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Full Length Research Paper

MR imaging enhancement and segmentation of tumor using fuzzy curvelet

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Medical image segmentation is a very important issue in medical imaging. An automatic brain MR image segmentation method has been proposed for tumor detection in this paper. Discretize local window and wrapping based Curvelet transform has been used to remove rician noise. A modified fuzzy C-mean algorithm is used for segmentation of brain MR image. Proposed system has been tested on different datasets of MR Images. Proposed system performs well on all types of MR images including T1, T2 and PD brain MR images.

Key words: Modified fuzzy C mean, wrapping based curvelet, brain magnetic resonance imaging segmentation.

INTRODUCTION

Image segmentation partition an image into significant regions with respect to a particular problem. Properties like gray level, color, texture, shape help to recognize regions and similarity of such properties is used to build groups of regions having a particular meaning. Segmentation is the process of extracting points, lines or regions, which are then used as inputs for complementary tasks such as registration, measurement, movement analysis, visualization, etc. Segmentation is an unsupervised technique. It can be supervised using model base approach. Medical imaging has been undergoing a revolution in the past decade with the advent of faster, more accurate and less invasive devices. Image segmen-tation plays a vital role in numerous biomedical-imaging applications, such as the quantification of tissue volumes, study of anatomical structure, diagnosis, localization of pathology, treatment planning and computer-integrated surgery (Sonka et al., 1996). Medical image segmentation is a very important issue in medical imaging. Accurate segmentation for any medical application is a subjective term. Segmentation is a primary step for medical images analysis. Different work in the field of medical images segmentation is presented in the following discussion. Magnetic resonance imaging (MRI) is a medical imaging technique. Radiologist used it for the visualization of the internal structure of the body. MRI is a type of scan that is often used to help diagnose health conditions that affect organs, tissue and bone. The scientific principles behind MRI were discovered in 1946, but it was not until the 1970s that the technology became available to make use of these principles. MRI provides rich information about human soft tissues anatomy (Chris et al., 2003), magnetic resonance imaging (MRI) can be used to look at almost all parts of the body, but it is most often used to study the brain and spinal cord, the heart and blood vessels, other internal organs, such as the lungs or liver, bones and joints and breasts. Human body is mostly made up of water molecules that consist of oxygen and hydrogen atoms. There is a smaller particle in the center of each particle which is called a proton. These protons are very sensitive to magnetic fields.

Images obtained by the MRI are used for analyzing and studying the behavior of the brain. It uses a powerful magnetic field to align the nuclear magnetization of hydrogen atoms or protons in water in the body. When radio frequency (RF) electromagnetic fields are applied hydrogen nuclei produce a rotating magnetic field detectable by the scanner. Protons have the ability to absorb

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energy at specific frequency and then re-emit that energy. A single proton has the ability of spin that cause rotational movement of it to enable easier understanding (Ganesan and Sukanesh, 2008). We proposed an automated system for segmentation of brain tumor. Discretize local window and wrapping based Curvelet transform has been used to remove rician noise. A modified Fuzzy C-Mean algorithm is used for segmentation of brain MR image. Main contributions of the proposed technique include:

i) Proposed method removes Rician noise from MR images without degrading the quality of the image.
ii) Proposed technique performed segmentation depending upon the information which is inside the image itself and does not need any prior information like feature, image type, its model and any other information.
iii) Proposed technique finds out adaptive and optimal threshold by using fuzzy based entropy.

The paper is organized as follows: Firstly, it contains related work. Proposed method has been described in details there after. Then, it contains implementation and results. Finally, conclusions and future work is presented.

RELATED WORK

Brain segmentation using Markov random field was introduced (Held et al., 1997). Karsten proposed segmentation algorithm for brain segmentation using Markov random fields. This model is built upon the information of non-parametric distribution of tissue intensities, correlation of neighborhood and signal inhomogeneities that comes at the time of capturing MR images. For smoothing inhomogeneities, bayes theorem is used for calculating posterior probabilities for the segmentation. A different segmentation method is proposed by Lee et al., (2005) in which Support vector machine classifier is combined with the discriminative random field to perform segmentation. Discriminative random field (DRF) is a multidimensional version of the conditional random field. Conditional random field maps the posterior probability of the labels. Chen and Huang, (2005) proposed a region based hidden Markov random field model (RBHMRF) for segmentation purpose. In this presented model, segmentation is done based on regions information of brain MR image. This proposed model incorporates the neighborhood information in terms of region. First, brain image is divided into two main regions. Region B contains the ventricles and surrounding voxels information and region A contains the information of the remaining voxels. Bias field estimates for this model is calculated by applying the method proposed by Guillemaud and Brady (1997). A fuzzy region-based hidden Markov model (frbHMM) segmentation is proposed by Huang et al. (2009). Fuzzy 3D HMM framework is established considering the irregular shaped homogenous region. In this technique multiple classes' labels are used instead of using a single true discrete label for regions. Classical iterative forward-backward technique is used for estimating the probabilities of the region classes. One method of brain images segmentation using prior knowledge is proposed by Chris et al. (2003). In this proposed technique, standard prior probability maps are used for generating a set of samples. This set of samples is then reduced using a minimum spanning tree graph-theoretical method by reducing the samples that are labeled incorrectly. This stage is known as pruning stage. Based on these samples, non parametric kNN classifier is trained for the whole dataset. Segmentation of brain MR image is performed on this trained kNN classifier. This technique some time does not produce appropriate results when intensity levels of the real brain part and its boundaries and edges overlapped with each other. This method is also dependent upon prior knowledge for probability density maps.

Fuzzy C-means (FCM) clustering (Bezdek, 1981) is an effective monitoring system which is applied in fields such as astronomy, geology, medical imaging, and target recognition and image segmentation for clustering, classifying designs and functional analysis. An image can be symbolized in the various spaces and functions FCM algorithm group; similar data points in the feature space into clusters for the classification of an image. Cost function is iteratively minimized that depends on the distance from the pixel to the cluster centers in the feature domain to achieve clusters. By using FCM algorithm has fuzzy memberships to each pixel group. FCM starts with an initial suspicion of the center of each cluster. FCM converges to a solution to the representation of the local minimum of convergence can be observed by evaluating the changes in the function and membership of the cluster center in two successive iteration steps.

PROPOSED METHODS

The proposed system consists of different image processing techniques. First of all Rician noise has been removed by discretized local window and wrapping based curvelet transform. Then modified fuzzy C mean has been used to automatically segment different objects present in image data. Proposed technique is robust and adaptive, since it works on medical as well as on conventional images. Details about the major components of the proposed algorithm are discussed in the following subsections one after the other.

Noise removal

Noise during image acquisition degrades the image quality and makes it difficult for human interpretation as well as computer-aided analysis of the images. The need for shorter acquisition times for patients in clinical studies often undermines the ability to obtain images having both high resolution and high SNR in MRIs. As the magnitude of the MRI signal is the square root of the sum of the squares of Gaussian distributed real and imaginary parts, it follows

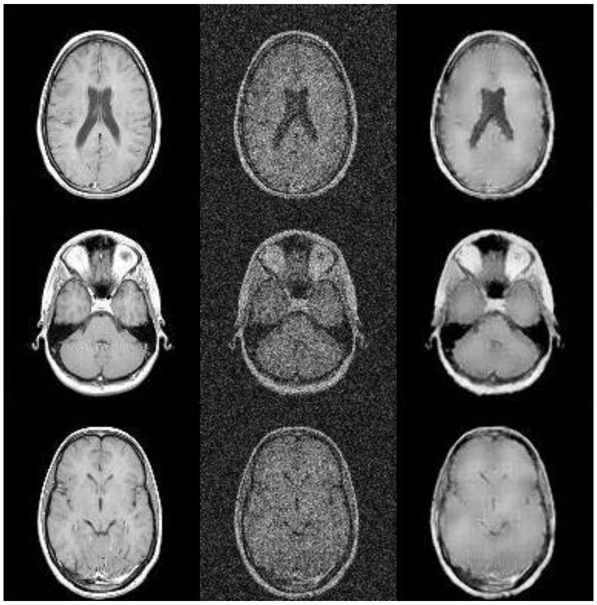

Figure 1. The 1st column shows original images, 2nd column shows noisy images with 20% Rician noise and 3rd column denoised image by curevelet transform.

a Rician distribution (Sijbers et al., 2004). The effects of Rician noise on MRI are more dominant because of the inherent nature of the process as the higher tissue anisotropy produces progressively lower intensities in MR images which increase the possibility of Rician noise. Hence, denoising should be performed to improve the image quality for more accurate diagnosis. In literature, Gaussian filters have been widely used for noise removal (Petersson et al., 1999); however, they do not perform good on edges because of blurring effect due to averaging of non similar patterns. Wavelet-based filters are also applied to MRI denoising (Delakis et al., 2007). However, these methods are prone to produce significant artifacts in the processed images because of their structure of the underlying wavelets. But wavelets also have some limitations as it does not handle the problem related to curve smoothness. For this purpose new multiresolution technique 'fast discrete curvelet' transform (Candes et al., 2006) is developed to overcome the intrinsic limitation of these conventional multiresolution techniques.
Curvelet transform has better directional and edge representation facilities. Curvelets gives sparse representation of objects that shows curve-punctuated smoothness. Curvelets have very imperative characteristic that is, it is adaptive in nature. It is adapted to reconstruction problems which have missing data. We have used wrapping based approach in our proposed system (Figure 1) (Candes et al., 2006).

Fuzzy based segmentation

After noise removal and the FCM algorithm was used to create a fuzzy partition, this illustrates the image using only the pixel intensity feature. For accurately finding the number of clusters, FCM algorithm is iterated for a range of hypothesized numbers of clusters; and best option for cluster is chosen based on cluster validity measure. Some cluster validity measures, the partition coefficient (PC) and the partition entropy (PE) (Bezdek, 1981) yielded amazingly good results for some of the test images. This might be partially due to the special nature of the data which is not common in clustering problems: the data is 1-D and at least one entry exists at each possible point. On the other hand, accepting the fact that different values might fit the given data (for example for segmentation at different detail), a threshold on the validity measure should be chosen below/above which is accepted. After finding out optimal number of clusters, we pass these optimal clusters to the spatial FCM. Spatial FCM also consider neighboring information of each pixel and return fuzzy membership matrix. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method was developed by Dunn in 1973 and improved by Bezdek (1981). It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \quad , \quad 1 \le m < \infty \tag{1}$$

Where m is any real number greater than 1, uij is the degree of membership of xi in the cluster j, xi is the ith of d-dimensional measured data, cj is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown earlier, with the update of membership uij and the cluster centers cj by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \quad , \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{2}$$

This iteration will stop when $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of Jm. The algorithm is composed of the following steps:

1) Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$

2) At k-step: calculate the centres vectors $C^{(k)} = [c_j]$ with $U^{(k)}$:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{3}$$

Uptake $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{4}$$

If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then stop; otherwise return to step 2.

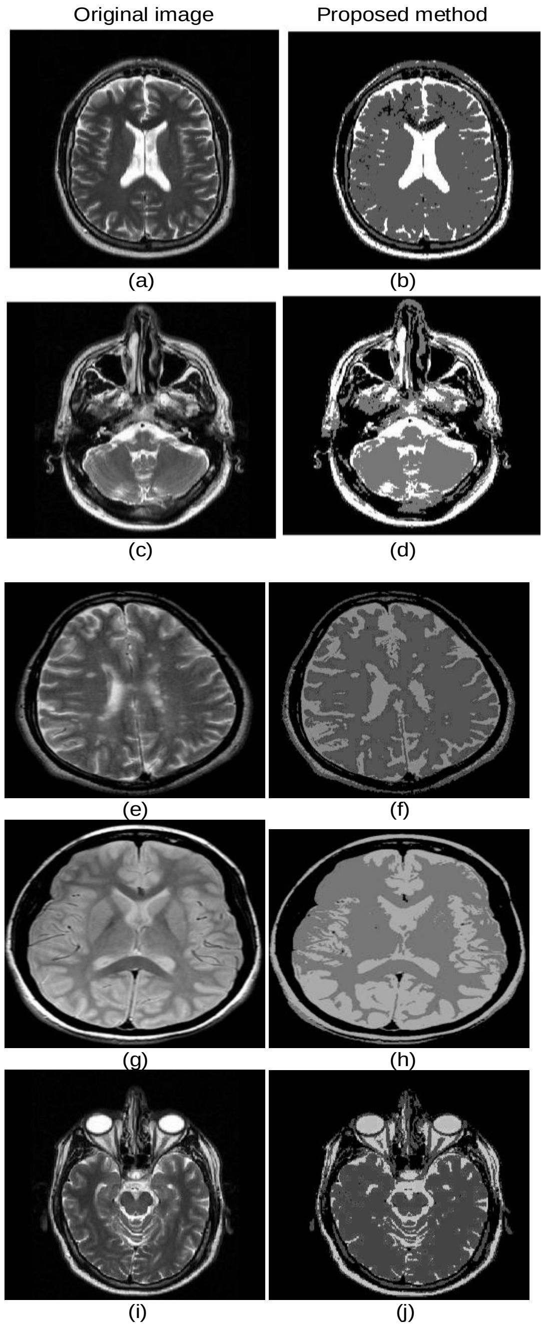

Figure 2. Results of our proposed system.

One of the significant uniqueness of an image is that neighboring pixels are extremely correlated (Boskovitz and Guterman, 2002). In other terms, these neighboring pixels hold similar feature values and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm (Chuang et al., 2006). To develop the spatial information, a spatial function is defined as:

$$h_{ij} = \sum_{k \in NB(x_j)} U_{ik} \tag{3}$$

Where NB(xj) stands for a square window centered on pixel xj in the spatial domain. A 3*3 window was used throughout this effort. Just like the membership function, the spatial function hij stands for the probability that pixel xj belongs to ith cluster.

The spatial function of a pixel for a cluster is large if the bulk of its neighborhood belongs to the same clusters. The spatial function is included into membership function as follows:

$$U'_{ij} = \frac{U_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{C} U_{kj}^{p} h_{kj}^{q}} \tag{4}$$

Where p and q are parameters to control the relative importance of both functions.

In a homogenous region, the spatial function simply fortifies the original membership and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious blobs can easily be corrected. The clustering is a two-pass process. The first pass is the same as that in standard FCM to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain and the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold (0.02). After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal. Two types of cluster validity functions, fuzzy partition and feature structure are often used to evaluate the performance of clustering in different clustering methods (Jaffar et al., 2010). There are different methods that have been proposed to compute optimal threshold. We have used a method based upon fuzzy entropy that finds out optimal and dynamic threshold according to the clusters find out by using well known method of FCM (fuzzy c-mean) (Jaffar et al., 2010). This method works as: first, it finds out histogram of the image. Then apply FCM to partition the image into different constituent parts and tries to find out clusters. We have also tried to validate those clusters by using some well known cluster validity measures. We have done this step so that we can analyze how many types of groups are in our image. First, this image is used to find histogram. Then based upon grey level histogram, it is fuzzified and then the error function is obtained by determining the contribution of each grey level to the fuzzy entropy of the partition. We have used fuzzy entropy based error functions.

The thresholds values are obtained from the error function, as the grey levels with the maximal levels of fuzziness respectively (Jaffar et al., 2010).

EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system is implemented by using the MATLAB environment. This system is tested on the images acquired from the brain web and some images obtained from the internet. We removed noise from the provided brain MR images using Discretize local window and wrapping based Curvelet transform. Results of the segmentation are shown in Figure 2. Qualitative measure is provided for quantifying the results of the segmentation. Figure 2b, d, f, h and j shows the result of our proposed technique when applied on different T1, T2 weighted and PD brain MR images. Results show that the brain MR image is quite accurately segmented into three tissues classes. As the segmentation is a subjective term.

CONCLUSION AND FUTURE WORK

We have presented an automatic segmentation of brain MR images. Discretize local window and wrapping based Curvelet transform has been used to remove Rician noise. A modified fuzzy C-mean algorithm is used for segmentation of brain MR image. FCM performs an adaptive thresholding process for computing threshold and the objective function. This is just the first step of a CAD system which is still under development. The results of the proposed system are shown on different MR images. One great benefit of our proposed system is that there is no need of any prior information about the input image type and it does not need any human expert interference. The next step works on brain tumor detection.

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