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Identifying Tumour in Brain Regions from FMRI Results Using Fuzzy Transform

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ABSTRACT: Functional magnetic resonance imaging (fMRI) provides the potential to study brain function in a non-invasive way. Massive in volume and complex in terms of the information content, fMRI data requires effective and efficient data mining techniques. This paper describes the approach for detection and extraction brain tumour from fMRI scan images of brain. To understand the complex interaction patterns, among brain regions we propose a novel clustering called interaction K-means (IKM), an efficient algorithm for partitioning clustering. The segmentation based on F-transform (Fuzzy-Transform) and morphological operations are performed to delineating the brain tumour boundaries and to calculate the area of the tumour. The F-transform is a professional intelligent method to handle uncertain information and to extract the salient edges and morphological operation helps to find the size of tumour and hence the severity can be diagnosed. The experimental results showed that the proposed algorithm produces perfectly accurate performance to brain tumour detection for fMRI brain images.

KEYWORDS: tumour detection from fMRI images, IKM clustering, fuzzy transform, morphological operations.

I. INTRODUCTION

Cancer is now the biggest cause of death in the world. Earlier detection of cancer is the only method to improve the survival rate. Presence of brain cancer can be diagnosed with the help of a CT or MRI scan image. Doctor analyses the CT image and predicts the presence of cancer nodule. This manual detection may have the chances for false detection. So a computerized method for cancer detection is needed. The main advantage of FMRI over CT scan is, it is not contain any radiation. In this paper, FMRI scan employed to implement the system. Several methods have been proposed for brain tumours detection and hence, could diagnose and detected more efficiently. Functional magnetic resonance imaging (fMRI) provides the potential to study brain function in a non-invasive way. The main objective is to find out objects having a similar intrinsic interaction pattern to a common cluster and forms clustering by means of IKM clustering. The segmentation based on F-transform (Fuzzy-Transform) and morphological operations are performed to delineating brain tumour boundaries and calculate the area of the tumour. We propose an automatic brain tumour detection and localization framework that can detect and localize brain tumour in magnetic resonance imaging. The proposed brain tumour detection and localization frame work comprises five steps: image acquisition, pre-processing, interaction clustering, modified histogram clustering and morphological operations. After morphological operations, tumours appear as pure white color on pure black backgrounds.

A. Brain Tumour

Brain tumours may be benign or malignant. Primary brain tumours are originated in the brain, and they do not spread or affect the surrounding tissues. Primary brain tumours also be malignant and affect surrounding tissues and its contain cancerous cells. Primary tumours are composed of cells just like those that belong to the organ or tissue where they start .The secondary brain tumours are spread to the brain from another place in the body. Brain tumours affect the normal brain activity. So accurate detection of tumour is important for human and increase the life expectancy.Brain tumours are classified into Glioblastoma,Gliomas, Medulloblastoma, Ependymomas, CNS Lymphoma, astrocytoma, meningioma and Oligodendroglioma.In medical imaging, an image is captured, digitized and processed for doing segmentation and for extracting important information. Due to the complex structure of brain

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tissues such as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) in the brain images, extracting of useful feature is a fundamental task. The methods aretime consuming. Therefore, there is a strong need to have efficient computer based system that accurately examine the boundaries of brain tissues along with less interaction of user interface.

B.FMRI

Functional Magnetic Resonance Imaging (FMRI) helps to study human brain function or activity in a non-invasive way. It provides an accurate visualize of anatomical structure of tissues. It also use computer to create images of the brain on film. It can also give high quality visualization of the location of activity in the brain resulting from sensory stimulation or cognitive function. It therefore allows the study of how the healthy brain functions, how it is affected by different diseases, how it attempts to recover after damage and how drugs can modulate activity or post-damage recovery. Patients can undergo functional MRIs (FMRI) to help delineate a roadmap of important structures (such as areas that control the arms, legs, or speech) prior to surgery.

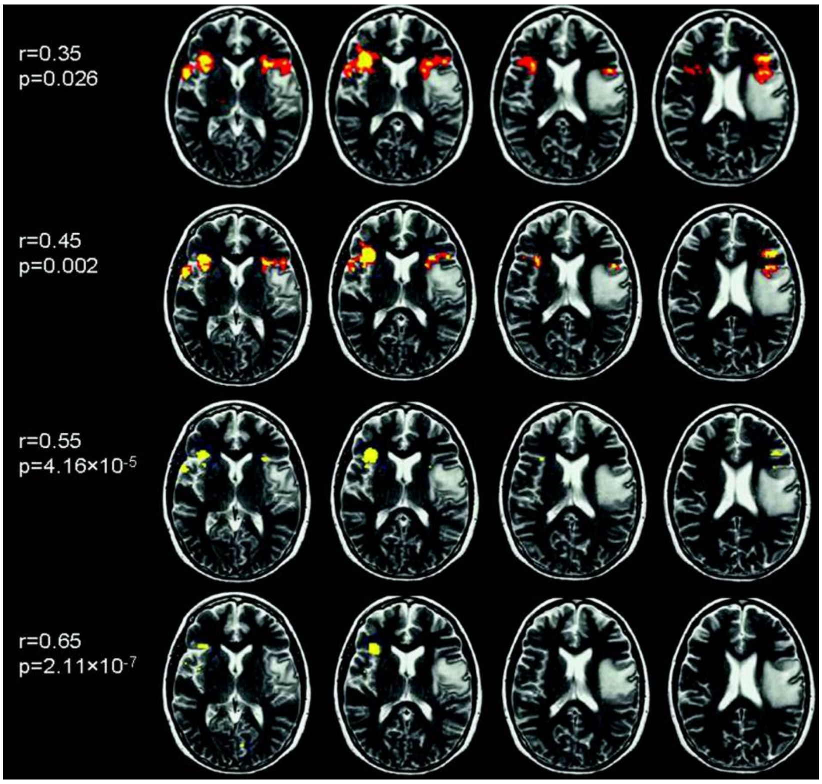

Fig 1 fMRI of Brain Tumor

II. RELATED WORK

In Existing systems authors used water shed methods,Watershed segmentation is a gradient-based segmentation technique. It considers the gradient map of the image as a relief map. It segments the image as a dam. The segmented regions are called catchment basins. Watershed segmentation solves variety of image segmentation problem. It is suitable for higher intensity value images. In marker controlled watershed segmentation, Sobel operator is used to distinct the edge of the objects.Finally, the area of the tumor region is detected by calculating the total number of pixels in which it represents the area of each pixel, horizontal and vertical dimensions of image and resolution of the image. Next, the location of the tumor region is determined. The tumor image obtained from the detection process is divided into two parts. The right part of the image is defined as the left hemisphere of the brain and the left part of the

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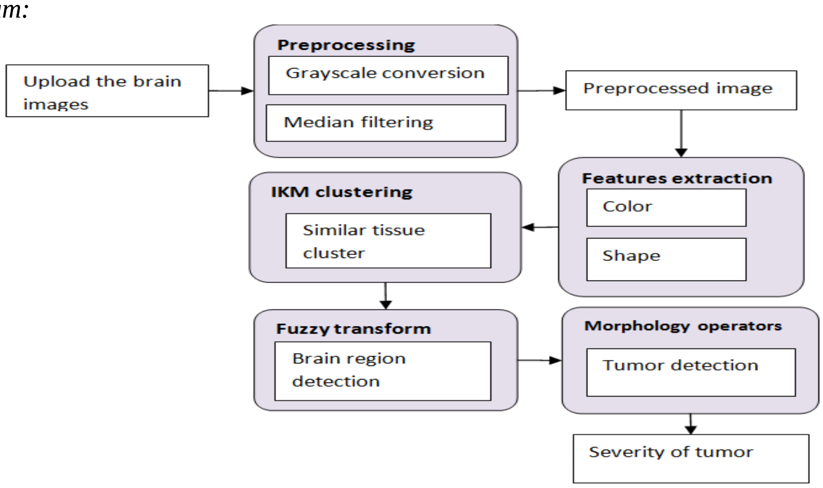
image is the right hemisphere of the brain. Then the total number of pixel for each part is calculated and compared. If the total number of pixel of each part is equal, the tumor is located in the center of the brain Otherwise, the other two conditions are checked out. If the pixel value of the right part of the image is greater than that of the left part, the tumor is located in the left hemisphere of the brain and else the tumor is located in the right hemisphere of the brain.
Region Growing is a region based segmentation method. This method manually selects the seed points. Selection of seed points is based on user criteria. It is an iteration based method like clustering algorithms.In the first step, it manually selects the seed points.In the upcoming steps, pixels in the region of seeds are examined and added to the region accordance with the homogeneity criteria. It will be continued until all pixels belongs to some region.At the last step, the object illustration is done by growing regions of pixels.A mean shift is a non-parametric clustering technique. Mainly, it is used for cluster analysis in computer vision and image processing. Mean shift algorithm clusters an n-dimensional dataset. First defining spherical window of radius r in data points and calculate the mean points within the window. Secondly, the spherical window moves to the next means and repeats until convergence. At each iteration, the spherical window will move to the dense portion of data set until maximum peak is reached.K mean is the unsupervised algorithm that solves the clustering problem. The procedure for k mean clustering algorithm is to segment the image using cluster values. Initially it defines k-centroids. Then, it calculates the distance between each pixel to the selected cluster centroid. Each pixel compares with k clusters centroids and finding distance using distance formula. Repeat the process until all pixels compared with cluster centroids.

III. PROPOSED ALGORITHM

A. *Proposed Methodology:*

A tumor can be defined as a mass which grows without any control of normal forces. Real time diagnosis of tumors by using more reliable algorithms has been the main focus of the latest developments in medical imaging and detection of brain tumor in MR images has been an active research area. The separation of the cells and their nuclei from the rest of the image content is one of the main problems faced by most of the medical imagery diagnosis systems. The process of separation i.e. segmentation, is paid at most importance in the construction of a robust and effective diagnosis system. Images Segmentation is performed on the input images. This enables easier analysis of the image thereby leading to better tumor detection efficiency. Hence image segmentation is the fundamental problem in tumor detection. A number of methods have been proposed in the past for brain tumor detection. After converting the image in the binary format, some morphological operations are applied on the converted binary image. The purpose of the morphological operators is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown as white color. This portion has the highest intensity than other regions of the image. Morphological operators are applied after the segmentation and clustering of image volume information.

B. *Architecture diagram:*



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B. Dataset uploading and pre-processing:

A dataset (or data set) is a collection of data. Most commonly a dataset corresponds to the contents of a single database table or a single statistical data matrix, where each column of the table represents a particular variable, and each row corresponds to a given member of the dataset in question. The dataset lists values for each of the variables, such as height and weight of an object, for each member of the dataset. The data sets are uploaded here. Data pre-processing is an important step in the data mining process. If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take considerable amount of processing time.Data pre-processing includes cleaning, normalization, transformation, feature extraction and selection, etc..,

C. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data .Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved.

D. IKM Clustering:

The algorithm IKM is a general technique for clustering multivariate time series. Increasing amounts of motion stream data are collected in multimedia applications. k-means clustering is a method of vector quantization originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.
An interaction based cluster C is defined by:

- A set of models MC = {MC,1, . . . ,MC,d} representing the dependencies of each single dimension with respect tothe other dimensions. We denote the model of dimension ai of cluster C by MC,i. For model MC,i we apply Vi _{A \ ai} as set of explanatory variables. We will address the question how to find a suitable set of explanatory variables below.
- A set of data objects OC associated to C.
- We denote the error of cluster C by EC which is provided by EC = _di=1EMi .
- The error of object O with respect to cluster C, denoted by EO,C is provided by EO,C = _di=1E1O,Mi .

The aim of interaction-based clustering is to obtain a non overlapping partitioning of *DS* into *K* clusters. Finally, each cluster should represent a specific interaction pattern which is characteristic for the assigned objects. Before addressing the problem of how to find the clusters, we need to describe how the set of models *MC* can be computed from the set of objects *OC* which are associated to a cluster *C*. Since we focus on linear models, this involves solving *d* regression problems. Multiple least square regression can be applied to derive the models.

E. Fuzzy Transform:

fuzzy transform algorithms are used to predict the tumour diseases. The method belonging to fuzzy modelling and discussed in this paper is the fuzzy transform (F-transform).It is a fuzzy approximation method (approximating a functional dependency i.e. a continuous function $f : X \to Y$) based on two transforms - a direct one and an inverse one. It deals with a fuzzy partition of the domain X given by fuzzy sets called basic functions Ai ⊂∼ X i = 1, . . . , n fulfilling several conditions.

Xn i=1 Ai(x) = 1 ∀x ∈ X……………………………. (1)

The technique deals with triangular shaped fuzzy sets or sinusoidal shaped fuzzy sets at most but the shape is not restricted at all so i.e. polynomial basic functions are allowed as well.Usually, the uniform fuzzy partition is used i.e. n equidistant nodes ci = ci−1 + h are fixed and basic functions are determined to fulfillAi(ci) = 1 and Ai(x) = 0 for x

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6∈(ci−1, ci+1). The direct F-transform is a discrete simplified representation of the function f given by a real vector [F1, . . . , Fn] where

Fi = R X f(x)Ai(x)dx R X Ai(x)dx …………………..(2)

Formula (2) represents the center of gravity of function values above the subdomain given by the support of the i-th basic functions which is weighted by membership degrees of elements x to the corresponding basic functions. It means that each component Fi of the F-transform expresses local information about the original function f. This fact is supported by the following equality

Fi = f(ci) + O(h 2)…............……………………... (3)

where h is the step between nodes of a uniform fuzzy partition. Let us stress that similar result is obtained even for non-uniform fuzzy partitions. Obviously, we can observe that the F-transform as a mapping from the space of continuous functions to the space of real vectors is linear. It means that if f, g, ψ are continuous functions on X such that ψ = αf + βg where α, β are real numbers. Then the following equality holds

[Ψ1, . . . , Ψn] = α[F1 . . . , Fn] + β[G1, . . . , Gn]…….. (4)

where [Ψ1, . . . , Ψn], [F1, . . . , Fn] and [G1, . . . , Gn] are the F-transforms of ψ, f and g w.r.t. the given fuzzy partition, respectively [12]. If we deal with an approximation of a function it is necessary to distinguish the approximation among other possible ones. This is usually guaranteed by a minimization of a certain criterion. It is provable that the F-transform components Fi minimize the following piecewise integral least square criterion

Φ(Q1,. . , Qn) = Z X ÃXn i=1 (f(x) − Qi) 2Ai(x) ! dx…(5)

The local closeness of the components to the function values given by (3) makes from the F-transform an appropriate candidate for replacing the original function in complex computations (as usual in many numerical methods). After finishing a numerical algorithm, its approximate result is supposed to be transformed back to the space of continuous functions. For this purpose, the inverse F-transform mapping has been proposed. It is gives a continuous function on X and it is given by a linear combination of the basic functions and the components Fi of the direct F-transform.
i.e. f F n (x) = Xn i=1 FiAi(x)…..……………………(6)

Indeed, the uniform convergence of a sequence of the inverse F-transform to the original function is an essential property. The convergence, local closeness, integral optimality given by (5) and low computational cost promises the F-transform method to be a useful approximation method for practice. Finally, let us recall a discrete version of the direct F-transform which is used in such case when no analytical description is at disposal or its usage is from unspecified reason impossible. Then the components are given as follows

Fi = PN j=1 f(xj)Ai(xj) PN j=1 Ai(xj)dx….………(7)

where (xj , f(xj)) j = 1, . . . , m is a set of (measured) samples which is at disposal and where N >> n, in principle. Of course, a more-dimensional case of any approximation method is highly desirable. Here, we briefly recall a direct extension of the method for functions f : X × Y → Z, for details. If the domain is given by a Cartesian product of two real intervals X × Y then we construct two independent fuzzy partitions, A1, . . . , An ⊂∼ X and B1, . . . , Bm ⊂∼ Y and the direct F-transform is then given by a real matrix composed from components Fij given as follows

Fij = R Y R X f(x, y)Ai(x)Bj (y)dxdy R Y R X Ai(x)Bj (y)dxdy…………….(8)

Obviously, all the mentioned properties (convergence, integral optimality, linearity etc.) are preserved.

F. Morphological Operations:

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Morphological operators are used to predict the tumour regions .Morphological image processing is a group of nonlinear operations related to the shape or morphology of features in an image. The basic morphological operators are erosion, dilation, opening and closing. The structuring element is tiny binary images with a small matrix of pixels take a value of zero or one. The matrix dimensions identify the size of the structuring element. The pattern of ones and zeros specifies the figure of the structuring element. An origin of the structuring element is regularly one of its pixels, although normally the origin can be outside the structuring element. The primitives of morphological operations are erosion and dilation.Erosion and dilation are dual operations with respect to set complementation. In this paper, erosion is applied to detect the tumour.The **erosion** of a binary image f by a structuring element s (denoted $f \ominus s$) produces a new binary image $g = f \ominus s$ with ones in all locations (x,y) of a structuring element's origin at which that structuring element s fits the input image f, i.e. $g(x,y) = 1$ is s fits f and 0 otherwise, repeating for all pixel coordinates (x,y).Computes a global threshold that can be used to convert an intensity image. Compute the morphological operation as shown above.The extracted region is then logically operated for extraction of massive region in given MRI image. Show only tumour portion of the image by remove the smallobject area. The area of the tumour region is calculated. The area of the tumour region is found by multiplying horizontal dimension,vertical dimension of the image with total number of pixelin the tumour region. the result of the proposed algorithm shows thefinal extracted brain tumour from MRI image.

IV. RESULTS

Thus the fMRI image with tumour area is shown as white region in same location as in input image using morphological operations. By using the results from morphological operations this system identifies the size of tumour region which helps to decide the severity of tumour.

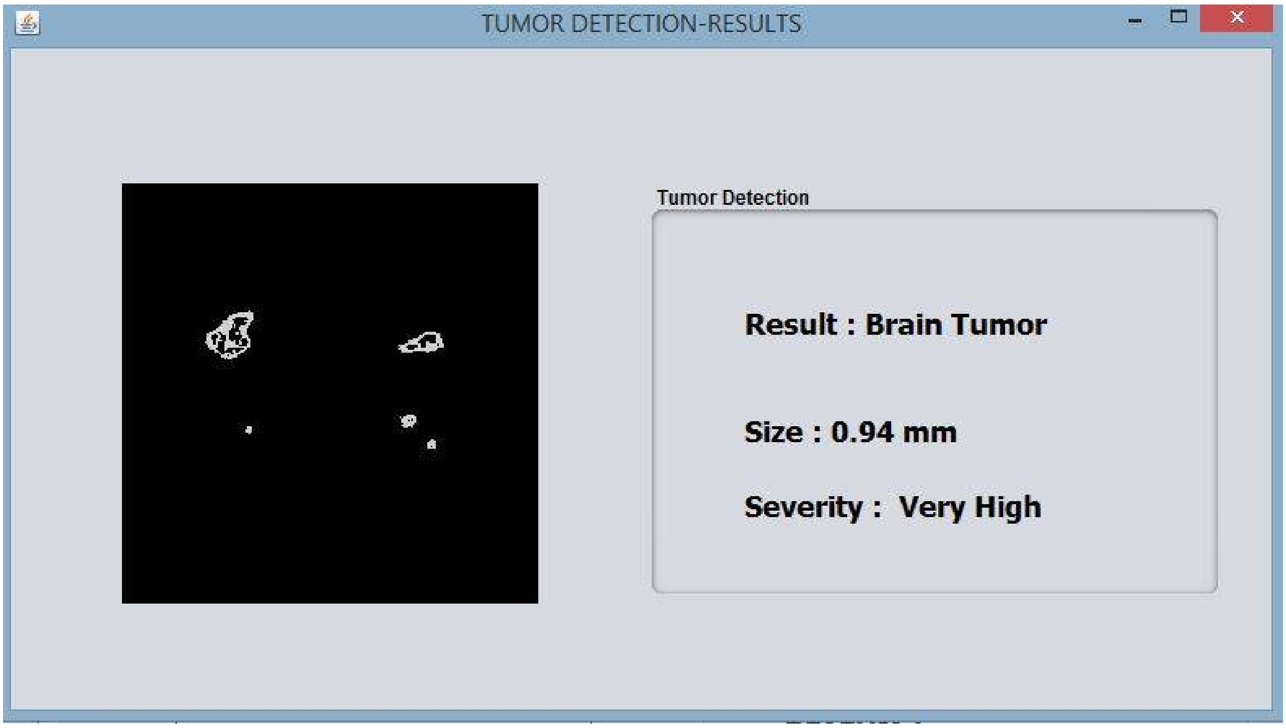

Fig.2 image showing tumor region and its size

V. CONCLUSION AND FUTURE WORK

This work has attempted to segment out the fMRI Brain scans utilizing interaction clustering with fuzzy transform strategy for recognition of tumor. Combination of brain region extraction with separating methods had

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known to be beneficial for the methodology of division of remedial images as preprocessing dislodged the undesirable noise from the scan images. Features extraction has been done to parameterize the capability of the method. The proposed strategy is producing great results for cerebrum fMRI images utilizing straightforward and simple approach.A new approach for cancer detection, which may be based on combination of matrix transformations techniques which not only reduce computational overhead but also reduces computational time. The transformations methods may be based on contrast and cluster shade gradient between the highly diffused tissue matters of brain. By doing this prominence of tumor in increased and easily mark able even when the contrast based artifacts are more.

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