Image Segmentation of MRI Images using KMCG and KFCG Algorithms

Dr. H. B. Kekre
Senior Professor
MPSTME, NMIMS
University,Vile parle(w),
Mumbai 56, India

Dr.Tanuja Sarode
Assistant Professor
TSEC, Bandra(W),
Mumbai–50,
India

Saylee Gharge
Lecturer, V.E.S.I.T
Ph.D. Scholar, MPSTME,
SVKM's NMIMS University,
Mumbai, India

Ms. Kavita Raut
Lecturer
TSEC, Bandra(W),
Mumbai – 50,
India

ABSTRACT
Segmentation of medical images is very important nowadays since the images for diagnosis by Radiologist are huge in number. In this paper, texture based segmentation algorithms are considered for comparison. The problem with some of these methods is, they need human interaction for accurate and reliable segmentation. Segmentation based on Gray level co-occurrence matrix gives better result for variance but computational complexity is more. Watershed has less complexity but gives over segmentation. Segmentation using Kekre's Median Codebook Generation (KMCG) and Kekre's Fast Codebook Generation (KFCG) algorithm show proper tumor demarcation by avoiding other part of the image.

General Terms
Algorithms

Keywords
Segmentation, GLCM, Watershed, KMCG, KFCG.

1. INTRODUCTION
Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Although a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem. In this paper MRI images are considered. Magnetic Resonance Imaging uses magnetization and radio waves, rather than x-rays to make very detailed, cross-sectional pictures of the brain. It has many advantages over conventional imaging techniques, such as high spatial resolution, excellent discrimination of soft tissues and rich information about anatomical structure. Segmentation of brain from three-dimensional (3D) magnetic resonance (MR) head images has many important research and clinical applications. The objective of segmenting different types of soft-tissue in MRI brain images is to label complex structures with complicated shapes, as white matter, grey matter, CSF and other types of tissues in neurological conditions.

The advantages of magnetic resonance imaging (MRI) over other diagnostic imaging modalities are its high spatial resolution and excellent discrimination of soft tissues. MRI provides rich information about anatomical structure, enabling quantitative pathological or clinical studies [1], the derivation of computerized anatomical atlases [2], as well as pre and intra-operative guidance for therapeutic intervention [3,4]. Such information is also valuable as an anatomical reference for functional modalities, such as PET [5], single photon emission computed tomography (SPECT), and functional MRI [6]. Advanced applications that use the morphologic contents of MRI frequently require segmentation of the imaged volume into tissue types.

This problem has received considerable attention. Such tissue segmentation is often achieved by applying statistical classification methods [7, 8].There are many conventional methods of MRI segmentation that uses image processing techniques such as region growing, edge detection, histogram equalization, etc. The problem with all these methods is that, they need human interaction for accurate and reliable segmentation. Human interaction is in terms of providing some initial knowledge externally for segmentation. This knowledge is in terms of a small amount of labeled data for some or all classes. This is usually time-consuming and expensive. The second fundamental aspect that makes segmentation of medical images difficult is the complexity and variability of the anatomy that is being imaged. It may not be possible to locate or delineate certain structures without detailed anatomical knowledge. This makes general segmentation a difficult problem, as the information must either be built into the system or provided by a human operator. Vector quantization segmentation algorithm attempts to overcome such drawbacks. Vector quantization is based on clustering algorithm. In clustering, the aim is to construct decision boundaries based on unlabeled training data. Clustering is the process of finding natural grouping clusters in multidimensional feature space. It is a difficult task because clusters of different shapes and sizes can occur in multidimensional feature space. A number of functional definitions of clusters have been proposed. Patterns within a cluster are more similar to each other than patterns belonging to different clusters [9]. Here, Image segmentation may be considered a clustering [10-12] process in which the pixels are classified into the regions based attribute on the texture feature vector, calculated around the pixel local neighborhood.

Recently, clustering has been applied to a wide range of topics and areas. Uses of clustering techniques can be found in pattern recognition, as is the case Gaussian Mixture Models for Human Skin Color and its applications in Image and Video databases [13], compression, as in Vector quantization by deterministic annealing[14], classification, as in Semi Supervised Support Vector Machines for Unlabeled Data Classification [15], and classic disciplines as psychology and business. This makes clustering a technique that merges and combines techniques from different disciplines such as mathematics, physics, statistics, computer sciences, artificial intelligence and databases among others. In section 2, different segmentation algorithms for MRI images are discussed. Results are displayed in section 3 and section 4 concludes the work.

2. Algorithms for MRI segmentation

Texture image segmentation identifies image regions that are homogeneous with respect to a selected texture measure. Recent approaches to texture based segmentation are based on linear transforms and multi-resolution feature extraction [16], Markov random filed models [17,18], Wavelets [19–21] and fractal analysis [22]. For this paper Gray Level Co-occurrence Matrix (GLCM) based features, commonly used Watershed algorithm, Kekre's Fast Codebook Generation (KFCG) Algorithm and Kekre's Median Codebook Generation (KMCG) Algorithm which is based on clustering algorithm are compared.

2.1 Gray Level Co-occurrence Matrix

Haralick [23] suggested the use of gray level co-occurrence matrices (GLCM) for definition of textural features. The values of the co-occurrence matrix elements present relative frequencies with which two neighboring pixels separated by distance d appear on the image, where one of them has gray level i and other j. Such matrix is symmetric and also a function of the angular relationship between two neighboring pixels. The co-occurrences matrix can be calculated on the whole image, but by calculating it in a small window which is scanning the image helps reducing the computational complexity. The co-occurrence matrix can be associated with each pixel as shown in an example given below.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

	Gray Levels			
	0	1	2	3
Gray Levels 0	P(0,0)	P(0,1)	P(0,3)	P(0,4)
1	P(1,0)	P(1,1)	P(1,2)	P(1,3)
2	P(2,0)	P(2,1)	P(2,2)	P(2,3)
3	P(3,0)	P(3,1)	P(3,2)	P(3,3)

P_H

4	2	1	0
2	4	0	0
1	0	6	1
0	0	1	2

P_V

6	0	2	0
0	4	2	0
2	2	2	2
0	0	2	0

P_{LD}

2	1	3	0
1	2	1	0
3	1	0	2
0	0	2	0

P_{RD}

4	1	0	0
1	2	2	0
0	2	4	1
0	0	1	0

Figure 2.1 The spatial occurrence calculations.

Above matrices are 4x4 because the image in Figure 4.1 has 4 gray levels 0, 1, 2, 3. In the same way for a 256 gray levels image one should compute 256x256 co-occurrence matrices at all positions of the image. It is obvious that such matrices are too large and their computation becomes memory intensive. Therefore, it is justified to use a less number of gray levels, typically 64 or 32. There is no unique way to choose the values of distance, angle and window, because they are in relationship with a size of pattern. In this work distance d=1 and angle $\theta=45^0$ are selected.

Using co-occurrence matrix textural features are defined as:

Maximum Probability: $\max(P_{ij})$ (2.1)

Variance=$(\sum(i - \mu_i)^2\sum Pij)\ (\sum(j- \mu_j)^2\sum P_{ij})$ (2.2)

Correlation=$(\sum_i \sum_j(i- \mu_x)(j-\mu_y)P_{ij} / \sigma_x\ \sigma_y$ (2.3)

where μ_x and μ_y are means and σ_x, σ_y are standard deviation

Entropy=$\sum_i \sum_j P_{ij} \log (P_{ij})$ (2.4)

Amongst all these features variance, probability and entropy have given the best results. Hence, results for these extracted features using gray level co-occurrence matrix are displayed below for window size 3x3.

2.2 Watershed Algorithm

The Watershed transformation is a powerful tool for image segmentation. Beucher and Lantuejoul were the first to apply the concept of Watershed to segmentation problems [24]. Watershed segmentation [25] classifies pixels into regions using gradient descent on image features and analysis of weak points along region boundaries. It uses analogy with water gradually filling low lying landscape basins. The size of the basins grows with increasing amounts of water until they spill into one another. Small basins (regions) gradually merge together into larger basins. Watershed techniques produce a hierarchy of segmentations, thus the resulting segmentation has to be selected using either some prior knowledge or manually. Hence by using this method the image segmentation cannot be performed accurately and adequately, if the objects are not constructed as desired to be detected.

In this approach, the image segmentation is not the primary step of image understanding. On the contrary, a fair segmentation can be obtained only if one knows exactly what is to be looked for in the image. In this work, Watershed algorithm for MRI is implemented by Basim Alhadidi et. al. [26].

2.3 Segmentation by Kekre's Median Codebook Generation (KMCG) Algorithm

From the previous section it can be inferred that even though variance using GLCM gives proper tumor demarcation for MRI images it requires huge computation time to calculate statistical properties for the image. Watershed algorithm is comparatively less complex, hence less computation time is required but this method gives over segmentation. Therefore, to achieve proper segmentation with less complexity, new algorithm using KMCG algorithm is used here for comparison.

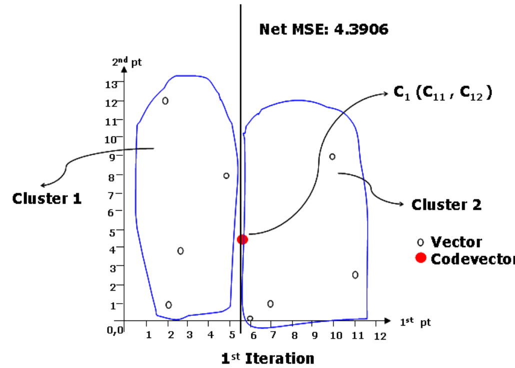
Input: Original Image for given T = (X1, X2,…, X_M} be the training sequence consisting of M code vectors. Assume that source is of length k, i.e. X_m= {Xm1,,…, X_{mk}} for m=1,2,…M. Let the code book size be 'N'.

1. Sort the matrix T with respect to the first member of all the vectors i.e first Column.
2. Compute initial code vector by taking the median of the matrix T. Current_code_book_size =1.
3. Matrix T is divided into two equal parts and sorted with respect to the second member of all the vectors.
4. Compute the codevectors by taking median of both the sorted matrices.
5. Current_code_book_size = current_code_book_size * 2;
6. Repeat step 3 while the current_code_book_size is less than or equal to N.
7. After the code vectors are formed, for each training vector find corresponding pixel in the original image and label it with the code vector number.
8. Search the code vector with value 255 in code book.
9. Keep that code vector as 255 and make the remaining code vectors as 0.
10. Reconstruct the image by replacing the code vector corresponding to the index.
11. Post processing is applied on reconstructed image to segment exact tumor.

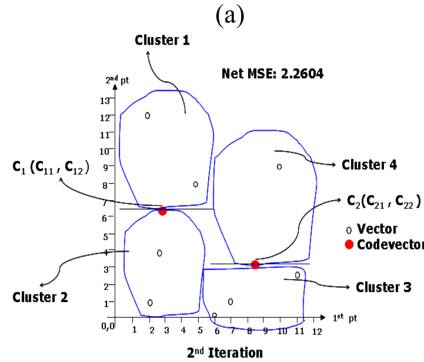
2.4 Kekre's Fast Codebook Generation (KFCG)

The algorithm reduces the codebook generation time since it avoids the Euclidean distance computations. Initially there is one cluster with the entire training vectors and the codevector C_1 which is centroid. In the first iteration of the algorithm, the clusters are formed by comparing first element of training vector with first element of code vector C_1. The vector X_i is grouped into the cluster 1 if $x_{i1} < c_{11}$ otherwise vector X_i is grouped into cluster 2 as shown in Figure 2.2(a).

In second iteration, the cluster 1 is split into two by comparing second element x_{i2} of vector X_i belonging to cluster 1 with that of the element c_{12} of the codevector C_1. Cluster 2 is split into two by comparing the element x_{i2} of vector X_i belonging to cluster 2 with that of the element c_{22} of the codevector C_2 as shown in Figure 2.2(b).



(a)



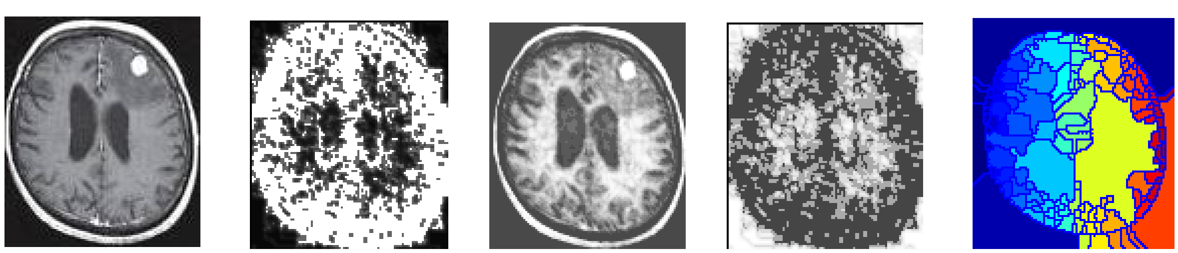
(b)

Figure 2.2 KFCG Algorithm for 2-D image

This procedure is repeated till the codebook size is reached to the size specified by user. The pictorial representation of this algorithm for two dimensional spaces is shown in Figure 2.2.

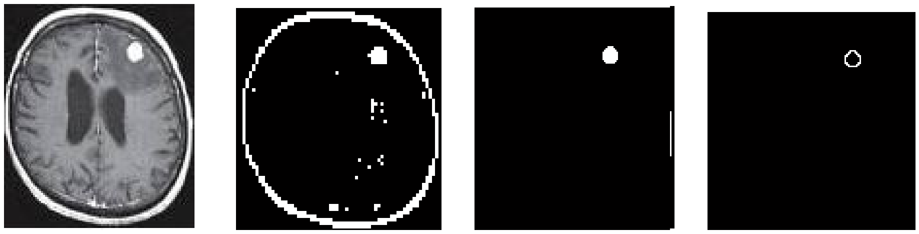
3. Results

Figure 3.1 show results using GLCM and watershed algorithm .Figure 3.1(a) indicate original MRI image, Figure 3.1(b)-(d) show results for probability, variance and entropy using GLCM. Figure 3.1(e) display result of watershed segmentation. Figure 3.2 shows result for segmentation using KMCG algorithm. Figure 3.2 (d) indicates image after extracting boundaries which separates tumor properly. Figure 3.3 shows results using KFCG algorithm. Figure 3.3(b) indicate result for first codevector using KFCG algorithm .After using dilation and erotion segmented image is displayed as Figure 3.3.(c).Figure 3.3 (d) shows edge detected map for Figure 3.3 (c).Then edge map is superimposed on original MRI image and displayed in Figure 3.3 (e).



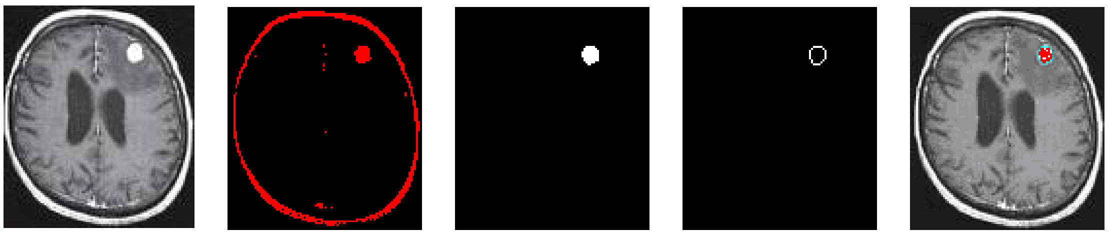
(a) (b) (c) (d) (e)

Figure 3.1(a) Original MRI image, (b) Probability using GLCM, (c) Variance using GLCM, (d) Entropy using GLCM, (e) Segmentation using watershed algorithm.



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

Figure 3.2 (a) Original MRI image, (b) Image after VQ segmentation, (c) Image after Extracting tumor Region, (d) Image after extracting boundary



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

Figure 3.3 (a) Original MRI Image, (b) Image for First Codevector using KFCG, (c) Segmented Image, (d) Edge detected Image, (e) Superimposed Image

4. CONCLUSION

From the results it is observed that, Variance using GLCM gives better result than probability and entropy but it requires huge time since its complexity is high. Watershed algorithm gives over segmentation but computation complexity is very less thus required less time for execution. Results by using KMCG are better than the previous two methods. Figure 3.3 shows results using KFCG which gives best result amongst these four algorithms. Segmentation by vector quantization shows better result than the texture based segmentation method .If KMCG and KFCG are compared than complexity of KFCG is less that KMCG and even results are better than KMCG. Tumor is properly detected by using KFCG algorithm.

5. ACKNOWLEDGEMENT

The authors would like to record their appreciation to Dr. Swaroop Nellore for his help in validating the results.

6. REFERENCES

[1] M. Shenton, R. Kikinis, F. Jolesz, et al. Abnormalities of the Left Temporal Lobe and Thought Disorder in Schizophrenia. N. Engl. J. Med,vol.327, pp. 604 - 612, August 1992.

[2] K. Hohne et al. A framework for the Generation of 3D Anatomical Atlases. SPIE, Visualization in Biomedical Computing, Vol. 1808,pp.169-213, 1992.

[3] R. Kikinis, F.A. Jolesz, W.E. Lorensen, H.E. Cline, P.E Stieg, Black 3d Reconstruction of Skull Base Tumors from MRI Data for Neurosurgical Planning. In Proceedings of the Society of Magnetic Resonance in Medicine Conference, 1991.

[4] R. Kikinis, D. Altobelli, W. Lorensen, W. Wells, and G. Ettinger. Pre- and intraoperative tumor localization using 3d renderings of mri's. 12th Annual Scientific Meeting of the Society of Magnetic Resonance in Medicine, 1993.

[5] D. Levin, X. Hu, K. Tan, et al. The Brain: Integrated Three-Dimensional Display of MR and PET Images. Radiology, vol.172, pp.783-789 1989.

[6] J. Belliveau, D. Kennedy, R. McKinstry, et al. Functional Mapping of the Human Visual Cortex by Magnetic Resonance Imaging. Science,vol.254 , pp, 716 -719, November 1991.

[7] M. Vannier, D. Jordan, W. Murphy, Multi-Spectral Analysis of Magnetic Resonance Images. Radiology,vol. 154, pp.221-224, 1985.

[8] M. Kohn, N. Tanna, G. Herman, et al. Analysis of Brain and Cerebrospinal Fluid Volumes with MR Imaging. Radiology,vol.178, pp. 115 -122, 1991.

[9] Jain AK, Duin RP, Mao J. Statistical pattern recognition: A review. IEEE Trans PAMI 2000;22: 4-37.

[10] Frigui H, Krishnapuram R. A robust competitive clustering algorithm with application in computer vision. IEEE Trans PAMI 1999;21:450-65.

[11] Tseng LY, Yang SB. A genetic approach to the automatic clustering problem. Patten Recognition 2001;34:415-24.

[12] Bandyopadhyay S. Simulated annealing using a reversible jump markov chain monte carlo algorithm for fuzzy clustering. IEEE Trans Knowledge Data Engg. 2005;17: 479-90.

[13] Yang, M., Ahuja "Gaussian mixture model for human skin color and its application in image and video databases", In Proc. of the SPIE: Conf. on Storage and Retrieval for Image and Video Databases (SPIE 99), Vol. 3656, 458–466.

[14] K. Rose, E. Gurewitz, G. C. Fox, "Vector quantization by deterministic annealing," IEEE Trans. Information Theory, vol. 38, no. 4, pp. 1249-1257, July 1992.

[15] G. Fung and O. L. Mangasarian "Semi-supervised support vector machines for unlabeled data classification", Optimization Methods and Software, 15, pp. 29–44, 2001.

[16] M. Unser, "Texture classification and segmentation using wavelet frames," IEEE transaction on Image Processing, vol. 4, No. 11, pp. 1549–1560, 1995.

[17] B. Wang and L. Zhang, "Supervised texture segmentation using wavelet transform," Proceedings of the 2003 International Conference on Neural Networks and Signal Processing, vol. 2, pp. 1078–1082, 2003.

[18] Chang-Tsun Li and Roland Wilson, "Unsupervised texture segmentation using multiresolution hybrid genetic algorithm," Proc. IEEE International Conference on Image Processing ICIP03, pp. 1033–1036, 2003.

[19] T. R. Reed and J. M. H. Du Buf, "A review of recent texture segmentation, feature extraction techniques," in CVGIP Image Understanding, vol.57, pp. 359–372, 1993.

[20] A. K. Jain and K. Karu, "Learning texture discrimination masks," IEEE transactions of Pattern Analysis and Machine Intelligence, Vol. 18, No. 2, pp. 195–205, 1996.

[21] Eldman de Oliveira Nunes and Aura Conci, "Texture segmentation considering multi band, multi resolution and affine invariant roughness," SIBGRAPI, pp. 254–261,2003.

[22] L.F. Eiterer, J. Facon, and D. Menoti, "Postal envelope address block location by fractal-based approach," 17th Brazilian Symposium on Computer Graphics and Image Processing, D. Coppersmith, Ed., pp. 90–97,2004,

[23] Robert M. Haralick , Statistical and Structural Approaches to Texture, IEEE Proceedings, vol. 67, issue.5,pp.786-804, May 1979.

[24] Serge Beucher and Christian Lantuejoul, "Use of watersheds in contour detection". International workshop on image processing, real-time edge and motion detection, 1979.

[25] Leila Shafarenko and Maria Petrou, "Automatic Watershed Segmentation of Randomly Textured Color Images", IEEE Transactions on Image Processing, vol.6,issue.11, pp.1530-1544, 1997.

[26] Basim Alhadidi, Mohammad H. et al, "Mammogram Breast Cancer Edge Detection Using Image Processing Function" Information Technology Journal vol.6, issue.2, pp.217-221, ISSN-1812-5638,2007