



Performance Analysis of Medical Image Segmentation using Hybrid Technique

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Abstract—The exploitation of medical images is done by several physical principals or modalities such as X-ray, CT, PET, MRI, etc. The essential task of Image segmentation is done on the images acquired from these modalities. This paper focuses on the segmentation using hybrid technique. The concatenation of Wavelets, Active contours and fuzzy c means has been done so as to attain efficient segmented image. Later on the MSE (mean square error) and PSNR (peak signal to noise ratio) are calculated to compare the quality of original image and segmented image.

Keyword— Image segmentation, Fuzzy c means, Active contour, Wavelets, Hybrid model.

I. INTRODUCTION

A human vision plays most important role in human perception. The machine vision is basically used in wide range of application due to limitation of human vision in visible band only. The imaging tasks like processing, analysis and visualizing are clearly distinguishable from each other. It is required to separate each of the objects so that the task of understanding becomes easy. Segmentation of an image is an essential task for separation of an image. It involves the partition of an image into its constituents based upon some characteristics such as colour, intensity, texture etc.

The main objective of segmentation is to simplify and change the representation of an image into meaningful image that is more appropriate and easier to analyze. Segmentation algorithms for monotonous images are based on one of two basic properties of gray scale values: discontinuity and similarity. The idea behind them is either to separate the regions or to group the regions based on common criteria (property) [1]. The point, line and edge detection falls under discontinuity based image segmentation. Thresholding, region growing, split and merge falls under similarity based image segmentation.

II. CLUSTERING

Clustering assigns a set of entities into the assemblies called clusters whose members are equivalent in some way. The basic purpose of cluster analysis is to distribute the set of N objects into C clusters such that the objects have intra cluster similarity and inter cluster dissimilarity. Clustering is a scientific tool that attempts to determine structures or certain patterns in the dataset. Clustering is an iterative process which leads to the optimization of the objective function. In data clustering mainly the centroid is used to classify each cluster on the basis of similarity.

Since clusters can be considered as the subsets of the data set, therefore one possible classification of clustering methods is according to whether the subsets are fuzzy or crisp (hard). In hard clustering, each data point belongs to exactly one cluster. K means clustering is an example of hard clustering. In soft clustering, a specific data point belongs to several clusters simultaneously with different degrees of membership [3].

A. Fuzzy C-Means (FCM):

FCM is the most popular fuzzy clustering algorithm used in data analysis. This technique is one of the unsupervised clustering techniques. It basically focuses on the clustering of data into two or more classes. FCM was first demonstrated by Dunn in 1973 and later improved by Bezdek [6]. FCM allows pixels or data to belong to multiple classes with variable degrees of membership. It is a flexible approach.

Let us consider $X=(x_1, x_2, \dots, x_N)$ which denotes an image with N pixels to be partitioned into c clusters, where x_i represents a particular pixel. The algorithm leads to minimization of the objective function using an iterative optimization defined as follows:

$$J = \sum_{j=1}^N \sum_{i=1}^C u_{ij}^m \|x_j - v_i\|^2 \quad (1)$$

where u_{ij} represents the membership function of pixel x_j in the i^{th} cluster, v_i is the i^{th} cluster center, and m is a constant. The parameter, m controls the fuzziness of the resultant partition [8].

Using the Euclidean standard, the distance metric d measures the resemblance of a feature vector x_j and a cluster centroid v_i in the feature space.

$$d^2(X_j, V_i) = \|x_j - v_i\|^2 \quad (2)$$

The pixels adjacent to the centroid of their clusters are allocated high degree of membership value, and the pixels which are far away from the centroid are allocated low membership values. In this way the objective function can be minimized [5]. The membership function tells about the probability of a pixel in specific cluster. The updating of membership functions and cluster centers are as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{\frac{2}{m-1}}} \quad (3)$$

and

$$v_i = \frac{\sum_{j=1}^N U_{ij}^m X_j}{\sum_{j=1}^N U_{ij}^m} \quad (4)$$

The advantage of FCM technique is that it provides better results of overlapping datasets. It also retains more information as compared to hard clustering techniques.

B. Active Contour Method:

Active contour basically deals with the contour (curve) that is dynamic in nature. The word snake describes about the slither movement of contour. The snake active contour was first proposed by Kass et al. He describes an active contour model using an energy-minimizing curve which is directed by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. Snakes are active contour models: they lock onto nearby edges, localizing them accurately.

Active contour method has become quite popular for a range of applications such as image segmentation and motion tracking, through the last decade. This methodology is based upon the use of deformable contours which match to various object shapes and motions. The fundamental idea is to start with first boundary shapes represented in a type of closed curves, i.e. contours, and iteratively change them by applying shrink/expansion operations according to the constraints of images. Those shrink/expansion operations, called contour evolution, are done by the minimization of an energy function like fixed region based segmentation methods or by the simulation of a geometric fractional differential equation (PDE) [2].

The energy minimizing parametric curve, C also known as snake, that is denoted by a vector $v(s) = (x(s), y(s))$, here x and y are coordinate functions of s, the normalized length of arc is denoted by $s \in [0, 1]$. In order to estimate the object boundary, active contour is placed in vicinity to a snake which depends on the associated energy function minimization. The energy function which is associated with the snake may be seen as the representation of the energy of the snake and the final snake related to the minimum of this energy. The evolving of the snake around boundary of the object is done by deforming its shape. It keeps on advancing until it reaches at a location of minimum energy function E_{snake}^* that is object's boundary. The energy function is defined as follows

$$E_{snake}^* = \int_0^1 (v(s)) ds \quad (5)$$

$$E_{snake}^* = \int_0^1 E_{int}(v(s)) + E_{ext}(v(s)) ds \quad (6)$$

$$E_{ext} = E_{image}(v(s)) + E_{con}(v(s)) \quad (7)$$

$$E_{snake}^* = \int_0^1 E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s)) ds \quad (8)$$

Here E_{int} , E_{ext} , E_{image} and E_{con} respectively indicate internal energy, external energy, external image energy and external constraint energy. The term internal energy, E_{int} states the shape and location of the snake and is used to preserve the continuity and smoothness of the snake. The term external energy, E_{ext} comprises two terms: the external image energy term and the external constraint energy term. The external image energy, E_{image} , states image information which is the negative magnitude of the gradient of an image, and it moves the snake towards the image features like lines, edge and particular contours. The term external constraint energy E_{con} is an optional term which drags the snake away or towards any particular feature in an image [4].

The main advantage of active contour is its self-adaptability. It adapts itself in the field of minimum energy. They can also track the dynamic objects in both spatial as well as temporal field. The active contours find application in many image processing areas, such as in image segmentation, edge detection, target object tracking, reconstruction and others [7].

C. Wavelets:

Wavelets based image processing has gained wide attention in biomedical imaging. Applications range from pure biomedical image processing techniques such as noise reduction, image compression and detection of microcalcifications in Magnetic resonance imaging (MRI), computed tomography (CT). Wavelets are the functions that are concentrated in time as well as frequency around certain point. A wavelet based waveform of effectively limited duration has an average value of zero. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet.

The Discrete Wavelet Transform is based on subband coding. Its basic idea is simple. Firstly the signal is put into two filters that is, high pass filter and low pass filter. Then the signal is decomposed into 2 parts, detailed part (high frequency) and approximation part (low frequency). The subsignal from the low filter will have the highest frequency equal to the half of original. According to the Nyquist sampling this change in frequency range means that only half of the original samples are kept. These samples are used to perfectly reconstruct the signal. At every level four subimages are obtained: 1 approximation and three detail subsignals on the horizontal, vertical and diagonal details.

The appropriate high pass and low pass filters are applied to the data at each level and also the down sampling is done at each level. The image is divided into four subbands (LL, LH, HL, HH) by using DWT. The subbands will have half of the size of the original image [9]. The LL subbands can be regarded as the approximation component of the image, while the LH, HL, HH subbands can be regarded as the detailed components of the image.

The advantage of using wavelets is due to noise robust nature. MR images are normally corrupted by random noise. This makes the automatic feature extraction of medical data complicated. So this it is used in order to obtain better performance analysis results [10].

III. PROPOSED METHODOLOGY

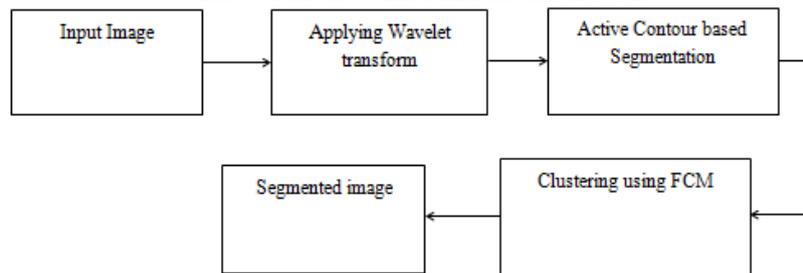


Fig. 1 Block diagram of proposed method

The steps followed by this hybrid technique:

1. Firstly the input image is obtained.
2. Then this image is applied to wavelet transform. The noise robust nature of wavelets provides better accuracy results.
3. After this operation, the active contour based segmentation is done. By this the snakes are placed near the contour of the region of interest.
4. The fuzzy c mean clustering is done by applying proper distance measure and membership function.
5. At last the segmented image is obtained.

IV. RESULT AND DISCUSSION

The proposed method is implemented in the MATLAB environment. This proposed a hybrid technique is robust to provide better results in terms of performance analysis. The results of this method are shown below..

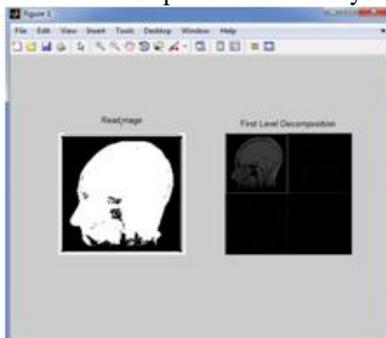


Fig. 4.1 Input image applied to wavelet transform

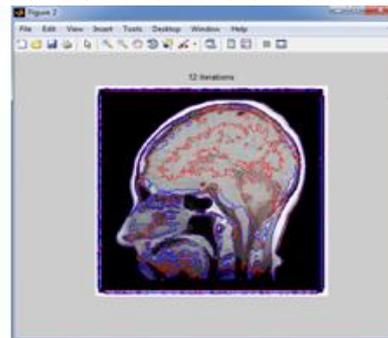


Fig. 4.2 Image obtained at 12th iteration after applying to active contour

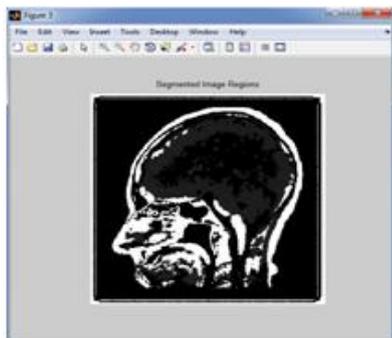


Fig. 4.3 Image obtained after applying FCM

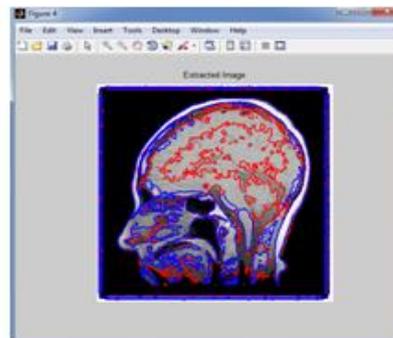


Fig. 4.4 Extracted image

Performance analysis

The Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare quality of image segmentation. The mean square error represents the cumulative squared error between two images (Compressed image and the original image), whereas PSNR represents a measure of the peak error. Lower the value of MSE, the lower the error. Formula to find PSNR and MSE is

$$m = (\text{double}(I) - \text{double}(J))^2 \tag{9}$$

where I= original image and J= segmented image

$$[r \ c] = \text{size}(J)$$

r=row and c= column of an image

$$\text{MSE} = \frac{\text{sum}(\text{sum}(m))}{(r*c)} \tag{10}$$

And $\text{PSNR} = 10 * \log_{10}(255.^2 / \text{mse})$ (11)

Table 1: Performance comparison using MSE

Input Images	MSE		
	FCM	Active Contour and FCM	Wavelet, Active contour and FCM
Brain.jpg	0.1739	0.0501	0.0279
Heart.jpg	0.1495	0.0441	0.0340
Head.jpg	0.1132	0.0846	0.0867

Table 2: Performance comparison using PSNR

Input Images	PSNR		
	FCM	Active Contour and FCM	Wavelets, Active contour and FCM
Brain.tif	55.7286	61.1389	63.6692
Heart.tif	56.3284	61.6816	62.8151
Head.gif	57.5927	58.7374	58.8546

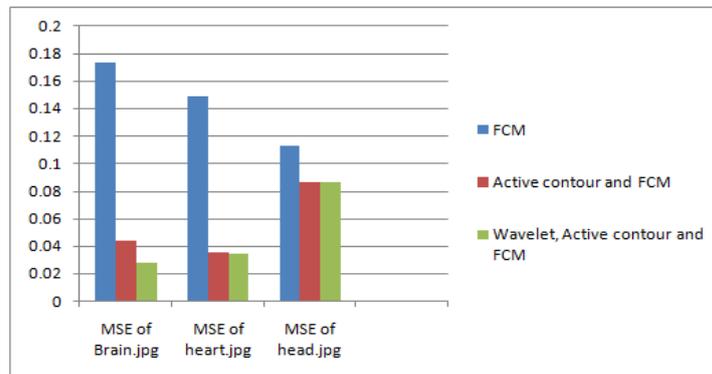


Fig. 4.5: Comparison using MSE shown by graph

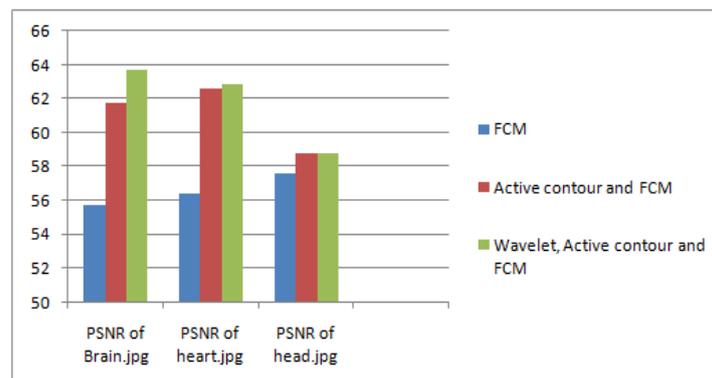


Fig. 4.6: Comparison using PSNR shown by graph

V. CONCLUSION

The segmentation and analysis of medical images are very important task in diagnosing several diseases. This research work represents a robust and efficient approach for segmentation of medical images. From the above made comparison it is concluded that Wavelet combined with the active contour and fuzzy c means gives better result both in terms of MSE as well as in PSNR.

REFERENCES

- [1] H.P Narkhede, "Review of Image Segmentation Tehniques", International journal of science and modern engineering ISSN: 2319-6386, Vol.1, Issue-8, July 2013.
- [2] M.kass, A.witkin, D.Terzopolas, "Snakes: Active Contour Models", International Journal of Computer Vision ,Vol.1, pp.321-331, 1988.
- [3] M.S.Yang, "A Survey of Fuzzy Clustering", Mathl.ComputingModelling, vol.18, No.11, pp.1-16, 1993.
- [4] Abhinav Chopra, Bharat RajuDandu, "Image Segmentation using Active contour Model", International Journal of Computation Engineering Research, Vol.2, No.3, pp.819-822, 2012.
- [5] Yong Yang, "Image Segmentation by Fuzzy C-means Clustering Algorithm with a Novel Penalty Term", Computing and Informatics, Vol.26, pp.17-31, 2007.
- [6] James C.Bezdek, R. Enrich, Wiiliam Full, "FCM: The Fuzzy C-Means Clustering Algorithm", Computers and Geosciences, Vol.10, No.2-3, pp.191-203, 1984.
- [7] H. Eviatar, R.L. Somorjai, "A fast, simple active contour algorithm for biomedical images", Pattern Recognition Letters, pp.969-974, 1996.
- [8] J.M. Keller and J.C. Bezdek , "A Possibilistic Fuzzy c-Means Clustering Algorithm", IEEE Transactions on Fuzzy Systems, Vol. 13, No. 4, Pp. 517–530, 2005.
- [9] Martin Vetterli et al., "Wavelets and filter banks: Theory and design", IEEE Transaction on signal processing Vol. 40 No.9, September 1992.
- [10] Yang Wang XiaoqianChe and Siliang Ma, "Nonlinear filtering based on 3D wavelet transform for MRI denoising", EURASIP Journal on Advances in Signal Processing, Springer, 2012.