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An Efficient Brain Image Segmentation based on Gradient Based Watershed transform in Level set method and classification using shape features for a medical diagnosis system

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ABSTRACT

We propose a simple, fast, robust and efficient technique to extract the skeleton based shape signatures for the brain image classification for a medical diagnosis system. The Improved Brain image classification system uses five shape features- two features have derived from combination of skeleton, region, and boundary information and the other three have been derived from distance mapped functional(level contours). All these shape features exhibit invariance to rotation and scaling. Brain image classification is one of the utmost imperative parts of clinical investigative tools. Brain images typically comprise noise, inhomogeneity and sometimes deviation. Therefore, precise segmentation of brain images is a very challenging task. Nevertheless, the process of perfect segmentation of these images is very important and crucial for a spot-on diagnosis by clinical tools. This research presents a more accurate segmentation using Gradient Based watershed transform in level set method for a medical diagnosis system. Experimental results proved that our method validating a much better rate of segmentation accuracy as compare to the traditional approaches, results are also validated in terms of the proposed five shape signatures.

1.INTRODUCTION

This research work proposed a brain MRI image segmentation technique based on 2 level gradient watershed transform using level-set method. The study of automatic brain tumor segmentation represents an interesting research problem in machine learning and pattern recognition. However, developing highly accurate automatic methods remains a challenging problem. This is because humans must use high-level visual processing and must incorporate specialized do- main knowledge to perform this task, which makes developing fully automatic methods extremely challenging.

This is well known fact that brain is one the complex organs in human body. The true diagnostic of any neurological disorder depends upon strength and suitability of the method employed for examining the acquired brain data. The area of image segmentation has received major attention due to the sensitivity of the examination task and due to the acute demand for minimizing the risk of regrowth of some of neurological disorder [31]. This area starts with the critical study of the existing methods and on the basis of gaps found in these methods, it creates an opportunity for introducing best suited new state-of-the-art automatic or semi-automatic brain MR image segmentation method(s).

Generally, the segmentation methods are divided into two broad classes, i.e. semi-automatic methods and fully automatics methods. Regarding fully automatic methods, the question that up to how much extent this method eliminates the involvement of the operator / expert still remains to be answered. For example if it is an Artificial Neural Network based method the training and testing data are prepared by human expert, if it's a clustering based approach then the selection of number of clusters depends upon expert. Finally, when it comes to verification and validation of the results produced by any of the chosen automatic image segmentation method, then the elimination of human expert becomes impossible. In our experiments, the data consist of magnetic resonance imaging (MRI) images of healthy brain and a magnetic resonance imaging (MRI) image of a brain with a tumor (frontal meningioma).

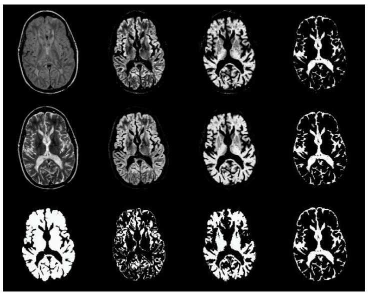


Figure 1. Slices from a standardized FSE PD, T2 study pair (left images of rows 1 and 2).

Figure 1. Slices from a standardized FSE PD, T2 study pair (left images of rows 1 and 2), the corresponding slices from the scenes depicting the fuzzy affinity relations for the GM, WM, and CSF objects (first row), the same slices from the scenes depicting the connectedness values (second row), and the hard (binary) segmented objects (third row). Binary mask for brain parenchyma is shown in the bottom left image. Now, how precisely the verification of the results has been carried out, how much accurate the training and the testing data sets were prepared and how much accurate the number of clusters in clustering based approaches were chosen depends upon the professional strength of the expert. Indeed, this quality of MRI data examination varies from expert to expert.

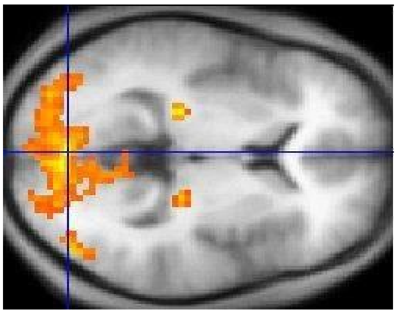


Figure 2. An MRI scan showing regions of activation in orange, including the primary visual cortex.

In medical imaging there is a massive amount of information, but it is not possible to access or make use of this information if it is efficiently organized to extract the semantics. To retrieve semantic image, is a hard problem. In image retrieval and pattern recognition community, each image is mapped into a set of numerical or symbolic attributes called features, and then to find a mapping from feature space to image classes. Image classification and image retrieval share fundamentally the same goal if there is given a semantically well-defined image set. Dividing the images which is based on their semantic classes and finding semantically similar images also share the same similarity measurement and performance evaluation standards.

A.Image Segmentation System and process

An image retrieval framework consisting of three stages; feature extraction, feature selection and image retrieval. Medical image segmentation [30] is the method of labeling each voxel in a medical image dataset to state its anatomical structure. The labels that result from this method have a wide variety of applications in medical research. Segmentation is a very common method so it is difficult to list most of the segmented areas, but a general list would consists of at least the following; the brain, heart, knee, jaw, spine, pelvis, liver, prostate, and the blood vessels. The input to a segmentation process is grayscale digital medical image, (like CT or MRI scan). The desired output restrains the labels that classify the input grayscale voxels. The use of segmentation is to give preeminent information than that which exists in the original medical images only. The set of labels that is produced through segmentation is also called a label map, which briefly tells its function as a voxel by voxel guide to the original imagery. Frequently used to improve visualization of medical image and allow quantitative measurements of image structures, segmentation are also important in building anatomical atlases, researching shapes of anatomical structures, and tracking anatomical changes over time.

A few data mining techniques are also used for segmenting medical image. Data mining is the method of discovering meaningful global patterns and relationships that lie hidden within very huge databases containing vast amount of data. Similar type of data is classified by using classification or clustering method, which is the elementary task of segmentation and pattern matching. Various techniques like neural networks, Bayesian networks, decision tree and rule-based algorithms are used to get the desired data mining outcomes in segmentation.

Magnetic Resonance Imaging (MRI) is noninvasive procedure and can be used safely for brain imaging as often as necessary. MRI images are used to produce accurate and detailed pictures of organs from different angles to diagnose any abnormalities. There are two types of MRI high field for producing high quality images and low field MRI for smallest diagnosis condition. MRI images allow the physician to visualize even hair line cracks and tears in injuries to ligaments, muscles and other soft tissues. MRI is based on the principle of absorption and emission of energy in radio free range of electron magnetic spectrum. Magnetic resonance imaging (MRI) is excellent for showing abnormalities of the brain such as stroke, hemorrhage, tumor multiple sclerosis or lesions.

B. Watershed Transform

In geography a watershed is the ridge that divides areas drained by different river systems. A catchment basin means in this sense an area from which rainfall flows into a river or reservoir. The watershed transform applies these ideas to the gray- scale image processing to enable solution of a variety of image segmentation problems. Understanding the watershed transform requires us to consider a gray-scale image as a topological surface, where the values of f(x,y) are interpreted as heights. The watershed transform finds the catchment basins and ridge lines in such a grayscale image. In terms of the problem related to image segmentation the key concept is to change the starting image into another o ne whose catchment basins are the objects or regions.

C. Image Segmentation using Level Set.

Deformable models are better tools to segment an image in a noisy background and/or the object under consideration deviates from its neighborhood. Deformable model frameworks can be implemented using finite difference schemes under Lagrangian, Eulerian, or Euler-Lagrangian formulations. Snakes is a well-known Lagrangian technique [9]. Level set functions are used in an Eulerian formulation using boundary value or initial value problem. Sethian et.al [4, 5] have used the level set implementation as boundary value problem. Chan-Vese presented a powerful implementation of level set under initial value condition, distance-mapped function [10]. The efficiency of system relies on building an effective and unique feature database. The process starts with the application of level set [4, 10, 26] to segment the object out of the image

D. Skeleton based Feature Extraction

The most challenging aspect of extracting skeleton with higher speed is still an open research problem and should be accurate, robust to rotation, scaling and translation. The next, challenging aspect is in extracting significant and effective feature signatures for the shape to improve the speed and efficiency in the object recognition process. The feature extraction phase is always preceded by segmentation process to separate out the object under consideration from its background. Level set deformable model of chan-vese is used in our work due to its inherent higher speed and accuracy.

E. Distance Mapping

Chan-vese has used Distance mapped level set function, to precisely separate out the object of interest from its background. For fast segmentation, the level set may be defined by city-block distance metric through the fast and robust Distance mapping with Scanning and Filling Technique (DSFT) [10]. At the steady state, the level set is a city-block distance map with the object and its background differentiated by the sign. In this work, distance map is used to extract the skeleton for the object under watch [10, 18].

F. Distance Metrics

The most straightforward way to measure, the similarity between two images is to compute the distance between them. The most frequently used accurate distance metric is Euclidean distance metric. The matching is decided by finding the smallest distance between the query image and similar images in database. Distance metric plays key role in image classification and content based image retrieval in comparison of query image and database image. Small variations in the distance may cause misclassification. Hence, a robust distance metric is the remedy to minimize the misclassification.

G. Organization of the paper

This Research presents a more accurate segmentation using Gradient Based watershed transform in level set method and classification for a medical diagnosis system. Organization of the paper as follows.The Introductory Section ends with a brief introduction of MRI image segmentation, skeletal features, distance metrics and its necessity in the field of medical imaging. In Section II, we explain a General review of traditional methods and techniques involve in medical MRI image segmentation. In section III we address the proposed work flow and used methodology for the medical image segmentation. Section IV Illustrate the results and validation parameters from the proposed segmentation technique. Section V explains conclusion and future regarding the proposed research work and problem scenario.

2. REVIEW OF EXISTING METHODS FOR MEDICAL IMAGE SEGMENTATION AND CLASSIFICATION.

Segmentation is the process of partitioning an image to several segments. The main difficulties in segmentation are:

- Noise
- The bias field (the presence of smoothly varying intensities inside tissues)
- The partial-volume effect (a voxel contributes in multiple tissue types)

A.Existing de-noising methods

In spite of the presence of substantial number of state–of–the–art methods of de–noising but accurate removal of noise from MRI image is a challenge. Methods such as use of standard filters to more advanced filters, nonlinear filtering methods, anisotropic nonlinear diffusion filtering, a Markov random field (MRF) models, wavelet models, non-local means models (NL-means) and analytically correction schemes. These methods are almost same in terms of computation cost, de-noising, quality of de-noising and boundary preserving. So, de-noising is still an open issue and de-noising methods needs improvement. On the other hand, nonlinear filters preserve edges but degrade fine structures, like, Markov random field method (MRF) [1], Wavelet-based methods [2, 3, 6], Analytical correction method [7, 8].

B.Image segmentation methods

Techniques such as thresholding, the region growing, statistical models, active control models and clustering have been used for image segmentation. Because of the complex intensity distribution in medical images, thresholding becomes a difficult task and often fails[11]. in the region growing method, thresholding is combined with connectivity [12].
Fuzzy C–means is a popular method for medical image segmentation but it only considers image intensity thereby producing unsatisfactory results in noisy images. [13]. A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect [12, 13, 14, 15, 16, 17]. Accurate estimation of the probability density function (PDF) is essential in probabilistic classification [19]. Non-parametric approach does not make any assumption in obtaining the parameters of PDF thereby making it accurate but expensive [20]. In parametric approaches, a function is assumed to be a PDF function. It is easy to implement but sometimes lacks accuracy and does not match real data distribution [19]. Learning vector quantization (LVQ) is a supervised competitive learning technique that obtains decision boundaries in input space based on training data [21]. Self-organizing maps (SOM) is an unsupervised clustering network that maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units [21]. The input data is organized into several patterns according to a similarity factor like Euclidean distance and each pattern assigns to a neuron. Each neuron has a weight that depends on the pattern assigned to that neuron. Watershed transform is a gradient-based segmentation technique where different gradient values are considered as different heights. A hole is made in each local minimum and immersed in water; the water will rise until local maximums. When two body of water meet, a dam is built between them. The water rises gradually until all points in the map are immersed. The image gets segmented by the dams. The dams are called watersheds and the segmented regions are called catchments basins [22, 23]. Its fast implementation method is proposed by [24, 25]. The over segmentation problem still exists in this method [22, 23].

The region growing starts with a seed, which is selected in the centre of the tumor region. During the region growing phase, pixels in the neighbor of seed are added to region based on homogeneity criteria thereby resulting in a connected region.

The main challenge lies in segmentation of brain with anatomical deviation like tumor with different shape, size, location and intensities. The tumor not only changes the part of brain which tumor exists but also sometimes it influences shape and intensities of other structures of the brain. Thus the existence of such anatomical deviation makes use of prior information about intensity and spatial distribution challenging.

The level set is used through DSFT to initialize, reinitialize and the internal curve is randomly launched, making the segmentation possible in less than 10 iterations [27]. The proposed method based on Skeleton and Distance mapped functional Signature features have been found to exhibits better performance with reduced computational complexity and improved retrieval efficiency as compared to other recent techniques.

3. MRI IMAGE SEGMENTATION USING GRADIENT BASED WATERSHED TRANSFORM IN LEVEL SET.

This research work proposed a brain MRI image segmentation technique based on 2 level gradient watershed transform using level-set method. The study of automatic brain tumor segmentation represents an interesting research problem in machine learning and pattern recognition. However, developing highly accurate automatic methods remains a challenging problem. This is because humans must use high-level visual processing and must incorporate specialized do- main knowledge to perform this task, which makes developing fully automatic methods extremely challenging. Unlike the standard level set methods, the tumor and non-tumor region information is embedded in the level set speed function to automatically extract the 2D tumor surface.

The first approach called the block 1 process uses the level set segmentation as a deformable model and defines its speed function based on intensity thresholding so that no explicit knowledge about the density functions of the tumor and non-tumor regions are required. The threshold is updated iteratively throughout the level set growing process. The second approach which is called as block 2 consists of two level gradient based watershed segmentation. We had also used some morphological operators along with watershed transform in order to extract a sharp segmented region. Basically, the level set method (LSM) is a numerical technique for tracking interfaces and shapes. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize these objects (this is called the Eulerian approach).

In our segmentation process, for using watershed segmentation different methods are used. Two basic principle methods are given below: 1) the computed local minima of the image gradient are chosen as a marker. In this method an over segmentation occurs. After choosing marker region merging is done as a second step; 2) Watershed transformation using markers utilizes the specifically defined marker positions. These positions are either defined explicitly by a user or they can be determined automatically by using morphological tools. After converting the image in the binary format, some morphological operations are applied on the converted binary image. The purpose of the morphological operators are to separate the tumor part of the image.

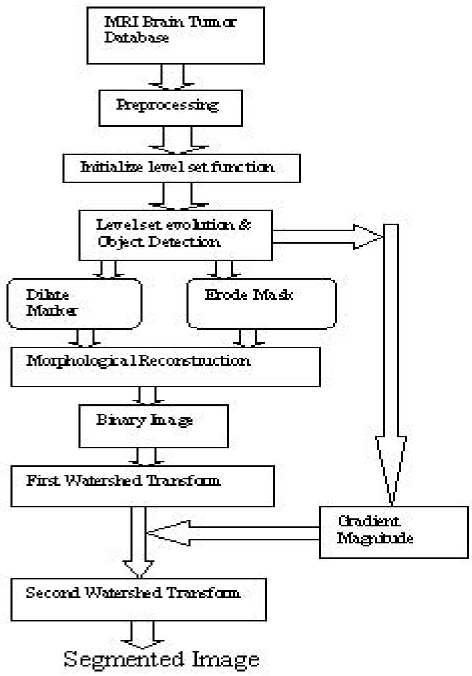


Figure 3. Employment of gradient based watershed transform on the output of level set segmentation used in our proposed methodology as a final block of segmentation.

The level set is defined through ‘Distance mapping using Scanning and Filling Technique’ (DSFT) [10] whose time complexity is invariant to the model curve size and hence random initialization ensures fast and efficient segmentation. The segmented result is a level set function with distance map such that the boundary of the object corresponds to zero level set. This distance map result of segmentation process encouraged us to use this information to extract the skeleton (S) and region (R) signatures along with the boundary (B) for building the shape signature database.

A.Shape Signatures from Skeleton

We propose significant and effective feature signatures for the shape to improve the speed and efficiency of the object recognition process. The feature extraction phase is always proceeded by segmentation process to separate out the object under consideration from its background. We use Chan-Vese model of level set for this purpose due to its higher speed and accuracy. The level set is defined by city-block distance mapping through DSFT that is very fast and invariant to the size of the initial curve, providing a function mapped with city-block distances for the feature extraction phase. Hence, it makes sense to use this available data to extract the skeleton for the given shape.

B.Skeleton Extraction

Skeletonization is a process for reducing foreground regions into a binary image and to a skeletal remnant that largely preserves the extent and connectivity of the original region while throwing away most of the original foreground pixels. The skeleton that is a set of centers of circles within a shape is one of the important areas in image processing and computer vision. The compact one – dimensional skeletal information which is very familiar to human visual perception has been widely used for shape analysis, shape retrieval, object recognition, character recognition, image analysis and biomedical images.

Skeletons have several different mathematical definitions in the technical literature, and there are many different algorithms for computing them. The skeletonization approaches can be classified into four types: thinning algorithm, discrete domain algorithms based on the Voronoi diagram, algorithm based on the distance transform, and algorithms based on mathematical morphology. From extracted skeleton, various approaches to reduce the noisy branches like pruning methods are introduced by measuring the significance assigned to skeletal points or smoothing the boundary before extracting the skeleton. However, existing skeleton extraction algorithms are very weak because of their high computational complexity, noise sensitivity, centeredness inside the underlying complex shape, partial occlusion or artifacts in a singular region from the given shape. This work highlights the power of city-block distance map in skeletonization of a given shape.

The readily available city-block distance map because of the level set based segmentation encouraged us to do so. In turn, DSFT (Distance mapping using Scanning and Filling Technique), was used to map the distances with city-block metric, due to its high speed and robustness. This fast approach of segmenting and the level set skeletonizing of the object has motivated to undertake the present work.

This property of distance map encourages one to easily extract the skeleton points simply by searching the point of slope deviation. The skeleton of an object can be extracted by scanning the distance map function row wise and column wise through forward or backward distances and searching for slope deviations. For example, with backward distances, a point (i, j) can be a skeleton point if one or both of the following conditions are true.

$$D(i, j-1) - D(i, j) \neq D(i, j) - D(i, j+1) \text{ and/or} \qquad \dots (1)$$

$$D(i-1, j) - D(i, j) \neq D(i, j) - D(i+1, j) \qquad \dots (2)$$

C.Shape Signatures from Level Contour

The output of the segmentation phase is a distance map with the object boundary represented by zero level set. This encouraged us to build shape signature in this distance map. Tables1 and 2 show the distance mapped function for two shapes. It can be easily inferred from these tables that the number of points on contours is a unique set for each shape. Here the number of pixels on the object boundary, unit distance away from the boundary and two units away from the boundary have a unique relationship that depends on the shape of the object boundary. The normalized differences have been computed by

$$r_{10} = \frac{I_0 - I_1}{I_0} \qquad \dots (3)$$

$$r_{20} = \frac{I_0 - I_2}{I_0} \qquad \dots (4)$$

$$r_{21} = \frac{I_1 - I_2}{I_1} \qquad \dots (5)$$

Where I_0, I_1, I_2 are sum of number of points on the object boundary, sum of number of points on unit distance away from the boundary, and sum of number on points of two units distance away from the boundary.

For example, table1 shows the distance mapped functional for a square object present in an image. In this case, the sum of number of points with 0s is I_0= 32, with 1s is I_1= 24, and with 2s is I_2=16. Here r_{10}=.25, r_{20}=.5, and r_{12}=.33.Similarly, for an image containing some irregular shaped object whose level set function is as shown in table2, the values are: I_0=28, I_1=20, and I_2=9 giving the normalized difference values as: r_{10} = .285, r_{20} = .678 and r_{21}= .55. These features are presented in Table3.

Table1: Distance mapped function for square object. Here zeros indicate the position of the boundary pixels and other values represent the distance from this boundary

-4	-3	-2	-2	-2	-2	-2	-2	-2	-2	-2	-3	-4
-3	-2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-2	-3
-2	-1	0	0	0	0	0	0	0	0	0	-1	-2
-2	-1	0	1	1	1	1	1	1	1	0	-1	-2
-2	-1	0	1	2	2	2	2	2	1	0	-1	-2
-2	-1	0	1	2	3	3	3	2	1	0	-1	-2
-2	-1	0	1	2	3	4	3	2	1	0	-1	-2
-2	-1	0	1	2	3	3	3	2	1	0	-1	-2
-2	-1	0	1	2	2	2	2	2	1	0	-1	-2
-2	-1	0	1	1	1	1	1	1	1	0	-1	-2
-2	-1	0	0	0	0	0	0	0	0	0	-1	-2
-3	-2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-2	-3
-4	-3	-2	-2	-2	-2	-2	-2	-2	-2	-2	-3	-4

Table2: Distance mapped function for irregular shaped object. Here zeros indicate the position of the boundary pixels and other values represent the distance from boundary.

-4	-3	-2	-2	-2	-2	-2	-2	-2	-2	-3	-4	-5
-4	-3	-2	-1	-1	-1	-1	-1	-1	-2	-3	-4	-4
-3	-2	-1	0	0	0	0	0	0	-1	-2	-3	-3
-3	-2	-1	0	1	1	1	1	0	0	0	-1	-2
-3	-2	-1	0	1	2	2	1	1	1	0	-1	-2
-3	-2	-1	0	1	2	3	2	2	1	0	-1	-2
-3	-2	-1	0	1	2	2	2	2	1	0	-1	-2
-3	-2	-1	0	1	1	1	1	1	1	0	-1	-2
-3	-2	-1	0	0	0	0	0	1	1	0	-1	-2
-3	-2	-2	-1	-1	-1	-1	0	0	0	0	-1	-2
-4	-3	-3	-2	-2	-2	-1	-1	-1	-1	-1	-2	-2
-5	-4	-4	-3	-3	-3	-2	-2	-2	-2	-2	-3	-3
-8	-5	-5	-4	-4	-3	-3	-3	-3	-3	-3	-3	-4

Table3: Shape features derived from distance map

Shape	r_{10}	r_{20}	r_{21}
Square	.25	.5	.33
Irregular	.285	.678	.55

The other two shape signatures are extracted from the skeleton, region, and boundary of the object.

D.Similarity Measures as an Important Issue in Image Classification Systems

Figure4. shows the typical architecture of CBIR system retrieves the relevant shapes from the shape database for the given query shape by computing the signature features of the query shape and comparing with similar feature set of corresponding shapes in the database. Relevant shapes having minimum distance (or maximum similarity) computed between features of query shape and feature set in shape database are retrieved. In building a CBIR system, two foundational issues need to be addressed.

1. Every shape in database has to be represented efficiently with unique significant optimum features.
2. The shape features should guarantee maximum number of relevant shape extraction from database with least time and space complexity

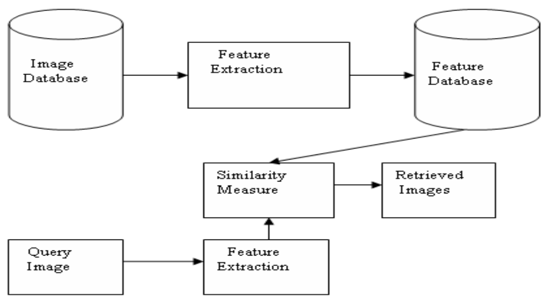


Figure4. Typical CBIR Architecture

E. Distance Metrics

A crucial parameter for classification is the choice of an appropriate distance metric to measure the similarity or dissimilarity between two images. Thus, the distance metric plays a key role in CBIR [28, 29]. It is essential to explore the different similarity measures to find out best distance metric for image retrieval. In conventional image retrieval technique, Euclidean distance is used to find the similarity between the query image and image database. Similarity score is used to find the best match of query image from the database image. The distance metric, which gives minimum distance between the query shape and its nearest shape in the database is the best metric. For better classification, the maximum of intra-class distance should be less than the minimum of the inter-class distances. Let P and Q represent the feature vectors for database image and query image respectively. The present work evaluates the CBIR performance for computing distance d(P, Q) using the following distance metrics:

F. Euclidean L_2 Distance

Euclid stated that the shortest distance between two points on a plane is a straight line and thus the equation (6) is predominantly known as Euclidean distance. Euclidean distance metric was often called Pythagorean metric since it is derived from Pythagorean Theorem. Euclidean distance metric is defined for p=2. In Euclidean distance metric difference of each feature of query and database image is squared which increases the divergence between the query and database image if the dissimilarity is more.

$$d_{Euc}(P,Q) = \sqrt{\sum_{j=1}^{N} | P_j - Q_j |^2} \qquad \dots (6)$$

Segmented Image

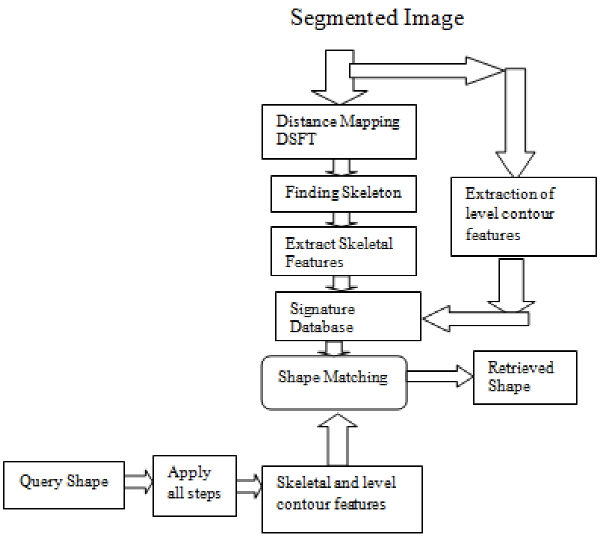


Figure5: extraction of features and comparison

4.Analysis of Results

In order to test the performance of the proposed segmentation method, a brain MRI is segmented in this research work. Figure below gives original MRI image representation. Figure6 is an Example Medical resonance imaging data samples taken from the internet database, these samples are captured from various angles throughout the brain area. Figure7 is some original dataset also considered which is taken from a local hospital in order to justify results from the proposed segmentation approach.

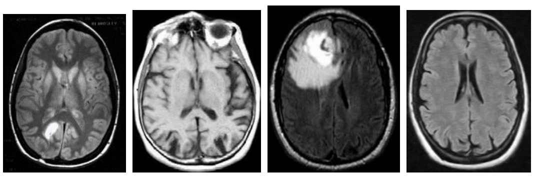


Figure6: Example Medical resonance imaging data samples taken from the internet database.

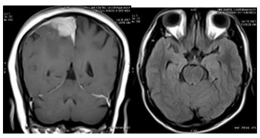


Figure7: Some original dataset also considered which is taken from a local hospital in order to justify results from the proposed segmentation approach.

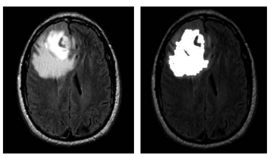


Figure8: It shows the preprocessing of image, thresholding operation on original input magnetic resonance imaging data, this thresholding was performed based on intensity of image pixels.

After the Application of Level Set Method in the selected thresholded region of MRI image, the region of interest from the boundary regions start converging. The segmented portion further extracted by passing it through a bank of Morphological operators and watershed transform. The level set method (LSM) is a numerical technique for tracking interfaces and shapes.

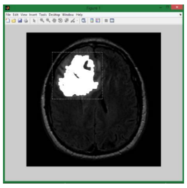


Figure9: Before applying level set operation on thresholded data.

We have to select a region on which we have to apply the level set segmentation (Whole area can also be considered if computation cost is not an issue in segmentation process)

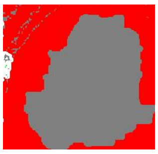


Figure10: Extracted Final Output of tumorous region in 2D from medical data

After extracting the desired region, the proposed two skeleton signatures are derived from shape region and boundary. These features are considered for result analysis in our work.

A.Distance Mapped Functional Signatures for Brain image classification

Brain image classification is one of the utmost imperative parts of clinical investigative tools for medical diagnosis system. This brain image classification process consists of two phases: the learning phase and the searching phase. In the learning phase, the features of the shape are computed for each object in each image in the database and the feature database is built. In the scanning phase, the features of the test object are computed and these features are compared with those in the feature database for the nearest match. The distance metric used to find the match can be Euclidean, city-block or chess-board.

In the learning phase, the object is segmented based on 2 level gradient watershed transform using level-set method level set method and the object boundary information is used to generate the distance mapped functional. The shape features are derived from this distance mapped functional. The features are the number of points on the object boundary, the number of points inside the object. Hence, the proposed method is invariant to scale and orientation. This makes the method more robust as it can match the shapes of the objects irrespective of the scaling and rotation of the object in the images.

B. Skeleton and Level Contour Based shape signatures for Brain image classification for medical diagnosis system.

We propose significant and effective feature signatures for the shape of the object through the skeleton and level contours. The proposed five shape features uniquely distinguish between different shapes - two features have derived from combination of skeleton, region, and boundary information and the other three have been derived from distance mapped functional(level contours). These shape signatures are robust to scaling, rotation, and position and are very precise. These signatures are primarily an integration of region, boundary, and convexity and concavity of the objects in images.

The shape signature proposed through Skeletonization is obtained from a simple City- block distance mapping using Scanning & Filling Technique (DSFT) [10, 18]. As mentioned obtaining Skeleton at faster rate is still an open problem. The DSFT technique involves only scanning through the rows, columns and updating each grid with a counter, which is independent of convolution, hence, is a fast method.
The proposed two skeleton signatures are derived from shape region and boundary.

- The first skeleton-based region signature is defined as ratio of number of points on the skeleton and number of points inside the object.
- The second signature is defined as ratio of number of points on the skeleton and number of points on the boundary of the object.

The procedures for shape signatures extraction from the skeleton, region, and boundary of the object is given below. The relationship used in this paper amongst the number of points having values on the skeleton, inside object, and on the boundary are the main features used to distinguish between different shapes and are presented below.

G.Skeleton based region signature of the given different shapes in the shape database given by S_R^T is the ratio of number of points on the skeleton and number of points inside the shape, denoted as

$$S_R^T = \frac{N_S}{N_I} \qquad \dots (7)$$

H.Skeleton based boundary signature of the given different shapes in the shape database given by S_B^T is the ratio of number of points on the skeleton and number of points on the boundary of shape, denoted as

$$S_B^T = \frac{N_S}{N_B} \qquad \dots (8)$$

I. For query shape, the shape signatures as given in above steps are denoted as

$$S_R^Q = \frac{N_S}{N_I} \qquad \dots (9)$$

$$S_B^Q = \frac{N_S}{N_B} \qquad \dots (10)$$

The procedures for shape signatures extraction from the level contours, number of pixels on the object boundary, unit distance away from the boundary and two units away from the boundary have a unique relationship that depends on the shape of the object boundary. The normalized differences have been computed by

$$r_{10} = \frac{I_0 - I_1}{I_0} \qquad \dots (11)$$

$$r_{20} = \frac{I_0 - I_2}{I_0} \qquad \dots (12)$$

$$r_{21} = \frac{I_1 - I_2}{I_1} \qquad \dots (13)$$

Where I_0, I_1, I_2 are sum of number of points on the object boundary, sum of number of points on unit distance away from the boundary, and sum of number on points of two units distance away from the boundary.

J. The similarity measure between features using Euclidean distance metric is given

$$D_E = \sqrt{\left(S_R^T - S_R^Q\right)^2 + \left(S_B^T - S_B^Q\right)^2} + \qquad \dots (14)$$

Where D_E is the Euclidean Distance between the shape signature of the Query shape and individual shape in the database.

S_R^T = Skeleton based region signature of training shapes, S_B^T = Skeleton based boundary signature of training shapes

S_R^Q = Skeleton based region signature of query shape, S_B^Q = skeleton based boundary signature of query shape

The results show that Gradient based Watershed transform in level set method can successfully segment a tumor provided the parameters are set properly in MATLAB R2013B. Our Hybrid approach algorithm performance is better for the cases where the intensity level difference amongst the tumor and non-tumor regions is higher. It can also segment non homogenous tumors providing the non-homogeneity is within the tumor section. This work proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of brain tumors.

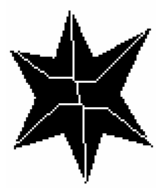
The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the classification methods investigated, the level set method and watershed transform is marked out best out of all others. The user interface in the main application must be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module. Finally the main program must receive the segmented image and the shape signature proposed through Skeletonization is obtained from a simple City- block distance mapping using Scanning & Filling Technique (DSFT) [80, 81] and Level contours. As mentioned obtaining Skeleton at faster rate is still an open problem. The DSFT technique involves only scanning through the rows, columns and updating each grid with a counter, which is independent of convolution, hence, is a fast method.

A.Robustness and Efficiency of Skeleton and Level Contour (SLC) Signatures

Generally, skeleton-based features do not perform well in retrieving concave shapes, especially with corners and smooth curve, concave shapes. The skeleton-based features are not sensitive to concave shapes. In the example shown in Figures11 (b) and (c) the red circle indicating the location of sharp corner changed to smooth curve concave shape. In many situations, some part of shape information is lost. Human beings can compensate the changes using knowledge, but poses a great challenge to machine. The changes can be compensated to better extent by combining skeleton features with level contour features. Because even though shape's skeleton features usually remain unchanged. Whereas, significant change in its level contours features have observed as shown in Table4. These level contours are concave controlled features.

Table4: Performance of skeleton and distance mapped function for sharp and smooth concave and convex shapes.

Shape	S_R	S_B	r_{10}	r_{20}	r_{21}
Star 5.11-a	.7483	.1031	.9867	.1026	.4450
Star 5.11-b	.7498	.1021	.9668	.0930	.4443
Star 5.11-c	.7637	.0992	.9623	.1188	.4323



(a) *(b)* *(c)*

Figure11: Stars with concave and convex variation and corresponding skeletons

5.Conclusion and Future Scope

This research article explain an extended review of existing and methodology culmination with a new methodology which is better and more accurate as compare to the traditional approaches. The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the classification methods investigated, the level set method and watershed transform is marked out best out of all others. Human beings can compensate the changes using knowledge, but poses a great challenge to machine. The changes can be compensated to better extent by combining skeleton features with level contour features. Because even though shape's skeleton features usually remain unchanged. Further work can be carried out to add Artificial Neural Network for better classification of brain tumor medical images. We also plan to extend the principles generated for automatic brain segmentation to the problem of lung segmentation for use in studies of lung diseases such as cystic fibrosis and emphysema, where the volume of the lungs is needed. A reliable consistent method for outlining the lungs is required for MR chest images. Early results with MR images are promising, and will be continued.

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