International Journal of Bioelectromagnetism

IJBEM

Volume 3, Number 2, pp. 59-64, 2001.



# Segmentation of Voxel Based Medical Images

**Tomi Heinonen[(ab)], Prasun Dastidar[(c)]**

*[(a)]Ragnar Granit Institute, Tampere University of Technology, Tampere, Finland*
*[(b)]Nokia Ventures Organization, Tampere, Finland*
*[(c)]Tampere University Hospital, Tampere, Finland*

Correspondence: Tomi Heinonen, Ragnar Granit Institute, Tampere University of Technology, P.O. Box 692, FIN-33101 Tampere, Finland. E-mail: Tomi.Heinonen@Nokia.com, phone +358 50 3738 611, fax +358 3 247 4013

***Abstract.*** Digital medical images enable computerized image analysis. One of the most important of these analysis techniques is segmentation, which can be applied, e.g., in model construction of the human body. There are numerous segmentation techniques available leading to different segmentation results. In this paper, we estimate voxel-based segmentation techniques, their efficiency and reliability. Several different techniques are presented in detail in order to provide general knowledge on the topic.

*Keywords: Segmentation; Image Processing; Boundary; Region Growing; Thresholding*

## 1. Introduction

Most of the new medical imaging devices are digital enabling computerized analysis of the produced images. In general, computerized image analysis corresponds for image enhancement, image restoration, image filtering, and image measurement. However, section images produced by e.g., Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) enable a variety of new image analysis applications. The most important from these is segmentation [Heinonen, 1999].

Segmentation corresponds to a decomposition of a scene into its components. On medical images, the segmented structures can be e.g., different organs and tissues. The main applications (see Fig. 1) of segmented images are volumetry (i.e., volume analysis of segmented structures), computer models (e.g., brain models and thorax models), and three-dimensional visualization (e.g., separate displaying of segmented structures). Some examples of these main applications are presented in the Fig. 2.

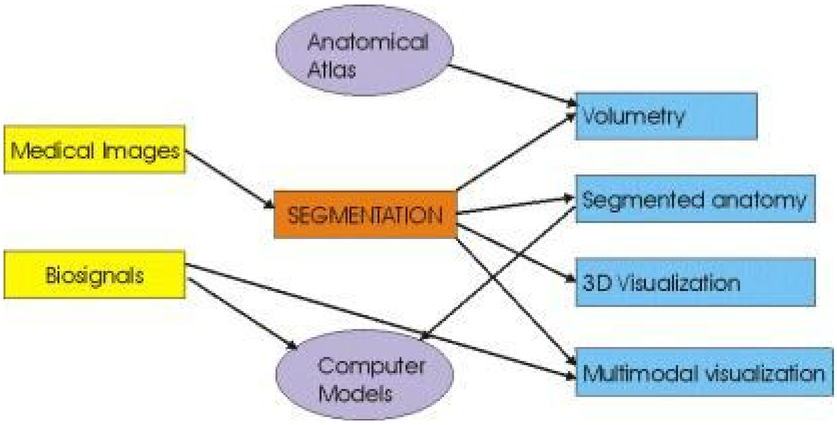


*Figure 1. Segmentation is a central technique in enabling volumetric analysis of medical images, construction of computer models for thorax and brain, and 3D visualization. Together with biosignals and computer models, it is possible to calculate electrical fields inside the body and present the results as multimodal visualization.*

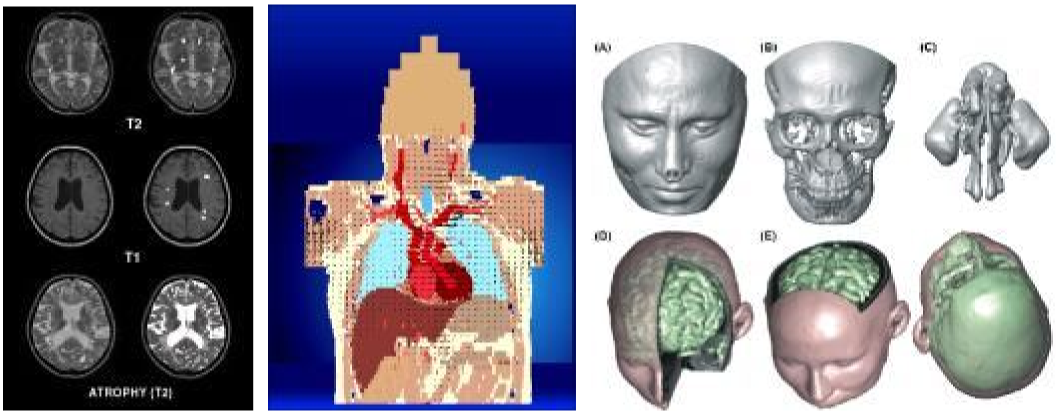


*Figure 2. On the left side, several MRI slices have been segmented in order to carry out volumetry of Multiple Sclerosis plaques and fluid spaces. On middle, one segmented slice of a thorax model is presented together with simulation results. On the rigth side, various 3D visualization modes of segmented images.*

## 2. Segmentation

In general, segmentation involves several stages, which are Image Enhancement, Feature Extraction, Segmentation, and Classification (see Fig. 4). All the stages are not always necessary and sometimes segmentation can lead directly to classification and vice versa. Image enhancement is capable of improving the image appearance (e.g., removal of noise, contrast stretching, etc), feature extraction emphasizes regions of interest (e.g., emphasizing borders), segmentation separates emphasized structures from background, and classification recognizes/classifies them [Jain A, 1989].

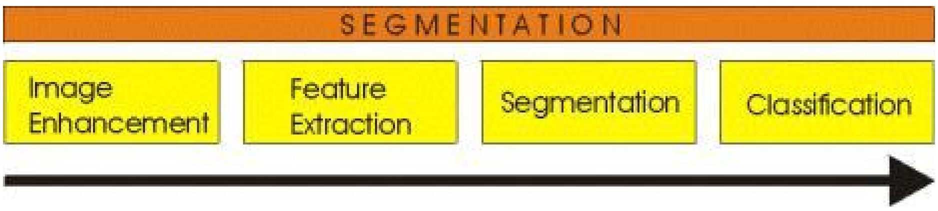


*Figure 3. Segmentation stages; Image enhancement is capable of improving the image appearance (e.g., removal of noise, contrast stretching, etc), feature extraction emphasizes regions of interest (e.g., emphasizing berders), segmentation separates emphasized structures from background, and classification recognizes/classifies them.*

Segmentation techniques can be classified using several criteria: Techniques detecting borders of organs/tissues are *Boundary* based techniques, techniques detecting similar intensities or textures are *Region* based techniques, *Hybrid* techniques utilize different methods (e.g., Boundary + Region) simultaneously with model parameters or multispectral images, and *Classification* applies common pattern recognition methodology to recognize structures.

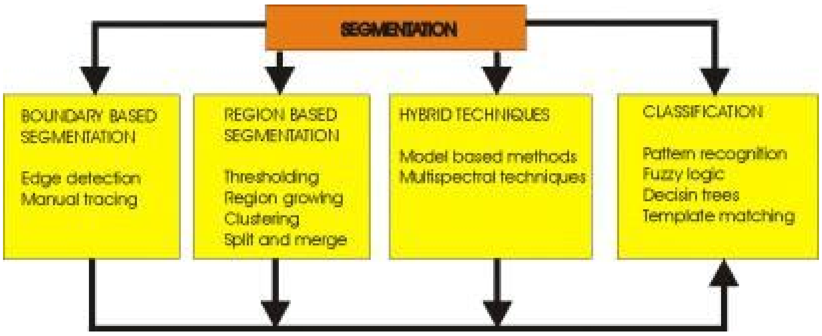


*Figure 4. Various Segmentation techniques – segmentation can lead to classification and vice versa.*

Different segmentation techniques produce different results: Boundary based segmentation provides models for edges and boundaries, which are often coded by chain links. Region based segmentation produces groups of voxels or just labels all the voxels in the image set. If the aim of the segmentation is to reconstruct a model to be used in simulations, boundaries are trivial to convert to labeled voxels (as long as the contours are closed), but converting labeled voxels to contours is more complex, hence it should keep in the focus what type of segmentation should be selected in particular applications. In addition, some techniques are sensitive to noise; therefore the quality of images also directs the selection of segmentation techniques.

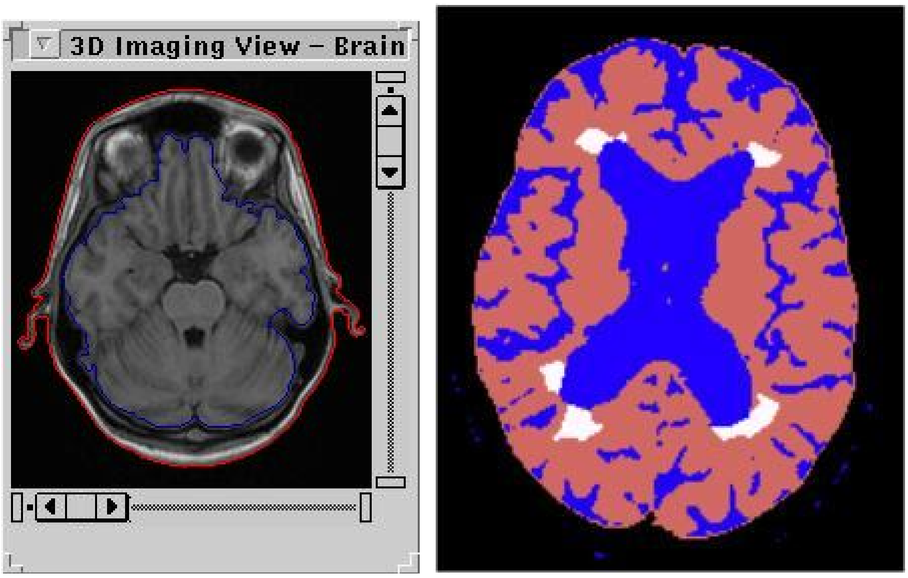


*Figure 5. On the left side; boundary based segmentation result. Scalp and cortex are surrounded by chain links. On the right side;region based segmentation result representing the brain, cerebrospinal fluid and multiple sclerosis plaques.*

## 2.1. Boundary Based Segmentation

The simplest Boundary based technique is manual tracing, which is still used in several clinical applications. The aim is to use a pointer (e.g., mouse) and operator's visual perception to mark boundaries between structures. This technique is laborious compared to other techniques but ensures accurate results. During the last two decades, this technique has greatly evolved towards edge detection and automatics. Conventional boundary-based segmentation techniques utilize different gradient operations [Jain, 1989]. Combining this technique with thresholding, results in a binary image emphasizing edges. To detect the edges, several simple techniques such as contour following, edge linking, heuristic graph search, dynamic programming, and shortest spanning trees [Kwok et al., 1997] have been developed. Quite often, conventional methods result in false or broken edges, due to complex and noisy images. In order to solve this, techniques called whole boundary methods based on spatial gradient features near boundaries have been studied [Bomans et al., 1990; Chakraborty et al., 1996; Yezzi et al., 1997]. These techniques yield better results. The use of gradients together with watershed transformation and morphological operators increase the performance of the boundary methods [Wang 1997]. Further, statistical techniques enable relatively effective edge detection regardless of noise [Thune et al., 1997].

Common feature for most of the boundary methods is the sensitivity to noise. In addition, complex structures (e.g., white matter of the brain) are difficult to surround using contours due to great number of separate contours.

### 2.2. Region Based Segmentation

Thresholding is the most commonly used segmentation method. It is based on homogenous regions instead of contours. It utilizes amplitude segmentation to find voxel groups of similar intensity [Sahoo et al., 1988]. Such procedure can be classified as manual, semi-automatic or automatic depending on the segmentation application and the definition of threshold coefficients. Because particular tissues and anatomical structures usually appear in similar intensities, thresholding is often applied as a feature extractor. However, when source images are enhanced or particular multi-spectral images are applied, it is possible that only the regions of interest appear in some constant intensity range, hence enabling automatic segmentation (e.g., segmentation of the bone from CT image set). Thresholding coefficients are often obtained from intensity histograms manually or using some algorithms to find peaks and valleys. The criteria how to choose appropriate coefficients depends on the segmentation application. One common criterion is to choose the coefficients so that the resulting image resembles the original image accurately. For this purpose, advanced methods have been developed based on histogram entropy and 2D histograms, which employ spatial information along with pixel intensities [Pun, 1981]. Such algorithms have evolved during the last years pursuing better quality [Sahoo et al., 1997], performance [Gong et al., 1998], and adaptivity to poor signal to noise ratio [Li et al., 1997]. Also methods based on measures, other than histograms, have been developed employing statistical information for spatial occurrences of pixel intensities [Ramac et al., 1997].

The method of clustering is based on partitioning an image to regions of similar features, such as shapes, textures, and intensities. Clustering has been applied in numerous projects concerning segmentation of multi-modal medical images, such as MR images of different pulse sequences [Taxt et al., 1994]. New clustering techniques involve complex mathematics and statistical analysis in order to increase the performance and pattern recognition properties [Yegnanarayana et al., 1997].

Region growing is maybe the most versatile method in medical image segmentation. It operates by merging neighboring pixels of similar features [Jain, 1989]. Usually the ‘seed’ is defined interactively, but in some cases prior knowledge of seed locations can be applied. The region growing process can be implemented either in 2D or 3D depending on the source images. The basic implementation of region growing applies pixel intensities in the decision of pixel merging; if the intensity of neighbor pixel is similar to the seed pixel, the pixels are merged. Image intensities are rarely homogenous and hence more advanced implementations of region growing include statistical or geometrical analysis, such as minimum variance [Revol et al., 1997]. Also conventional methods, such as ‘split and merge’ techniques and thresholding have been used as feature extractors to produce images with uniform intensities

[Yong et al., 1986]. Region growing operation is then applied to these images. Some new region growing techniques have been developed to operate without seed parameters [Mehnert et al., 1997], and to include classification.

Region-based techniques are not as sensitive to noise as boundary based methods, hence enabling effective segmentation of noisy images. However, boundary based techniques rely on changes in the gray level rather than their actual values enabling effective boundary segmentation for regions of varying intensity. Therefore several research projects are aiming to combine boundary and region based segmentation [Chakraborty et al., 1996; Tabb et al., 1997].

### 2.3. Other Techniques

It is also possible to analyze images statistically applying feature variables or vectors (e.g., shape, texture, intensity, similarity, etc). This type of computed parameters are compared model parameters and thereafter classified. Different image processing techniques, such as thresholding can be utilized as a feature extractor. Other new promising techniques are Fuzzy logic [Caillol et al., 1997], neural networks [Lee et al., 1997], fractal algorithms [Neil et al., 1997], and Wavelets.

Also multispectral images and more than one modality at a time can be utilized. For example, MRI scan of the head can be automatically segmented from T1 and T2 weighted images, because bone appears black on both image modalities. In the case of thorax, the situation is more complicated hence reliable automatic segmentation is still far away.

## 3. Discussion

Even though segmentation is useful in medical practice it has numerous difficulties; human anatomy varies a lot and pathological lesions increase the complexity and decrease the predictability of the anatomy, hence automatic segmentation is not always reliable. On the other hand, manual and semiautomatic approaches suffer from variability; inter and intra observer studies have demonstrated great variability, especially when small structures are regions of interests.

Other problems are associated with artifacts and noise on the images. It is quite often the case, that patient images are noisy due to patient movement, because imaging scans require relatively long time. Most of the segmentation techniques are sensitive to noise and therefore results are not accurate – or processing can require hours.

In general, computer-processing capabilities double every 1.5 year. Therefore demanding segmentation algorithms will be useful in near future, leading to accurate segmentation. Also new promising technologies associated with Fuzzy logic, neural networks, and computer vision systems can provide useful solutions for medical image processing.

The development of MRI devices has lead to several new imaging sequences capable of emphasizing particular tissues and conditions (e.g., Flair imaging, which can be applied in Multiple Sclerosis studies). It is in prospect, that combination of different imaging sequences can enable accurate automatic segmentation. It is probably possible in the future to develop such imaging sequences capable of visualizing electrical properties of the tissues. In this case, segmentation would not be required in model constructions.

### References

Bomans M, Hohne K, Tiede U, Riemer M. 3-D Segmentation of MR images of the head for 3-D display. *IEEE Transactions on Medical Imaging,p* 9:177-183, 1990.

Caillol H, Pieczynski W, Hillion A. Estimation of fuzzy gaussian mixture and unsupervised statistical image segmentation. *IEEE Transactions on image processing*, 6(3):425-436, 1997.

Chakraborty A, Staib L, Duncan J. Deformable boundary finding in medical images by gradient and region information. *IEEE Transactions on medical imaging*, 15(6): 859-870, 1996.

Gong J, Li L, Chen W. Fast recursive algorithm for two-dimensional thresholding. *Pattern recognition*, 31(3):295-300, 1998.

Heinonen T. Application of magnetic resonance image segmentatin in neurology. PhD Thesis, Tampere University of Technology, Tampere, 1999.

Jain A. Fundamentals of digital image processing. Prentice-Hall International, Englewoods Cliffs, USA. 1989.

Kwok S, Constantinides A. A fast recursive shortest spanmning tree for image segmentation and edge detection. *IEEE Transaction on image processing* 6(2); 328-332, 1997.

Lee J, Chen C, Sun Y, Tseng G. Occluded object recognition using multiscale features and hopfield neural networks. *Pattern recognition* 30(1): 113-122, 1997.

Li L, Gong J, Chen W. Grey-level image thresholding based on Fisher linear projection of two-dimensiona histogram. *Pattern recognition* 30(5): 743-749, 1997.

Mehnert A, Jackway P. An improved seeded region growing algorithm. *Pattern recognition letters* 18:1065-1071, 1997.

Neil G, Curtis K. Shape recognition using fractal geometry. *Pattern recognition* 30(12):1957-1969.

Ramac L, Varshney P. Image thresholding based on Ali-Silvey distance measures. *Pattern recognition* 30(7):1161-1174, 1997.

Revol C, Jourlin M. A new minimum variance region growing algorithm for image segmentation. *Pattern recognition letters* 18:249-258, 1997.

Sahoo P, Soltani S, Wong A, Chen Y. A survey of the thresholding techniques. *Computing vision and graphics in image processing* 41:233-260, 1988.

Sahoo P, Wilkins C, Yeager J. Threshold selection using Renyi's entropy. *Pattern recognition* 30(1):71-84, 1997.

Tabb M, Ahuja N. Multiscale image segmentation by integrated edge and region detection. *IEEE transactions on image processing* 6(5):642-652, 1997.

Taxt T, Lundervold A. Multispectral analysis of the brain using magnetic resonance imaging. *IEEE Transaction on medical imaging* 13(3):470-481, 1994.

Thune M, Olstad B, Thune N. Edge detection in noisy data using finite mixture distribution analysis. *Pattern recognition* 30(5):686-699, 1997.

Wang D. A multiscale gradient algorithm for image segmentation using watersheds, *Pattern recognition* 30(12):2043-2052, 1997.

Yegnanarayana M, Khemaini D. A cluster algorithm using an evolutionary programmin-based approach. *Pattern recognition letters* 18:975-986, 1997.

Yezzi A, Kichenassamy S, Kumar A, Olver P, Tannenbaum A. A geometrical snake model for segmentation of medical imagery. *IEEE transactions on medical imaging* 16(2):199-209, 1997.

Yong T, Fu K. Handbook of pattern recognition and image processing. Academic Press, New York, 1986.