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A Novel Framework for Fully Automated ROI Segmentation of Brain MR Images

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ABSTRACT

Brain region-of-interest (ROI) segmentation based on structural magnetic resonance imaging (MRI) scans is an essential step for many computer-aid medical image analysis applications. Due to low intensity contrast around ROI boundary and large inter-subject variance, it has been remaining a challenging task to effectively segment brain ROIs from structural MR images. The proposed system is the implementation of noise removal and segmentation algorithm. The Rician noise in MRI (Magnetic Resonance Image) degrades the image quality and thus, accuracy in segmentation is reduced and localization of brain may not be precise. The proposed system is a robust approach is proposed which estimates and removes the Rician noise of MRI for improving segmentation and detection of tumours. First, a robust Rician noise estimation algorithm is employed to identify all the pixels with high Rician noise. Second, a bilateral filter based denoising algorithm is employed to filter image in the wavelet domain. Successively a bilateral filter parameter optimization method is adopted, which uses the noise, contrast and frequency components in MRI to select suitable filter parameters for Bilateral Filter (BF). It is suitable for edge preserving and for adaptive denoising to segment image correctly. Further, after denoising the image, the contrast of the image is improved as a pre-processing step before the image segmentation. Next, SVM-based image segmentation algorithm is employed to segment the MRI .

Keywords : MRI, SVM, Rician noise, Contrast Enhancement, Classification.

I. INTRODUCTION

The MRI images are normally affected by a type of noise called Rician Noise. The presence of noise hampers diagnosis. For this, a few pre-processing and post processing techniques are adopted depending upon a type of application. This improves segmentation results. Also, a fully automated or semi-automated segmentation is desirable in clinical studies to improve the quality of diagnosis. First big challenge is related to an isolation of certain region on MRI affected by noise degradations. Accuracy in identification of certain regions and tissues affected by diseases is the first step in proper diagnosis. It is now established that an MRI imaging is better option for medical diagnosis because it has better contrast ratio compared to the Computer Tomography (CT) based Images. In this work, authors have focused on developing a fully automated imaging procedure in which denoising and contrast enhancement are performed for segmentation followed by extracting parameters for further processing of image. The segmentation of brain MRI is difficult owing to the artifacts and in-homogeneities in the image acquisition1. The major cause of it is noise which also prevents an automated segmentation. Additionally, intensity in-homogeneity and partial volume effects also cause hurdles. The noise found in magnetic resonance imaging system has a Rician noise distribution. It, however, can be eliminated by suitable use of denoising algorithms. The radio frequency field is not homogeneous due to which data acquisition results in shading. This is called intensity in-homogeneity. A few pixels called mixels are occupied by more than one class of tissues often termed as partial volume effect.

For better segmentation of the noise affected MRI, initially the denoising algorithm is applied to estimate and remove the noise if any present in the image. Further the contrast of the image is enhanced to have better segmentation. After the pre-processing steps, SVM algorithm is employed to segment the region of interest. Thus these steps are performed to achieve better segmentation results.

II. RELATED WORK

Liang Sun et al., proposes Brain region-of-interest (ROI) segmentation based on structural magnetic resonance imaging (MRI) scans is an essential step for many computer-aid medical image analysis applications. To address this issue, it propose an anatomical attention guided deep learning framework for brain ROI segmentation of structural MR images, containing two subnetworks. The first one is a segmentation subnetwork, used to simultaneously extract discriminative image representation and segment ROIs for each input MR image. The second one is an anatomical attention subnetwork, designed to capture the anatomical structure information of the brain from a set of labeled atlases.

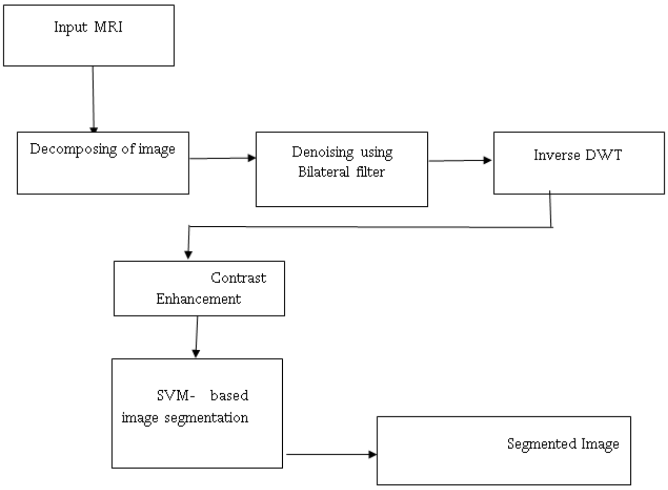
Biao Jie et al., proposes each node in a brain network denotes a particular brain region, which is a specific characteristics of brain networks. Accordingly, in this paper, we construct a novel sub-network kernel for measuring the similarity between a pair of brain networks and then apply it to brain disease classification. Different from current graph kernels, our proposed sub-network kernel not only takes into account the inherent characteristic of brain networks, but also captures multi-level (from local to global) topological properties of nodes in brain networks, which are essential for defining the similarity measure of brain networks.

M. Liu et al., proposes propose a landmark-based deep multi-instance learning (LDMIL) framework for brain disease diagnosis. Specifically, we first adopt a data-driven learning approach to discover disease-related anatomical landmarks in the brain MR images, along with their nearby image patches. Then, our LDMIL framework learns an end-to-end MR image classifier for capturing both the local structural information conveyed by image patches located by landmarks and the global structural information derived from all detected landmarks

H. Wang et al., proposes a new solution for the label fusion problem in which weighted voting is formulated in terms of minimizing the total expectation of labelling error and in which pairwise dependency between atlases is explicitly modelled as the joint probability of two atlases making a segmentation error at a voxel. This probability is approximated using intensity similarity between a pair of atlases and the target image in the neighbourhood of each voxel.

W. Bai et al., proposes a multi-atlas method is proposed for cardiac MR image segmentation. The proposed method is novel in two aspects. First, it formulates a patch-based label fusion model in a Bayesian framework. Second, it improves image registration accuracy by utilising label information, which leads to improvement of segmentation accuracy

III. ARCHITECTURAL DESIGN



IV. METHODOLOGY

The proposed system includes the following modules.

- Input Image
- Bilateral Filter
- Contrast Enhancement
- Segmentation

Input Image

The input image dimensions are $I \in R^{w\times h\times d}$, extracted. where w, h and d are the dimension of the input MR image. The aim of brain ROI segmentation is to automatically segment the MR image into multiple ROIs and obtain its label map LI. To capture the complicated anatomical structures of the human brain, it uses a set of labeled atlases to guide the network training process.

Bilateral Filter

A method in which Histogram of an image is obtained and its contrast is adjusted is called as histogram equalization. Some images are having backgrounds and foregrounds with different intensities; In these cases the equalization technique can be applied. It is also known as spatial domain method.

Contrast Enhancement

The conventional image processing morphological operators like erosion and dilation are used for the enhancement of contrast using algorithm. The Figure 3. shows that algorithm enhancing the contrast of MRI to improve the visual quality of the image. As the MRI is of low contrast image and also the contrast of the MRI is further degraded by presence of Rician noise and thus, noise removing algorithm is a necessary for contrast enhancement. The contrast is given as

$$|C| = \frac{S_{max} - S_{min}}{S_{max} + S_{min}}$$

Segmentation

Image segmentation can be broadly classified into different categories. The different algorithms have benefit for a suitable segmentation problem. A Support Vector Machine (SVM) is employed for segmentation of images with brain tumors from the MRI slices. The forthcoming sections are introduced with SVM and SVM based segmentation process for both, synthetic and real-time images. It method essentially generates new synthetic support vectors (SVs) from the obtained by training a standard SVM with the available label samples. Then, original and transformed SVs were used for training the virtual SVM.

$$f(x) = \sum_{x_j \in S} a_j y_j K(x_j, x) + b$$

Where, xj indicates the trainings, yj ∫ {+1,–1} represents class label with S as a set of support vectors. The vectors can be support vector set, error set or well classified set. Depending on the size of the image and the segmentation, the efficiency of the vector set may vary. The dual formulation of the above expression is given by;

$$\min_{0\le a_i \le C} W = \frac{1}{2}\sum_{i,j} a_i Q_{ij} a_j - \sum_i a_i + b\sum_i y_i a_i$$

V. CONCLUSION

The proposed system is a complete framework for accurate and robust segmentation of brain in MRI by incorporating appropriate pre-processing stages and by adopting the efficient simple SVM algorithm. The proposed segmentation algorithm is better option for the MRI even with image artifacts like rician noise, intensity in-homogeneity and partial volume effect. By including suitable pre-processing steps, the segmentation is improved if compared to the existing techniques. Though the proposed technique has various stages like noise estimation, removal, contrast enhancement and segmentation, it leads to the improved results which show the importance of the individual stages. The noise level has a significant effect on segmentation performance which is indicated by the values observed for Dice Coefficient, MCR and RMSE. To reduce this effect, the denoising algorithm is applied prior to the segmentation. It has a positive impact on the overall performance of automatic image segmentation system.

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