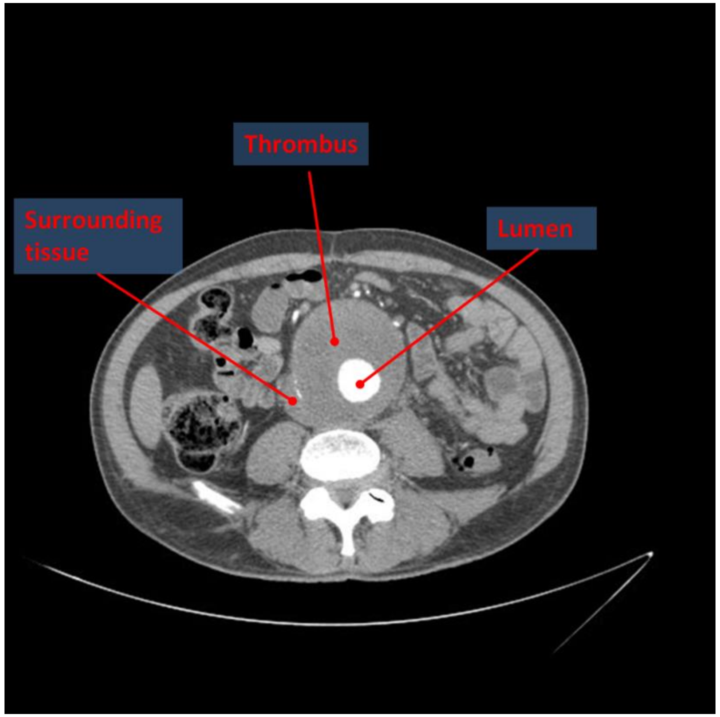
- Introduction
- Methods
  - Active Learning
  - Random Forest Classification
  - Feature Set Construction
- Results
- Conclusions
- Future works

Introduction

Several segmentation methods for vascular structures have been developed…

But,

segmentation of abdominal images, specially the AAA thrombus is still a challenging task.

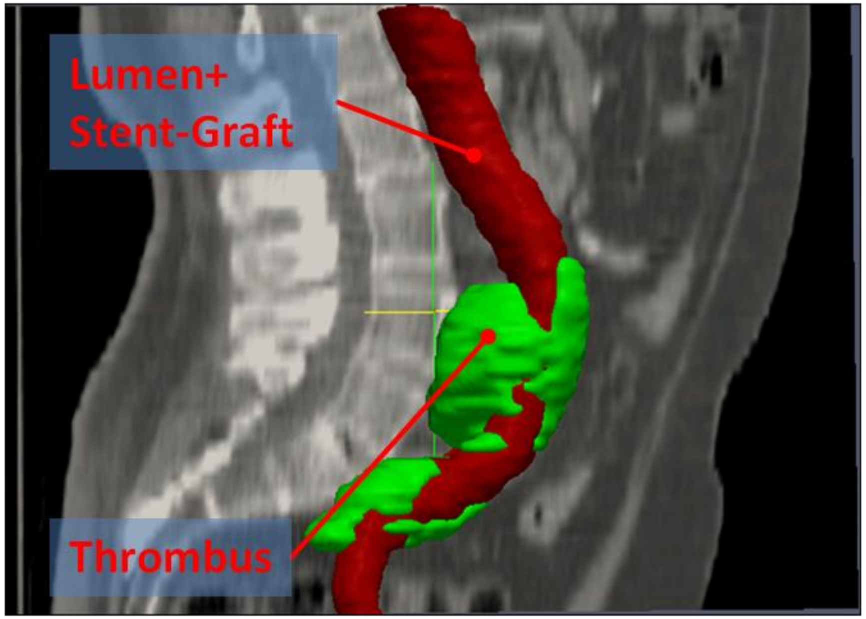


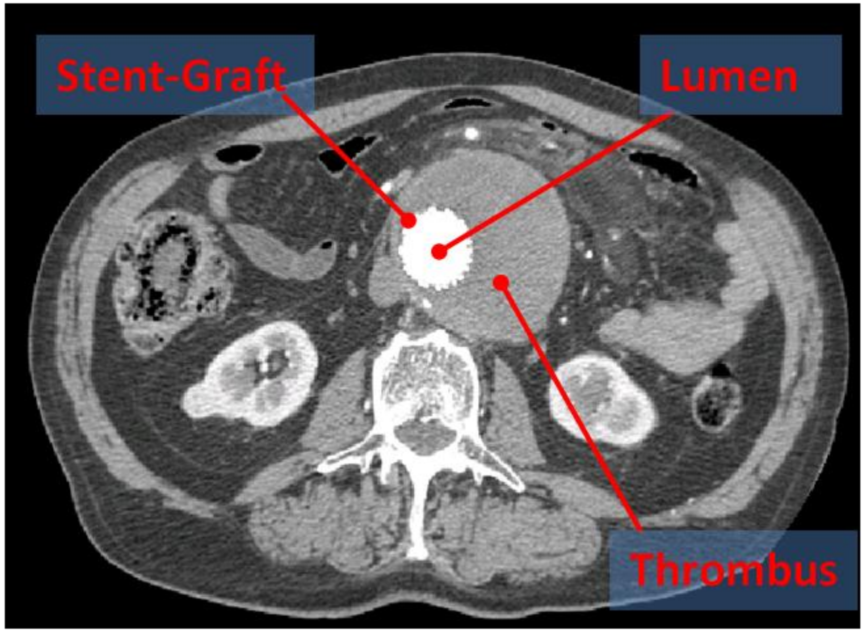
Introduction

- Abdominal Aortic Aneurysms (AAA) is a focal dilation of the aorta in the abdominal region.

- Endovascular prosthesis for aneurysm repair (EVAR): effective technique to reduce the pressure and rupture risk of aneurysm

- The most widely used technique for EVAR monitoring Computerized Tomography (CT) images of the abdominal region after an intravenous contrast agent has been injected





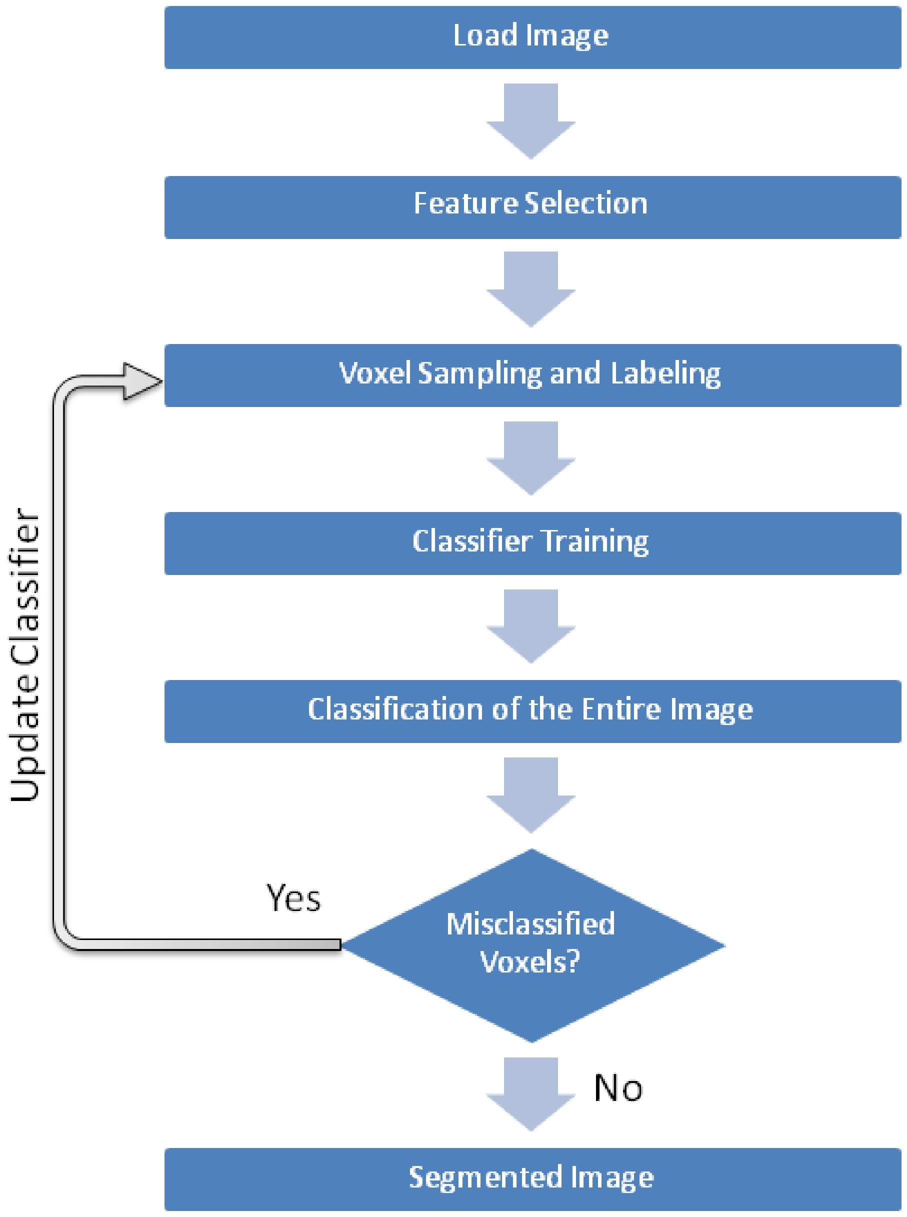
Introduction: our approach

- Our detection and segmentation problem can be described as a **multiclass classification** of voxel samples into aortic lumen, thrombus, bones (column) and background.

- We perform the classification with a supervised method: **discriminative random decision forest**.

- We build the training data in an iterative **active learning** process

Introduction: our approach



Methods: Active learning

- Statistical learning models → common practice for other research areas like remote sensing

- Characteristics:

  - Performances strongly depend on the **information gain** provided by the features used to train the classifier

  - Construction of the training set a cumbersome task requiring extensive **manual analysis** of the image

  - Typically done by visual inspection of the scene and **successive labeling** of each sample

•Training set is highly redundant
•Slow training phase.
•Noisy pixels

Methods: Active learning

So, how are we building the training set?

- As small as possible
- Focused on those pixels effectively improving the performance of the model
- The model returns to the user the pixels whose classification outcome is the most uncertain.
- After accurate labeling by the user, pixels are included into the training set

Which Classifier? Random Forest

- ***x*** is a random sample of ***d***-dimensions
- To make a prediction for a new sample **x**, the trained RF could be used for classification by majority vote among the trees of the RF

$$\hat{c} = majority\,vote\{C_u(x)_1^u\}$$

- The number of trees in the forest should be suficiently large to ensure that each input class receives a number of predictions: set to 200.
- The number of variables randomly sampled at each branch: set to 5.

Feature set construction

- Initially we choose a wide variety of the most common image intensity features as well as different radius values $(1,2,4...2^n)$ around the voxel of interest.

Computationally too expensive!

We compute the information gain provided by each feature and radius value.

Feature set construction

Image Feature
Gaussian blur
Mean
Median
Maximum
Laplacian

Finally selected Image features to build the training set

Results

- Tested on a real human contrast-enhanced datasets
- The CT image stack consists of images with 512 x 512 x 354 voxels resolution, and 0.725x0.725x0.8 mm. spatial resolution.
- We train over the set of features different classifiers and we show the results for accuracy, area under the ROC (AUC) and the residual minimum square error (RMSE).
- Ten-fold cross validation is used in every experiment.
- The final result is the average outcome of the 10 iterations on the test data.

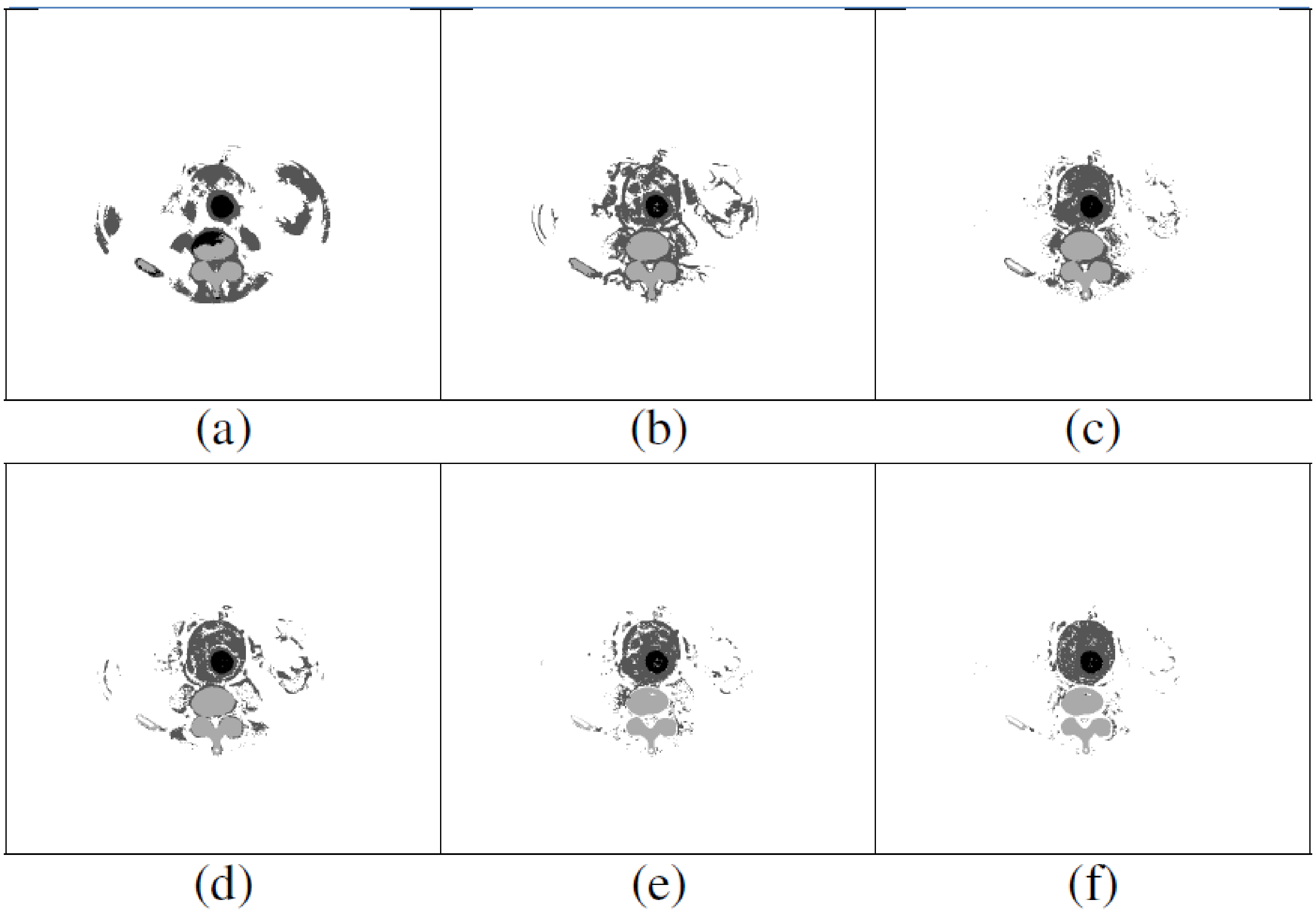
Results

Classifier	Accuracy	AUC	RMSE
SVM	77.4663	0.830	0.2828
MLP-BP	92.3157	0.968	0.1725
RBF	76.6355	0.853	0.2771
LMT	96.6771	0.976	0.1251
Bayes-Net	83.9045	0.938	0.2644
Random Forest	98.0270	0.999	0.0938

Cross-validation results over the abdominal image features computed from the CT datasets for thrombus segmentation

Results

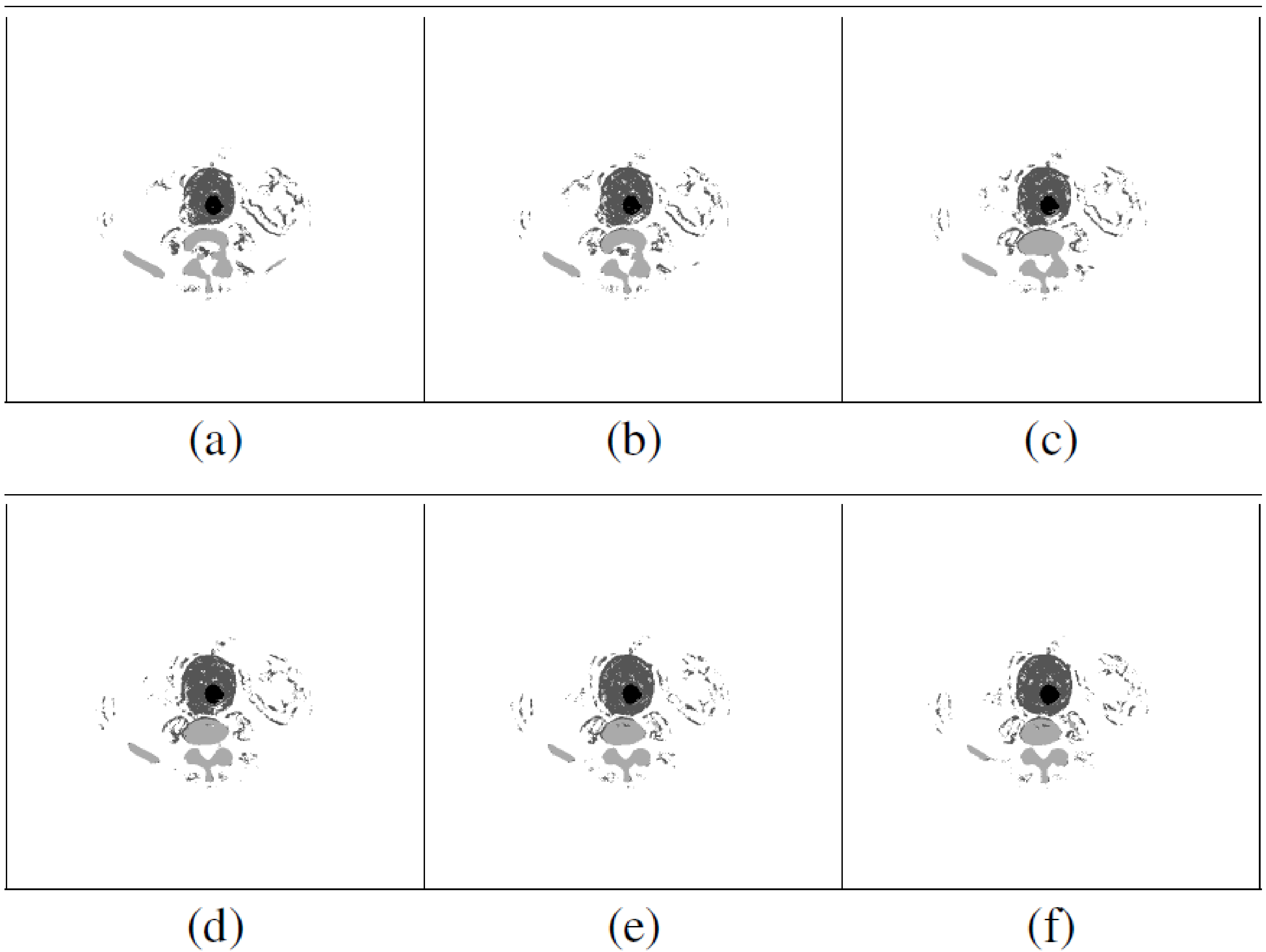
6 iterations in the Active Learning process



(a) (b) (c) (d) (e) (f)

Results

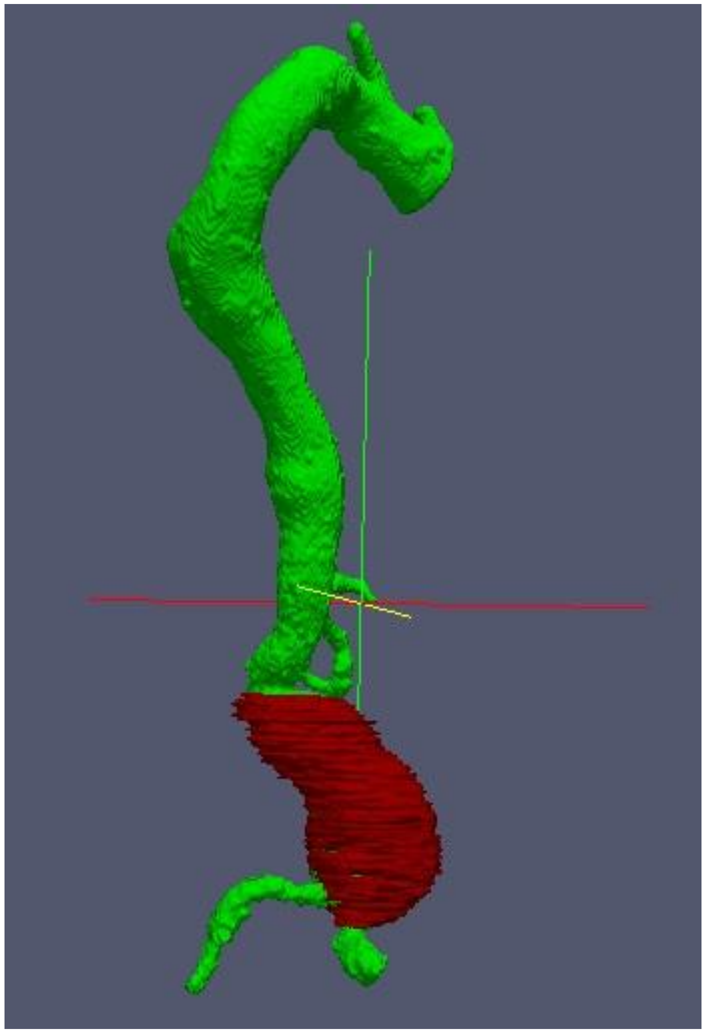
The classier build with the training set corresponding to the image features of just one slice detects and segments the anatomical structures in several consecutive slices.



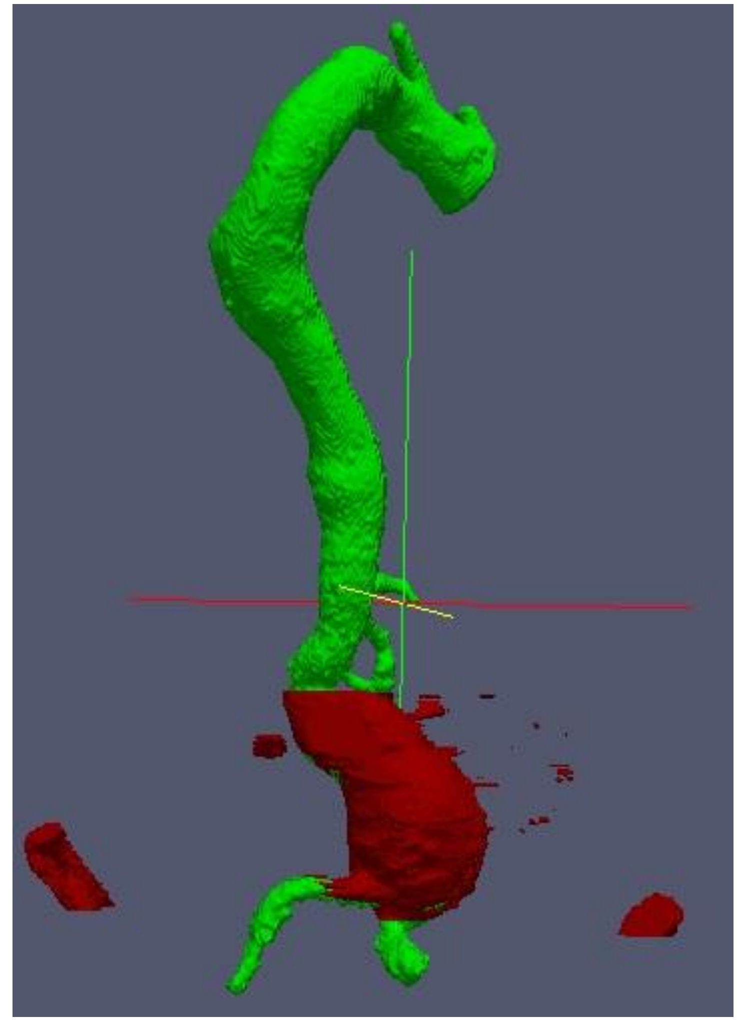
(a) (b) (c) (d) (e) (f)

Results

3D volume rendering



Manual thrombus segmentation



Thrombus segmentation after Active Learning Classification

Conclusions

- We use **Active learning** techniques to build feature sets
- Evaluation of the **information gain** provided by a variety of intensity based features
- We compare the **Random Forest** classier with other common classifiers →Better performance
- **Efficient tool** for discriminating voxels corresponding to specific anatomical structures in abdominal CT images (thombus)

Future works

- Improve the training set →
  - Add more (significant) features
  - Add samples with highest uncertainty.
- Test the method in a large number of datasets.
- Create 3D classifier models