Segmentation of Brain Portion From MRI of Head Scans Using K-Means Cluster

[1]K. Somasundaram, [2]S. Vijayalakshmi and [3]T. Kalaiselvi
Department of Computer Science and Applications
Gandhigram Rural Institute, Deemed University, Gandhigram–624 302, India
E-mail: [1]somasundaramk@yahoo.com; [2]lakshmiviji.gru@gmail.com, [3]kalaivpd@gmail.com

Abstract

Segmentation is one of the essential processes in image processing. The objective of this paper is to segment human brain area from other non-brain area in MRI of head scans. In our method, brain portion is detected using clustering technique. The proposed method clusters the image into 15 regions using k-mean clustering technique. The non brain parts like skull, sclera, fat, skin were clustered to regions according to its intensity. These regions were eliminated and the remaining regions are merged to form the brain portion. The proposed model has been tested on various image slices and found to give good segmentation. Experimental results show that the proposed method gives an average value of 0.95 for Jaccard co-efficient, 0.97 for Dice, 0.96 for Sensitivity and 0.98 for specificity.

Keywords: Image processing, Segmentation, Clustering method, K-means cluster, MRI.

1. Introduction

Segmentation of brain portion in magnetic resonance images (MRI) of head scans is essential for doing various other diagnostic study and computer aided surgeries. There are several methods to extract brain portion in MRI [1] - [13]. Atkins and Mackiewich developed SFU method [4]. This method uses an active contour and snake algorithm, to produce the results. But this method failed in complex anatomical brain structure and abnormal structures. In Exbrain method [5] segmentation is achieved through threshold value, morphological operations and connected component analysis. One drawback of this method is the manual intervention to set the parameters. In 3DIntracranical [6] method, histogram and probability density function based approach is used for segmentation. Watershed [7] operated under the assumption of white matter connectivity, and gives over segmentation problem. BSE method [8] utilizes spatial information, anisotropic diffusion process and Marr-Hildreth edge detector to detect the brain portion. But it performs badly in poor contrast images. BET [9] makes use the shape information, centre of gravity (COG) in the head image. It expands the sphere centered on the COG and produces the brain mask. The main drawback of this method is fails in large neck portion images and intensity in homogeneity. MCS [10] is an automatic hybrid method incorporating BSE.

It requires more user interaction to input the parameters. HWA [11] combines watershed algorithm and deformable surface models to extract the brain. Its demerits are relatively slow and remove the substantial non-brain tissue from the difficult face and neck regions. Lee [12] compared the performance of automatic methods, BET and BSE with semiautomatic methods. It is time consuming process while combining automatic and semiautomatic method. T2- BEA [13] uses brain anatomy details to extract the brain volume. T2-BEA is used for our quantitative study.

In this paper, we propose a simple and automatic method to extract brain portion using k-means clustering algorithm. An MRI scan consists of a stack of 2-Dimensional slices called MRI volume. Each slice represents different tissues in the head, like scalp, skull, cerebrospinal fluid (CSF), brain etc. As a result the image contains intensities of different levels. The pixels with similar intensities can be grouped. For grouping, we make use of k-means clustering algorithm. Experiments on some sample slices gave satisfied results. The results were evaluated using Jaccard, Dice, Sensitivity and Specificity co efficient. Further, the results obtained are compared with BEA method.

The remaining part of the paper is organized as follows. In Section 2, we give the basic principles used in our scheme. In section 3 we present our proposed method. Results and discussions are given in section 4. In section 5 the conclusion is given.

2. BASIC PRINCIPLES USED IN THIS STUDY

2.1. Cluster

Clustering refers to the process of grouping samples so that the samples are similar within each group. The groups are called clusters. Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other.

In image analysis, clustering can be used to find groups of pixels with similar gray levels or local textures in order to discover the various regions in the image. A number of clustering techniques are available. In our model, k-means clustering algorithm is used to cluster the image pixels.

2.2 K-Means Algorithm

K-Means algorithm is an unsupervised clustering algorithm that partition (or cluster) n data points into k disjoint subsets S_j containing n_j data points [14]. The input data points were classified into multiple classes based on their inherent distance from each other. It computes the intensity distribution of the intensity. The centroid of the cluster is mean value of all data points with respect to k. K-Means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. K-Means algorithm partitions the data into k mutually exclusive clusters, and returns a vector of indices indicating to which of the k clusters it has assigned.

This algorithm is composed of the following steps with a data set c_i, i = 1, 2,… K

Step 1. Initialize the centroids $c_i = 0$, i = 1,…,K

Step 2. Assign each data point to the group that has the closest centroid.

Step 3. When all points have been assigned, calculate the positions of the K centroids

Step 4. Repeat steps 2 and 3 until the centroids no longer move. This produces a separation of the data points into groups from which the metric to be minimized can be calculated.

The clusters are found by minimizing the objective function,

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| p_i^{(j)} - c_j \|^2 \qquad (1)$$

where $\| p_i^{(j)} - c_j \|^2$ is a measure of intensity distance between a data point $p_i^{(j)}$ and the cluster center c_j.

2.3 Finding Non-Brain Region

K-Means is used to cluster pixel intensities in an image into k clusters. This provides a simple way to “segment” an image into K regions with similar intensities. Run the K-Means algorithm with input vector of intensities and assign each pixel the “grayscale” of the cluster it is assigned to. k-means puts pixels into k groups based on intensity similarities. The result is a set of regions in an image, where each region is relatively homogeneous in terms of pixel intensity. K-Means can be used as a simple technique for region-finding. The brain portion in a slice will be in some cluster numbers. The boundary can be found in last 3 to 5 clusters. We can merge the last few regions to get brain boundary and eliminate the skull and cerebrospinal fluid.

2.4 Quantitative Analysis on Clusters

K-Means requires the number of clusters to initialize. The brain image consists of overlapped intensity regions. When fewer numbers of clusters are used, the tissues in skull and non-brain portions cannot be distinguished from brain tissues. When more number of clusters (about 15) is used, the regions containing the brain portion can be distinctly identified.

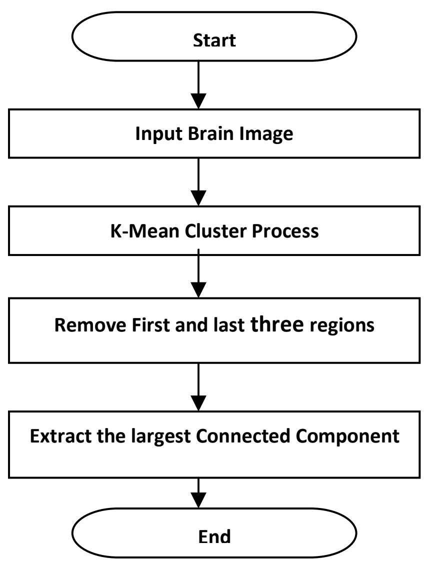

Fig. 1 Flow Chart of our Proposed Method

3. PROPOSED METHOD

In the proposed scheme, each slice is partitioned into 15 clusters using k-means algorithm. The first and last 3 clusters which contain non brain region and background are removed. Rests of the clusters are merged and the largest connected component (LCC) analysis is done to extract the brain.

3.1 Performance Evaluation Techniques

To evaluate the performance of the proposed method we make use of Jaccard similarity index (J), Dice co-efficient (D), Sensitivity (S) and Specificity (Sp), [15] given by:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{TP}{TP+FP+FN} \tag{2}$$

$$D(A,B) = \frac{2|A \cap B|}{|A|+|B|} = \frac{2TP}{2TP+FP+FN} \tag{3}$$

where A represents the total pixels of the image segmented by the proposed method and B represents the total pixels in the image segmented by BEA result. TP and FP are true positive and false positive, which are defined as the number of pixels correctly and incorrectly classified as brain tissue by the proposed automated method. TN and FN are true negative and false negative, which are defined as the number of pixels classified correctly and in correctly. For quantitative analysis, we also make use of sensitivity and specificity is given by:

$$S = \frac{TP}{TP+FP} \tag{4}$$

$$Sp = \frac{TN}{TN+FP} \tag{5}$$

The parameter S and Sp are computed between the proposed method and BEA algorithm. The sensitivity is the percentage of pixels recognized as brain pixels and specificity is the percentage of pixels recognized as non-brain pixels by our proposed method.

3.2 Materials

We use some slices of T1 and T2 weighted axial head scans of normal and abnormal brain images obtained from the whole brain atlas (WBA) [16] for our experiments.

4. Results and Discussion

The proposed algorithm was applied on a variety of images and the images are segmented. The result of applying the proposed method is shown in Fig 2. We note from Fig 2(c) that the brain portion extracted accurately.

Table 1: Clusters and number pixels.

Image	Number of clusters	Aptful No of labels	Number of pixels at skull
T1brain	20	13,14,15,16	599
	18	16,17,18	555
	15	13,14,15	599
	13	12,13	536
	12	11,12	579
	9	9	466

(a) (b) (c)

Fig. 2 (a) Original Image, (b) K-means Clustered image, (c) Detected Brain

Table 1shows the number of clusters and the number of pixels in each cluster that forms the cluster. We note from Table 1 that the maximum of pixels (599) was obtained for a cluster of 15. The Cluster number is analyzed using various numbers of clusters. All the regions with the detection criteria were verified to remove the non brain portion. Each slice was divided into 9 to 20 clusters. After a few trials we found that dividing them into 15 clusters gives the best result to identify the brain region. (See Fig. 3 and 4)

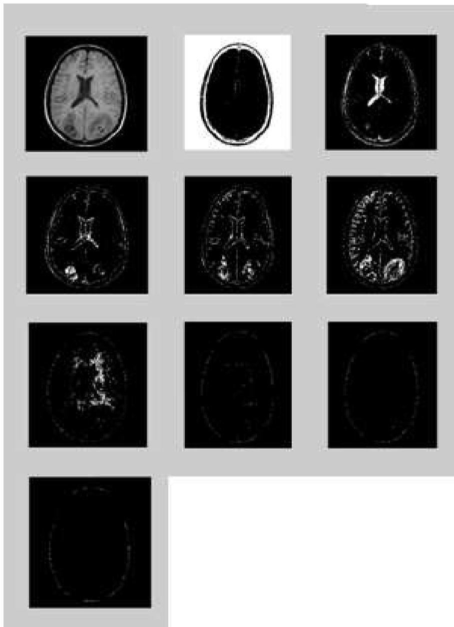

Fig. 3 Cluster regions 9

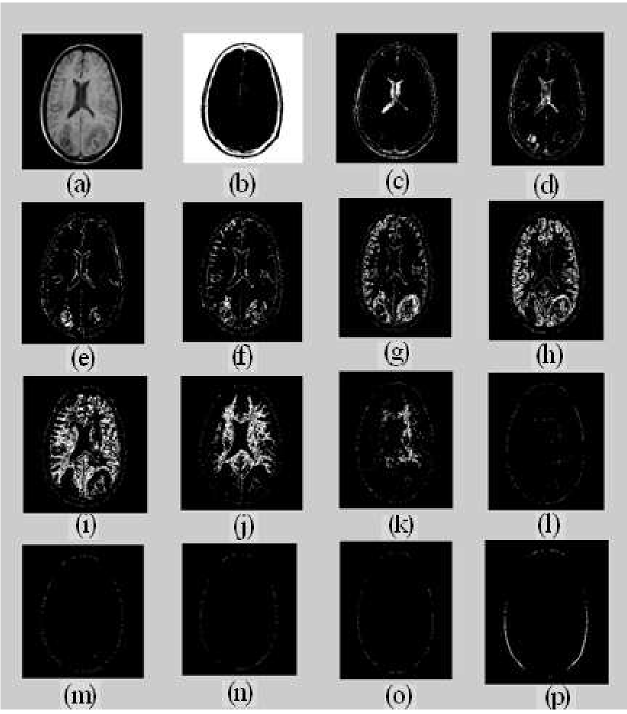

Fig.4 Cluster regions of 15 (a) Original,(b) - (p) images for clusters 1 -15

Table 2: Computed values for parameters Jaccard (J) Dice (D), Sensitivity (S) and Specificity (Sp) were compared with BEA method

Image name	Jaccard	Dice	Sensitivity	specificity
Image 1	0.9720	0.9858	0.9770	0.9974
Image 2	0.9690	0.9842	0.9732	0.9979
Image 3	0.9345	0.9661	0.9680	0.9901
Image 4	0.9767	0.9882	0.9767	1
Image 5	0.9852	0.9652	0.9869	0.9987
Image 6	0.9616	0.9804	0.9655	0.9983
Image 7	0.9503	0.9745	0.9524	0.9943
Image 8	0.9112	0.9535	0.9200	0.9988
Image 9	0.9400	0.9692	0.9439	0.9994
Image 10	0.9568	0.9652	0.9584	0.9236
Average	0.9557	0.9732	0.9622	0.9887

We carried out experiments by applying the proposed method on some MRI axial T1 weighted images and performed quantitative and qualitative analysis. For qualitative analysis we compared the performance of the proposed method with BEA [13]. Fig 5 shows the T2 weighted image samples and results produced by proposed method and BEA. For quantitative analysis, the Jaccard (J), Dice (D), Sensitivity and Specificity (Sp) parameters were calculated using the eq (2) - (5). It can be seen from Table 2 that the proposed method gives the best average values more than 95% for J, D, S and SP. From Table 2 and Fig 5, we observe that the proposed method gives good results.

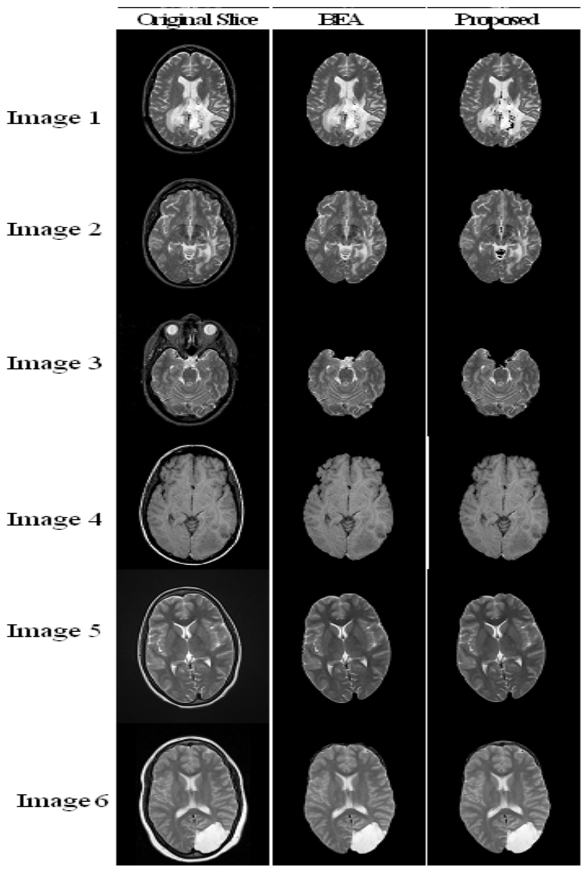

Fig. 5 Brain portion extracted using the existing and proposed method for the selected slices from WBA dataset. Column 1 shows original axial head slice; column 2 brain portion extracted using BEA and column 3 by the proposed method.

6. Conclusion

In this paper, we have proposed a method based on K-means to extract brain portion from T2 weighted MRI of head scans. We employed K-means algorithm to cluster the pixel value in the MRI of head scans to segment into 15 clusters. By eliminating the clusters having non-brain region, the brain portion is extracted. This method has been tested only on few MRI slices. This method can be improved to extract brain portion from all slices in a given MRI volume.

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Somasundaram. K was born in the year 1953. He received the M.Sc degree in Physics from University of Madras, India in 1976, the Post Graduate Diploma in Computer Methods from Madurai Kamaraj University, Madurai, India in 1989 and the Ph.D degree in theoretical Physics from Indian Institute of Science, Bangalore, India in 1984. He is presently the Professor and Head of the Department of Computer Science and Applications, Gandhigram Rural Institute, Gandhigram, India. His research interests are in image processing, image compression and medical imaging. He has published more than 100 papers in national and international Journals.

Vijayalakshmi. S , currently working as an Assistant Professor (adhoc) in Department of Computer Science and Applications, Gandhigram Rural Institute, Dindigul, Tamilnadu, India. She received her Master of Computer Applications (MCA) degree in 2010 from same University. She did her Master of philosophy, computer science (Mphil) in Madurai kamaraj University. Her research focuses on Brain Tumor analysis in MRI of Head scans.

Kalaiselvi T, currently working as an Assistant Professor in Department of Computer Science and Applications, Gandhigram Rural Institute, Dindigul, Tamilnadu, India. She received her Bachelor of Science (BSc) degree in Mathematics and Physics in 1994 and Master of Computer Applications (MCA) degree in 1997 from Avinashilingam University, Coimbatore. She received her Ph.D (Full-time) degree from Gandhigram Rural Institute in February 2010. Her research focuses on MRI of Human Brain Image analysis to enrich the Computer Aided Diagnostic process, Telemedicine and Technology (ICGST).