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Brain Tumor Segmentation Based on GLCM Feature Extraction using Probabilistic Neural Network

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Abstract:
The paper presents the MRI brain diagnosis support system for structure segmentation and its analysis using K-means clustering technique integrated with Fuzzy C-means algorithm. The method is proposed to segment normal tissues such as White Matter, Gray Matter, Cerebrospinal Fluid and abnormal tissue like tumour part from MR images automatically. These MR brain images are often corrupted with Intensity In homogeneity artefacts cause unwanted intensity variation due to non- uniformity in RF coils and noise due to thermal vibrations of electrons and ions and movement of objects during acquisition which may affect the performance of image processing techniques used for brain image analysis. Due to this type of artefacts and noises, sometimes one type of normal tissue in MRI may be misclassified as other type of normal tissue and it leads to error during diagnosis. The proposed method consists of pre-processing using Gaussian filter to remove noise and K-means clustering technique integrated with Fuzzy C-means algorithm segments normal tissues by considering spatial information because neighbouring pixels are highly correlated and also construct initial membership matrix randomly. The results will be presented as segmented tissues and classification using neural network classifier.

Index terms: MRI images, SFCM, feature extraction, segmentation.

1. INTRODUCTION

In today's digital era, storing and analysis of medical image had been digitized. Even with state of the art techniques, detailed interpretation of medical image is a challenge from the perspective of time and accuracy. The key task in designing image processing and a computer vision application is the accurate segmentation of medical images. The Computed Tomography Scanner (CT scanner) and MRI is one of the most revolutionary healthcare machines developed in the 21st century. The CT scanner was founded on a technique where images of tissues were depicted on radiographic film. MRI and CT Scans are used in the field of identifying the internal parts of the human body, especially for Brain Tumors (BT). The tumor cell is contemporary within skull and grows within skull and it is called primary tumor. Malignant brain tumors are primary brain tumors. The tumor presents outside the skull and enter into the skull region called secondary tumor. Metastatic tumors are examples of secondary tumors. The tumor takes up place in the skull and hamper with the traditional operating of the brain. Tumor shifts the brain towards skull and increases the pressure on the brain. Disclosure of tumor is the first step in the doctoring. Brain contains more number of cells that are interconnected to one another. Peculiar cells control different parts of the body. Some cells control the leg movement, likewise others cells of the brain controls other parts in the body. Brain tumors may have different types of syndrome ranging from headache to stroke, so symptoms will vary depending on tumor location. Different location of tumor causes different functioning disorder. The segmentation of brain tumors in magnetic resonance images (MRI) is denounce and ambitious task because of the variety of their conceivable shapes, locations, image intensities. The aim of this paper is to contribute to this domain, by proposing an original method, which is automatic and general enough to address the variability issues. Existing methods are classically prorated into region based and contour based methods, and is usually enthusiastic to full enlarged tumors or clear-cut types of tumors. In the first class, Clark et al. [1] have proposed a method for tumor segmentation using knowledge based and fuzzy classification, where a learning process prior to segmenting a set of images is necessary. Other methods are based on statistical pattern recognition techniques such as [2–4]. These methods fail in the case of large deformations in the brain. Existing contour based methods are not fully automatic and need some manual operation for initialization. Lefohn et al. [5] have proposed a semiautomatic method using level sets. Another segmentation method based on level sets was introduced by Ho et al. [6] that uses T1-weighted images both with and without contrast agent for tumor detection.

2. LITERATURE SURVEY

A) Robust Fuzzy Local Information C-Means Clustering Algorithm: This paper presents a variation of fuzzy c-means (FCM) algorithm that provides image clustering. The proposed algorithm incorporates the local spatial information and gray level information in a novel fuzzy way. The new algorithm is called fuzzy local information C-Means (FLICM). FLICM can overcome the disadvantages of the known fuzzy c-means algorithms and at the same time enhances the clustering performance. The major personality of FLICM is the use of a fuzzy local (both spatial and gray level) harmony measure, aiming to guarantee noise insensitiveness and image detail preservation. Furthermore, the proposed algorithm is fully free of the empirically adjusted parameters incorporated into all other fuzzy c-means algorithms proposed in the literature. Experiments achieve on fabricated and realworld images show that FLICM algorithm is compelling and efficient, providing robustness to noisy images. [24]

B) Region Entropy Based Objective Evaluation Method for Image Segmentation: Many image segmentation methods have been proposed over the last few decades. However, the results of segmentation are usually evaluated only visually, qualitatively, or indirectly by the effectiveness of the segmentation on the subsequent processing steps. Such methods are each of two intuitive or tied to particular applications. A few quantitative evaluation methods have been proposed, but these early methods have been based entirely on empirical analysis and have no theoretical grounding. In this paper, we put forward the concept of segmentation entropy, based on which a novel objective segmentation evaluation method is proposed. This method uses region entropy as the basis for measuring the uniformity of pixel characteristics within segmented regions and segmented entropy as a whole measure to provide a relative approximate score that can be used to compare both various parameterizations of one scrupulous segmentation Method as well as fundamentally different segmentation techniques. [25]

C) Local-based Fuzzy Clustering for Segmentation of MR Brain Images: Accurate segmentation of magnetic resonance images (MRI) corrupted by intensity in homogeneity is a challenging problem and has received an enormous amount of attention lately. On the basis of the local image model we propose a different segmentation method for MR brain images without estimation and correction for intensity heterogeneity. Firstly, we obtain clustering context based on the distributing disciplinarian in anatomy that gray matter (GM) is always between white matter (WM) and cerebrospinal fluid (CSF) in brain, which ensure the three tissues exist together in each one. Then the size of the context is optimized by a minimum entropy criterion. Finally, FCM algorithm is independently performed in each context to calculate the degree of membership of a pixel to each tissue class. The proposed methodology has been evaluated for simulated images and shown the better results. [26]

D) Combined Wavelet and Curvelet Denoising of SAR Images using TV segmentation: Fabricated aperture radar (SAR) images are debouched by speckle chattering due to random interference of electromagnetic waves. The freckle degenerate the aspects of the images and makes interpretations, analysis and classifications of SAR images harder. Therefore, some speckle abatement is necessary prior to the processing of SAR images. The freckle chatter can be modelled as multiplicative *i.i.d.* Rayleigh chatters. The discrete curvelet transform is a new image representation approach that codes image edges more efficiently than the wavelet transform. On the other hand, wavelets transform codes homogeneous areas better than curvelet transform. In this paper, two combinations of time invariant wavelet and curvelet transforms will be used for de-noising of SAR images. Both of the methods use the wavelet transforms to de-noise homogeneous areas and the curvelet transform to denoise areas with edges. The segmentation between homogeneous areas and areas with edges is done by using total variation segmentation. Simulation results suggested that these de-noised schemas can achieve good and clean images. [27]

E) Lip contour extraction using RGB colour space and fuzzy c-means clustering: Lip contour extraction is very important issue in visual speech recognition systems (lip reading). To extract the lip contour, proper segmentation is needed. There are many approaches for image segmentation such as colour segmentation (histogram-based and clustering-based) that have been widely used in different areas. In this paper we use RGB colour space and fuzzy C-means clustering for lip segmentation. Compared to previous methods, we obtain a simple feature for lip region extraction using RGB components which can be used as input to C-means clustering algorithm for lip region extraction. Then the outputs of the C-means clustering algorithm are fed into active contour model to obtain final lip region. We tested the proposed algorithm with different images and results showed good segmentation for different speakers with different illumination. [28]

3. EXISTING SYSTEM

- Partial derivatives
- Wavelet based de-noising
- Thresholding and K means clustering methods for segmentation

4. PROPOSED SYSTEM

The Paper proposes to spot the tumor from MRI scanned medical images using multi clustering model and morphological process. The segmentation refers to the process of partitioning a digital image into multiple segments. The brain MRI is taken and its noises are removed using filters and then applied spatial Fuzzy C means Clustering algorithm for the segmentation of MRI brain images. The morphological process will be used to smooth the tumor region from the noisy background. The segmented primary and secondary regions are compressed with hybrid techniques for telemedicine application.

5. METHODOLOGIES

5.1) DT-CWT
5.2) GLCM
5.3) PNN
5.4) SFCM

5.1) DT-CWT

The multidimensional (M-D) dual-tree CWT is no detachable but is based on a ciphering adequate, separable filter bank (FB). The theory behind the dual-tree transforms shows how compound wavelets with good properties can be designed, and illustrates a range of applications in signal and image processing. We use the manifold number symbol C in CWT to avoid distractions with the often-used acronym CWT for the (different) continuous wavelet transform.

5.2) GLCM

The gray-level co-occurrence matrix can proclaim secure properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. To illustrate, the following figure shows how Graycomatrix foretell the first three values in a GLCM. In the output GLCM, element (1, 1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. GLCM (1, 2) encompass the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the

GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Graycomatrix unbroken processing the input image, scanning the image for other pixel pairs (*i,j*) and recapitulate the sums in the corresponding elements of the GLCM.

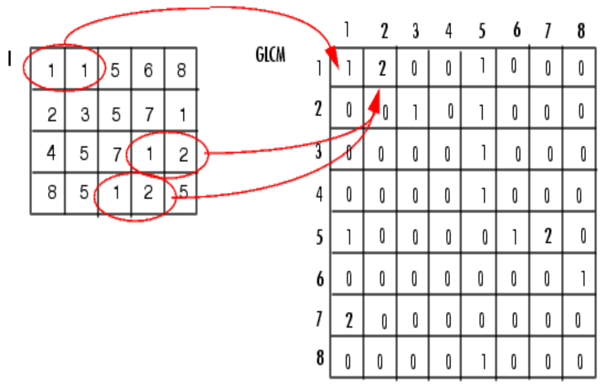

Figure.1.glcm feature selection

FEATURE EXTRACTION

Feature extraction is a crucial step in the foundation of any pattern classification and aims at the extraction of the relevant information that characterizes each class. In this process relevant features are extracted from objects/ alphabets to form feature vectors. These feature vectors are then used by classifiers to recognize the input unit with target output unit. It becomes easier for the classifier to classify between different classes by looking at these features as it allows fairly easy to distinguish. Feature extraction is the growth to reacquire the most important data from the raw data. Feature extraction is finding the set of parameter that define the shape of a character precisely and uniquely. In feature extraction phase, each character is delineated by a feature vector, which becomes its integrity. The major goal of feature extraction is to extract a set of features, which maximizes the recognition rate with the least amount of elements and to generate similar feature set for variety of instance of the same symbol. The widely used feature extraction methods are Template matching, Deformable templates, Unitary Image transforms, Graph description, Paperion Histograms, Contour profiles, Zoning, Geometric moment invariants, Zernike Moments, Spline curve approximation, Fourier descriptors, Gradient feature and Gabor features.

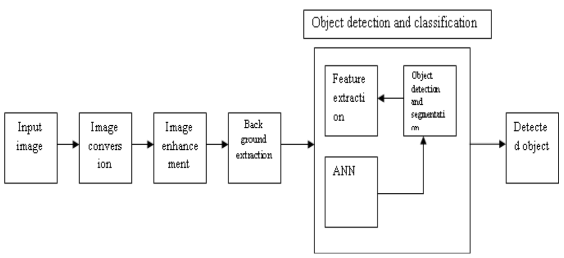

Figure.2.Feature extraction

5.3) PNN

Probabilistic (PNN) and General Regression Neural Networks (GRNN) have collateral architectonics, but there is a integral inequality: Probabilistic networks perform classification where the target variable is categorical, whereas general regression neural networks percolate regression where the intention variable is continuous. If you select a PNN/GRNN network, DTREG will erratically favoured the factual type of network based on the type of target variable.

Architecture of a PNN:

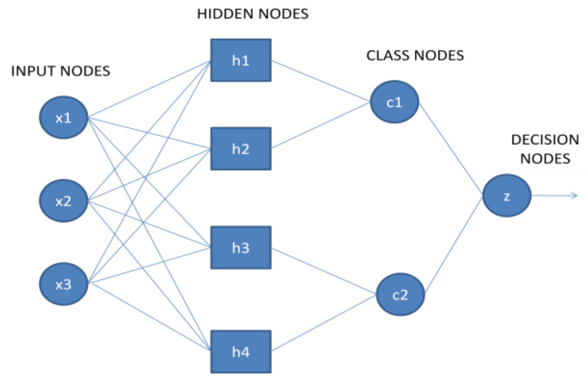

Figure.3.PNN architecture

How PNN network work:

Probabilistic neural networks are rudimentary coincidental to *K-Nearest Neighbour* (k-NN) models. The basic idea is that a conjecture target value of an item is inclined to be about the look-alike as other items that have close values of the conjecture variables. Consider this figure:

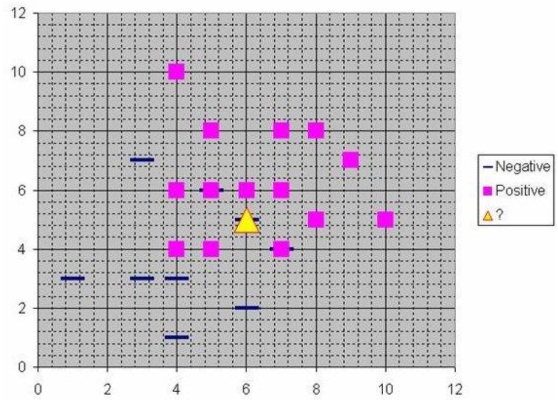

Figure.4.working with PNN

Predicate that each case in the training set has two forecaster variables, *x* and *y*. The cases are sketch using their *x,y* accommodates as shown in the figure. Also predicate that the forecaster variable has two pigeonholed, *positive* which is symbolize by a square and *negative* which is symbolize by a dash. Now, suppose we are trying to forecast the value of a new case delineated by the triangle with forecaster values *x*=6, *y*=5.1. Should we forecast the target as positive or negative? Notice that the triangle is position almost exactly on top of a dash illustrating a negative value. But that dash is in a fairly noteworthy position set side by side to the other dashes which are clustered below the squares and left of centre. So it could be that the substrata negative value is an odd case.

5.4) SFCM

Neighbouring pixels possess highly correlated intensities, and probability of their belongingness to the same cluster high .therefore spatial relationship is important of clustering. In other words, these neighbouring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This geographical relationship is paramount in clustering, but it is not utilized in a standard FCM algorithm. To exploit the spatial information, a spatial function is defined as

$$hij = \sum_{k \in NB\,(xj)} (u_{ik}) \text{.....................} \quad (1)$$

Where NB (x j) impersonates a square window focalized on pixel x j in the geographical domain. A 5! 5 windows were used brought out this work. Just like the membership function, the geographical function hij impersonates the anticipation that pixel x j belongs to ith cluster. The geographical function of a pixel for a cluster is large if the superiority of its propinquity belongs to the same clusters. The geographical function is assimilated into membership function as follows:

$$u_{ij} = u_{ij}^{p} h_{ij}^{q} / \sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q} \text{ .... (2)}$$

P and q are parameters to control the relative importance of both functions. In unvarying region, the geographical functions simply fortify the original membership, and the clustering result remains unchanged. However, for a clamorous pixel, these formulas diminish the weighting of a clamorous cluster by the labels of its neighbouring pixels. As a result, misclassified pixels from clamorous or specious splotch can effortlessly be reformed. The geographical FCM with parameter p and q is symbolize SFCM p, q. Note that SFCM1, 0 is interchangeable to the decorous FCM.

5.4.1) SFCM ALGORITHM

1. As in the standard FCM, initialize cluster centres v is fuzzification parameter m and the value ∈> 0

2. Calculate the membership matrix u= $[u_{ij}]$ in the feature space according to equation (2).

3. Map the membership from the feature space to the spatial domain and calculate the spatial function according to algorithm (1). Clustering is procedure with the new membership that is the result of spatial function from the equation (2).

4. Update the cluster centres with equation.

5. If $|U^{(1+1)} - U^{(1)}| \leq \in$, where is the iteration number, then go to step2.

6. Calculate final cluster centres.

7. Perform the maximum membership segmentation.

6. RESULT:

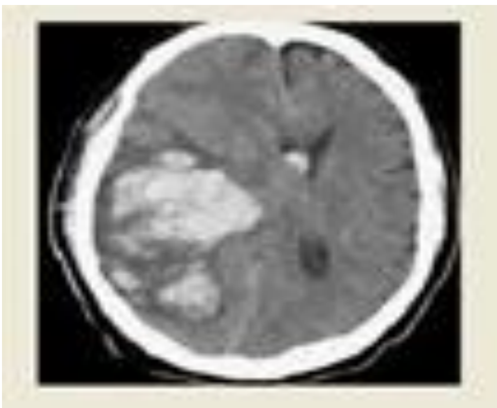

Figure.5.Input image

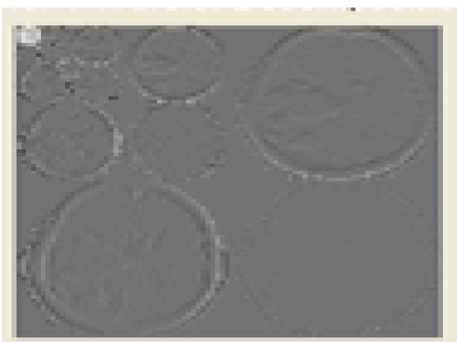

Figure.6. Feature extracting an image

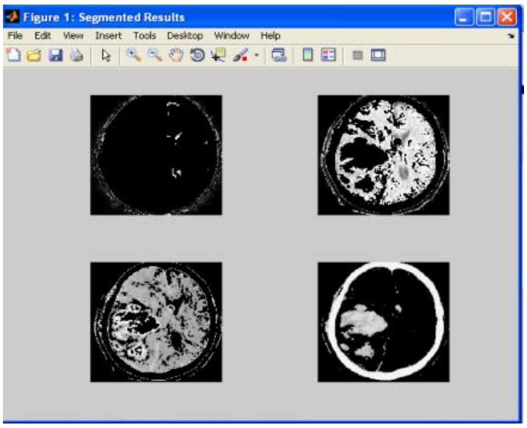

Figure.7. Segmented results

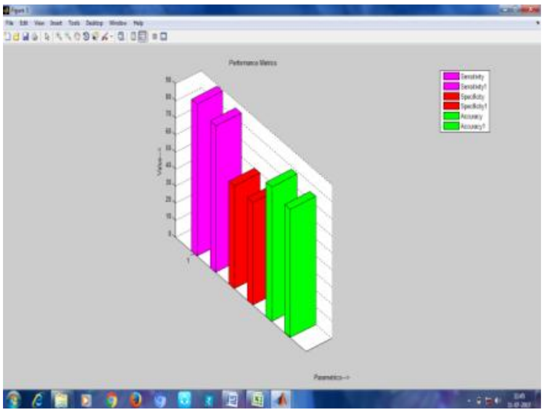

Figure.8. Comparison of existing and proposed

7. CONCLUTION

The miniature was also certified profitably by using guidance set data. The consequence has shown very fewer amount of inaccuracy to the actual output data. Therefore a PNN using probability frequency function and Bayes's decision rule can be worn as a countermeasure for designation obstacle with full aggregate of Training and Learning. Farther other soft figure out tools can be worn for inaccuracy comparison.

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