A BRIEF REVIEW OF SEGMENTATION METHODS FOR MEDICAL IMAGES

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Abstract

For medical diagnosis and laboratory study applications we cannot directly use image that are acquired and detect the disorder because it is not efficient and unrealistic. These images need processing and extracting portions from them that can be used for further study or diagnosis. The main goal of this paper is to give overview about segmentation methods that are used for medical images for detecting the edges and based on this detection the disease prediction and diagnosis is done. There are a lot of tools available for this purpose such as STAPLE and FreeSurfer whole brain segmentation tool etc. Some of these methods are semi-automatic i.e. they require human intervention for their completion and some of them are automatic. The methods are totally divided into four types namely, edge based segmentation, region based segmentation, data clustering and matching. The aim of segmenting medical images is that to detect the ROI and diagnose for a disease based on the detected part. Segmentation is partitioning a image into meaningful regions based upon a specific application. Generally segmentation can be based on the measurements like gray level, color, texture, motion, depth or intensity. Segmentation is necessary in two situations, namely, set-off segmentation i.e. when the object to be segmented is interesting in itself and can be used separately for further studies, and secondly concealing segmentation i.e. suppose there are some noise or vision blockers in the image, so this segmentation aims at deleting the disturbing elements in an image. This paper focuses only on the working of different methods that are used for segmentation whether they segment well or poor.

Index Terms: *Image Registration, Image Segmentation, Reinforcement Learning,*

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1. INTRODUCTION

Medical images are not always meant to be of the internal organs of human body. These can be images of either internal or external organ that are captured for diagnosis of some disease or for laboratory study. The medical images can be visible light medical image for the area of dermatology and wound care; these images are still images of external organs and are visible to naked eyes. Another type is invisible light medical images that are clinical images obtained from radiology i.e. MRI or CT scans. The processing of such images forms a very interesting field comprising of computer science, electrical engineering, mathematics, physics and medicine. The aim of processing these images is to mine some relevant information from diagnosis point of view [1]. The segmentation of medical images part focuses only on the computational analysis of the images and not on their acquisition. Medical diagnosis can be of two types, namely, cytopathology and radiography. We only focus on the radiography i.e. MRI or CT scans. For diagnosing the disease from a medical image the image has to undergo various processes not only segmentation. Actually segmentation can be the last one. The image must first be enhanced, then it has to be registered with the images in the training dataset and then it has to be segmented [2].

There are a lot many methods used for finding out the region of interest in a scene and annotate data. Segmentation methods can be broadly classified in four categories, namely, edge based, region based, data clustering and matching. In the edge based segmentation, as the name suggests the entire edge of the image is detected with fine details and the diagnosis are established on this basis. In region based segmentation the image as a whole is divided into regions and sub regions for the sake of segmentation and assigning different measures for these regions they can be distinguished and the image is segmented [1]. Data clustering means creating clusters of pixels of similar data or based on some predefined threshold or some criterion and depending on that differentiating the data(as in pixels to be particular) from each other. Finally, we suggest some optimizing techniques for improving the results that are obtained after segmenting images. And lastly for matching method a sample template is necessary so that template can be fitted in the original image and can search for the best matching part of the image. Not all the methods are used for medical images but few are. Lastly we conclude by specifying which method is best suited for image segmentation in medical images and some suggestions regarding combination of methods,

2. EDGE BASED SEGMENTATION

Image segmentation is more often referred as edge detection or finding the inner boundaries of the image and separating different components of the image. The edge detection technique consists of making a decision as to whether a pixel is and edge or not. This can also be said as finding the connected components in an image. These techniques includes high emphasis spatial frequency filtering, gradient operators adaptive local operators, functional approximations and line and curve fitting. Pfaltz gave an efficient algorithm for this known as **connected components** algorithm. This algorithm works on raster scan technique, where each pixel is visited in turn, starting at top-left corner of the image and scanning along each row, finishing at the bottom-right corner. The pixels are considered as one that are edges and one that are non-edge pixels. For each non-edge pixel, (i, j), if its already visited neighbors (i-1, j) and (i, j-1) are all edge pixels then create a new category and place the examining pixels in that category, else if all its neighbors are in a single category, then (i, j) is also placed in same category. One possibility is that its neighbors belong to more than one category then (i, j) is allocated to one of them and a note is kept that these categories are connected and therefore should be considered as a single category.

In edge based segmentation, earlier methods used were Sobel filter, derivative of Gaussian and Laplace of Gaussian but this methods cannot detect edge details and it remains difficult to segment thin areas because the edge pixels obliterate details in case of medical images. For example, in test image, the details of characters are obliterated by these methods. One method that is useful is **boundary code** to solve this problem. This technique consists of making a decision as to whether a pixel is and edge or not. Boundary code can segment narrow elongated areas without dividing them because a virtual edge does not occupy the pixel area with edge pixels. The coding of images is also known as image encryption. Boundary coding uses image coding method to segment images. BC is the edge information of pixels derived from four neighborhoods (left, right, up, down) by an interest pixel, and set boundaries using a homogeneity parameter. The boundary code of 4 neighbors derives below equation:

$$Boundary\ Code = \sum_{i\,\in\{right,up,left,down\}} B_i \times 2^{i-1}$$

$$B_i = \begin{cases} 1 & if\ H(direction) = false \\ 0 & otherwise \end{cases}$$

$$direction \in \{right, up, left, down\}$$

Here, direction is the direction of the edge at right, up, left and down of the interest pixel. H(direction) is the homogeneity criterion of neighboring regions located in these direction. Homogeneity criterions are derived from several assumptions for example; homogeneity of neighboring pixels is difference among pixels. When BC is used for segmentation we can segment the image to merge neighboring regions. Merging conditions are determined by the boundary conditions of the neighboring pixels referenced from the BC [6]. The algorithm goes as follows, here a bold line is boundary, L_{any} is any number, L_{new} is new number and L_1 and L_2 are examples of different labels (L_1 is lower number than L_2)

1. Scan the pixels using raster scanning in the image and interest pixel is given a label number according to following assumptions when it has no label number for the segment:
   (a) When both boundaries exist, give the interest pixel the new label number L_{new}.
   (b) When either boundary exists, give interest pixel the same label number as the neighboring pixel L_1 that is located on the no-boundary side.
   (c) When neither of the boundaries exist and the label number of both neighbors is L_1, give the interest pixel the same label number as the neighbor pixel L_1.
   (d) When nethier boundaries exist and the label numbers of both neighbors are different, give the interest pixel the low number of the neighboring label numbers. All high numbers of the neighboring label numbers L_2 are transformed into low label numbers L_1.
2. Refer to BC of interest pixel and check the boundaries of up and left, set the label number that is given to the interest pixel.
3. Repeat the above process for all pixels.

The working of the above assumptions is shown in fig. 1.

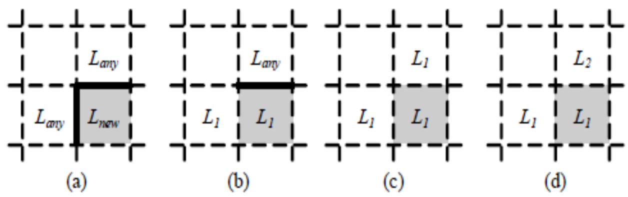

Fig 1 classes of neighboring pixels and the adding class at the interest pixel in assumptions (a)-(d).

The **general approach** towards segmentation using edges is 1. Compute an edge image, containing all edegs of an original image, 2. Process the edge image so that only closed object boundaries remain, and 3. Transform the result to an ordinary segmented image by filling in the object boundaries. The difficulty lies in second step because transforming an edge image to closed boundaries requires the removal of edge that are caused by noise or other artifacts, the bridging of gaps at locations where no edge was detected and intelligent decisions to connect those edge parts that make up a single object. Algorithm for this approach is:

1. Compute an edge image Δf from image f. any preferred gradient operator can be used for this.
2. Threshold Δf to an image $(\Delta f)_t$, so we have a binary image showing edge pixels.

3. Compute a Laplacian image Δf from f. any preferred discrete or continuous Laplacian operator may be used.
4. Compute image g = $(\Delta f)_t * \mathrm{sgn}(\Delta f)$.

The sgn operator returns sign of its arguments. Resulted image g will therefore contain only three values: 0 at non-edge pixels, 1 at edge pixels on the bright side of an edge and -1 at edge pixels on the dark side on an edge. The edge linking part is completed using Hough Transform.

Also **watersheding** is considered as a method in edge based segmentation. Watershed transformation is separating overlapping objects in an image. A watershed is formed by 'flooding' the image from its local minima, and forming 'dams' where waterfronts meet. When the image is totally flooded, all dams together form the watershed of an image. The basic idea is that when the edgeness image as a 3D landscape, the catchment basins of the watershed corresponds to objects, i.e. the watershed of the edgeness image will show the object boundaries. Some pre or post processing is necessary for avoiding oversegmentation. For protecting image from oversegmenting, set all grey values below a threshold to zero. This ensures no dams are formed early in the flooding process. Since such dams are caused by very weak edges, they are likely to correspond to object boundaries, and should not be part of segmentation watershed. If again some oversegmentation is seen in the image use active contour or snake to change its location and shape until it best satisfies predefined conditions. The process of watersheding is as follows:

1. Search minimum and maximum pixel value of image g(x, y) as min and max. Assign the coordinate of min to M_i. the image will be flooded as integer flood increments from n = min +1. let $C_n(M_i)$ as the coordinate in the catchment basin associated with minimum M_i that are flooded at stage n.
2. Compute

$$C_n(M_n) = C(M_i) \cap T[n]$$

If (x, y) ϵ $C(M_i)$ and (x, y) ϵ T[n], $C_n(M_i) = 1$ at location (x, y); otherwise $C_n(M_i) = 0$. Then let C[n] denote the union of the flooded catchment basins at stage n:

$$C[n] = \bigcup_{i=1}^{R} C_n(M_i)$$

Set n = n + 1.

3. Derive set of connected components in T[n] denoting as Q. for each connected component q ϵ Q[n], there are three conditions:

a.If q ∩ C[n - 1] is empty, connected component q is incorporated into C[n – 1] to form C[n] because it represents a new minimum is encountered.

b. If q ∩ C[n – 1] contains one connected component of C[n – 1], connected component q is incorporated into C[n – 1] to form C[n] because it means q lies within the catchment basin of some regional minimum.

c.If q ∩ C[n – 1] contains more than one connected component of C[n – 1], it represents all or part of a ridge separating two or more catchment basins is encountered so that we have to find the points of ridge(s) and set them as "dam".

4. Construct C[n] and set n = n + 1.
5. Repeat step 3 and 4 until n reaches max + 1.

There are many advantages and disadvantages of this method some of them are, advantages, boundaries of each region obtained are continuous, disadvantage, segmentation result has over-segmentation problem and the algorithm is very time consuming [4].

3. REGION BASED SEGMENTATION

Image segmentation in case of region based is thought of as division of an image into regions or categories which is similar to different objects or parts of objects. This method attempts to partition or group regions according to common image properties, i.e. intensity values of original image, or values computed based on an image operator, or patterns that are unique to each type of region, or spectral profiles that provide multidimensional image data [1]. Combinations of these properties can be used to segment depending on type of data available. Region growing is also classified as a pixel based image segmentation method since it involves the selection of initial seed points. Region based segmentation is a technique for determining the region directly. The main goal of segmentation is to partition an image into regions. Some methods such as thresholding achieve this goal by looking for the boundaries between regions based on discontinuities in gray levels or color properties.

The first method in region based segmentation is **seeded region based** method. As the name itself suggests that this method needs some predefined or user selected seed points in the image. The processing would be started from this seed points and other neighboring pixels would be added to this points and the region would be formed. The criterion examines the neighboring pixels of initial "seed points" and determines whether the pixel neighbor should be added to the region or not. An example for this method is as shown in fig 2. The figures 2 (a) shows the lightning then in (b) the seed points are selected and accordingly the segmentation is carried out in (c), (d), (e) and (f).

The major problem is of choosing the seed points. This depends on the nature of the problem (as for now image). Suppose if the target needs to be detected using infrared images for example, choose the brightest pixel. With no prior knowledge about the image we can compute histogram and choose the gray level values corresponding to strongest peaks [2]. Similarly, the criterion can be average intensity, variance, color, texture, shape, size, pixels in certain gray level range etc.

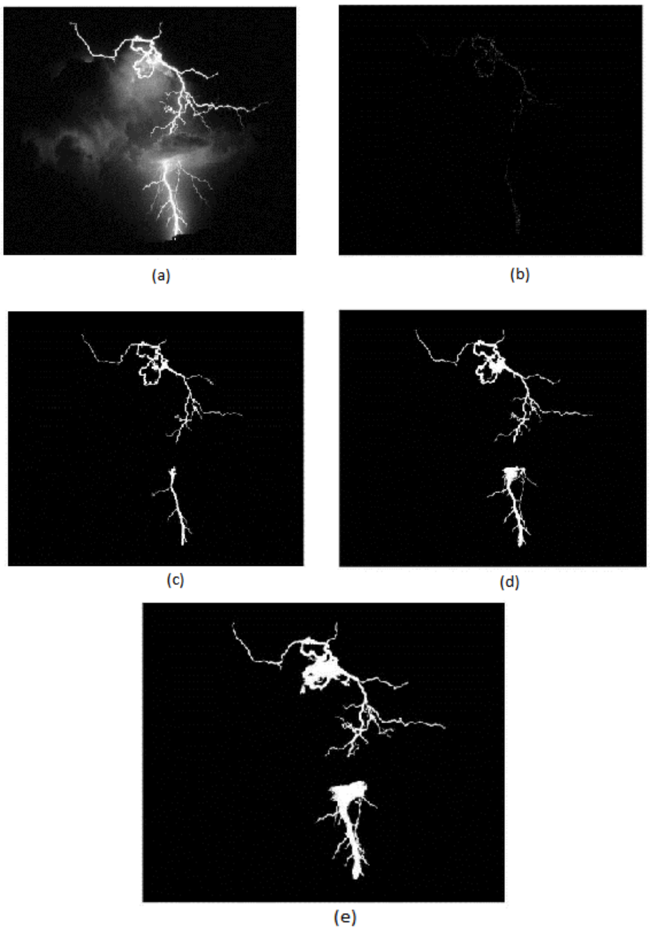

Fig-2: shows the seed region segmentation method implemented on original image (a). Next (b) seed points selected. (c) Threshold 225~255. (d) Threshold 190~255. (e) Threshold 155~255.

The algorithm for seeded region based method goes as follows:

1. Select the initial seed points say, $p_1, p_2, \ldots, p_n$
2. Compute difference between the pixel values of initial seed points and its neighboring points.
3. If compute difference < threshold, add the neighboring point to the cluster where seed point belonged.
4. Recompute the boundary of the cluster and set the boundary points as new seed points.
5. Recompute the mean pixel values of the clusters.
6. Repeat step 2 to 5 for all pixels until they are allocated to a cluster.

The advantages of seeded region based methods are firstly it correctly separates the regions that have the same properties we define. Secondly it provides the original images which have clear edges with good segmentation results. Thirdly it is simple to implement. We can choose multiple criteria at same time. The disadvantages of this method cause very severe effects on the final results of segmentation. First disadvantage selection of seed points and deciding criterion for similarity. And also the power and time consumption is very high for this method.

The second method in region based segmentation is **unseeded region based** method. Unseeded region segmentation method is derived from seeded region based with the difference of no provision of seed explicitly. The seed points are generated by segmentation procedure itself. Therefore, this method achieves full automation of the system with the benefit of robustness from being a region based segmentation method [3]. The working of unseeded region based method goes as follows:

1. Initialize first cluster C_1 containing single image pixel and running state of process compose of a set of identified clusters $C_1, C_2, \ldots, C_n$.
2. Define set of all unassigned pixels which borders atleast one of the clusters as S

$$S = \left\{ x \,!\in \bigcup_{i=1}^{n} C_i \wedge \exists k : N(x) \cap C_k \neq \emptyset \right\}$$

Where x is the pixels and $N(x)$ represents a current neighboring pixels of point x and g(x) is value of pixel at x so difference δ is

$$\delta(x, C_i) = \left| g(x) - mean_{y \in C_i}[g(y)] \right|$$

3. Choose a point $z \in S$ and cluster C_j where $j \in [l, n]$

$$\delta\left(z, C_j\right) = \min_{x \in S, k \in [1,n]} \{\delta(x, C_k)\}$$

If $\delta\left(z, C_j\right)$ < t, add pixel to cluster C_j else select most considerable similar cluster C.

If $\delta\left(z, C\right)$ < t, add pixel to C cluster.

4. After the pixel would be allocated, mean pixel value of cluster must be recomputed.
5. Repeat step 2 to 4 until all pixels are allocated to one cluster and updates are not possible.

This algorithm shows the exact working of unseeded region method. The drawback of this method is over segmentation and also we have to define the total number of clusters we want in final output.

One more method can be added to region based segmentation i.e. **thresholding**. Thresholding is the simplest way to perform region based segmentation and it is used extensively in many image processing applications. Thresholding is based on the concept that regions corresponding to different tissue types can be classified by using a range function applied to the intensity values of image pixels. The major drawback of the threshold based approach is lack of sensitivity and specificity needed for accurate classification. The simple threshold rule for classifying elements will read the intensity values of each data element and categorize it as true if the value is above the threshold and false if it is below the threshold value. The example of this method is shown in fig. 3 which shows the soil images. Fig. 3 (a) shows the soil image applying threshold 13, (b) shows soil image processed with threshold 20, similarly (c) image has threshold 29, and (d) has threshold 38. The thresholding techniques are based on the postulate that all pixel whose value lie within a certain range belongs to one class. Such methods neglect all the spatial information of the image and do not cope well with noise or blurring at boundaries. Given a threshold t, the pixel located at position (i, j), with gray scale value $P_{i,j}$, is allocated to category 1 if

$$p_{ij} \leq t$$

Otherwise, the pixel is allocated to category 2.thresholding can be considered part of histogram thresholding method, multivariate classifiers and contextual classifiers.

In region based segmentation, other methods also exist such as region splitting and merging and JSEG. The goal of region splitting and merging is to distinguish the homogeneity of image. In that the splitting step consists of predicate and if that is satisfied by the region then the region is merged with the similar region. The region based segmentation method works very well for synthetic images but for medical images it results into over segmentation and loss of robustness.

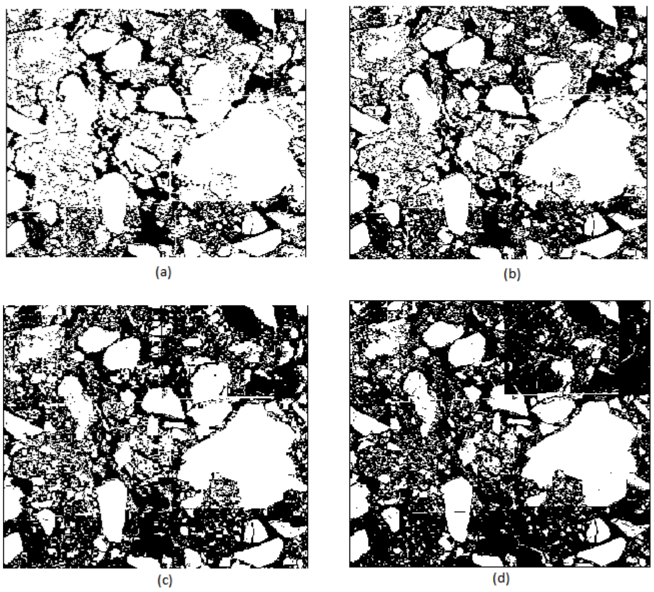

Fig 3- shows image of soil with different threshold values (a) threshold = 13, (b) threshold = 20, (c) threshold = 29, (d) threshold = 38

4. DATA CLUSTERING

Segmentation of images can also be viewed as clustering the similar points or pixels from the image into different cluster such that pixels in same cluster exhibit some similar properties or satisfy particular criterion and pixels from different clusters do not possess any similarity. The concept of data clustering majorly depends on use of the centroid to correspond to each cluster and classify based on the similarity of centroid of each cluster. Data clustering can be sub divided into partitional clustering and hierarchical clustering and it also comprises of various clustering algorithms. Here the main difference between the two types is that hierarchical method produces a nested series of partitions (these partitions are represented using a dendrogram, representing the nested grouping of patterns and similarity levels at which groupings change), while partitional methods produce only one partition. The hierarchical method is more accurate whereas mostly used partitional methods in applications involving large datasets, like the ones related with images because construction of dendrograms is computationally prohibitive. Computational time complexity for hierarchical clustering is $O(n^3d)$ where n is the number of pixels of image and d is number of features and that for partitional clustering is O(nd) or $O(n^2d)$. The major drawback of data clustering algorithms is that they do not regard spatial information which is of main source of information for medical images. As a partitional algorithm produces clusters by optimizing a criterion function the combinatorial search over the set of possible results would solve the inherent problem that it presents. However this is not ethically correct, so the algorithm is run multiple times with different starting states producing a set of results. This set is evaluated by measuring the distances among the different clusters of pixels in the feature space in order to choose the best final configuration [5]. The difference between region based segmentation and clustering is that clustering does not use spatial information whereas basis of region based are on spatial information.

The first method in data clustering is **partitional clustering**. In partitional clustering as the name suggests we have a large dataset and carve it up according to some notion of the association between items inside the set. The problem with partitional clustering is we have to select the number of desired output clusters before we start to classify data. The algorithm that is used as partitional clustering method is squared mean algorithm. One of the main aspects in partitional clustering is convergence criterion. The concept of partitional clustering is to start with a random initial point and keep reassigning the patterns to clusters based on the similarity between the pattern and the centroid of clusters until a convergence criterion is reached [4]. This criterion must work well with isolated and compact clusters. The squared error for a clustering L of a pattern set R is

$$e^2(R,L) = \sum_{j=1}^{K} \sum_{i=1}^{n_j} \left\| x_i^{(j)} - c_j \right\|^2$$

where $x_i^{(j)}$ is the pattern belonging to the j^{th} cluster and c_j is the centroid of the j^{th} cluster. The second most famous algorithm for partitional clustering is k-means clustering. The steps for this algorithm are as follows:

1. Define the exact number of clusters we want in the final output and set the number as N. Randomly select N number of patterns in the whole database as the N centroids of N clusters.

2. Classify each pattern to the most similar cluster centroid. Here similar means with respect to the pixel value.
3. Recalculate the cluster centroids and then there are N centroids of N clusters as in step 1.
4. Repeat step 2 to 3 until the convergence criterion is achieved.

the criteria may be any condition that can be fulfilled and results can be achieved for example, no reassignment of any patterns from one cluster to another or minimal decrease in squared error. The advantages of this algorithm is it is easy to implement and has time complexity O(n) where n is the number of patterns which is faster than hierarchical clustering. The disadvantage of this method is that it is dependent on selection of initial random centroids. So if we choose different set of centroids for same data then also the final results are affected.

The second method in data clustering is **hierarchical clustering**. The main part of hierarchical clustering is to construct the dendrogram representing the nested grouping pattern and similarity levels at which groupings change. For example let us consider the eight labels A, B, C, D, E, F, G, H in three clusters as shown in fig. 4. The dendrogram of these clusters is as shown in fig 5.

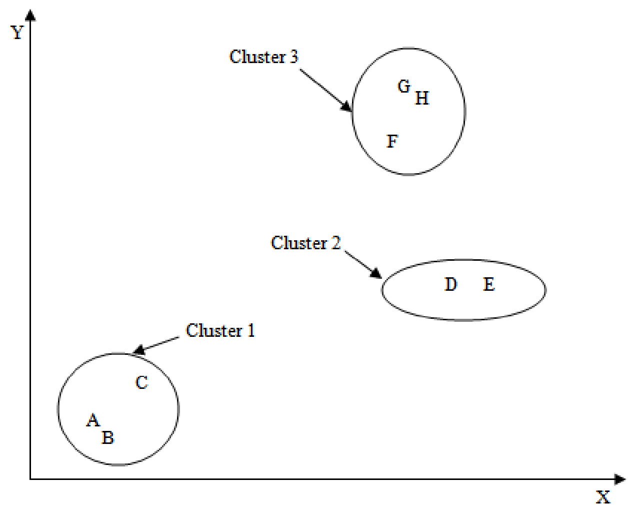

Fig 4- shows eight labels in three clusters

Hierarchical clustering is divided into two kinds of algorithms namely, agglomerative algorithm and divisive algorithm. Firstly let us see details of **agglomerative algorithm**:

1. Each pattern from the database is considered as cluster C_i and compute proximity matrix including the distance between each pair of patterns.
2. The proximity matrix is then used to find out the most similar pair of clusters and then merge these two clusters into one cluster. After that, update the proximity matrix.
3. Repeat step 1 and 2 for all patterns in one cluster or just till we achieve similarity criterion.

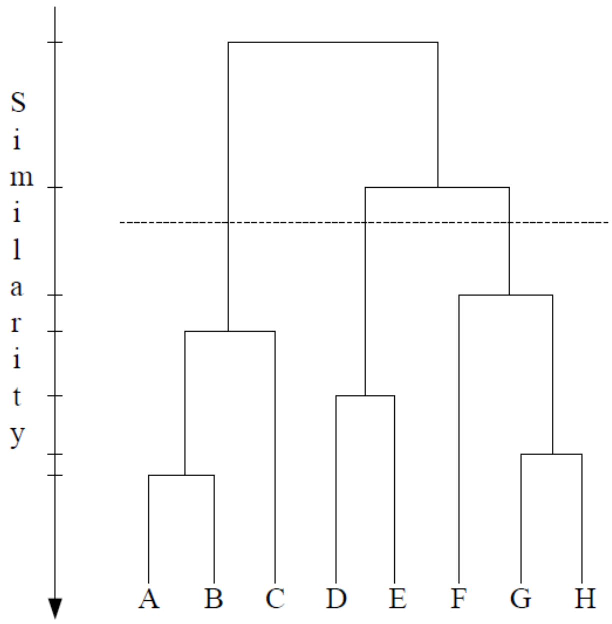

Fig 5- shows dendrogram created from labels and clusters and the similarity criteria in fig 3.

The most popular way of defining distance between two clusters can be given as, suppose $D(C_i,C_j)$ as distance between clusters C_i and C_j and suppose d(a, b) as a distance between patterns a and b. then the distance definition is

$$D(C_i,C_j) = \min(d(a,b)), \qquad for\ all\ a \in C_i, b \in C_j$$

Which means distance between two cluster is the minimum of all pairwise distances between patterns in two clusters.

The next algorithm in hierarchical clustering is **divisive algorithm**. It has to define the distance between pattern x and cluster C as d(x ,C) = the mean of the distance between x and each pattern in the cluster C. The algorithm goes as follows:

1. Consider single cluster of the whole database i.e. for image, the whole image.
2. Find pattern x_i in cluster C_i that satisfies

   $$d(x, C_i) = \max (d(y, C_i))$$

   for all y ϵ C_i, where i=1, 2, …, N and N is the current number of cluster in the whole database.
3. Split x_i as a new cluster $_{Ci+N}$ and then recalculate $d(y, C_i)$ and $d(y, C_{i+N})$. if $d(y, C_i) > d(y, C_{i+N})$, then split y out of C_i and merge it into C_{i+N}.
4. Repeat step 2 and 3 for all clusters until they do not change anymore.

The advantage of this method is dendrogram is useful in checking the process and relationship of hierarchical clustering and we only need to compute the distances between each pattern instead of calculating the centroid of clusters. The only disadvantage of this method is computation time required to draw dendrogram.

5. MATCHING

This is not a very recognized method used for segmenting images. For this method we want to locate an object in the image, and we must have an example available as a template for knowing how the object looks like. We can find the object by matching the template to various image locations until we have found the object [7]. The most straightforward way of determining whether the template fits would be to place the template at a certain image location and see whether the grey values of the template and underlying image grey values match or not. However, because there will generally be some differences between the image and template values because of noise and other artifacts, this is not used more often. More useful is a quantitative measure of fit such as

$$M_1(p,q) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(g(x,y) - f(x+p,y+q))^2$$

where f is the image, g the M * N template, and the variables p and q determine the location of the template in the image. This measure will be small if the template is smaller to the part of the image under investigation; then all grey value differences are small and the sum M_1 will be small [7]. The location of optimal template fit is found by minimizing M_1 to p and q. another measure that uses actual grey value differences instead of their squares:

$$M_2(p,q) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}|g(x,y) - f(x+p,y+q)|$$

M_2 puts less weight on relatively large grey value differences than M_1. But perhaps the most commonly used measure is the cross correlational M_3, which is given by

$$M_3(p,q) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} g(x,y) - f(x+p,y+q)$$

The maximum value of M_3 with respect to p and q is assumed to indicate the location in the image where the template fits best. But this method is not suitable for medical images because of the only disadvantage i.e. this method requires a sample template for matching.

CONCLUSIONS

in this paper, we investigated many different methods that can be used for image segmentation in medical images. From the above discussion we conclude that edge based segmentation and region based segmentation methods prove to be good for accurate segmenting images with little or no human intervention. These two methods are less prone to computational complexities and time consumption. Also now-a-days many hybrid methods are developed for segmenting images. Hybrid methods as the name says are combination of existing methods for improving accuracy. Some examples are combining watershed algorithm and Boundary Code, unseeded region based and thresholding, histogram thresholding and k-means clustering etc. using the combinations i.e. hybrid systems we can improve the final results that are obtained and segment the image more accurately. Another method that is used recently in many applications is generating labels from region based segmentation and assigning different labels to different patterns.

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BIOGRAPHIES

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