Performance Analysis of Unsupervised Clustering Methods for Brain Tumor Segmentation

Tushar H Jaware and Dr. K B Khanchandani
Department of E&TC, Shri Sant Gajanan Maharaj College of Engineering,
Shegaon, MS, India

Abstract:
Medical image processing is the most challenging and emerging field of neuroscience. The ultimate goal of medical image analysis in brain MRI is to extract important clinical features that would improve methods of diagnosis & treatment of disease. This paper focuses on methods to detect & extract brain tumour from brain MR images. MATLAB is used to design, software tool for locating brain tumor, based on unsupervised clustering methods. K-Means clustering algorithm is implemented & tested on data base of 30 images. Performance evolution of unsupervised clustering methods is presented.

Keywords: MRI, clustering, tumor

1. Introduction
The influence and impact of digital images on modern society is tremendous, and image processing is now a critical component in science and technology. The rapid progress in computerized medical image reconstruction, and the associated developments in analysis methods and computer-aided diagnosis, has propelled medical imaging into one of the most important sub-fields in scientific imaging.

In past few years, MRI has drawn considerable attention for its possible role in tissue characterization. Brain tumor is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Image segmentation is a process to identify regions of interest from digital images. In brain tumor studies, accurate and reproducible segmentation and characterization of abnormalities are not straightforward. For instance, a major problem in tumor treatment planning and evaluation is determination of the tumor extent.

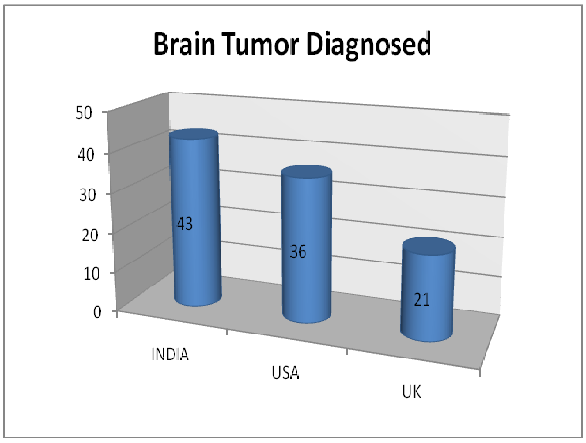


Figure 1. Diagnosis Rate in different Countrie

In MRI images, the amount of data is too much for manual segmentation. The procedure is tedious, time, labor consuming, subjective and requires expertise. This gave way to methods that are computer-aided with user interaction at varying levels. These methods are automatic and objective and the results are highly reproducible. We designed software tool for locating brain tumor, based on unsupervised clustering methods and analyzed its performance.

2. Material and methods

In this paper we use luminosity-based segmentation method. This paper analyses k mean clustering techniques to locate tumors in brain MRI. The input is axial view of the human brain. The contrast of the gray level MR image is adjusted and then clustering algorithm is applied. The position of tumor objects is separated from other items of an MR image by using clustering algorithms and histogram-clustering.

After the clustering process, the cluster containing the tumor is selected as the primary segment. Histogram clustering is applied to eliminate the pixels which are not related to the tumor pixels. The performance of the clustering algorithms is found based on volumetric analysis of tumor & computational speed by applying to a database of 30 images.

3. Algorithm

The algorithm has two stages, first is pre-processing of given MRI image and after that segmentation and then perform morphological operations.

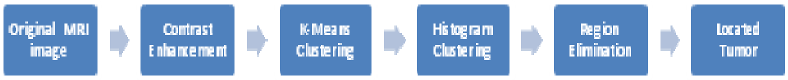


Figure 2. Stages of software implementation

4. Contrast Enhancement

Due to the less contrast of MR images, first we have to increase the contrast of an image. The three techniques can be used for this:

- Imadjust increases the contrast of the image by mapping the values of the input intensity image to new values such that, by default, 1% of the data is saturated at low and high intensities of the input data.
- Histeq performs histogram equalization. It enhances the contrast of the images by transforming the values in an intensity image so that the histogram of the output image approximately matches a specified histogram(uniform distribution by default)
- Adapthisteq performs contrast-limited adaptive histogram equalization. Unlike histeq, it operates on small data regions (tiles) rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram (uniform distribution by default). The contrast enhancement can be limited in order to avoid amplifying the noise which might be present in the image.

5. Clustering Algorithms

This system is implemented using morphological operations and the algorithms i.e. K-Means algorithm

5.1. K-Means clustering:

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problems. The procedure follows a simple and easy way to classify a given data set through a given no. of clusters (assume k clusters) fixed a priority. The main idea is to define k centroids, one for each clusters. These centroids should be placed in a cunning way because of different location causes different results. So the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point, we need to re-calculate k new centroid as barycentres of the cluster resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop, we may notice that the k centroid change their location step by step until no more changes are done. In other word, centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^2 - c_j \right\|^2,$$

Where $\left\| x_i^2 - c_j \right\|^2$ is chosen distance measure between a data point and the cluster centre is an indicator of the distance of the n data points from their respective cluster centre.

5.2. K-Means clustering Algorithm:

No. of cluster= k

1. Pick k cluster centre, either randomly
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster centre

$c^i = argmin_j \left\| x_i^2 - c_j \right\|$

3. Re-compute the cluster centre by averaging all of the pixels in the cluster.
4. Repeat steps 2 &3 until convergence is attained (e.g.no pixels change clusters)

6. Cluster Selection

After the clustering process, the cluster containing an area of interest (tumor) is selected as the primary segment.

7. Histogram Based Clustering

To eliminate the pixels which are not related to the interest in the selected cluster, histogram clustering is applied.

8. Region Elimination

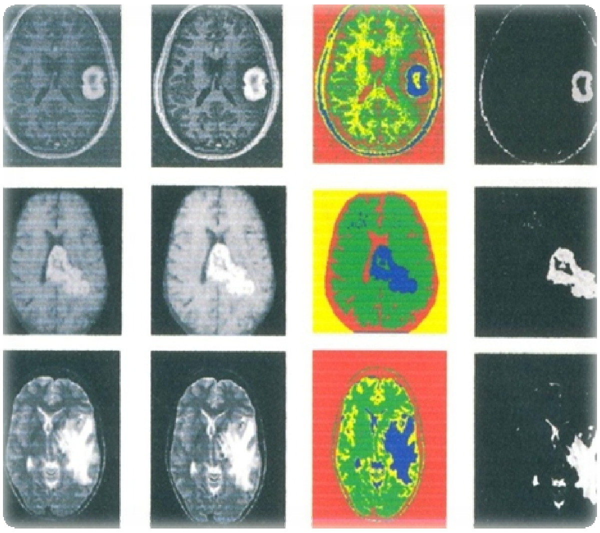
The output of histogram clustering consists of tumor region as well as the other regions which has the same luminance and colour values as the tumor. The regions which are smaller than the tumor are eliminated.

9. Discussion

In the proposed paper, we locate the brain tumor in MR image using morphological operations and the clustering methods. We designed the graphical user interface (GUI) for user friendly environment. The results obtained for this clustering method are given below:

10. Results for K-Mean clustering:

Figure 3 shows three different original brain MR images, contrast enhancement of the images, segmented images using K-means algorithm and finally located tumor. Fig 1.4 shows the performance of the unsupervised clustering methods with the no. of tumor pixels and execution time to locate the brain tumor.



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

Figure 3:(a) Input MR Image (b) Enhanced Image (c) Segmented Tumor (d) Located brain tumor

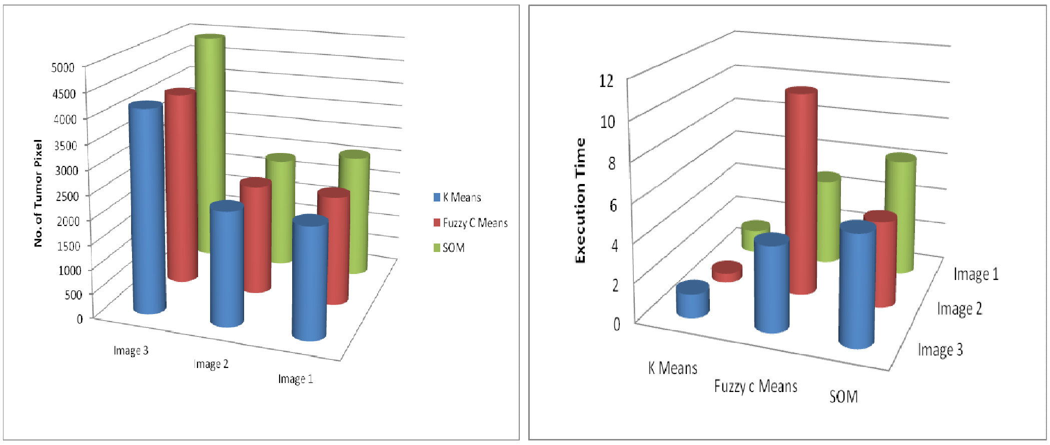


Figure 4.Performance based on no. of tumor pixel & execution time

In this paper we segmented the brain tumors in axial view of MR images with the help of unsupervised clustering method i.e. K-means clustering. The unsupervised clustering methods gave the better results than traditional method.

The performance analysis and comparison is done f on the basis of no. of tumor pixels in segmented brain tumor and the execution time for the same. Regarding the no. of tumor pixels, K-means clustering gave a better result than the other methods. The clustering algorithms were tested with a data base of 20 MRI brain images. K-means clustering achieved almost 90%result.

References

[1]M. Mancas, B. Gosselin, B. Macq, 2005, "Segmentation Using a Region GrowingThresholding", Proc. of the Electronic Imaging Conference of the International Society for Optical Imaging (SPIE/EI 2005), San Jose (California, USA).

[2] Dong-yong Dai; Condon, B.; Hadley, D.; Rampling, R.; Teasdale, G.; "Intracranial deformation caused by brain tumors: assessment of 3-D surface by magnetic resonance imaging"IEEE Transactions on Medical Imaging Volume 12, Issue 4, Dec. 1993 Page(s):693 – 702

[3] Matthew C. Clark “Segmenting MRI Volumes of the Brain With Knowledge- Based Clustering” MS Thesis, Department of Computer Science and Engineering, University of South Florida, 1994

[5] http://noodle.med.yale.edu

[6] http://documents.wolfram.com/

[7] Dzung L. Pham, Chenyang Xu, Jerry L. Prince;"A Survey of Current Methods in Medical Medical Image Segmentation" Technical Report JHU / ECE 99-01, Department of Electrical and Computer Engineering. The Johns Hopkins University, Baltimore MD 21218, 1998.
[8] M. Sezgin, B. Sankur " Survey over image thresholding techniques and quantitative performance evaluation" J. Electron. Imaging 13 (1) (2004) 146-165.
[9] Chowdhury, M.H.; Little, W.D,;"Image thresholding techniques" IEEE Pacific Rim Conference on Communications, Computers, and Signal Processing, 1995. Proceedings. 17-19 May 1995 Page(s):585 – 589
[10] Zhou, J.; Chan, K.L.; Chong, V.F.H.; Krishnan, S.M "Extraction of Brain Tumor from MR Images Using One-Class Support Vector Machine" 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005, Page(s):6411 – 6414
[11]T. Logeswari, M. Karnan, ―An improved implementation of brain tumor detection using segmentation based on soft computing‖, Page(s): 006-014, Journal of Cancer Research and Experimental Oncology Vol. 2(1), March 2010.