InImpact: The Journal of Innovation Impact: ISSN 2051-6002 : http://www.inimpact.org
Special Edition on Innovation in Medicine and Healthcare : Vol. 6. No. 1 : pp.12-15 : imed13-014

Active Learning enhanced with Expert Knowledge for Computed Tomography Image Segmentation

J. Maiora[1,3], G. García[2], B. Ayerdi[3], M. Graña[3], M. De Blas[4]

[1]*Electronic Technology Department –EUP, University of the Basque Country, San Sebastian, Spain.*

[2]*Systems Engineering and Automatic Control Department –EUP, University of the Basque Country, San Sebastian, Spain.*

[3]*Computational Intelligence Group, University of the Basque Country, San Sebastian, Spain.*

[4]*Radiology Department, Donostia Hospital, San Sebastián, Spain.*

Abstract

Our objective is to create an interactive image segmentation system of the abdominal area allowing quick volume segmentation requiring minimal intervention of the human operator.

Our contribution to tackle this problem is to enhance an Active Learning image segmentation system with Expert Knowledge, allowing quick and accurate volume segmentation requiring minimal intervention of the human operator. As a first step, image segmentation is produced by a Random Forest (RF) classifier applied on a set of standard image features. The human operator is presented with the most uncertain unlabeled voxels to select some of them for inclusion in the training set, retraining the RF classifier. The approach is applied to the segmentation of the thrombus in CTA data of Abdominal Aortic Aneurysm (AAA) patients. The expert knowledge on the expected shape of the target structures is used to filter out undesired detections.

We have performed computational experiments over 8 datasets between 216 and 560 slices each that consists in real human contrast-enhanced datasets of the abdominal area. The performance measure of the experiments is the true positive rate (TPR). 3-fold cross validation is applied. We average the TPR obtained on each slice at each iteration of the process, with a corresponding variance value. Surface rendering is computed to show a 3D visualization of the segmented thrombus.

Accurate segmentation is obtained after a few iterations in areas where it is difficult to distinguish the anatomical structures from surrounding tissues due to a variety of noise conditions and similar the gray levels (i.e. thrombus).

INTRODUCTION

Our purpose is to get an interactive image segmentation system of the abdominal area allowing quick volume segmentation requiring minimal intervention of the human operator**.** The segmentation of certain abdominal anatomical structures such as the AAA thrombus, is still a challenging task due to the low contrast of signal intensity values between the aneurysm thrombus and its

surrounding tissue (Figure 1) [1][2]. We pose the segmentation of CT data volumes as a voxel classification problem. We perform Active Learning [3] on the central slice containing part of the thrombus, and we apply the results to the rest of the volume, to test the generalization power of the approach. The Active Learning oracle in the experiments is the ground truth provided by manual segmentation.

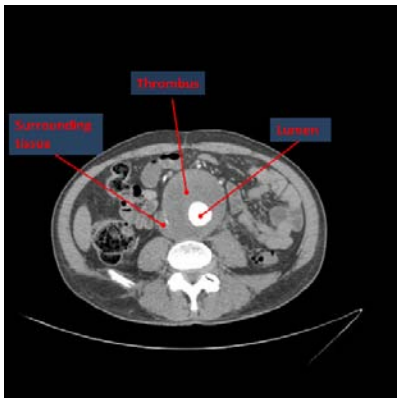


Figure 1: Axial view of abdominal area in a CT orthoslice using the contrast agents.

METHODS

Active Learning

Our contribution to tackle this problem is to enhance Active Learning with Expert Knowledge for an interactive image segmentation system which will allow quick volume segmentation requiring minimal intervention of the human operator. As a first step, image segmentation is produced by a Random Forest (RF) classifier[4] applied on a set of standard image features. The human operator is presented with the most uncertain unlabeled voxels to select some of them for inclusion in the training set, retraining the RF classifier[5]. The approach is applied to the segmentation of the thrombus in CTA data of Abdominal Aortic Aneurysm (AAA) patients. The segmentation is also constrained by knowledge on the expected shape of the target structures[6].
Active learning focuses on the interaction between the user and the classifier. In the context of classifier based image segmentation, the system returns to the user the pixels whose classification outcome is most uncertain. After accurate labeling by the user, pixels are included into the training set in order to retrain the classifier[7]. The classification model is optimized on well-chosen difficult examples, maximizing its generalization capabilities.

Expert Knowledge

The segmentation is constrained by knowledge on the expected shape of the target structures. In this case it would take into account the known characteristics of the thrombus[8] (which do not consider in the active learning process):

- It is a connected component.
- It has a roughly circular shape.
- Its radius decreases as we move away from the center

- *x, y* coordinates of the centroid of each cut, have a minimum variation between successive slices.

RESULTS

We have performed computational experiments over 8 datasets to test the proposed approach. Each dataset consists in real human contrast-enhanced datasets of the abdominal area with 512x512 pixel resolution on each slice. Each dataset consists of between 216 and 560 slices and 0.887x0.887x1 mm spatial resolution corresponding to patients who suffered Abdominal Aortic Aneurysm. The datasets show diverse sizes and locations of the thrombus.
Fig. 2 shows the performance of the Active Learning based image segmentation algorithm for 4 CT volumes of AAA patients. We plot the average True Positive Rate (TPR) of the RF classifiers built integrating the Active Learning process and Expert Knowledge.
A 3D volume rendering of the Aorta's lumen (green) and thrombus (red) of one patient is shown in Fig.3. Fig.3(a) shows the rendering of the ground truth given by volume manual segmentation. Fig.3(b) shows the result of the segmentation based on the Active Learning enhanced with Expert Knowledge classifier built from the thrombus' central slice. The structure of the thrombus is well delineated.

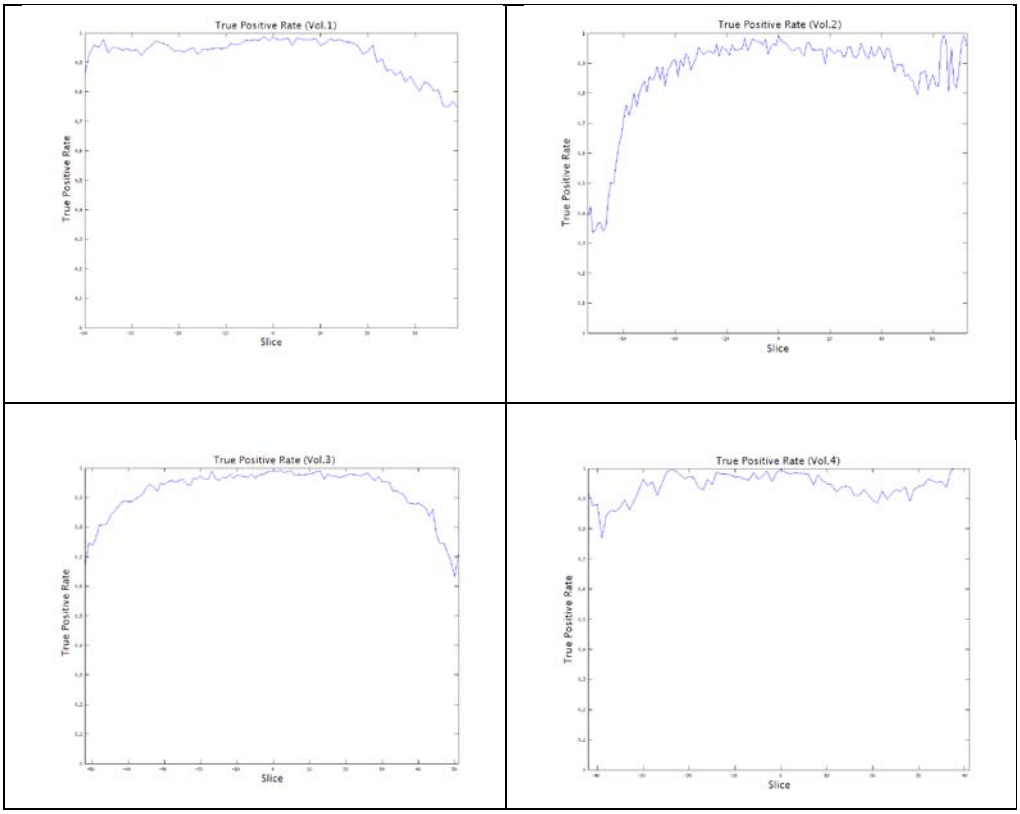
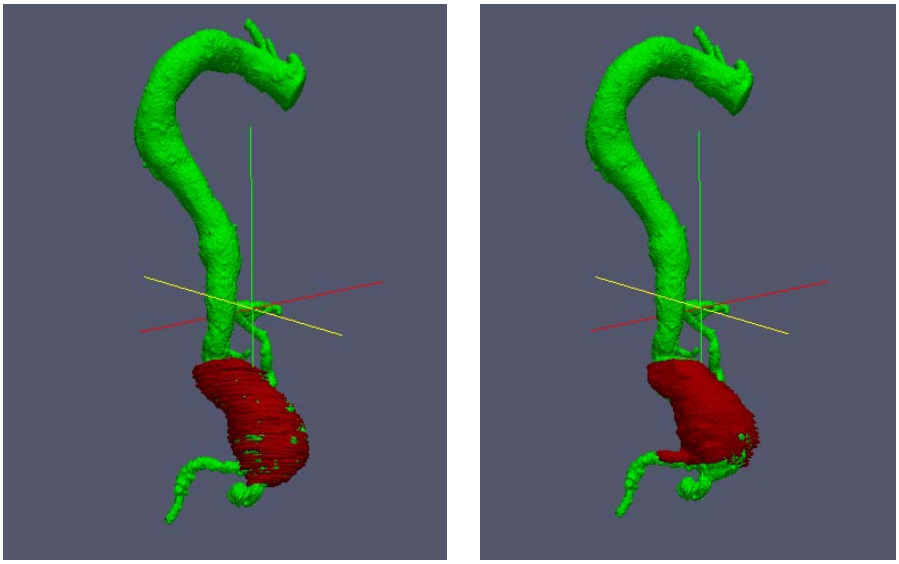


Figure 2: True Positive Rate for each slice where thrombus is present tested in 6 of the CT volumes of AAA patients.



(a) (b)

Figure 3: Volume rendering of aortic lumen (green) and thrombus (red) obtained from the segmentation of one CT volume. (a) manual segmentation of the ground truth, (b) result of Active Learning enhanced with Expert Knowledge classifier.

BIBLIOGRAPY

1. M. Subasic, S. Loncaric, and E. Sorantin, “3-D image analysis of abdominal aortic aneurysm.,” *Stud Health Technol Inform*, vol. 77, pp. 1195–1200, (2000).
2. J. Maiora and M. Graña, “Abdominal CTA Image Analisys Through Active Learning and Decision Random Forests: Aplication to AAA Segmentatio,” in IJCNN, (2012).
3. D. Tuia, E. Pasolli, and W. J. Emery, “Using active learning to adapt remote sensing image classifiers,” *Remote Sensing of Environment*, (2011).
4. L. Breiman, “Random forests,” *Machine learning*, vol. 45, no. 1, pp. 5–32, (2001).
5. E. Geremia, O. Clatz, B. H. Menze, E. Konukoglu, A. Criminisi, and N. Ayache, “Spatial decision forests for MS lesion segmentation in multi-channel magnetic resonance images,” *NeuroImage*, vol. 57, no. 2, pp. 378–390,(2011).
6. J.Cronenwett, W.Krupski, and R.Rutherford, *Abdominal aortic and iliac aneurysm*. Vascular Surgery, (2000).
7. M. F. Fillinger, “Imaging of the thoracic and thoracoabdominal aorta.,” *Semin Vasc Surg*, vol. 13, no. 4, pp. 247–263, (2000).
8. M. Yaqub, M. K. Javaid, C. Cooper, and J. A. Noble, “Improving the Classification Accuracy of the Classic RF Method by Intelligent Feature Selection and Weighted Voting of Trees with Application to Medical Image Segmentation,” in in *Machine Learning in Medical Imaging*, vol. 7009, pp. 184–192, Heidelberg, (2011).