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Grupo de Inteligencia Computacional

A hybrid system for survival analysis after EVAR treatment of AAA

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Outline

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  - Image Processing: Segmentation and Registration.
  - Neural Network Classification Algorithms
- Results
- Conclusions

Introduction

- Abdominal Aortic Aneurysm(AAA) is a focal dilation in the abdominal aorta
- EVAR: endovascular prosthesis insertion
- Prosthesis displacement/endoleaks →Expansion and risk of rupture
- Postoperative monitoring required

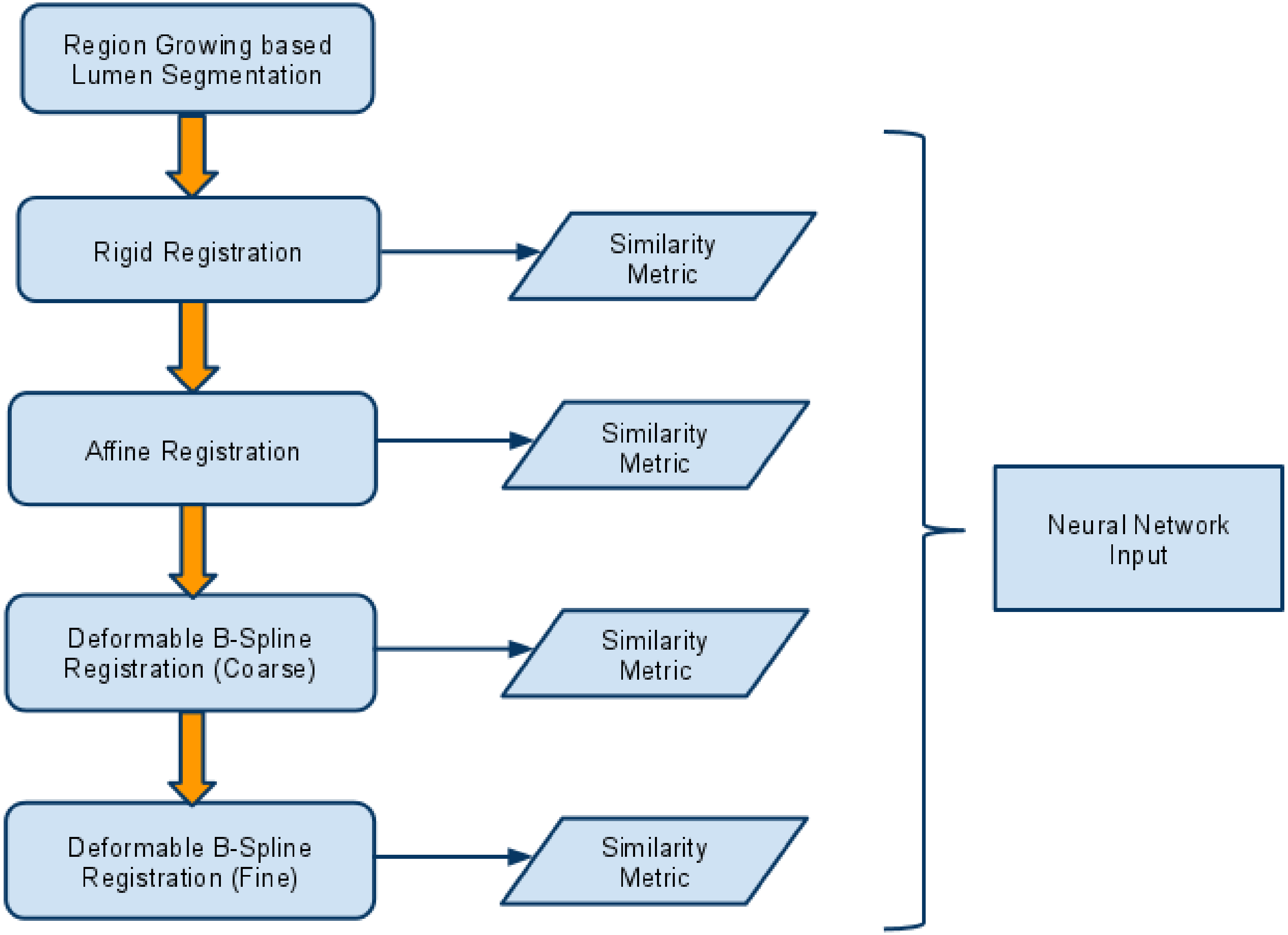
Introduction

- Decision suport systems → Artificial Neural Networks

- Computerized Tomography (CT) images of the abdominal region for monitoring (with and without contrast).

- The aim of our work is to make an automatic analysis of the AAA and classify them as favorable or unfavorable

Introduction: our approach

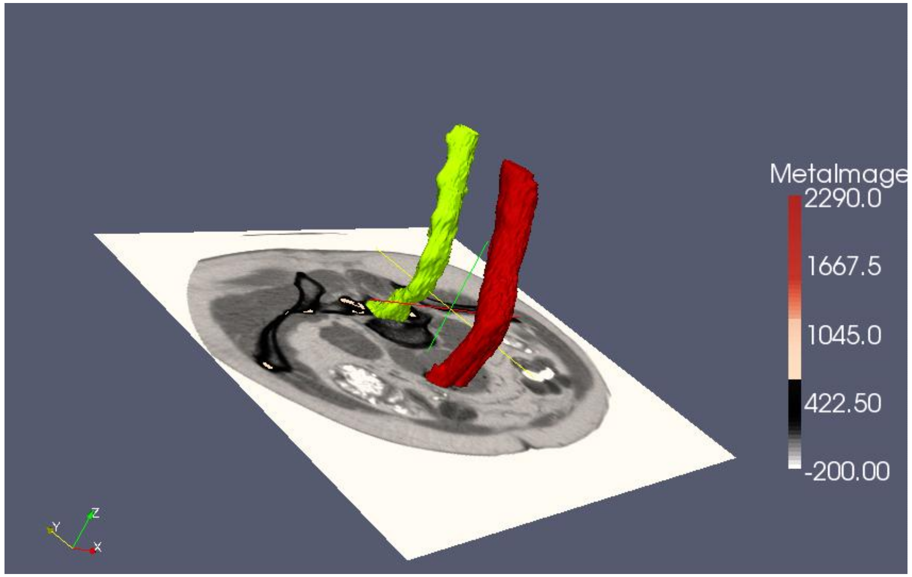


Methods: Lumen Segmentation

- Region Growing based Lumen Segmentation: At least a seed point placed in the lumen is required

- We have used a User-Guided Level Set Segmentation (UGLSS)

- The algorithm, implemented in Insight Toolkit, includes voxels that lie in a confidence interval of the current segmented region in an iterative process



Methods: Lumen Segmentation

- An evolving contour is a closed surface C(t,u,v) parameterized by variables u, v and by the time variable t. The contour evolves according to the following partial differential equation (PDE):

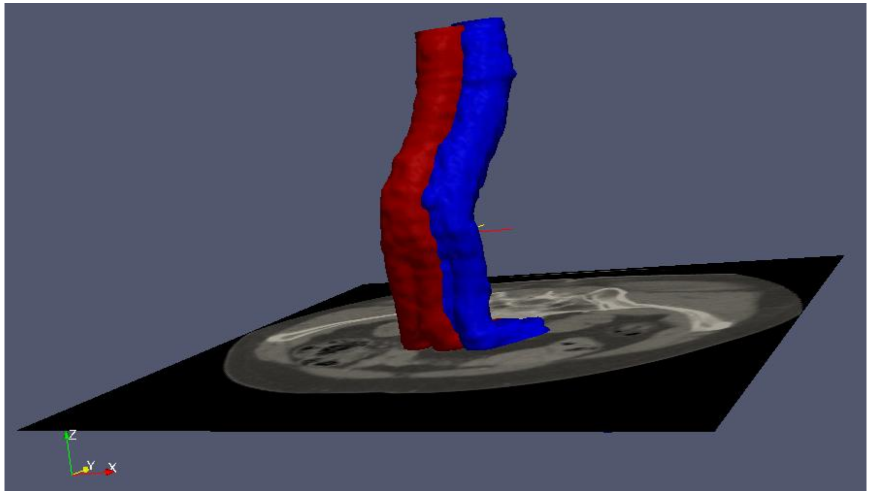
$$\frac{\partial}{\partial t} C(t,u,v) = F\overrightarrow{N}$$

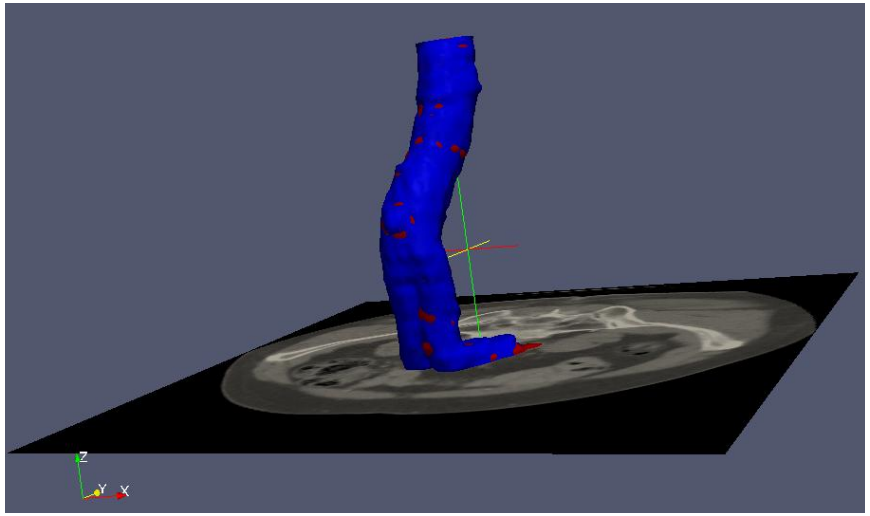
- We compute the external force F by estimating the probability that a voxel belongs to the structure of interest and the probability that it belongs to the background at each voxel in the input image:

$$F = \alpha(P_{obj} - P_{bg}) + \beta_K$$

Methods: Lumen Registration

- Registration: the process of finding a spatial transform that maps points between two images.
- Our case: intra-subject, mono-modal
- Rigid, affine, deformable (B-Splines)
- Linear interpolator, Mutual Information metric, Regular Step Gradient Descent optimizer





Methods: Feature Extraction

- We use two similarity metrics as imput features of the neural networks: the sum of squared intensity differences (SSD) and mutual information (MI).
  - SSD is suitable when the images have been acquired through similar sensors and thus are expected to present the same intensity range and distribution.

$$SSD = \frac{1}{N} \sum_{x_A \in \Omega^T_{A,B}} |A(x_A) - B^T(x_A)|^2$$

  - Mutual information is a measure of how much information one random variable has about another. The information contributed by the images is simply the entropy of the portion of the image that overlaps with the other image volume, and the mutual information is a measure of the joint entropy with regard to the marginal entropies.

$$I(A,B) = H(A) + H(B) - H(A,B)$$

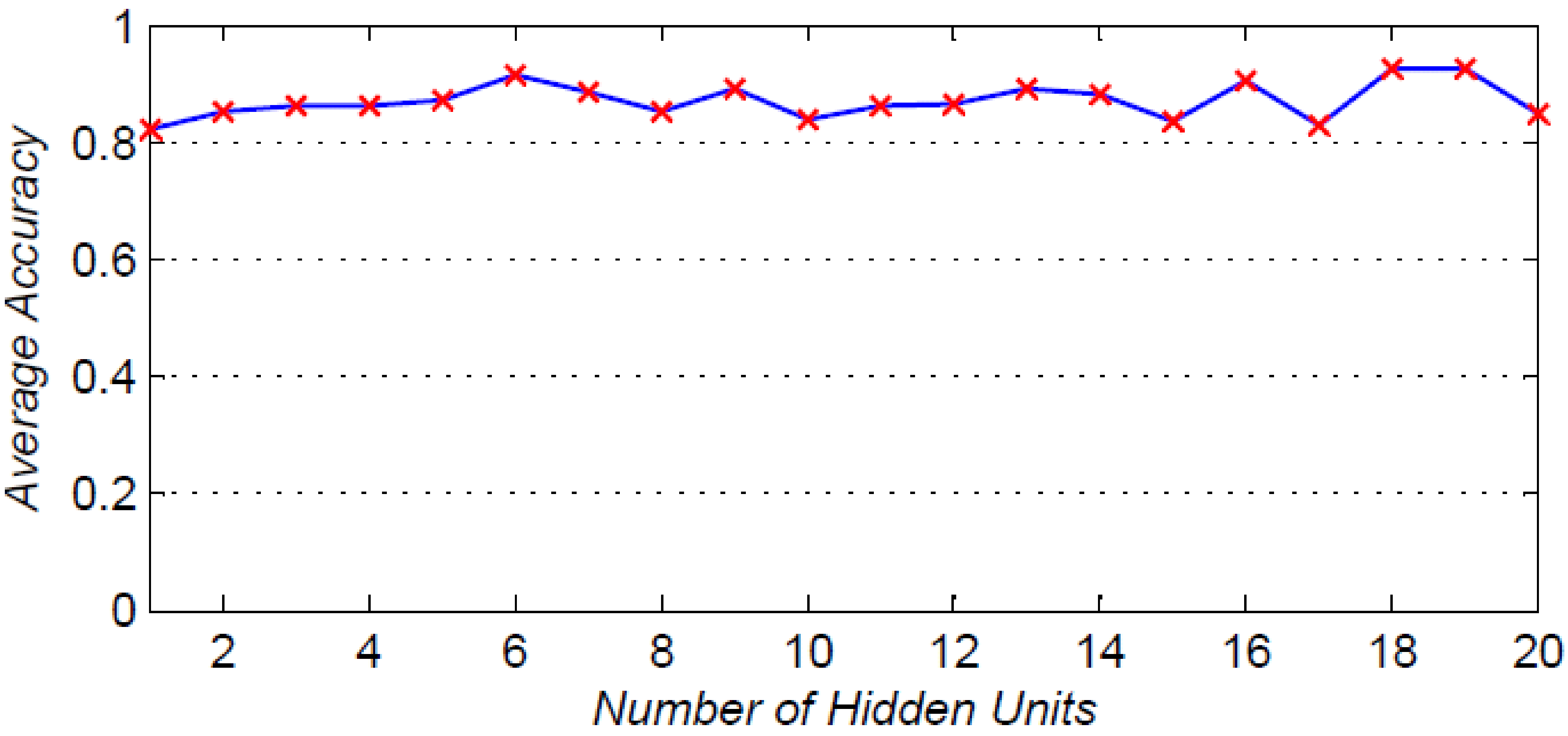
Methods: Classification Algorithms

- We deal with two class classification problem, given a collection of training/testing input feature vectors and the corresponding labels.
- Backward propagation of errors, or backpropagation (BP), is a non-linear generalization of the squared error gradient descent learning rule for updating the weights of artificial neurons in a single-layer perceptron, generalized to feed-forward networks, also called Multi-Layer Perceptron (MLP).
- We build the feature vectors with the values of the different registration modalities for each dataset. So, we have 8 features for each registered image pair.
- We train over the set of features different neuronal architectures varying the number of neurons in the hidden layers from 1 to 20. We train the network 50 times for each number of hidden units and we obtain the average accuracy.
- We use one-leave-out cross validation.

Results

- We tested the approach with 3 patients–with 5 datasets each- treated with stent-graft devices
- The CT image stack consists of images with 512 x 512 x 354 voxels resolution, and 0.725x0.725x0.8 mm. spatial resolution.
- We have computed the mean squares and mutual information similarity metrics for the evaluation of the registration. A decrease of both metric is observed in the consecutive registration methods.
- An increase in the performance is observed from 1 to 6 hidden units, then the obtained results are variable and we can even notice that due to the Hughes effect, for a large number of hidden layers the performace does not improve becouse of overfitting.
- We use one-leave-out

Results



1
0.8
0.6
0.4
0.2
0
Average Accuracy
2
4
6
8
10
12
14
16
18
20
Number of Hidden Units

Conclusions

- A registration process is carried out over binary images improving on the works that perform registration over point sets, which always involve a greater loss of information

- The feature vectors have been built with the similarity measures of the segmented lumen after rigid, affine and deformable registration. The datasets of the patients have been previously validated by the medical team as having a favolable or unfavorable evolution.

- The proposed feature extraction is very effective in providing a good discrimination between patients that can easily be exploited by the classifier construction algorithms.

- It could lead to a model that would predict the evolution of other patients and provide support for the decision.

Future works

- Further ongoing works with a more extensive database is on the way to confirm our conclusions in the framework of collaboration with a team of medical clinical experts.

- It would also be necessary to compare the results with other binary classifiers as Support Vector Machines (SVM), Relevance Vector Machine, RVM, Logistic Model Tree, LMT, Adaboost as a boosting method, or radial basis functions Neural Networks, RBF.