Application of Clustering Algorithms in Segmentation and Classification of Abnormal MR Brain Images with 3D Volumetric Analysis

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Abstract: Magnetic resonance imaging (MRI) system projects the maps of anatomical structures, which includes a high contrast based soft tissue. Essentially, the MRI scanner is used to measure the magnetic resonance of hydrogen (1H) nuclei in water and lipid. The segmentation of an image necessitates the division or separation of the image into areas of similar attribute. In many image processing applications, feature extraction is the ultimate goal that is used for description, interpretation and understanding the frame/image provided by the user/input device. The segmentation of brain tumor from magnetic resonance images is an essential task executed by medical experts or by the computer aided algorithm in order to extract the region of similar type. Three dimensional reconstructions of abnormal regions from a sequence of 2D MR brain images is an important task that help the radiologist to diagnosis it accurately and it also helps in surgical process and research. This research evaluates and analyse the clustering algorithms involved in segmenting abnormal region from MR brain images. Perform 3D rendering process with slice interpolation to acquire the 3D view of the extracted abnormal region. Volumetric calculation is presented with the extracted region to help the radiologist to estimate the stage of cancer.

Keywords: Magnetic Resonance Imaging (MRI), Human Visual System (HVS), CCA (Connected Element Analysis).

I. INTRODUCTION

This chapter presents the basics of the anatomy of brain and its structure; it presents different abnormalities that are prevalent in the Brain. Different diagnostic methodologies that were used to extract the features or predict the symptoms were resent. Apart from all, this chapter presents the objectives of this work, its scope and applications.

A. Human Brain

Human brain attracts attention from researchers especially because of the magnificent mechanism [1]. It weighs three pounds but has ability to control every function of human body in amazing manner and born with ability to sense information from outside world in exceptional manner [2]. Human brain is regarded as the supreme organ with exceptional governing skills to govern the prominent things such as emotions, memory, intelligence and creativity [3]. Brain composition is segregated into three segments namely cerebrum, cerebellum and brainstem, the connection between cerebrum and cerebellum is designed in the most exceptional way with the use of brainstem [4]. Brainstem is considered as an important section of the brain anatomy, which acts as relay center and intends to create a connection between remaining two sections till the spinal cord. Human brain is a sensory mechanism, which is designed to keep control of all the necessary senses such as smell (nose), vision (eyes), touch (skin), taste (tongue) and hearing (ear). However, the most interesting aspect of human brain being as sensory system has ability perform multiple senses at one time, which is an important thing, without which human cannot perform multiple tasks throughout his lifetime [5].

B. Anatomy Of Brain

Human brain is divided anatomically in different ways into various regions and vision process is done in three regions based the development of embryonic [6]. By taking specific criteria into consideration i.e. embryonic development, the three regions division are done and named as forebrain, midbrain and hindbrain [7].

C. Image Acquisition

The invention and development of computers have been the pillar for the modern science and technology and digital image is the predominant area, which is also a technology based on computer. Digital image processing provisions for a variety of applications ranging from daily needs like mobiles, laptops, photography to high level research fields like medicine, satellites, radars, remote sensing, etc. Digital image processing has the ability to process the information visualized by human visual system (HVS) and daily millions of new images are generated that require automatic processing, manipulation [8].

Significance Of MRI: MRI has become a familiar medical term and is considered as the best neuro-imaging tool for assessing and following up the examination of the patients for various causes. It is advantageous for its high contrast resolution and ability to prevent use of the ionizing radiations. This particular medical imaging technique is also not preferred for the detection of the small lesions and iso-dense lesions. Among its several benefits, MRI technique
has been selected in this study for its ability to generate images in the sagittal, axial, and coronal planes. This can also be helpful in improved localization of the lesion within the 3D space, eventually permitting structures to become more explicitly delineated. Basing on the above discussion and individual understanding, it becomes apparent that the contrast enhanced T1 weighted 3D Watts–axial images are sufficient for detection and division of the mainstream of brain tumors along with its components like edema and necrosis. Therefore, within our advocated system for segmenting brain tumors in this thesis, the contrast enhanced T1 weighted 3D Watts –axial images are the inputs of the system.

D. Problems / Abnormalities In MR Brain Images

The most challenging task in modern medical imaging systems is to identify the abnormality in the acquired MRI brain images and the reason behind the abnormalities detection failure is brain complex structure and it needs different convergence techniques which act in very high speed. The two-step process implemented for detection of MRI image is as follows

- Classification algorithms are tremendously increased in past two decades and the brain image abnormalities detection is classified by using the reputed classification approach and the resultant classified based on various parameters to distinguish between the normal and abnormal.
- The volumetric analysis is carried into latter step on the segmented data which is acquired from previous step i.e. classification approach. The entire process is automatic consumes less time and achieves more performance compare to traditional approaches.

Several automated techniques which are used for MRI abnormalities detection are as follows

- Artificial Neural Networks (ANN)
- Fuzzy techniques

II. LITERATURE SURVEY

Pratik et al.presented a method that detects the brain tumor as well as calculate the area of brain tumor from the MR image [9]. Firstly, the axial MR images are loaded into the memory as a database. All the input MR images are converted from RGB to gray scale format to produce a noise free image. Linear filtering method and Sobel mask techniques are used to compute the gradient degree of an image, which is a 2D vector that points to the direction in which the image intensity grows fastest. Watershed segmentation is a technique, which is used to transform the gradient of a gray level image in a topographic surface, which can be built up by flooding process on a gray tone image. The main drawback of watershed segmentation is that it will produce number of segmented regions in an image, which leads to over segmentation at each local minimum of embedded image. To overcome this problem internal and external markers are introduced by the gray scale image and finding pixels between the internal markers respectively which in turn produce watershed ridgelines, which are superimposed on the actual image for final segmentation. CCA (Connected element analysis) extracts the region that isn't separated by boundary of ultimate segmental region known as connected component that is more divided into segments for calculation of affected space in pixels. Therefore from the literature it's ascertained that use of marker watershed segmentation with connected component analysis calculates tumor area with the tiniest unit activity of element.

III. SEGMENTATION ALGORITHMS

A. Segmentation

Segmentation of an image is nothing but partitioning of an image into distinct regions in which the areas are partitioned on the basis of their attribute values. The usefulness of image segmentation is in image analysis and interpretation or we can say that if we are interested to work in interested regions only then we should apply image segmentation algorithm there. Segmentation techniques are divided as either discourse or non-contextual. The latter take no account of spatial relationships between options in a picture and cluster pixels along the idea of some international attribute, e.g. gray level or color. Discourse techniques to boot, exploit these relationships, e.g. cluster along pixels with similar gray levels as well as spatial locations [11]. A great sort of segmentation way has been projected within the past decades, and some classification is important to gift the ways properly here. A discourse categorization does not appear to be potential though, as a result of even too terribly completely different segmentation approaches could share properties that define singular categorization as shown in Fig.1. These categorizations are very important task for future work like detecting and tracking [12]. Mostly used image segmented are categorized as below,

- Threshold based segmentation
- Edge based segmentation
- Region based segmentation
- Clustering techniques
- Matching

Fig. 1. Example of edge-based segmentation.
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Top left: original 400 × 350 artificial image with added noise.

Top middle: edge-ness image; computed using a scale space operator (f_n) with σ = 1 pixel.

Top right: same image after thresholding.

Bottom left: sign of Laplacian image. Laplacian image computed using a scale space operator (f_n) with σ = 1 pixel.

Bottom middle: product of Laplacian sign and threshold edge image. Bottom right: result after filling in of the boundaries.

If we add noise in the image, then there is some changes in the artifacts like edges are not perfect that is boundaries we got are not exact. So algorithm is not that much efficient so we have to add some less noise content to get good results.

B. Data Normalization

Because of different kinds of data point in HSL and CIELAB color spaces, we must normalize the datasets. In our system, Soft max algorithm is used for the data normalization. The Soft max can extend softly toward its maximum and minimum value, but never getting there. The transformation using Soft max is more or less linear in the middle range, and has a smooth nonlinearity at both ends. The output range is between 0 and 1. A function in principle used to achieve the needed S-curve is the logistic function.

\[ f(x_i) = \frac{1}{1 + e^{-x_i}} \]  

The logistic function yields the needed S-curve but not over the needed range of values, and there is also no way to choose the range of linear response. In order to resolve this problem, \( \{x\} \) should be first transformed linearly to vary around the mean \( \mu \) in the following way

\[ x_i' = \frac{x_i - \mu}{\sigma_x} \sqrt{\frac{x_i - \mu}{\sqrt{\pi}}} \]  

Where: \( x \) is the mean value of variable \( x \), \( \sigma_x \) is the standard deviation of variable \( x \), \( \lambda \) is the linear response measured in standard deviation. It describes in terms of how many normally distributed standard deviations of the variables are to have a linear response. In our case, we set \( \lambda = 10 \) in order to make the Pillar algorithm is described as follows. Let \( X = \{x_i | i=1,\ldots,n\} \) be data, \( k \) be number of clusters, \( C = \{c_i | i=1,\ldots,k\} \) be initial centroids, \( SX \subseteq X \) be identification for \( X \) which are already selected in the sequence of process, \( DM = \{x_i | i=1,\ldots,n\} \) be accumulated distance metric, \( D = \{x_i | i=1,\ldots,n\} \) be distance metric for each iteration, and \( m \) be the grand mean of \( X \). The following execution steps of the proposed algorithm are described as:

1. Set \( C=\emptyset, SX=\emptyset, \) and \( DM=\{ \}
2. Calculate \( D \leftarrow dis(X,m) \)
3. Set number of neighbors \( nmin=\alpha \cdot n / k \)
4. Assign \( dmax \leftarrow \arg \max(D) \)
5. Set neighborhood boundary \( nbdis=\beta \cdot dmax \)
6. Set \( i=1 \) as counter to determine the \( i\)-th initial centroid
7. \( DM = DM + D \)
8. Select \( j \leftarrow \arg \max(DM) \) as the candidate for \( i\)-th initial centroids
9. \( SX = SX \cup j \)
10. Set \( D \) as the distance metric between \( X \) to \( j \).
11. Set \( n\leftarrow number \) of data points fulfilling \( D \leq nbdis \)
12. Assign \( DM(j)=0 \)
13. If \( n < nmin \), go to step 8
14. Assign \( D(SX)=0 \)
15. \( C = C \cup j \)
16. \( i = i + 1 \)
17. If \( i \leq k \), go back to step 7
18. Finish in which \( C \) is the solution as optimized initial centroids.

However, the computation time could take a long time if we apply the Pillar algorithm directly for all elements of high resolution spatial data points. To solve this problem, we reduce the matrix size to 5%, and then we apply the Pillar algorithm[13]. After getting the optimized initial centroids, apply clustering using the K-means algorithm and then acquire the position of final centroids. Make use of these final centroids as the initial centroids for the real size of the spatial matrix as, and then apply the image data point clustering using K-means.

IV. 3D MODELING OF BRIAN

To construct and envision a 3D model of the tumor, the tumor first needs to be segmented on the MR slices using the active contour segmentation method. This division extracts tumor contours on the slices. The contour points are then used to build up a 3D set of points (“point cloud”), which allowed generating a tetrahedral mesh using the Delaunay triangulation as shown in Fig.2. To generate the final surface plot of the tumor model, the surface of the tetrahedral mesh is visualized. The surrounding areas of the tumor and the tumor tissue itself can be studied by adding moveable image slices in all three anatomical planes. The accurate position of a contour point in relation to the other points in the 3D space...
is defined by the MR scan properties image position, image orientation and pixel spacing, which are delivered as DICOM attributes for each slice, and can be calculated by

\[
\begin{bmatrix}
X \\
Y \\
Z \\
1
\end{bmatrix} =
\begin{bmatrix}
X_0 & \Delta X & 0 & S_x & 0 \\
X_0 & 0 & \Delta Y & S_y & 0 \\
X_0 & \Delta Y & 0 & 0 & S_z \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
x \\
y \\
z \\
1
\end{bmatrix}
\]

(3)

Fig. 2 Principle of 3–D rendering and modeling.

Here \( P_{xyz} \) are the coordinates in units of millimeter, \( S_{xyz} \) the value of the image position \( X_{xyz} \) and \( Y_{xyz} \) are the orientation of the image attributes and ‘x’ and ‘y’ are the spatial pixel ordinates of the image.

V. SEGMENTATION AND VOLUME CALCULATION

The segmentation of an image requires the division or separation of the image into sections of similar attribute. The ultimate goal in a large number of image processing applications is to extract vital features from the image data, which a depiction, interpretation, or understanding of the scene can be provided by the machine. The segmentation of brain tumor from magnetic resonance images is an essential task executed by medical experts or by the computer aided algorithm to extract the region of similar type. In this work image processing based segmentation algorithms are used[14]. The following are the steps involved in the proposed approach.

For region extraction:
- Read a T1-weighted abnormal MR image
- Apply morphological operations for skull stripping
- Apply Clustering algorithms for segmentation using
- Calculate the performance of these algorithms

For Volume Calculation:
- Merge the segmented portions of the images
- Render these images into a multi dimensional spatial data
- Apply Iso surface models to project the 3D rendered surface [10]
- Calculate the volume based on equation below

\[
\text{Tumour Volume} = (\text{interslice gap} + \text{slice thickness}) \times \sum_{i=1}^{n} A_i
\]

Fig. 4. Process of the proposed approach.

Where ‘n’ indicates the total number of slices containing tumour and the ‘A’ is the area tumour on each slice which is given as

\[
A_i = \text{no.of pixels in tumour region} \times \text{slice dimension}
\]

Volumes Calculation:  
FCM  
SFCM  
K-Means

85.23  
85.88  
84.915

A. Classification Of Brain Abnormality

Below figure depicts the approach followed in this section. Fig.3 shows the proposed approach in this paper, the features for the given image is computed and classified using SVM & HMM if found abnormal then the image is segmented as stated in our papers[15].
VI. CONCLUSION

This section presents the proposed approach of 3D rendering process, Classification, tumor extraction and Volume calculation. It is shown the analysis that HMM classifier is out-performing that SVM around 8-10 %. Apart from this, SFCM algorithm is providing the efficient segmentation output for the given set of brain images. Slice interpolation approach with Isonormals is applied for rendering and 3D projection. A mathematical formula is presented in terms of slice gap and area which is used to calculate the volume of the abnormal region.

VII. REFERENCES


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