A Boosting Approach for Multiple Sclerosis Lesion Segmentation in Multi-Spectral 3D MRI

Michael Wels* Martin Huber† Joachim Hornegger*

1 Purpose

Quantitatively assessing disease progression in terms of lesion volume is a major concern in the case of multiple sclerosis (MS)—a common neuropathological disease of young adults that primarily affects cerebral white matter within the human brain. As multi-spectral 3D magnetic resonance imaging (MRI) is the method of choice for the examination of that type of disease we propose a knowledge-driven approach for MS lesion segmentation in multi-spectral 3D brain MRI data based on the recently introduced [1] probabilistic boosting trees (PBT).

2 Methods

In order to distinguish foreground, i.e. lesion, and background, i.e. non-lesion, voxels within multi-spectral MR volumetric data we build a PBT in a similar manner to [2] to derive a discriminative model in terms of posterior probabilities for individual voxels from manually segmented training data. By additionally using context information by means of Haar-like features that are computed on a local neighborhood surrounding the voxel to be classified the PBT model is enabled to capture class specific characteristics despite the well-known drawbacks of the MR medical imaging modality such as Rician noise, partial volume effects, and intensity inhomogeneities. Subsequently in the segmentation process, the probabilities obtained by the model are refined by stochastic relaxation [3] and a Laplacian level set approach taken from the Insight Segmentation and Registration Toolkit (ITK, www.itk.org). As the axial resolution of the input data is low our approach is restricted to operate on down-sampled 2D axial slices without taking into account inter-slice neighborhood relations.

The framework's first step PBT recursively groups boosted ensembles of weak classifiers to a tree structure during learning from annotated data. When AdaBoost [4] is chosen as the boosting strategy this resembles building a binary regression tree as the final boosted classifier generated within each inner node asymptotically approaches an additive logistic regression model [5]. The overall posterior probability can then be computed by appropriate traversation of the tree.

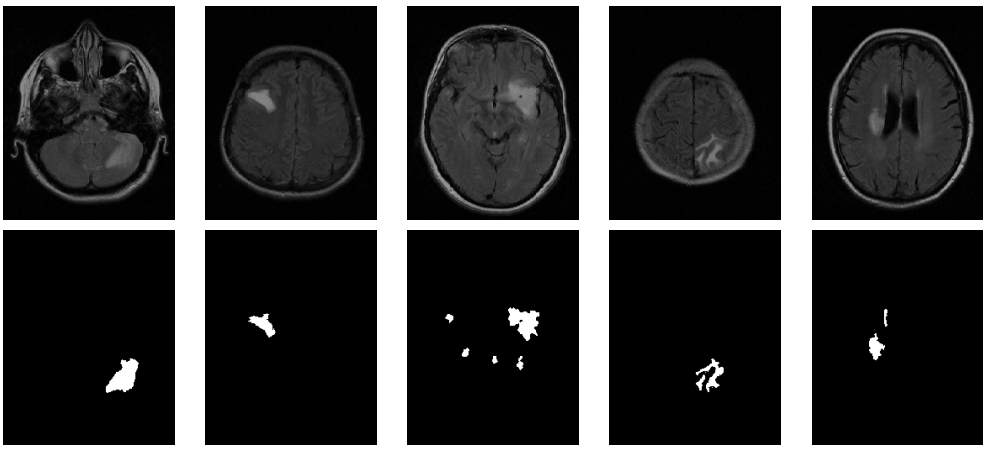
For the purpose of classification it is tried to capture the structural variability of foreground and background voxels by not only considering multi-spectral intensity and gradient values but also several hundreds of Haar-like features [6, 7] computed on a 15×15 square centered at the voxel of interest.

The posterior probabilities obtained by PBT that determine the segmentation are smoothed by stochastic relaxation independently from the initial features used by PBT itself. The final result is then attained by means of the Laplacian level set filter from ITK as mentioned above.

3 Results

For training and evaluation purposes there were six manually segmented multi-spectral MRI scans available. The leave-one-out approach was applied to train six different classifiers from approximately 70,000 randomly selected training samples, i.e. voxels, uniformly distributed over all input slices. Three

*University Erlangen-Nuremberg
†Siemens AG, Erlangen



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

Figure 1: Segmentation results obtained by leave-one-out validation. The first row shows selected slices of the FLAIR sequences of five different data sets. The second row shows the associated segmentation result

of the six classifiers reach a Dice coefficient of more than 70% on their test data set, two reach about 50% and one fails with 0% due to the lack of significant MS lesions in the associated data volume. However, for a fully automated approach volumetric overlap of more than 50% can be considered a remarkable achievement.Figure 1 gives a visual impression of the segmentation results obtained.

4 Conclusion

The method for segmentation of MS lesions in multispectral 3D brain MRI data discussed in this paper makes use of structural information by additionally taking into account the context of a voxel for the purpose of classification. The presented results show that by doing so supervised techniques like PBT can be employed for MRI tissue classification even though they are usually—when relying on individual voxel intensities only—considered inappropriate due to the typically large inter-scan variations. Future work involves further assessment and refinement of the proposed method and investigation of alternative structural features that can be used in the context of boosting.

References

[1] Tu, Z.: Probabilistic boosting-tree: Learning discriminative models for classification, recognition, and clustering. In: IEEE Intl. Conf. Comput. Vis., Beijing, China. (2005) 1589–1596

[2] Tu, Z., Zhou, X., Comaniciu, D., Bogoni, L.: A learning based approach for 3D segmentation and colon detagging. In: Europ. Conf. Comput. Vis., Graz, Austria. (2006) 436–448

[3] Sonka, M., Fitzpatrick, J.M.: Handbook of Medical Imaging, Vol. 2: Medical Image Processing. SPIE—The International Society of Optical Engineering, Bellingham, Washington, USA (2004)

[4] Freund, Y., Schapire, R.E.: A decision-theoretic generalization of on-line learning and an application to boosting. In: Europ. Conf. Comput. Learning Theory. (1995) 23–37

[5] Friedman, J., Hastie, T., Tibshirani, R.: Additive logistic regression: a statistical view of boosting. Stanford University, Department of Statistics, Technical Report (1998)

[6] Lienhart, R., Kuranov, A., Pisarevsky, V.: Empirical analysis of detection cascades of boosted classifiers for rapid object detection. In Michaelis, B., Krell, G., eds.: DAGM-Symposium. Volume 2781 of Lect. Notes in Comp. Sci., Springer (2003) 297–304

[7] Viola, P., Jones, M.: Robust real-time object detection. In: 2nd International Workshop on Statistical Learning and Computational Theories of Vision, Vancouver, Canada. (2001) 1–25