Volume 2, No. 2, February 2011
Journal of Global Research in Computer Science
ISSN-2229-371X
REVIEW ARTICLE
Available Online at www.jgrcs.info

A Survey on Brain Image Segmentation Methods

Prof. Samir Kumar Bandyopadhyay
Dept. of Computer Sc. & Engineering,
University of Calcutta
Kolkata, India
e-mail:skb1@vsnl.com

***Abstract*:** For the past decade, many image segmentation techniques have been proposed. These segmentation techniques can be categorized into three classes, (1) characteristic feature thresholding or clustering, (2) edge detection, and (3) region extraction. This survey summarizes some of these techniques. In the area of biomedical image segmentation, most proposed techniques fall into the categories of characteristic feature thresholding or clustering and edge detection. We present current segmentation approaches are reviewed with an emphasis placed on revealing the advantages and disadvantages of these methods for medical imaging applications.

Keywords- Boundary formation, Clustering, Edge detection, Gradient operator, Region extraction and Segmentation

INTRODUCTION

Diagnostic imaging is an invaluable tool in medicine today. Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other imaging modalities provide an effective means for noninvasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes [1-5], diagnosis [6], localization of pathology [8], study of anatomical structure [8], treatment planning [9], partial volume correction of functional imaging data [7], and computer integrated surgery [10].

Automatic segmentation of brain magnetic resonance (MR) images to the three main tissue types: white matter (WM), gray matter (GM), and cerebro-spinal fluid (CSF) is a topic of great importance and much research. It is known that volumetric analysis of different parts of the brain is useful in assessing the progress or remission of various diseases, such as Alzheimer's disease, epilepsy, sclerosis, and schizophrenia [11].

Computational applications are gaining significant importance in the day-to-day life. Specifically, the usage of the computer aided systems for computational biomedical applications has been explored to a higher extent. Medical image analysis is an important biomedical application which is highly computational in nature and requires the aid of the automated systems. These image analysis techniques are often used to detect the abnormalities in the human bodies through scan images. Automated brain disorder diagnosis with MR images is one of the specific medical image analysis methodologies.

Brain tumor pathologies are the most common fatality in the current scenario of health care society. Hence, accurate detection of the type of the brain abnormality is highly essential for treatment planning which can minimize the fatal results. Accurate results can be obtained only through computer aided automated systems.

Magnetic Resonance Imaging (MRI) is the state-of the-art medical imaging technology which allows cross sectional view of the body with unprecedented tissue contrast. MRI plays an important role in assessing pathological conditions of the ankle, foot and brain. It has rapidly evolved into an accepted modality for medical imaging of disease processes in the musculoskeletal system, especially the foot and brain due to the use of non-ionizing radiation. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes.

Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field [3-4]. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion.

Widely used homogeneity criteria include values of intensity, texture, colour, range, surface normal and surface curvatures. During the past many researchers in the field of

© JGRCS 2010, All Rights Reserved

medical imaging and soft computing have made significant survey in the field of image segmentation [5-8].

Image segmentation techniques can be classified as based on edge detection, region or surface growing, threshold level, classifier such as Hierarchical Self Organizing Map (HSOM), and feature vector clustering or vector quantization. Vector quantization has proved to be a very effective model for image segmentation process [9]. Vector quantization is a process of portioning an n-dimensional vector space into M regions so as to optimize a criterion function when all the points in each region are approximated by the representation vector Xi associated with that region.

There are two processes involved in the vector quantization: one is the training process which determines the set of codebook vector according to the probability of the input data, the other is the encoding process which assigns input vectors to the code book vectors. Vector quantization process has been implemented in terms of the competitive learning neural network (CLNN)[10]. Self-Organizing Map (SOM) [11] is a member of the CLNNs and this can be the best choice when implementing vector quantization using neural network [11-16]. The importance of SOM for vector quantization is primarily due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure.

The main shortcoming of the SOM is that the number of neural units in the competitive layer needs to be approximately equal to the number of regions desired in the segmented image. It is not however, possible to determine a priori the correct number of regions M in the segmented image. This is the main limitation of the conventional SOM for image segmentation.

The HSOM directly address the aforesaid shortcomings of the SOM. HSOM is the combination of self-organization and topographic mapping technique. HSOM combine the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The hierarchical segmentation process for a hierarchical structure is called abstraction tree. The abstraction tree bears some resemblance to the major familiar quad tree data structure [17] used in the several image processing and image analysis algorithms.

Clustering is the process of grouping a data set in a way that the similarity between data within a cluster is maximized while the similarity between data of different clusters is maximized [18] and is used for pattern recognition in image processing. To recognize a given pattern in an image various techniques have been utilized, but in general two broad categories of classifications have been made: unsupervised techniques and supervised techniques.

In the unsupervised method, data items that are to be clustered are not pre-classified while in supervised clustering the data points are pre-classified. One of the well-known unsupervised algorithms that can be applied to many applications such as image segmentation [19], fuzzy c means (FCM) [20] etc. FCM algorithm is one of the popular fuzzy clustering algorithms which are classified as constrained soft clustering algorithm.

A soft clustering algorithm finds a soft partition of a given data set by which an element in the data set may partially belong to multiple clusters. Moreover, there is a constraint on the function that the membership degree of a point in all the clusters adds up to 1[21-22]. The researchers in this field have used SOM or HSOM or FCM separately as one of the tool for the image segmentation of MRI brain for the tumor analysis. Some of the papers propose a hybrid technique combining the advantages of HSOM and FCM and implemented for the MRI image segmentation process to detect various tissues like white matter, gray matter, cst and tumor.

The automated diagnosis involves two major steps: (a) Image classification & (b) Image segmentation. Image classification is the technique of categorizing the abnormal input images into different tumor groups (brain tumors are of many types) based on some similarity measures. The accuracy of this abnormality detection technique must be significantly high since the treatment planning is based on this identification. The second step is image segmentation which is used to extract the abnormal tumor portion which is essential for volumetric analysis. This volumetric analysis determines the effect of the treatment on the patient which can be judged from the extracted size and shape of the abnormal portion. Many research papers with different approaches for image classification and segmentation are reported in the literature.

REVIEW WORKS ON BRAIN IMAGE SEGMENTATION

The primary goal of brain image segmentation is to partition a given brain image into non-intersecting regions representing true anatomical structures such as grey matter, white matter, etc. Over the last decade, many methods have been proposed to tackle this problem. A partial list includes edge-based methods [23], knowledge or rule-based methods [24], statistical model-based methods [25], neural network methods [27], and deformable model based methods [26]. In spite of this progress, automatic segmentation of brain structures remains a very challenging task. This paper presents a new hybrid method which integrates multi-scale analysis, image normalization and elastic template deformation.

Methods for performing segmentations vary widely depending on the specific application, imaging modality, and other factors. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver. General imaging artifacts such as noise, partial volume effects, and motion can also have significant consequences on the performance of segmentation algorithms.

Furthermore, each imaging modality has its advantages and disadvantages. There is currently no single segmentation method that yields acceptable results for every medical image. Methods do exist that are more general and can be

© JGRCS 2010, All Rights Reserved

applied to a variety of data. However, methods that are specialized to particular applications can often achieve better performance by taking into account prior knowledge. Selection of an appropriate approach to a segmentation problem can therefore be a difficult dilemma.

To perform meaningful segmentation of image, regions of different gray levels should be merged if the regions are from the same object. The watershed segmentation generates spatially homogeneous regions which are over segmented. In contrast to classical area based segmentation, the watershed transform [28] was executed on the gradient image. The gradient defined the first partial derivative of an image and contains a measurement for the change of gray levels.

A variety of segmentation schemes exist in the literature. As it is very difficult to estimate automatic or semiautomatic segmentation results against an in vivo brain, manual segmentation by experts is still considered to be the “gold standard” or “ground truth” for any automated algorithm.

However, manual partitioning of large amounts of low-contrast/ low-signal-to-noise ratio (SNR) brain data is strenuous work and is prone to large intra observer and observer variability. Fully automated intensity-based algorithms, on the other hand, exhibit high sensitivity to various noise artifacts, such as intra tissue noise, inter tissue intensity contrast reduction, partial-volume effects, and others [29-32].

Reviews on methods for brain image segmentation (e.g., [31]) present the degradation in the quality of segmentation algorithms due to such noise, and recent publications can be found addressing various aspects of these concerns (e.g., partial-volume effect quantification [7]). Due to the artifacts present, classical voxel-wise intensity- based classification methods, such as -means modelling and mixture of Gaussians modeling (e.g., [11] and [25]), may give unrealistic results, with tissue class regions appearing granular, fragmented, or violating anatomical constraints. Incorporating spatial information via a statistical atlas provides a means for improving the segmentation results (e.g., [13] and [18], [22]). The statistical atlas provides the prior probability for each pixel to originate from a particular tissue class.

Algorithms that are based on the maximum a posteriori (MAP) criterion utilize the atlas information in the algorithm iterations to augment the information in the presence of noisy data. Co-registration of the input image and the atlas, a computationally intensive procedure, is critical in this scenario [23]. It is important to note that the quality of the registration result is strongly dependent on the physiological variability of the subject and may converge to an erroneous result in the case of a diseased or severely damaged brain. Moreover, the registration process is applicable only to complete volumes. A single slice cannot be registered to the atlas, thus, cannot be segmented using these state-of-the-art algorithms.

An additional conventional method to improve segmentation smoothness and immunity to noise is to model neighbouring voxels interactions using a Markov random field (MRF) statistical spatial model [9], [13], [27]. Smoother structures are obtained in the presence of moderate noise as long as the MRF parameters controlling the strength of the spatial interactions are properly selected. Too high a setting can result in an excessively smooth segmentation and a loss of important structural details [15]. In addition, MRF-based algorithms are computationally intractable unless some approximation is used which still requires computationally intensive algorithms. Algorithms that use deformable models to incorporate tissue boundary information [19] imply inherent smoothness but require careful initialization and precisely calibrated model parameters in order to provide consistent results in the presence of a noisy environment. Several works can be found in the literature, such as fuzzy connectedness segmentation methods, that attempt to provide an alternative to the MRF modeling (e.g., [20] and [26]). In [26-35], as in many other works, there still seems to be a need for a large number of parameters for the task.

CONCLUSION

This paper provides an overview of current methods used for computer assisted or computer automated segmentation of anatomical medical images. Methods and applications that have appeared in the recent literature are briefly described. We refer only to the most commonly used radiological modalities for imaging anatomy: magnetic resonance imaging (MRI), X-ray computed tomography (CT), ultrasound, and X-ray projection radiography.

REFERENCES

[l] D. Marr, et al., Proc. Roy. Sot. London,B 207:181-217(1980).
[2] M. Sonka, et al., IEEE Trans. Med. Img. 15:443-452(1998).
[3] K. Held, et al, IEEE. Trans. Med. Img. 16:878-886(1997).
[4] C. C. Lin, et al., Pro. Int. Sot. Magn. Reson. Med. 4th Ann. Meetin 1634(1996).
[5] G. E. Christensen, et al., IEEE. Trans. Img. Proc. 10:1435-1447(1998)
[6] M. Tabb, et al., IEEE Tran. Img. Proc. 6:642-654(1997)
[7] S.-P. Pei, et al., Image and Vision Computing 13:711-723(1995)
[8] K. Held, E. R. Kops, B. J. Krause,W. M.Wells, and R. Kikinis, “Markov random field segmentation of brain MR images,” IEEE Trans. Med. Imag., vol. 16, pp. 878–886, Dec. 1997.
[9] T. Kapur, E. L. Grimson, R. Kikinis, andW. M.Wells, “Enhanced spatial priors for segmentation of magnetic resonance imagery,” Lect. Notes Comput. Sci., vol. 1496, pp. 148–157, 1998.
[10] J. Zhang, “The mean field theory in EM procedures for blind Markov random field image restoration,” IEEE Trans. Image Processing, vol. 2, pp. 27–40, Jan. 1993.
[11] J. C. Rajapakse and F. Kruggel, “Segmentation of MR images with intensity inhomogeneities,” Image Vis. Computing, vol. 16, no. 3, pp. 165–180, 1998.
[12] K. V. Leemput, F. Maes, D. Vandermeulen, A. Colchester, and P. Suetens, “Automated segmentation of MS lesions from multi-channel MR images,” Lect. Notes Comput. Sci., vol. 1679, pp. 11–21, 1999.

© JGRCS 2010, All Rights Reserved

[13] R. Guillemaud and J. M. Brady, "Estimating the bias field of MR images," IEEE Trans. Med. Imag., vol. 16, pp. 238–251, June 1997.
[14] M. E. Brummer, "Optimized intensity thresholds for volumetric analysis of magnetic resonance imaging data," Proc. SPIE, vol. 1808, pp. 299–310, 1992.
[15] A. Kundu, "Local segmentation of biomedical images," Comput. Med. Imag. Graph., vol. 14, pp. 173–183, 1990.
[16] C. M. Bishop, Neural Networks for Pattern Recognition. Oxford, U.K.: Oxford Univ., 1995.
[17] W. M.Wells, E. L. Grimson, R. Kikinis, and F. A. Jolesz, "Adaptive segmentation of MRI data," IEEE Trans. Med. Imag., vol. 15, pp. 429–442, Aug. 1996.
[18] S. Geman and D. Geman, "Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images," IEEE Trans. Pattern Anal. Machine Intell., no. PAMI–6, pp. 721–741, June 1984.
[19] J. Besag, "On the statistical analysis of dirty pictures (with discussion)," J. of Royal Statist. Soc., ser. B, vol. 48, no. 3, pp. 259–302, 1986.
[20] S. Z. Li, Markov Random Field Modeling in Computer Vision. Berlin,Germany: Springer-Verlag, 1995.
[21] T. Lei and W. Sewchand, "Statistical approach to X-ray CT imaging and its applications in image analysis—Part II: A new stochastic modelbased image segmentation technique for X-ray CT image," IEEE Trans. Med. Imag., vol. 11, no. 1, pp. 62–69, 1992.
[22] J. Besag, "Spatial interaction and the statistical analysis of lattice systems (with discussion)," J. Roy. Stat. Soc., ser. B, vol. 36, no. 2, pp.192–326, 1974.
[23] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proc. IEEE, vol. 77, pp. 257–286, Feb. 1989.
[24] N. Aspert, D. Santa-Cruz, and T. Ebrahimi, "Mesh: Measuring errors between surfaces using the Hausdorff distance," in Proc. IEEE Int.Conf. Multimedia Expo (ICME'02), 2002, vol. 1, pp. 705–708.
[25] R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification. New York: Wiley, 2001.
[26] G. Dugas-Phocion, M. A. G. Ballester, G. Malandain, C. Lebrun, and N. Ayache, "Improved EM-based tissue segmentation and partial volume effect quantification in multi-sequence brain MRI," in Proc. Int. Conf. Med. Image Comput. Comput. Assisted Intervention (MICCAI), 2004, pp. 26–33.
[27] G. Gerig, M. Jomier, and M. Chakos, "Valmet: A new validation tool for assessing and improving 3-D object segmentation," in Proc. Int. Conf. Med. Image Comput. Comput. Assisted Intervention (MICCAI), 2001, vol. 2208, pp. 516–528.
[28] J. L. Marroquin, B. C. Vemuri, S. Botello, F. Calderon, and A. Fernandez-Bouzas, "An accurate and efficient bayesian method for automatic segmentation of brain MRI," IEEE Trans. Med. Imag., vol. 21, no. 8, pp. 934–945, Aug. 2002.
[29] T. McInerney and D. Terzopoulos, "Medical image segmentation using topologically adaptable surfaces," in Proc. 1st Joint Conf. Comput. Vision Virtual Reality and Robotics in Medicine and Medial Robotics and Computer-Assisted Surgery, 1997, pp. 23–32.
[30] D. L. Pham, "Spatial models for fuzzy clustering," Comput. Vision Image Understand., vol. 84, no. 2, pp. 285–297, 2001.
[31] D. L. Pham, C. Xu, and J. L. Prince, "Current methods in medical image segmentation," Ann. Rev. Biomed. Eng., vol. 2, pp. 315–337, 2000.
[32] M. Prastawa, J. Gilmore, W. Lin, and G. Gerig, "Automatic segmentation of neonatal brain MRI," in Proc. Int. Conf. Med. Image Comput. Comput. Assisted Intervention (MICCAI), 2004, pp. 10–17.
[33] T. Rohlfing and C. R. Maurer, Jr., "Nonrigid image registration in shared-memory multiprocessor environments with application to brains, breasts, and bees," IEEE Trans. Inf. Technol. Biomed., vol. 7, no. 1, pp. 16–25, Mar. 2003.
[34] A. Ruf, H. Greenspan, and J. Goldberger, "Tissue classification of noisy MR brain images using constrained GMM," in Int. Conf. Med. Image Comput. Comput. Assisted Intervention (MICCAI), 2005, pp. 790–797.
[35] Z. Xue, D. Shen, and C. Davatzikos, "Classic: Consistent longitudinal alignment and segmentation for serial image computing," Inf. Process. Med. Imag., vol. 3565, pp. 101–113, Jul. 2005.

© JGRCS 2010, All Rights Reserved