An Integrated Method of MRI Brain Image Segmentation using Bias Field Correction Based Modified FCM Algorithm

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Abstract- The aim of this paper is to propose a new integrated method for medical MRI image segmentation using bias field correction based a modified FCM algorithm. The magnetic resonance imaging has become one of the most important forms of medical imaging for the diagnosis, prevention and monitoring of neurological disorders. In particular, the diffusion weighted imaging (DWI Diffusion-Weighted Image) is highly sensitive to achieve early detection of ischemic changes in the acute phase of stroke. This paper presents the application and comparison of an adaptive segmentation method previously developed and validated, using a technique of estimating nonparametric including bandwidth intensive or radiation variables, in order to quantify the area of the lesion ischemic cerebral infarction caused by only from the information contained in the DWI images. The method was applied to real images, keeping all parameters constant during the segmentation process for the entire database.

Key words : MRI, segmentation, FCM, Bias field correction, DWI.

INTRODUCTION

The magnetic resonance image has become one of the medical imaging modalities more important for the diagnosis, prevention and monitoring of neurological disorders. In particular, the DWI is highly sensitive to achieve. Diffusion weighted imaging (DWI) is a specialized magnetic resonance imaging technique that depends on the random movement of water molecules inside and between the intracellular and extracellular spaces. Regions with restricted mobility of water molecules yield a greater DW-MRI signal and appear bright[1]. In apparent diffusion coefficient (ADC) maps, regions that contain high water mobility appear bright. Measurement of ADC would be expected to be useful in brain tumor assessment because variations in water mobility can be found within tumors for various reasons (e.g. necrosis, variations in cellularity) and adjacent to tumors (e.g. vasogenic edema), this likely provides information not readily available from conventional MR imaging [2]

Fig 1._T2 MRI of brain

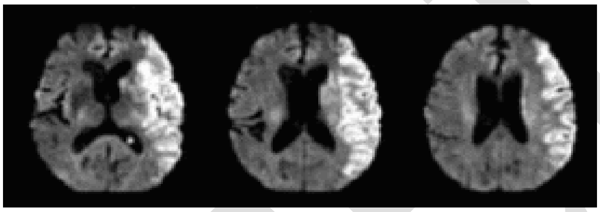

Fig 2. DWI of brain

this type of imaging features on other imaging modalities, as are its high spatial resolution, excellent soft tissue discrimination and the fact be virtually non-invasive technique. MRI provides a highly effective means of observing brain anatomy. Since the morphometric analysis provides quantitative measurements of location, volume, shape and homogeneity of components of brain structures[4]. This type of analysis, together with neuropsychological, neurological, psychiatric and functional neuroimaging coupled with observations can be used to answer questions about brain structure and function.

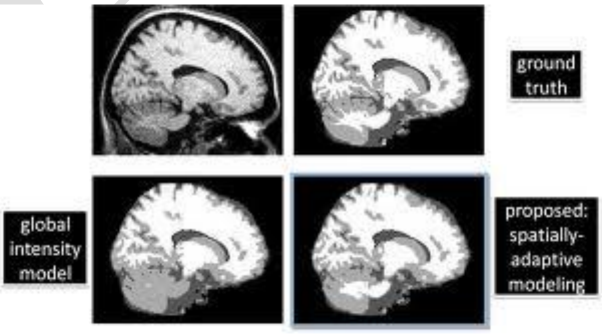

Fig 2. Brain Tissue Segmentation

The study through images of structural brain changes can provide useful information for diagnosis and clinical management of patients with dementia. Magnetic Resonance Images can show abnormalities that are visible on the CT not scanning. They also have the potential to detect abnormal signals, enabling a diagnosis difference between Alzheimer's disease and vascular dementia.

While in vascular dementia direct observation of MR images allows immediate diagnosis, structural analysis of this same type of images in Alzheimer's disease has a very important role and complex because it allows assessing changes such as cortical atrophy [6]. While this cellular manifestation of the disease cannot be studied in live atrophy that occurs can be observed in the MR images cerebral and quantified from Digital Image Processing [8]. The objective of this work is classified, without professional intervention, the image in white matter (WM), gray matter (GM), cerebro-spinal fluid (CSF), blood vessels (BV), tumor and edema (Figure 1). The white matter is distributed within the cortex, while that on the outside thereof is located gray matter; cerebro-spinal fluid, by its part, flows into the cerebral ventricles, the subarachnoid space and the ependymal canal [13].

Image clustering of various malignant brain tumor tissues of microscopic range in H&E Stain are analyzed through Euclidean distance metric and Fuzzy K-Means clustering and this method can be used for pattern recognition because it provides a good object separation. Developing such tools for characterizing and effectively classifying texture patterns in medical images would greatly assist in the interpretation of clinical images and in investigating the relationship between descriptors of texture and branching patterns and the associations between morphology and function or pathology[15].Manual segmentation of brain tumors by medical practitioners is a time consuming task and has inability to assist in accurate diagnosis. Several automatic methods have been developed to overcome these issues. But Automatic MRI (Magnetic resonance Imaging) brain tumor segmentation is a complicated task due to the variance and intricacy of tumors to over by this problem we have developed a new method for automatic classification of brain tumor. In the proposed method the MRI Brain image classification of tumors is done based on Fluid vector flow and support vector machine classifier. In this method Fluid Vector Flow is utilized for segmentation of two dimensional brain tumor MR images to extract the tumor and that tumor can be projected into the three dimensional plane to analyze the depth of the tumor. Finally, Support vector machine classifier is utilized to perform two functions. The first is to differentiate between normal and abnormal. The second function is to classify the type of abnormality in benign or malignant tumor[16].The Proposed system consists of multiple phases. First phase consists of Preprocessing and segmentation, the second phased consists of first order and second order GLCM (Gray level Co-occurrence Matrix) based features extraction from segmented brain

MR images. Third phase classify brain images into tumor and non-tumors using Feed Forwarded Artificial neural network based classifier. After classification tumor region is extracted from those images which are classified as malignant using two stage segmentation process. Experiments have revealed that the technique was more robust to initialization, faster, and precise[17].The proposed method consists of four stages namely Preprocessing, feature extraction, feature reduction and classification. In the first stage anisotropic filter is applied for noise reduction and to make the image suitable for extracting the features. In the second stage, Region growing base segmentation is used for partitioning the image into meaningful regions. In the third stage, combined edge and Texture based features are extracted using Histogram and Gray Level Co-occurrence Matrix (GLCM) from the segmented image. In the next stage PCA is used to reduce the dimensionality of the Feature space which results in a more efficient and accurate classification. Finally, in the classification stage, a supervised Radial Basics Function (RBF) classifier is used to classify the experimental images into normal and abnormal. The obtained experimental are evaluated using the metrics sensitivity, specificity and accuracy. For comparison, the performance of the proposed technique has significantly improved the tumor detection accuracy with other neural network based classifier SVM, FFNN and FSVM [19].

The combination of segmentation, edge detection regions proved automatic and robust technique segmentation from sequences DWI infarcted brain regions cerebrovascular. Ischemic Compared with segmentation reference control injuries, brain, the segmentation technique was evaluated in this study had a high quantifying significant correlation average lesion volume (r = 0.938, p <1.2x10-9) and the average value of the Average apparent diffusion coefficient (r = 0.906, p <4.02x10 -8). This method has proven to be desirable for the quantification infected injury accidents ischemic brain.

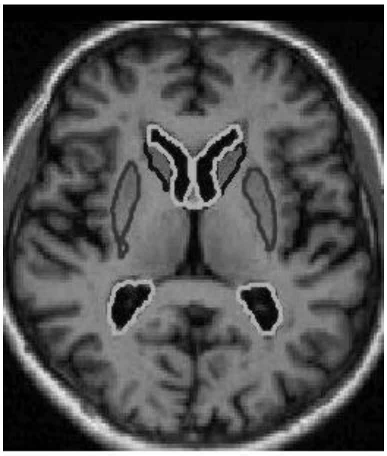

Fig 3. Image of an axial slice through the brain showing segmentations of some subcortical structures

This paper proposes to implement and evaluate a bias field correction based segmentation algorithm for FCM ischemic lesions segmentation, brain images from DWI, which turn is based on confidence map's edges. The proposed method segmentation is completely run by the information contained in the images DWI[12]. In this context, the MRI sequences may contribute to reduce the huge social impact a stroke as long as they can be analysis tools provided with images for accurate and immediate distinction of ischemic tissues in the region already affected by an infection. As in the case of other pathologies are not ischemic CNS (CNS Central Nervous System), MRI can help reveal the hemodynamic change of tissue ischemia induced.

METHODOLOGY

This paper proposes to implement and evaluate a technique bias field correction based Modified FCM algorithm for segmentation of brain from ischemic injury, DWI images, which is considered a wide variable intensity band is based in turn on confidence map's edges. The proposed segmentation method is completely run by the Information in DWI images, not required to adjust the parameters of the algorithm individually and has no need of any correction procedure of the image sequences, so we consider the technique is shown to be robust in the DWI case process images and segment cerebral ischemic injury.

$$\leq \sum_{i=1}^{n_{SV}} |(\alpha_i - \alpha_i^*)| \cdot |K(\mathbf{x}_i, \mathbf{x})| \quad (1)$$

$$\leq \sum_{i=1}^{n_{SV}} C \cdot |K(\mathbf{x}_i, \mathbf{x})| \quad (2)$$

An improved estimation algorithm CM may be obtained by including a weighting in the slicer, the weights being as far

$$K(\mathbf{x}_i, \mathbf{x}) = \exp(-\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2p^2}) \quad (3)$$

Number significant clusters present in the feature space are automatically determined by the number of significant trends detected

$$|f(\mathbf{x})| \leq C \cdot n_{SV} \quad (4)$$

The number of Cu-significant stimuli present in the feature space is determined automatically by the number of significant trends detected

$$R_{pred}(\omega) = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (y_{t\arg et} - f(\mathbf{x}_{test}, \omega))^2 \quad (5)$$

$$\hat{\sigma}^2 = \frac{n}{n-d} \cdot \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (6)$$

$$\hat{\sigma}^2 = \frac{n}{n-d} \cdot \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (7)$$

$$= \frac{n}{n - \frac{n}{k}} \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (8)$$

A precise diagnosis of the acute stage cerebral ischemic injury is extremely important for treatment and prognosis. Likewise, knowing the size and location of the lesion detected early during therapeutic window is critical. The visualization of the lesion may help predict cognitive consequences functional patient.

In step early ischemia, the technique of Computed tomography is the method that has been used to distinguish between ischemic and hemorrhagic stroke. Without But with CT only 30% to 60% of ischemic lesions are still invisible in an acute stage. Moreover, during the first hours after the start ischemic infarction MRI has 20%, 30% of false-negative results and this percentage increased from 30% to 50% during the first 3 to 6 hours after the onset of symptoms infarction. Because the above, the conventional CT or MRI is not generally used to predict the presence and extent of ischemic damage in the acute stage of stroke.

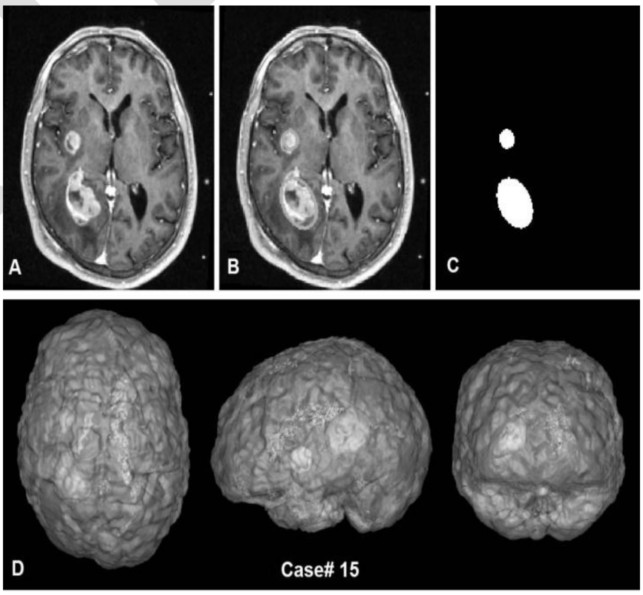

Fig 4. Tumor-Brain Automatic Detection and Segmentation

In this paper the MRI sequences could help to reduce the huge social impact of a stroke, if image analysis tools for accurate and immediate distinction of a tissue ischemic region already affected by an infection can be provided. As in the case of other conditions, which are not Ischemic Central Nervous System (SNC), MRI can help reveal hemodynamic and tissue changes induced ischemia. This proposal allows detecting and quantifying the different tissues a brain, automatically more sensitive and considerably less opinion and thus a first step towards early diagnosis of atrophy cerebral.

RESULT

The segmentation method was not for CM responsive to the case where the patient ischemic injury volume was small 3D segmentation methodology proposal can be summarized as presented below. Calculation trusted edge map from the data to be segmented. Filtered through the process and WPS. Analysis adjacency of regions, using transitive closure operations and pruned. It was less than 50%, in these ischemic injury cases control was formed by several small regions and only by the automatic method was segmented one, or is other brain regions were cleaved as part of an ischemic injury when there are also techniques and atlas-based segmentation have been proposed to solve the problem of segmentation of pathological lesions from conventional MRI. Although segmentation methods work well atlas-based segmentation of pathological regions from conventional MRI is difficult to use in the case of ischemic damage due to the overlap of currents in a DWI sequence exists between the infarct region and normal tissue. Also, many of the segmentation techniques discussed and reported ischemic lesions in the area of strokes require initial considerations, such as the number of tissue classes present in the image, a database of multi-parametric data, rankings, multi-level and requirements for pre-processing of the image to correct bias, either a local or global registration between an atlas and the MRI of the patient.

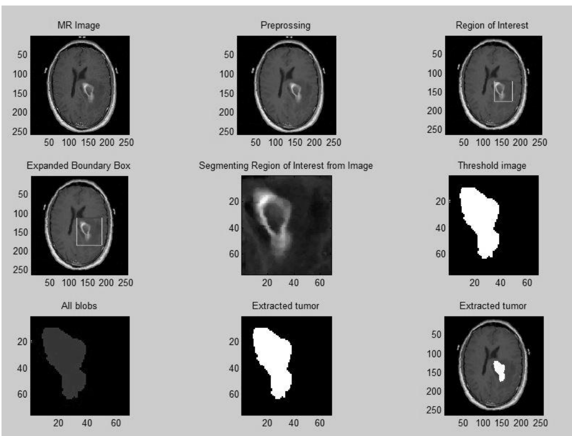

Fig 5. MATLAB Image Segmentation

A segmentation method based on DWI sequences has been proposed for finding the volume of ischemic injury, which is exclusively guided by the data and information I contained in the image, based on the CM algorithm fixed radius and requires No statistical consideration priori, or any kind of initialization or preprocessing of the image. The method threw good and promising results. It was a robust estimation method, without. But the disadvantage is presented that was not sensitive to injury ischemic whose volume was small. However, one advantage is that a fixed set of parameters required for the method only once so initially, so must not be set for each subject, and was regarded as a robust estimate since neither require any procedure correction a priori.

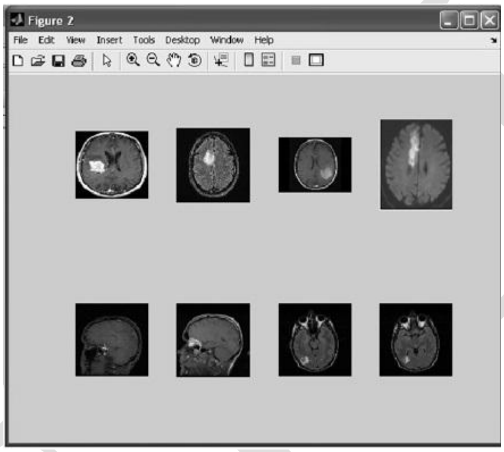

Fig 6. Modeling for Image Analysis of Brain Tumor

Segmenting the initial volume of an ischemic injury is considered of great diagnostic importance and clinical evaluation in decision making on the type of thrombolytic therapy in patients who have suffered a myocardial acute cerebral. We can conclude that the CM method is fully evaluated Guided by the information contained in the DWI, using a parameter set requiring no fixed set for each subject, plus the use of maps confidence edges so preserved edges suitable ischemic injury and is a robust estimate because not require any correction process prior.

DISCUSSION AND CONCLUSION

The approach is fully automatic, so that plays a role important in the clinical evaluation of treatment of ischemic stroke cerebral. This paper presents a method for automatic image segmentation Brain MRI. The method is accurate and efficient, being the results practically independent expert. The GRNN is involved in the process builds and trains from a single image, allowing classify other images taken with the same protocol with less than 1% error, and a very low computation time, characteristic of the consultation stage of the type neural networks used. The success of the segmentation depends subsequent quantification of the gray and white matter and CSF measurement therefore the evolution of brain atrophy A parametric Fluid Vector Flow (FVF) active contour model is utilized for automatic segmentation of tumor in brain MR images and the segmented tumor is visualized in three dimensions for depth analysis. Since a tumor doesn't exhibit any prior shape, delineating the tumor accurately is a difficult task.

FVF is utilized for segmentation because it can deform in all directions for capturing the tumor. It also addresses the issues of limited capture range and the inability to extract complex contours with acute concavities.Segmentation aids in visualization of area of tumor[14].

In this methodology, we have fostered a striking tumor revealing technique by maneuvering kernel ascertained SVM . The propositioned outlook encompasses of preprocessing, segmentation, feature extraction and classification. In a preprocessing step, the noise is jettisoned and to instigate the image appropriate for the ensuing stages. In segmentation stage , the neoplasm regions are dissected over region growing method. In feature extraction, certain explicit feature will be extorted by manipulating texture as well from intensity. On the classification stage, the kernel based SVM is fabricated and smeared to training of support vector machine (SVM) to maneuver automatic detection of tumor in MRI images. For comparative exploration, our proposed approach is surpassed with existing research[18].

The segmentation of the initial volume of a lesion Ischemic is considered of great importance for diagnosis and clinical evaluation in decision on the type of thrombolytic therapy in patients who have suffered a stroke sharp. We conclude that the CM method evaluated variable radius proved to be sensitive to infarcts whose volume is small, plus it is fully guided by information DWI sequence contained in the patient, where the use of confidence maps edges adequately preserved edges of the ischemic injury. The approach is fully automatic, so it plays an important role in clinical evaluation of the treatment of myocardial cerebral ischemic.

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