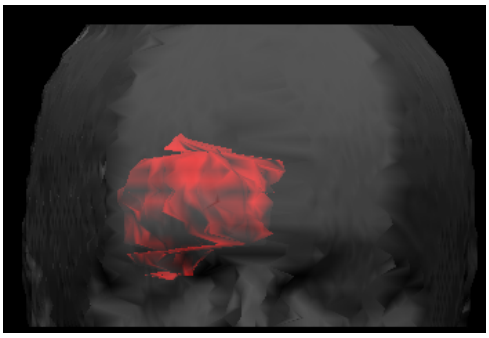
and homogeneous regions with smoothed region borders were formed by the operation. This final segmentation identifies the pathological area as closed region. A comparison shows a good match of the automatically located region to the interactively defined one in Figure 3.

Segmented data may serve as input for surface reconstruction and thus for an automatic generated visualization of pathological areas.



Therefore a contour extracting component and the automatic set–up of an assignment graph based on a connected component algorithm is required. This serves as input for standard surface reconstruction of selected tissue types [5].

**Figure 6.** 3D–Visualization: Coronal view of tumor inside skull

The 3D–visualization given in Figure 6 shows the reconstructed tumor inside the skull of a patient and might be used for operation planning.

## 4 Conclusion

This work addresses the automatic segmentation of tomographic images, which is performed in a two–step processing pipeline. While step one of the pipeline implements texture discrimination methods for pixel based classification, step two realizes a postprocessing and eliminates classification errors. The used segmentation pipeline shows good generalization capabilities on a base of over 70.000 texture test samples in a statistical evaluation. The segmentation of pathological tissue can be performed with classification rates of approx. 96%. The results serve as input for 3D–visualization.

## 5 Acknowledgment

I would like to thank the department of Biophysics and Medical Radiation Physics of the German Cancer Research Center, who kindly provided the datasets used in this work.

## References

[1]. C. Busch : "Wavelet Based Texture Segmentation of Multi–Modal Tomographic Images", in: Computer & Graphics, vol.21, no.3, pp.347–358, (1997)

[2]. K.H. Höhne et al., "3D Visualization of Tomographic Volume Data using the Generalized Voxel Model". The Visual Computer 6, no. 1, 28–36, (1990)

[3]. T. Kohonen: "The Self–Organizing Map", Proceedings of the IEEE, Vol. 78, No. 9, pp. 1464–1480, (1990)

[4]. C. Tsai, B.S. Manjunath, R. Jagadeesan, "Automated Segmentation of Brain MR Images". Pattern Recognition, Elsevier Science, vol. 28, no. 12, pp. 1825–1837, (1995)

[5]. M. J. Zyda et al.: "Surface construction from planar contours" Computer&Graphics, vol. 11, no. 4, pp.393–408, (1987)

## 3 Results

The outlined segmentation pipeline was tested on over 70.000 test samples stemming from 11 patients with identical pathology. The investigated data sets (MRI–data with $T_2$–weighted band, *pw*–weighted band and an additional *ct*–band) were classified with different classifiers. The overall comparison of the results is shown in Figure 2.

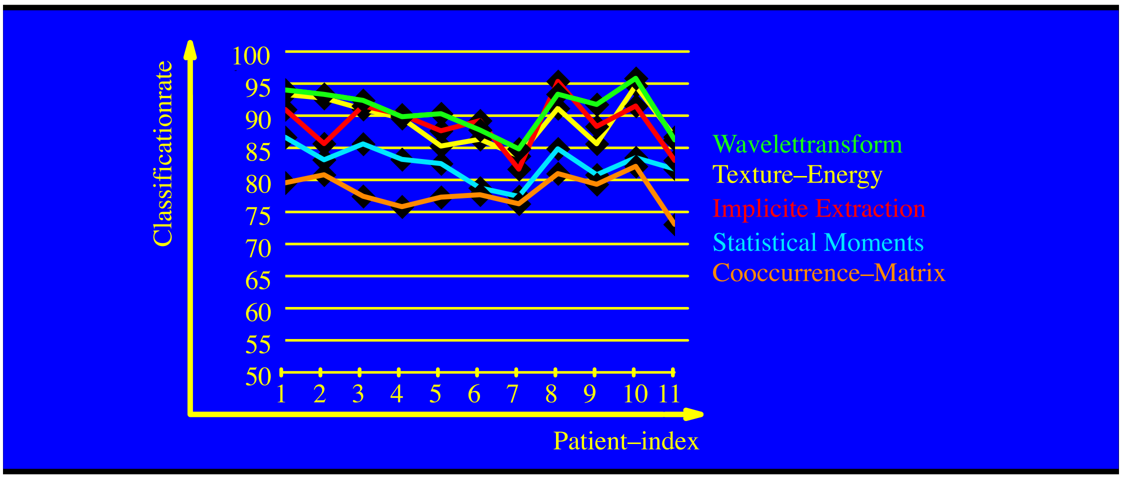



**Figure 2.** Statistical evaluation: right–positive average over all classes

The statistic evaluation was performed using the leaving–one–out method in such a way that classification rates from Figure 2 represent mere generalization capabilities. It indicates that energy based techniques such as *wavelet transform* or *textural energy* are superior to the statistical based methods.

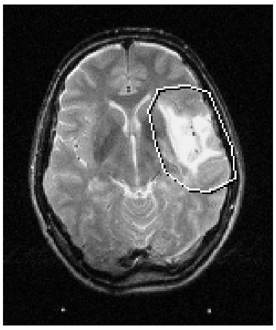


**Figure 3.** $T_2$–weighted band from original data set

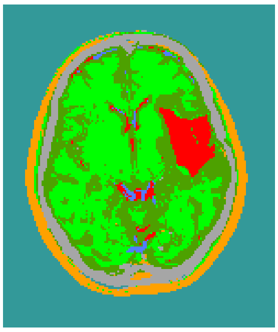


**Figure 4.** Classification result of Figure 3

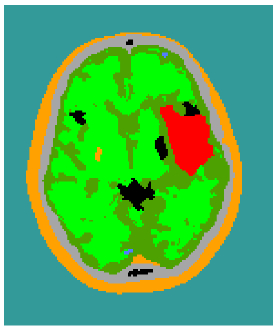


**Figure 5.** Segmentation resu

The above Figures show the results of both steps of the segmentation pipeline. In Figure 3 the $T_2$–weighted band from the original data set is shown. The white polygon shows the isoline definition from irradiation planning that was interactively determined by an expert. A classification result is given in Figure 4. Misclassifications, especially confusions between *tumor* and *CSF* can be observed inside the ventricular system. These classification errors are identified and eliminated by the postprocessing step of the segmentation pipeline. It can be stated, that all misclassified isolated pixels from Figure 4 were removed

## 2 Methods

The work of this paper relies on a segmentation pipeline for tomographic data such as magnetic resonance imaging. An overview of the segmentation pipeline is shown in Figure 1, while a more detailed description of its components can be found in [1]. The pixel based approach employes a twostep processing analysis, where step 1 is the mere texture discrimination and classification. A subsequent postprocessing of classified data provides a segmentation result that can be used for application system such as 3D–visualizer or volumetric tools.

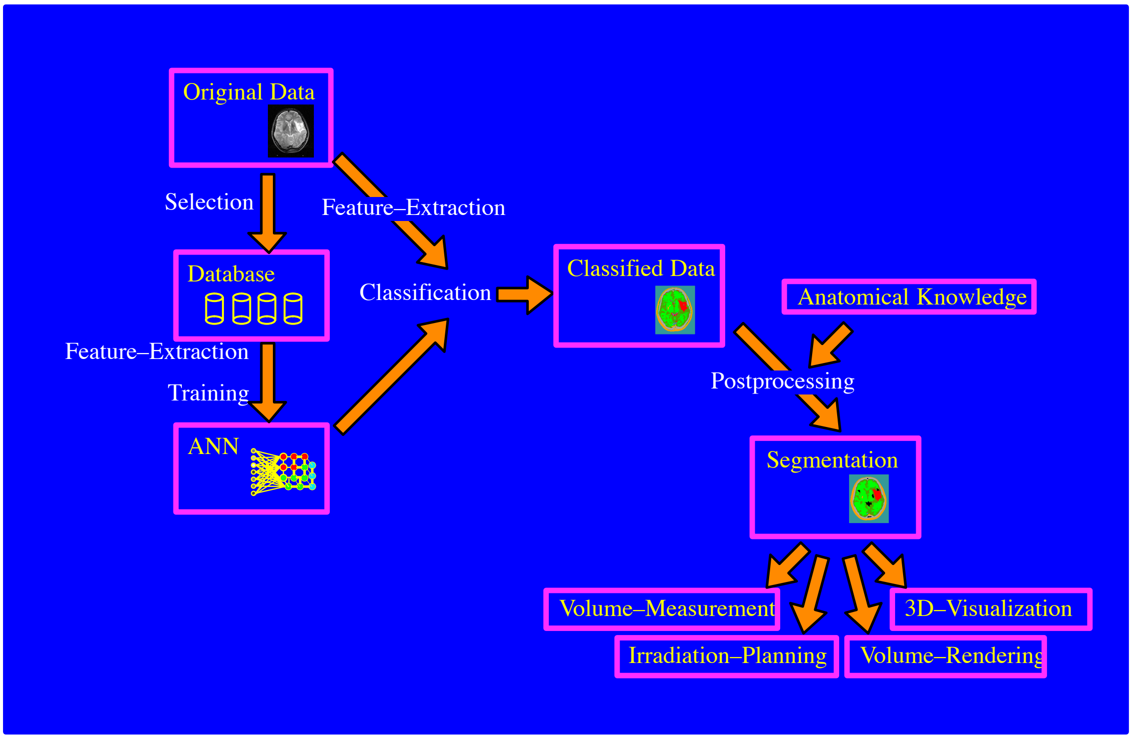



**Figure 1.** Two–step segmentation pipeline

Well known texture discrimination methods like *wavelet transform, statistical moments, cooccurrence matrices* and *textural energy* are integrated in the pipeline. A comparative study on their individual suitability in terms of classification rates can be found in [1].

The embedded classification technique in the segmentation pipeline is the Kohonen Feature Map [3], that provides a cluster analysis of the tomographic input data and after additional learning–cycles with Kohonen's LVQ–learning on a training set defined by an expert, it serves as a supervised classifier.

The second step of the segmentation pipeline uses a postclassifying filtering method based on the anatomical knowledge about neighborhood relations among investigated tissue types. This postprocessing bases on the use of morphological operations, which are extended for color–coded images [1]. The postclassifying filtering is necessary, in order to remove isolated pixels. Furthermore the filtering leads to a closing of homogeneous regions, such that the result can be considered as a *segmentation* of the initial dataset.

# Texture–based Segmentation for Automatic Surface Reconstruction

Christoph Busch

Computer Graphics Center
Rundeturmstr. 6
D–64283 Darmstadt
Tel: +49 6151 155 508
Fax: +49 6151 155 480
E–mail: busch@igd.fhg.de

## Abstract

**This paper reports a segmentation pipeline for automatic analysis of multi–modal tomographic images. It aims as a computer based support at the localization of pathological tissue such as brain tumors. The segmentation pipeline includes texture analysis, classification with Kohonen Feature Map and knowledge based morphological postprocessing. Furthermore the paper sketches a statistical investigation of different texture discrimination methods such as the wavelet transform. Segmentation results that have been reached with this pipeline are used for surface reconstruction and 3D–visualization of pathological tissue.**

***Key Words: texture analysis, tomographic data, color–coded morphological operations, surface reconstruction, 3D–visualization***

## 1 Introduction

Segmentation of medical images remains a challenging task, nevertheless imaging techniques have been developed and improved over the last years. As a consequence a variety of approaches were made, in order to segment tomographic image data stemming from computer tomography (CT) or magnetic resonance imaging (MRI). The approaches in general address the identification and distinction of tissue types such as grey and white matter separation as well as the localization of pathological tissue. Reliable and robust results of segmentation algorithms are required by various applications such as irradiation planning, volumetric measurement for tumor regression observation or surface reconstruction for 3D–visualization. Applying image analysis techniques to multi–modal images often involves interactive or semiautomatic techniques [2]. Although there are different approaches that realize an automatic segmentation scheme for tomographic images, they do have common drawbacks: They either rely on a high number of image bands, which results in stressful long acquisition times, or their capability is limited to a small number of detectable anatomical classes, such as cerebospinal fluid (*CSF*), *gray* and *white matter* separation as elaborated in [4].