Research Paper
Impact Factor: 4.164
Refereed Journal

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

BRAIN TUMOUR DETECTION USING K HARMONIC MEANS, EXPECTATION MAXIMIZATION AND HIERARCHICAL CLUSTERING ALGORITHM

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Abstract
Image processing has become an area of boundless possibilities to explore as the advances in research field in this domain are gaining momentum. Brain Tumor Detection [BTD] is a crucial task these days. The model explores the effectiveness of using four different feature selection and three different segmentation techniques, respectively, to discriminate tumor regions from normal tissue in multimodal brain MRI. The proposed model combines three algorithms like K Harmonic Means [K-HM], Expectation Maximization [EM] and Hierarchical Clustering [HC]. The various parameters like accuracy, time consumption, features extracted and iterations are studied and the best practices will be put into practice.

I. Introduction

Brain tissue and Tumour segmentation in images have been an active research area. Extraction of good features is fundamental to successful image segmentation. Due to complex structures of different tissues such as the Gray Matter (GM), White Matter (WM), and Cerebro Spinal Fluid (CSF) in the MRbrain images, extraction of useful features is a challenging task.

Variability in Tumour location, shape, size, and texture properties further complicates the search for robust features. Posterior Fossa (PF) Tumour is usually located near the brain stem and cerebellum. About 55–70% pediatric brain Tumours arise in the PF. Due to narrow confinement at the base of the skull, complete removal of PF Tumours poses nontrivial challenges. Therefore, accurate segmentation of PF Tumour is necessary.

1. Tumour

A Tumour is an acronym for a neoplasm or a solid lesion formed by an abnormal growth of cells Termed Neoplastic (TN) which looks like a swelling. Brain Tumours are composed of the cells that exhibit abnormal and unrestrained cell division. Brain Tumour can be benign or malignant, benign being non-cancerous and malignant are cancerous. Malignant Tumours are classified in to two types like Primary and Secondary Tumours. Benign Tumour is less harmful compared to malignant as in malignant Tumour it spreads rapidly invading other tissues of brain, progressively worsening the condition causing death.

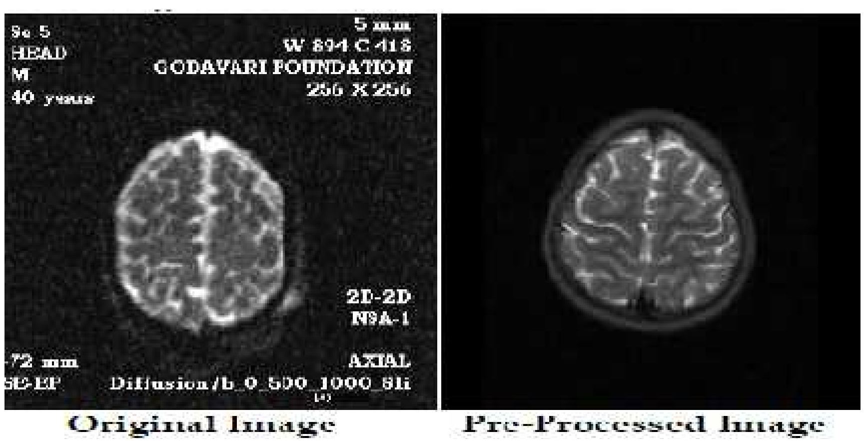


Fig. 1.1 Brain Tumour Focus

2.Clustering Methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic.
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center.
3. Re-compute the cluster centers by averaging all of the pixels in the cluster.
4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters).

In this case, variance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic.

3. Histogram-Based Methods
Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image.[1] Color or intensity can be used as the measure.

4. Model Based Segmentation
The central assumption of such an approach is that structures of interest/organs have a repetitive form of geometry. Therefore, one can seek for a probabilistic model towards explaining the variation of the shape of the organ and then when segmenting an image impose constraints using this model as prior. Such a task involves (i) registration of the training examples to a common pose, (ii) probabilistic representation of the variation of the registered samples, and (iii) statistical inference between the model and the image. State of the art methods in the literature for knowledge-based segmentation involve active shape and appearance models, active contours and deformable templates and level-set based methods.

5. Multi-Scale Segmentation
Image segmentations are computed at multiple scales in scale-space and sometimes propagated from coarse to fine scales; see scale-space segmentation.Segmentation criteria can be arbitrarily complex and may take into account global as well as local criteria. A common requirement is that each region must be connected in some sense.

6. Semi-Automatic Segmentation
In this kind of segmentation, the user outlines the region of interest with the mouse clicks and algorithms are applied so that the path that best fits the edge of the image is shown. Techniques like Siox, Livewire, or Intelligent Scissors are used in this kind of segmentation.

7. Neural Networks Segmentation
Neural Network segmentation relies on processing small areas of an image using an artificial neural network[23] or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map.

II. Image Segmentation
The first step is to separate the image blobs in the color filtered binary image into individual regions. The process consists of three steps. The first step is to fill up black isolated holes and to remove white isolated regions which are smaller than the minimum face area in training images. The threshold (170 pixels) is set conservatively. The filtered image followed by initial erosion only leaves the white regions with reasonable areas as illustrated in the figure below:

Secondly, to separate some integrated regions into individual faces, the Roberts Cross Edge detection algorithm is used. The Roberts Cross Operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. It thus highlights regions of high spatial gradients that often correspond to edges. The highlighted region is converted into black lines and eroded to connect crossly separated pixels.

1. Edge Extraction Template
Next a different method of face template. Realizing that much of what distinguishes lies within its feature, convert all grayscale images to black and white, and then use edge extraction to extract the important features, then combine them to form a template face. The above edge was constructed from a sampling of 25 images taken from the training set.

Edge detection is a terminology in image processing and computer vision, particularly in the areas of feature detection and feature extraction, to refer to algorithms which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities.

The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world. It can be shown that under rather general assumptions for an image formation model, discontinuities in image brightness are likely to correspond to:

1. discontinuities in depth,
2. discontinuities in surface orientation,
3. changes in material properties and
4. Variations in scene illumination.

2. A Simple Edge Model

Although certain literature has considered the detection of ideal step edges, the edges obtained from natural images are usually not at all ideal step edges. Instead they are normally affected by one or several of the following effects:

1. Focal blur caused by a finite depth-of-field and finite point spread function.
2. Penumbral blur caused by shadows created by light sources of non-zero radius.
3. Shading at a smooth object edge.
4. Localspecularities or interreflections in the vicinity of object edges.

$$f(x) = \frac{I_r - I_l}{2}\left(\operatorname{erf}\left(\frac{x}{\sqrt{2}\sigma}\right) + 1\right) + I_l.$$

At the left side of the edge, the intensity is $I_l = \lim_{x \to -\infty} f(x)$, and right of the edge it is $I_r = \lim_{x \to \infty} f(x)$. The scale parameter σ is called the blur scale of the edge.

To illustrate why edge detection is not a trivial task, let us consider the problem of detecting edges in the following one-dimensional signal. Here, we may intuitively say that there should be an edge between the 4th and 5th pixels.

5	7	6	4	152	148	149

If the intensity difference were smaller between the 4th and the 5th pixels and if the intensity differences between the adjacent neighboring pixels were higher, it would not be as easy to say that there should be an edge in the corresponding region. Moreover, one could argue that this case is one in which there are several edges.

5	7	6	41	113	148	149

3. Color Segmentation

Detection of skin color in color images is a very popular and useful technique for face detection. Many techniques have reported locating skin color regions in the input image. While the input color image is typically in the RGB format, these techniques usually use color components in the color space, such as the HSV or YIQ formats. That is because RGB components are subject to the lighting conditions, thus the face detection may fail if the lighting condition changes. Among many color spaces, this project used YCbCr components since it is one of existing functions which would save the computation time.

4. Detection

In the skin color detection process, each pixel was classified as skin or non-skin based on its color components. The detection window for skin color was determined based on the mean and The color segmentation has been applied to a training image and its result is shown in the below figure. Some non-skin objects are inevitably observed in the result as their colors fall into the skin color space.

III. Expectation Maximization Clustering

An Expectation–Maximization (EM) algorithm is an iterative method for finding maximum likelihood or Maximum A Posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

1. Algorithm

An iterative algorithm, in the case where both $\boldsymbol{\theta}$ and $\mathbf{Z}$ are unknown:

1. First, initialize the parameters $\boldsymbol{\theta}$ to some random values.
2. Compute the best value for $\mathbf{Z}$ given these parameter values.
3. Then, use the just-computed values of $\mathbf{Z}$ to compute a better estimate for the parameters $\boldsymbol{\theta}$. Parameters associated with a particular value of $\mathbf{Z}$ will use only those data points whose associated latent variable has that value.
4. Iterate steps 2 and 3 until convergence.

The algorithm as just described monotonically approaches a local minimum of the cost function, and is commonly called hard EM. The k-means algorithm is an example of this class of algorithms.

2. Edge Detection

Canny (1986) considered the mathematical problem of deriving an optimal smoothing filter given the criteria of detection, localization and minimizing multiple responses to a single edge. He showed that the optimal filter given these assumptions is a sum of four exponential terms. He also showed that this filter can be well approximated by first-order derivatives of Gaussians. Canny also introduced the notion of non-maximum suppression, which means that given the pre-smoothing filters, edge points are defined as points where the gradient magnitude assumes a local maximum in the gradient direction.

Although his work was done in the early days of computer vision, the Canny edge detector (including its variations) is still a state-of-the-art edge detector. Unless the preconditions are particularly suitable, it is hard to find an edge detector that performs significantly better than the Canny edge detector.

The Canny-Deriche detector (Deriche 1987) was derived from similar mathematical criteria as the Canny edge detector, although starting from a discrete viewpoint and then leading to a set of recursive filters for image smoothing instead of exponential filters or Gaussian filters.

The differential edge detector described below can be seen as a reformulation of Canny's method from the viewpoint of differential invariants computed from a scale-space representation.

IV. Results and Discussion

Computational Costs of KHM in Each Iteration In each iteration, calculating all the pair wise distances from N data points to K centers (of Dimensional vectors) costs O(N*K*D). KM and EM (linear mixing) share the same cost on this part. After getting the coefficients pi, k, calculating the linear combinations, mk = S pi,k*xi , costs another O(N*K*D). EM costs the same on this part. KM costs less (O(N*D)) on this due to the partitioning but an additional O(N*K) comparison and assignment (marking) operations are used to do the partitioning. After calculating the distances, all quantities used in the algorithm no longer depend on the dimension and all other costs are O(N*K). The leading asymptotic term for all three algorithms are the same, O(N*K*D).The asymptotic computational complexity per iteration for KM, KHM and EM (linear mixing model) are all O(N*K*D). It is the convergence rate and the convergence quality (dependency on the initialization) which differentiate them in real world applications. This is due to the partitioning nature; faster algorithms/implementations have been designed for KM using trees to do spatial partition of either the centers or the data.

Hierarchical Clustering

The hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. Strategies for hierarchical clustering generally fall into two types:

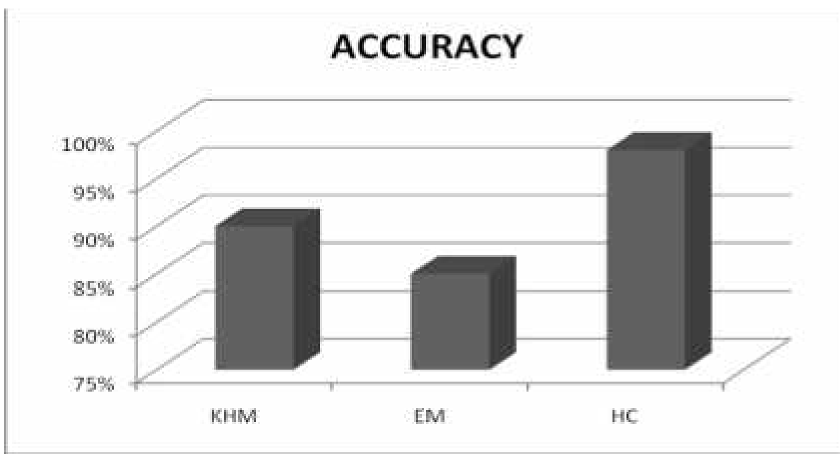
Agglomerative: This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.

Divisive: This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy. In general, the merges and splits are determined in a greedy manner. The results of hierarchical clustering are usually presented in a dendrogram. The algorithm criterion includes:

1. The sum of all intra-cluster variance.
2. The decrease in variance for the cluster being merged (Ward's criterion).
3. The probability that candidate clusters spawn from the same distribution function (V-linkage).
4. The product of in-degree and out-degree on a k-nearest-neighbor graph (graph degree linkage).
5. The increment of some cluster descriptor (i.e., a quantity defined for measuring the quality of a cluster) after merging two clusters.

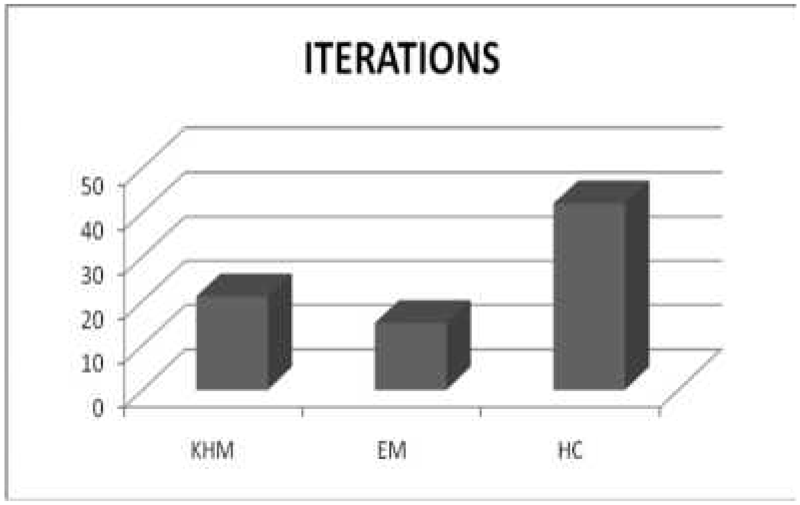
The first parameter is accuracy and hierarchical clustering outperforms the other methods as shown.

FACTORS	KHM	EM	HC
ACCURACY	90%	85%	98%

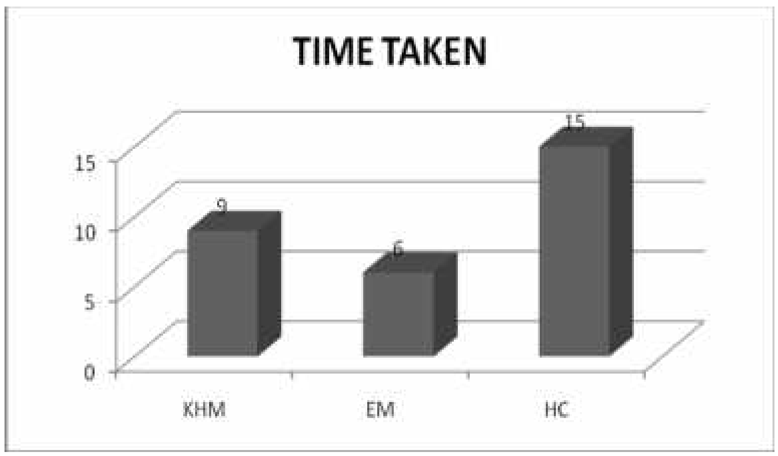


The next is about the convergence of the iterations and EM takes less iteration, while KHM and HC are more.

DETAILS	KHM	EM	HC
ITERATIONS	21	15	42



Therefore it may be concluded that EM takes lesser time due to the lesser number of iterations.



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