International Journal of Electrical and Electronics Engineers
Vol. No. 9, Issue No. 01, January-June 2017
ISSN (O) 2321-2055
ISSN (P) 2321-2045

A NOVEL APPROACH FOR CANCER DETECTION FROM BRAIN MR IMAGES

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ABSTRACT

Brain tumour is an augmentation of cells in the brain that escalate in an unusual and unconstrained way. *The paramout advantages of MRI are providing high qulity resolution of soft tissues and no affecting the measured signal by the bones. For these reasons, MRI is used predominantly for soft tissue inspection to spot pathological changes, such as malignant tumours. Brain MR Images with various segmentation techniques are often use for brain abnormality detection. Clustering approach is extensively used in biomedical applications selective for brain tumour detection in abnormal magnetic resonance (MRI) images. Fuzzy clustering using fuzzy C-means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency. The image enhancement methods are used to enhance the contrast of the input images drastically. In this document a new skull stripping and fuzzy c-means clustering based MR Image segmentation method is proposed for brain abnormality detection. Contrast enhancement (mid-range stretching) is used to advance the image quality for segmentation. To confirm the proposed methodology, it is tested successfully on number of datasets of approximately 400 MRI images.*

Keywords: ***Magnetic Resonance Imaging (MRI), Fuzzy C-means Clustering (FCM), Image Segmentation, Image Enhancement***

I. INTRODUCTION

Tumour is an abnormal augmentation of tissue resulting from uncontrolled, progressive **multiplication** of cells. However all tumour may not be cancerous, tumour is main source of brain abnormalities. The multifaceted anatomical formation of tissues will be not well distinguishable and borders of tissues may overlie due to noise and in homogeneity artefacts. which are resulting from the achievement of data. In this case, the distinctive of individual matter is complicated even for skilled individual eye.

Image enhancement techniques advance the feature of images by removing blurring and noise, increasing contrast and sharpness of medical images. The enhancement stage includes resolution enhancement and contrast enhancement. There are many image enhancement approaches like contrast stretching, range compression, histogram equalization and noise smoothing. Due to advantages of contrast enhancement for brain MR Images as image enhancement technique, contrast enhancement with midrange stretching [3] is used in this paper.

In medical imaging, image segmentation is the partition of image into its element regions (a prerequisite for labelling of organs), organelles and anatomic substructures found in images. Segmentation is the signal and image processing correspondent of anatomic or surgical categorization that results in separate components, normally much less in number than the individual image elements (pixels or voxels). Segmentation is achieved by subjective or objective methods that combine and aggregate close by homogeneous image elements based on some quantifiable characteristic (or quality) such as intensity, texture, gradient or many others. Based on approach, the segmentation algorithms can divide to either edge detection based methods, region based methods, statistical methods, hybrid methods or knowledge based methods. The objective of this research paper is to detect abnormalities in brain by the segmentation of White Matter (WM) and Grey Matter (GM) [1, 2]. The WM has a high content of fat and the GM contains more water. The different composition of these tissues gives a contrast in the brain MR scans that permits its discrimination. This is the basic of the segmentation process used for brain MR Images. In this paper, Fuzzy C-means clustering technique with erosion (morphological function used for skull stripping) is used for MR image segmentation.

II. BRAIN TUMER

There are more than 120 types of known brain and central nervous system (CNS) tumours. Nowadays, the majority of medical institutions use the World Health Organization (WHO) classification system to categorize brain tumours. The WHO classifies brain tumours by cell origin and cells behaviour, from the least aggressive (benign) to the most aggressive (malignant). Some tumour types are assigned a grade, ranging from Grade I (least malignant) to Grade IV (most malignant), which signifies the rate of enlargement. In broader sense, brain tumours can be classified into two common groups: primary and secondary.

2.1 Primary Brain Tumer

Tumours that initiate within brain tissue are identified as primary brain tumours. Primary brain tumours are categorized by the type of tissue in which they arise. The most common primary brain tumours are gliomas, which start in the glial (supportive) tissue. There are many types of gliomas. A few of them are:

- **Astrocytomas**: Develop from small and star shaped cells called astrocytes. They may grow in the brain or spinal cord anywhere. In adults, astrocytomas most frequently grow in the cerebrum.
- **Oligodendrogliomas**: Arise in the cells that generate myelin, the fat covering to protects nerves. These tumours also usually arise in the cerebrum. They grow little by little and usually do not diffuse into surrounding tissue.
- **Ependymomas:** Usually develop in the lining of the ventricles. They may also take place in the spinal cord.

There are other types of primary brain tumours that do not start in glial tissue. Some of the most common are:

- **Meningiomas**: Arise from the meninges. Usually they are benign. These tumours grow very slowly so the brain may be capable to adjust to their existence. Meningiomas may grow quite large before they cause symptoms.
- **Schwannomas**: They are also benign tumours that arise from schwann cells, which produce the myelin.
- **Craniopharyngiomas:** Expand in the region of the pituitary gland close to the hypothalamus. They are usually benign; however, they are sometimes considered malignant because they can press on or harm the hypothalamus and affect very important functions.
- **Germ cell tumours**: Arise from primitive (developing) sex cells or germ cells. The most common type of germ cell tumour in the brain is germinoma.
- **Pineal region tumours**: Occur in or around the pineal gland, a tiny organ close to the center of the brain. This tumour can be slow growing (pineocytoma) or fast growing (pineoblastoma).

2.2 Secondary Brain Tumer

Secondary brain tumours are tumours caused from cancer that originates in another part of the body. The multiplication of cancer inside the body is called metastasis. Cancer that spreads to the brain is the same disease and has the same name as the original (primary) cancer. For example, if lung cancer spreads to the brain, the disease is called metastatic lung cancer because the cells in the secondary tumour resemble abnormal lung cells, not abnormal brain cells.

III. IMAGE ENHANCEMENT METHOD

The main purpose of enhancement is to improve the overall perceptual feature of image using algorithms or to offer enhanced input for other automated image processing techniques so that precise results can be obtained. The enhancement methods can broadly classified as spatial domain methods and frequency domain methods. Image pixels are directly deal in spatial domain techniques and pixel values are manipulated to attain wanted enhancement. Some of them are point processing methods, histogram processing etc. In frequency domain methods, the image is first transferred in to frequency domain and all enhancement operations are performed on the frequency domain of the image.

IV. SEGMENTATION METHOD

Image segmentation is the process of segmenting a digital image into various segments where every division has similar kind of pixels [14]. For MR Images, segmentation is the process of removal of the White matter (WM), Gray matter (GM) and Cerebrospinal Fluid (CSF). Commonly used image segmentation methods for MR images are classified as edge detection based methods, region based methods, statistical methods, hybrid methods and knowledge based methods.

4.1 Edge Detection Based Image Segmentation Method

These methods are oriented to identify significant edges in an image. There are a number of edge detection algorithms such as active contours [4] or level-sets that generate a set of edges (points, pixels, or fragments) in the image.

4.2 Region Based Image Segmentation Method

These methods oriented regions in the image (region-based) such as region rising, or divide and combine [5]. The first method of region growing was the (SRG) seeded region growing method. In this method we take a set of seeds as input along with the image. The seeds mark each of the objects to be segmented [15]. Then the regions are iteratively grown by comparing all unallocated adjacent pixels to the regions. Split-and-merge segmentation is based on a square tree partition of an image.

4.3 Statistical Methods Based Image Segmentation Method

In these methods image segmentation is based on statistical examination of image statistics(data), and pixel values. Structural information is usually ignored. The most recognized methods are thresholds, clustering and fuzzy connectedness [6]. A statistical representation is presented that describes the distributions of main tissue classes in single-channel MR cerebral images. Using the representation, cerebral images are segmented into gray matter, white matter and cerebrospinal fluid (CSF).

4.4 Hybrid Image Segmentation Method

It is a group of methods for segmentation, which uses statistical characteristics of the image. These segmentation techniques include elements of the earlier three categories by taking benefits from all of them. Mathematical morphology-based methods are also taken in consideration among the hybrid methods. Most general hybrid methods for image segmentation are watershed method and gradient progress.

4.5 Knowledge Based Image Segmentation Method

Active Appearance Model (AAM) is most common knowledge based image segmentation process. It properties of segmented objects (shape, colour, texture, etc.) in general and uses atlas originals or models of segmented objects in the case of medical images. Atlas is generated automatically or manually from the set of instruction statistics or information entered physically based on human knowledge. Algorithm seeks the change of familiar objects, templates in the Atlas and the objects found in the image all through the segmentation. This procedure is usually called the atlas-warping and uses a linear transformation.

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V. PROPOSED METHODOLOGY

The proposed methodology is shown in Fig-1

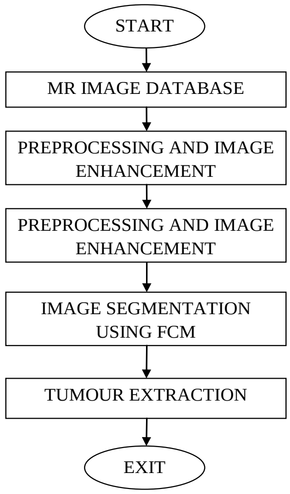

Fig-1: Proposed Methodology

5.1 MR Image Database

The images used are collected from radiologists and prominent database sites [11, 12]. MR brain tumour image database comprising of around 400 256*256 gray level images with intensity value ranges from (0 to 255).

5.2 Preprocessing and Image Enhancement

After normalizing the images, features are extracted from them. Every single pixel of the gray-scale image is mapped to a number between 0 and 1.For the brain tissue images, the value of intensity is between 0.2 and 0.7. Due to this process of normalization, the range of intensity values is diminished making feature extraction much effortless than before. The variation amidst the intensity of two adjoining pixels is entitled as "Contrast". High contrast images have a superlative variation than low contrast images. Low-contrast images appear usually due to the reasons like poor or non-uniform lighting conditions or due to non-linearity or small dynamic range of the imaging sensor. The diversity stretch technique improves the brightness differences uniformly across the dynamic range of the image.The mid range stretching is a powerful tool for enhancing images. The mid-range stretching takes into examination, the intensity values of brain and non-brain tissues. Accordingly it highlights the brain tissues and lightens the non-brain tissues in the MRI image.

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The Contrast stretching (mid-range starching) transformation applied on images is given by

$$g(x,y) = \begin{cases} \alpha * f(x,y) & 0 \le f(x,y) \le a \\ \beta * (f(x,y) - a) + g(x,y) \text{at a} & a < f(x,y) \le b \\ \gamma * (f(x,y) - b) + g(x,y) \text{at b} & b < f(x,y) \le L \end{cases} \quad (1)$$

Where, $L = 2^k-1$ = No of intensity levels, a = L/3, b = 2L/3 and k= No of bits used for intensity levels.

When there is need of contrast stretch, slope of this transformation is chosen to be greater than unity. This transformation is used for mid range stretching of brain MR Images so $\alpha < 1$, $\beta > 1$ and $\gamma < 1$.

5.3 Image Segmentation

Segmentation for brain infected regions from MR images is a crucial task for learning tissue building, computing and eliciting anomalous areas in the brain. In proposed methodology, erosion as morphological function is used for skull stripping and Fuzzy C-means clustering technique is used for segmentation.

Skull stripping is a crucial step in neuro-imaging analysis[8]. Double Thresholding, Erosion and Region Filling are three steps involved in the process of skull stripping of brain MR Images. The double thresholding uses two thresholds viz upper and lower threshold. Since intensity values of brain tissues occupy the range of 0.2 -0.7 so gray-scale image is converted to binary image by adjusting every pixel in the range 0.2*255-0.7*255 to white and the leftover pixels to black. Thus majority of pixels, corresponding to non-brain tissues, are discarded. Thresholding function is given by

$$g(x,y) = \begin{cases} 1 & 0.2 * 255 \le f(x,y) \le 0.7 * 255 \\ 0 & Otherwise \end{cases} \quad (2)$$

Erosion is applied on the image after thresholding. The underlying idea of morphology is to erode an image with a simple, pre-defined shape known as structuring element. Here disk is used as structuring element. This disk eliminates all the undesirable pixels devoted for the skull portion of the image. The erosion of the binary image A by the structuring element B is defined by:

$$A \ominus B = \{z \in E \mid B_z \subseteq A\} \quad (3)$$

Where, E is Euclidean space or an integer grid.

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B_z is the translation of B by the vector z, i.e.

$Bz = \{b + z \mid b \in B\}, \forall z \in E$ (4)

The morphological filtering is used to fill holes in images. In case tumour is acquainted, the obtained eroded image contains holes in the brain MR image. Hence in order to earn the entire skullstrip image containing the tumour portion, the region filling algorithm is used to the generated mask. The conventional imfill algorithm [13], based on morphological reconstruction, is used to fills holes present in the eroded image.

FCM (fuzzy C-means) is a monotonous algorithm based on the principle of fuzzy clustering. Fuzzy clustering uses a membership function to designate a value between zero and one to every pattern [9]. The FCM algorithm [10] partition a finite accumulation of pixels into a collection of "c" fuzzy clusters concerning some already mentioned principle. Several kinds of parallel measures can be resort to analyse classes based on the data and the application. Few cases of values that can be used as similarity measures include distance, connectivity and intensity. In the proposed work, segmentation of images is done into four clusters as white matter, grey matter, CSF and the unusual tumour region based on the feature values.

Fuzzy clustering algorithm is based on optimization of the basic c-means primary function or some alteration of it. The objective function for FCM is given by

$J(X,Y,U) = \sum_{j=1}^{K} \sum_{i=1}^{N} U_{ij}^{m}\, d^2(X_i Y_j)$ (5)

Where, $X = (X_{i,}\ i = l \dots N)$

K: Number of cluster, N: Total number of pixels

Y_j: Centre of i^{th}cluster

$d^2(X_i Y_j)$: Distance between Y_j and the pixel X_i

U_{ij}^{m} : Degree of membership and m: Fuzzy degree

The objective function J is minimized under the following two constraints:

$0 \le U_{ij} \le 1, \forall i \in \{1..N\}\ and\ \forall j \in \{1..K\}$ (6)

$\sum_{j=1}^{K} U_{ij} = 1 \quad \forall i \in \{1, \dots\dots, N\}$ (7)

Taking these constraints into account and computing the first derivatives of J. The matrix U satisfies the conditions:

$U_{ij} = \left(\sum_{i=1}^{k} \left(\frac{d^2(X_i Y_j)}{d^2(X_i Y_j)} \right)^{\frac{1}{m-1}} \right)^{-1} \forall i \in \{1, \dots\dots, N\}$ (8)

$$Y_j = \frac{\sum_{i=1}^{K} U_{ij}^{m} X_i}{\sum_{i=1}^{K} U_{ij}^{m}} \forall\, i \in \{1, \ldots \ldots, N\} \qquad (9)$$

The FCM algorithm constantly mends J by calculating equations 8 and 9, just before the following stop criterion is fulfilled

$$\left\| Y^{new} - Y^{old} \right\| < \varepsilon \qquad (10)$$

Where, ε: Convergence error.

Parameter m represents degree of fuzziness of the partition introduced by[8] .The value of parameter m has an impact on the process of FCM algorithm and according to Besdek [10] the parameter m should be firmly greater than 1.

FCM algorithm is explained in following steps:-

Step 1: Initialize the parameter, X = ($X_{i,}$ i = l ... N)

Step 2: Initialize the matrix U by membership degree arbitrary values in the interval [0,1] and also fulfils the situation in equation 7.

Step 3: Repeat the following steps:

i. Update matrix Y cluster centres in equation 9

ii. Update matrix U degree of membership in equation 10 to obtain stability of the matrix Y.

VI. RESULTS

The proposed methodology is tested on 400 MR brain images which were collected from the different database management website. These datasets include MRI images of several tumour patients of different age groups. The proposed method successfully identifies tumour images and extracts the tumour. Output images at different stages of proposed methodology for four different brain MR images are shown in Fig 2 to Fig 5.

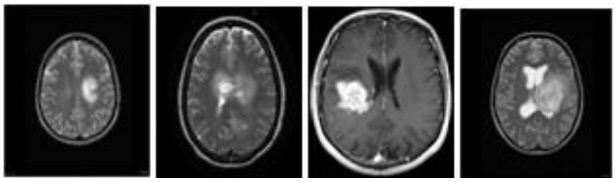

Fig-2: Original Brain MR Images

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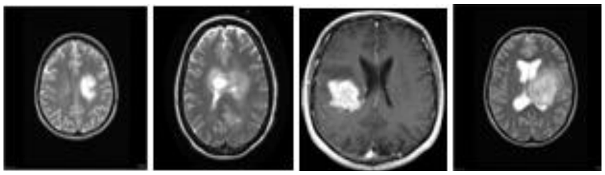

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Fig-3: Enhanced Brain MR Images

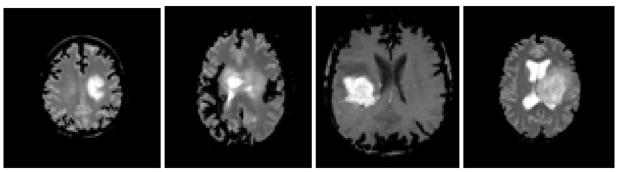

Fig-4: Skull Striped Brain MR Images

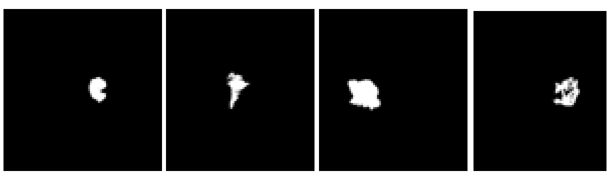

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Fig-5: Cluster Brain MR Images

From the above images it is clear that the hybrid approach of using morphological operation and Fuzzy C-means clustering for segmentation efficiently identified the tumour from the datasets images.

VII. CONCLUSION

Proposed approach combines and cooperate morphological functions and FCM to conquer the restraints confronted in the clustering process. The algorithm is suitable for input MRI images of all sizes since it accordingly extracts the area under consideration. Proposed midrange stretch enhancement has settled to be advantageous in acquiring desired quality image which serves as an input for segmentation. The enhanced images are successfully segmented and the tumour is extracted from images.

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