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A Novel Image Segmentation Algorithm for Clinical CT Images Using Wavelet Transform, Curvelet Transform and Multiple Kernel FCM

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Abstract

The clarity of medical image, which is directly acquired from the scanning machine, is very less. Image enhancement is one of the best and efficient techniques to increase the quality of image. A combined approach of different techniques such as Wavelet, Curvelet and Multiple Kernel Fuzzy C-Means algorithm was carry out in this paper. Wavelet and Curvelet transforms are used for denoising purpose. Due to wavelet transform's excellent localization property, it is more suitable for denoising the homogeneous areas of the image. Curvelet transform is a new multiscale representation and it is most suitable for the objects with curves. It is a new extension of the wavelet transform and ridge let transform and preferred for two dimensional images. Multiple Kernel Fuzzy C-means (MKFCM) algorithm is used for segmentation purpose of the image. Parameters such as mean, standard deviation, entropy and peak signal-to-noise ratio are used to measure thesegmentation efficiency. From the experimental results it is clear that the proposed segmentation technique produces maximum efficiency and is suitable for the segmentation of Clinical CT images. The main advantages of the proposed technique are simplicity, reliability and fast convergence.

Keywords: Wavelet Transform, Curvelet Transform, Entropy and Multiple Kernel Fuzzy C-Means

1. Introduction

Segmentation is the process of partitioning an image into multiple segments, so that it will be easy to separate and analyze individual parts of the image. The main aim of segmentation is to locate objects and boundaries in an image. In general, it is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. It is an important process of applications ranging from medical, education, research in image-guided surgery and surgical simulation. Soft segmentation allows each pixel to belong to multiple categories with various degrees of membership and it can be converted to hard segmentation by using the maximum classification rule. By using this rule a pixel is assigned to the class with which it has the highest membership value. In this work tumor in the brain is separated from its background using two stages of research, pre processing or enhancing the clinical CT image with wavelet and curvelet transforms and segmentation using multiple kernel FCM.

2. Materials and methods

The research proposes a hybrid technique for brain image segmentation which is based on the combination of wavelet and curve let transforms and multiple kernel fuzzy c -means algorithm to identify and extract the defected region from clinical CT image. The first step in the technique is pre processing in which noise is removed from the image using wavelet and curve let transforms and multiple kernel fuzzy c-means algorithm is used for the segmentation purpose.

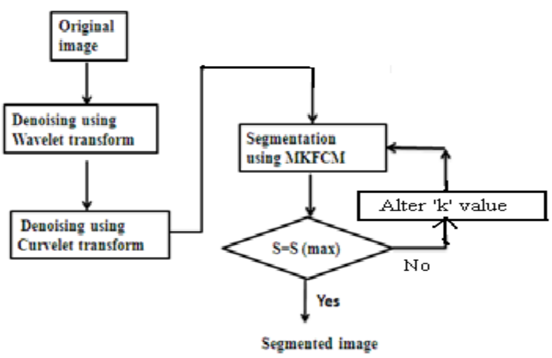


Fig. 1 Flow chart of the proposed method

This combined technique overcomes the limitations of the existing techniques and also the segmentation efficiency is also increased. The original image which is acquired from the CT scan is given as input image and it is denoised using the combination of Wavelet transform and Curvelet transform which exhibit a denoised image. Then the denoised image is segmented by using multiple kernel fuzzy C-means algorithm. Then finally the segmentation result is checked for different kernel values and the best one is selected which provides the better results for homogeneous areas.

3. Related work

3. 1. Pre-processing

Pre-processing is the basic step in medical image segmentation which includes the removal of noise from the brain CT image. This will remove the noise in the image as well as smoothen the image which is most suitable for segmentation. Different types of filtering techniques were used to remove the noises such as white noise, rician noise and salt and pepper noise
[2, 3] in the image.
Curvelet is a new multi-scale representation and most suitable for objects with curves. It is a new extension of the wavelet transform in two dimensions [3]. It differs from other transforms in the degree of localization. It improves the classification of abnormal tissues in the images and reduces the surrounding noise. The most commonly used set of discrete wavelet transforms were formulated by the Belgian mathematician Ingrid Daubechies [3]. It is purely based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function in which each resolution is twice than that of the previous scale. Daubechies derives the family of wavelets, in which, the first one is the Haar wavelet.
Image denoising using wavelet transform includes three steps,

1. A linear forward wavelet transforms
2. Nonlinear thresholding step and
3. A linear inverse wavelet transforms

Wavelet thresholding, which is proposed by Donoho, is an image estimation technique that exploits the capabilities of wavelet transform for image denoising. It removes noise by killing the coefficients that are insignificant relative to some threshold. Researchers have developed various techniques for choosing denoising parameters and so far there is no best universal threshold determination technique. It is again subdivided as,

Universal or Global Thresholding
- Hard Thresholding
- Soft Thresholding
- Sub Band Adaptive Thresholding

The hard thresholding operator is defined as

$$D(U, \lambda) = U \text{ for all } |U| > \lambda \quad (1)$$

Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The soft thresholding operator is defined as,

$$D(U,\lambda) = \mathrm{sgn}(U)\max(0,|U|-\lambda) \quad (2)$$

Soft thresholding shrinks coefficients above the threshold in absolute value. Wavelet sub band adaptive thresholding techniques are adopted along with filtering of wavelet coefficients [3]. It is a method of removing noise from images by the empirical wavelet coefficients in the wavelet domain and it is a non linear image denoising procedure to removing the noise. Visu shrink is a thresholding technique which applying the Universal threshold proposed by Donoho and Johnstone. It does not deal with the minimization of mean squared error. Another disadvantage of this particular method is that it cannot remove speckle noise. It can be used to remove additive noise only [2].Sure shrink is a thresholding method, obtained by applying sub band adaptive threshold. It is purely based on Stein's Unbiased Estimator for Risk (SURE), a method for estimating the loss in an unbiased fashion. Let wavelet coefficients in the jth sub band be $\{ X_i : i = 1,\ldots,d\}$and it is smooth and adaptive, which means that if the unknown function, contains abrupt changes or boundaries in the image [3].

Even though the wavelet transform is an efficient technique for image processing applications, it is unable to provide additional information about the geometry of the singularities of a function, which was easily achieved by using curvelet transform.

The curvelet transform uses the following steps for denoising operation.

1) Input image f is decomposed into sub bands as S0, D1, D2, D3, etc. using wavelet Transform.
2) Low frequency components (LL) are separated from the above sub bands using low Pass filter technology.
3) High frequency components (HH) are separated from the above sub bands using high pass filter technique.
4) Image with low frequency component is "smooth" and can be efficiently represented using wavelet base.
5) Image with discontinuity curves effect the high-pass components and they can be represented efficiently.

3.2. **Segmentation**

Fuzzy c-means clustering algorithms is an important technique for dividing data into a set of disjoint groups with high intra cluster and low inter cluster similarities [4, 5]. Fuzzy c-means clustering algorithm is used for spherical clusters only. Multiple kernel fuzzy c-means algorithm is a new extension to the FCM. This multiple Kernel fuzzy c-means algorithm is used to provide a better analysis tool for pattern classification. It uses multiple kernels and automatic adjustment of kernel weights. It makes the kernels as less crucial [1]. The proposed algorithm, especially with the spatial constraints are more robust to noise and outlier in image segmentation than the algorithms with the kernel substitution. Traditionally, fuzzy *C*-means (FCM) clustering algorithm has been widely used for image segmentation. For improving its efficiency, kernel trick and spatial constraints were adopted.

Goals of adopting the kernel functions:

- To induce a class of new robust distance measures for the input space and then replace non-robust measure to cluster data or segment images effectively.
- To reveal the inherent non-Euclidean structures in data.
- To retain simplicity of computation.

In image segmentation, the input data are derived from various sources so that input features like pixel colour, intensity and texture have to be selected. The performance depends on neighbourhood [18, 19]. For large neighbourhood, the input factor is in high dimension, which causes higher computational complexity. At the same time small neighbourhood may reduce the pattern seperability. The multiple kernel methods are one of the most popular and researched subjects within machine-learning community nowadays [1]. It is widely used for pattern recognition and cluster analysis. Typical examples are Support Vector Machines (SVM), Kernel Fisher Linear Discriminate Analysis (KFLDA), Kernel Principal Component Analysis (KPCA), Kernel Perceptron Algorithm (KPA), etc. i.e. the basic idea behind the kernel method is to transform the original low-dimensional inner-product input space into a higher dimensional feature space through some nonlinear mapping [12]. The general framework of MKFCM algorithm aims to deal with the minimization of objective function

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} \left\| \varphi_{com}(x_j) - \varphi_{com}(o_i) \right\|^2 \tag{3}$$

To enhance the Gaussian-kernel-based KFCM by adding a local information term in the objective function,

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}(1 - k(x_j, o_i)) + \alpha \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}(1 - k(\bar{x}_j, o_i)) \tag{4}$$

Where, x_j is the intensity of pixel *j*. In this new objective function, the additional term is weighted sum of differences between the filtered intensity x_j (the local spatial information) and the clustering prototypes [13]. The differences are also measured using the kernel induced distances. A composite kernel that joins different shaped kernels can be defined as

$$k_{\mathrm{com}} = k_1 + \alpha k_2 \tag{5}$$

Where, *k*1 is still the Gaussian kernel for pixel intensities, and then the composite kernel is designed as,

$$k_L = w_1^b k_1 + w_2^b k_2 + w_3^b k_3 \tag{6}$$

By using this idea, the above mentioned formulation could also be extended for the multivariate input data by respectively applying the estimator to each dimension of input vectors and therefore be applicable to kernel clustering based image segmentation [1].

Advantages of direct transformation:

1) It includes a class of robust non-Euclidean distance measures, if robust kernels are used.
2) It inherits the computational simplicity of the Fuzzy C-Means algorithm.
3) It interprets the clustering results intuitively.
4) It is also used for copying with data set with missing values easily.

In this section, some successful enhanced KFCM based image-segmentation algorithms are studied that consider both the local spatial information and its pixel intensity [14]. These types of algorithms are proved actually the special cases of MKFCM based methods, which mingle a kernel for the spectral information and a kernel for the local spatial information. After that, several new variants of MKFCM-based image-segmentation algorithms are developed. These new variants demonstrate the flexibility of MKFCM in kernel selections and combinations for image-segmentation problems and offer the potentials of improvement in segmentation results [18, 19].The MKFCM algorithm evaluates the centroids so as to minimize the influence of outliers. Unlike FCM, it does not attempt fuzzification for elements having membership values above the calculated threshold. This reduces the computational burden compared to FCM; also there is an absence of external user-defined parameters [13]. The removal of the initial trial and error factor makes MKFCM algorithm more robust, as well as insensitive to the fluctuations in the incoming data.

The flexibility in selecting the kernel functions; it offers a new approach to combine the different information from the multiple heterogeneous or homogeneous sources in the kernel space. Especially, in image segmentation problems, the input data involve in the properties of image pixels and it is sometimes derived from very different sources [1]. The pixel intensity is directly gained from image itself, but the texture information of a pixel might be obtained from some wavelet filtering of the image. Therefore, we can define different kernel functions purposely for the intensity information and the texture information separately, and these kernel functions are combined and composite kernel in MKFCM is applied to obtain better image segmentation results.

4. Performance Measure for Image Segmentation Efficiency

4.1. Peak signal-to-noise ratio (PSNR)

Peak Signal to Noise Ratio (PSNR) is defined as the ratio between maximum signal power and the noise power and expressed as follows:

$$\text{PSNR} = 10\log_{10} \frac{(2^n - 1)^2}{MSE} \tag{7}$$

Where n' denotes the number of bits per pixel and MSE is Mean Squared Error.

4. 2. Mean squared error (MSE)

The MSE represents the average of the squares of the "errors" between our actual image and our noisy image and given by,

$$MSE = \frac{1}{mn} \sum_{i=0}^{m=1} \sum_{j=0}^{n=1} \| f(i,j) - g(i,j) \|^2 \tag{8}$$

Where f represents the matrix data of our original image, g represents the matrix data of degraded image with noise, m represents the numbers of rows of pixels of the images, n represents the number of columns of pixels of the image, i represent the index of that row, j represents the index of that column.

4.3. Entropy (H)

Entropy is a factor which indicates the information profusion of image content. If the value of entropy is larger, which implies that segmented image contains the abundant information from the input images. It is used for comparing the difference of image details

$$H = -\sum_{i=0}^{255} P_i \log_2 P_i \tag{9}$$

Where, P_i represents the probability of pixel gray value i.

4.4. Histogram Statistics

Histogram of the segmented image using various techniques is also obtained and its values are compared with the existing system.

5. Simulation Results and Discussion

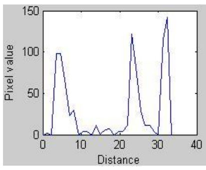
Simulation results show that when compared with all existing techniques, segmentation using Multiple Kernel Fuzzy C Means method gives better performance .It is an extremely simple,flexible and an effective algorithm for the identification of Brain Tumor from clinical CT images.
Intensity profile of the images is also gives almost uniform response to MKFCM technique. The processing time of the proposed technique is somewhat greater than the other techniques. But it can be tolerated, when it gives better performance results. PSNR and Entropy of the proposed system is calculated and found to be higher than the other segmentation techniques.


Input CT image

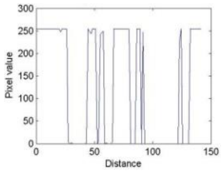

Segmentation using Local Threshold


Segmentation using Global Threshold


Segmentation using Gradient Technique

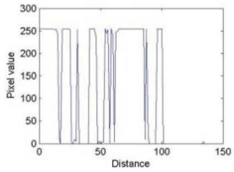


Intensity Profile of Input CT Image
Using



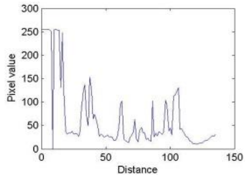
Intensity Profile of Segmented Image Using

Local Threshold



Intensity Profile of Segmented Image Using

Global Threshold



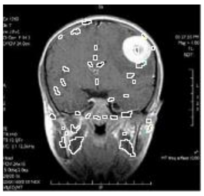
Intensity Profile of Segmented Image

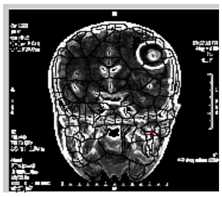
Global Threshold


Segmentation using Modulated Intensity Gradient
Gradient Technique

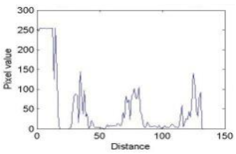

Segmentation using Wavelet Transform

Technique

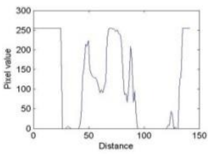

Segmentation using Watershed Technique


Segmentation using Watershed and

Technique



Intensity Profile of
of
Segmented Image Using
Using
Modulated Intensity
Grad
Gradient Technique

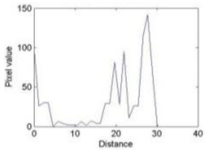


Intensity Profile of

Segmented Image Using

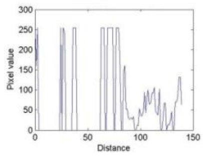
Wavelet Transform

Technique



Segmented Image Using

Watershed Technique



Intensity Profile

Segmented Image

Watershed and

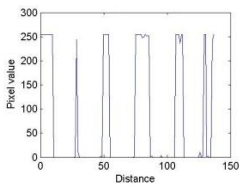
Technique


Segmentation using Edge Detection Technique

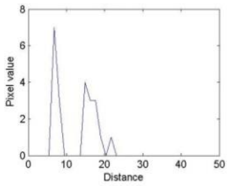

Segmentation using FCM Technique


Segmentation using KFCM Technique

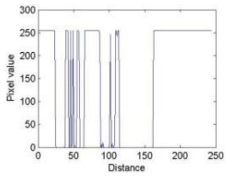

Segmentation using MKFCM Technique



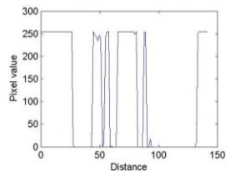
Intensity Profile of Segmented Image Using Edge Detection Technique



Intensity Profile of Segmented Image Using FCM Technique



Intensity Profile of Segmented Image Using KFCM Technique



Intensity Profile of Segmented Image Using MKFCM Technique

Figure.3.Experimental Results for various Image Segmentation Techniques

Table.1. Comparative Analysis of Image Segmentation Statistics and Performance Measure of various Image Segmentation Techniques with the Proposed System

Name of the Segmentation Technique	Image Statistics			Histogram Statistics		PSNR	Entropy
	Mean	STD Deviation	Histogram Max.	Standard Deviation	Processing Time (mS)		
Local Threshold	186	120	7.4e+005	5e+004	30	2.6575	1.2748
Global Threshold	190	112	7.6e+005	5e+004	46	2.218	1.3663
Gradient Technique	160	126	6.2e+005	4e+004	46	0.7436	1.2537
Modulated Gradient Technique	165	110	6.3e+005	3.9e+004	61	1.6531	3.0967
Edge Detection Technique	170	79	6.9e+005	4.3e+004	14	1.5313	1.2919
Wavelet Transform Technique	193	100	7.0e+005	4.5e+004	30	0.3817	2.8583
Watershed Algorithm	180	110	6.1e+005	3.9e+004	46	2.7324	2.1032
FCM Technique	192	115	7.5e+005	4.9e+004	61	1.3528	1.5180
KFCM Technique	186	122	7.4e+005	5e+004	58	2.5157	1.3155
Proposed Method(MKFCM) Technique	**150**	**62**	**7.2e+005**	**3.4e+004**	**65**	**3.1342**	**3.8115**

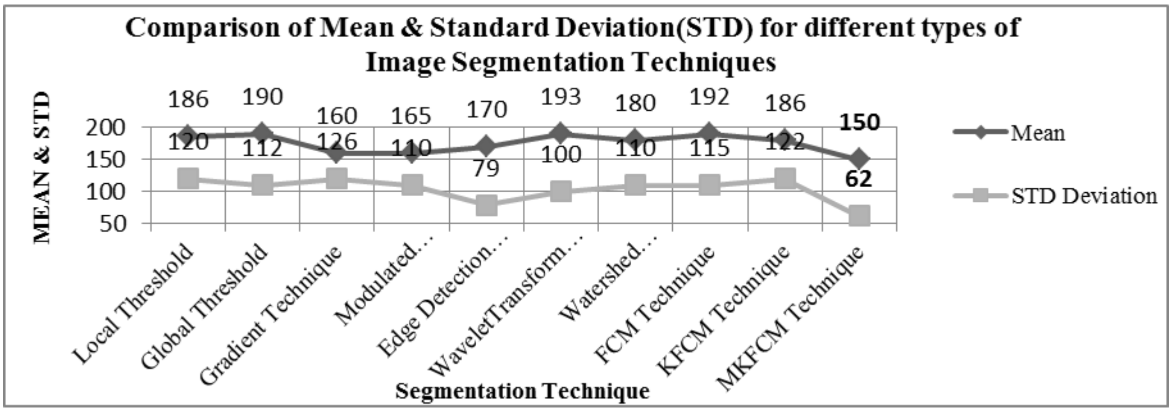


Figure.4. Comparison of Mean and STD for different types of Image Segmentation Techniques

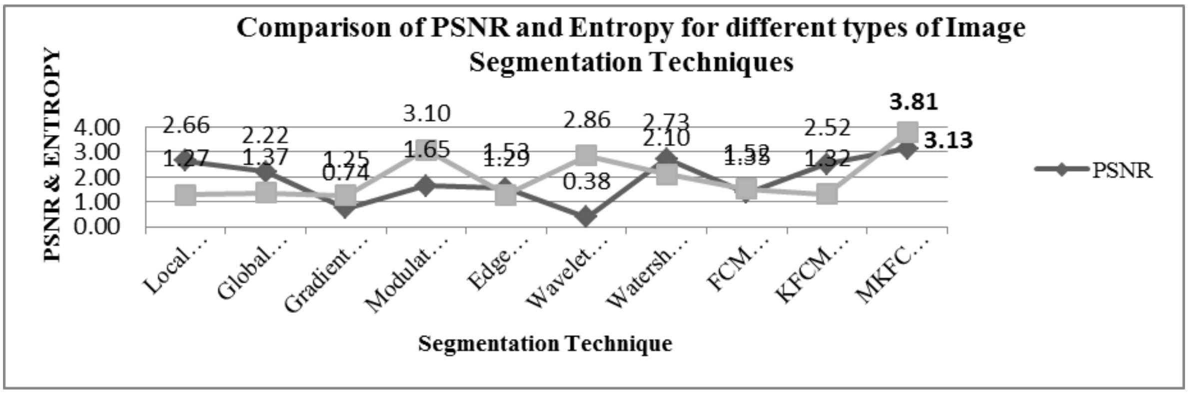


Figure.5.Comparison of PSNR and Entropy for different types of Image Segmentation Techniques

6.Conclusion

This paper presents a robust and efficient approach for the segmentation of noisy medical images. The proposed approach makes use of wavelet and curvelet transforms with Multiple kernel Fuzzy C-Means clustering for the segmentation of noisy medical images. The presented approach has been found more suitable for various noise levels. The experiments with original clinical Brain CT images have been demonstrated. The efficiency of the proposed approach in segmenting the noisy medical CT image is increased to 96.5% which is greater than the existing techniques. Simulation results show that PSNR and Entropy are achieved as 3.14 and 3.81 (2.73 and 3.1 in existing techniques). In future decided to improve this algorithm to suitable for other imaging techniques like MRI, PET and SPECT also.

No. of Noisy CT images Tested	No. of CT images Segmented and Disease Identified after Denoising	Segmentation Efficiency in %
29	28	96.55%

From the tabulation it is clear that out of 29 number of noisy CT images tested, 28 no. of images were identified as tumour affected images. Therefore the segmentation efficiency achieved with noisy images is 96.55%.

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