CASCADE OF BOOSTED CLASSIFIERS AND ACTIVE APPEARANCE MODEL FOR SPINE ELEMENTS LOCALIZATION AND SEGMENTATION

D. Gaweł[1], M. Nowak[1], K. Łyduch[1], P. Główka[2] and T. Kotwicki[2]

[1]*Chair of Virtual Engineering, Poznan University of Technology, Poznan, Poland*
[2]*Department of Spine Disorders and Pediatric Orthopedics, University of Medical Sciences, Poznan, Poland*

1. Introduction

Magnetic Resonance Imaging (MRI) is a medical imaging technique widely used for visualization of internal body structures. The popularity of this method grows every year, because of its non-harmfulness, as opposed to Computed Tomography (CT). Usage of advanced computer science techniques including Machine Learning and Active Appearance Model gives an opportunity of automatic image interpretation. Presented solution was developed by specialists form Poznan University of Technology in cooperation with University of Medical Sciences and Rehasport Clinic and can be an answer for increasing needs for visualization in medicine.

2. Materials and Methods

Presented method is based on Machining Learning (ML) [1] and Active Appearance Model (AAM) [2] techniques. For the research purposes almost 50 MRI examinations were used. The data was provided by Rehasport Clinic. At the beginning DICOM images are read. Due to low quality of the images (low resolution, intensity inhomogeneity and high noise) the initial filtration algorithm is introduced.

Afterwards, to extract each vertebra from the images, Machine Learning technique based on Cascade of Boosted Classifiers [3] and extended set of Haar-like features is used. The process consists of two major stages: training the classifier and vertebrae localization.

In the next stage the tissue segmentation is performed. The process uses the Active Appearance Model (AAM) technique that combines Statistical Shape Model with gray-level Appearance Model. The method focuses on recognizing predefined characteristic features from vertebrae images. The detected features are afterwards used for defining the tissue boundaries.

3. Results

The method was tested on a set of 50 previously unseen vertebrae images. The spine tissue was manually segmented by experts and compared with Machine Learning Results. For the numerical evaluation three measures were used [4]: True Positive Fraction (TPF), False Negative Fraction (FNF) and False Fraction (FF). False Fraction (FF) is the most important measure as it combines information both about over- and under-segmentation. The table (see Table 1) presents segmentation results obtained by experts and introduced segmentation method. The difference between the average FF value for experts (91.32%) and presented method (90.19%) is less than 2%.

4. Conclusions

Statistical analysis of obtained segmentation results confirmed a good segmentation performance and possible application for spine elements extraction, however the procedure for full automation needs further work related to implementation of additional algorithms including, but not limited to, exchange of information between different stages and initialization of characteristic features localization.

In the future automatic segmentation could be used for creation of discrete (Figure 1) and continuous (Figure 2) 3D spine models, allowing better understanding of the pathology by the physicians and patients.

	TPF	FNF	FF	σ_{TPF}	σ_{FNF}	σ_{FF}
Computer segmentation	92.28±0.95	7.72±0.95	90.19±1.01	3.42	3.42	3.64
Expert segmentation #1	96.17±0.92	3.83±0.92	91.67±1.27	3.32	3.32	4.58
Expert segmentation #2	95.13±0.83	4.87±0.83	92.11±1.00	2.98	2.98	3.60
Expert segmentation #3	97.74±0.43	2.26±0.43	91.09±1.33	1.56	1.56	4.78
Expert segmentation #4	97.56±0.37	2.44±0.37	91.49±1.47	1.33	1.33	5.32
Expert segmentation #5	92.46±1.33	7.54±1.33	90.22±1.31	4.81	4.81	4.74

Table 1: Comparison (percentage) of True Positive Fraction, False Negative Fraction and False Fraction for data segmented using presented method and manually segmented by experts (significance level α=0.05). To achieve reliable results a mean value obtained from 100 procedure passes with 25 algorithm iterations each is presented. σ_{TPF} – standard deviation for True Positive Fraction, σ_{FNF} - standard deviation for False Negative Fraction, σ_{FF} - standard deviation for False Fraction.

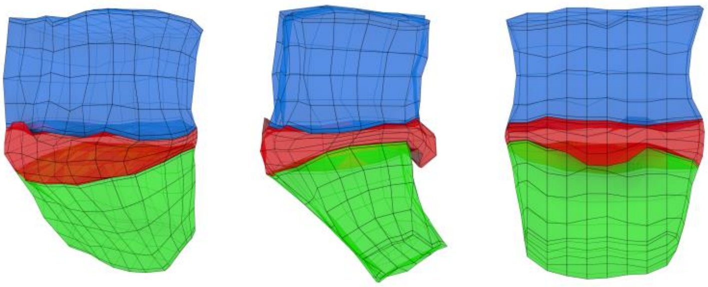

Figure 1. Discrete STL 3D model created manually from characteristic features. The pathology of vertebrae and intervertebral disc is clearly visible.

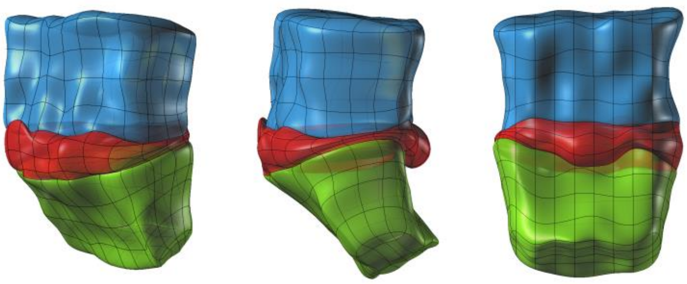

Figure 2. Continuous NURBS model created manually from characteristic features, easily convertible to Finite Element mesh. The pathology of vertebrae and intervertebral disc is clearly visible.

Acknowledgments This work was supported by The National Centre for Research and Development under the grant – decision no. DZP/PBS3/2296/2014.

References

[1] Sergios Theodoridis. *Machine learning: a Bayesian and optimization perspective*. Academic Press, 2015.

[2] Gareth J Edwards, Christopher J Taylor, and Timothy F Cootes. Interpreting face images using active appearance models. In *Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on,* pages *300*-305. IEEE, 1998.

[3] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on,* volume 1, pages I-I. IEEE, 2001.

[4] Tom Fawcett. An introduction to roc analysis. *Pattern recognition letters,* 27(8):861-874, 2006.