JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Integrating an Image Moment with Image Transform for Better Energy Optimization in MRI Brain Tumor Images

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Abstract: The goal of feature extraction is to reduce the original data set by evaluating specific features, or characteristics, that distinguish one input pattern from another. Features play a vital role in image retrieval process. In this paper we propose a system where we use Fast Discrete Curvelet transform (FDCT) and Hu moments combined to extract features from the Brain MRI Data. FDCT is a multi-scale and multi-dimensional transform where we have taken wrapping based method for our study. Fast Fuzzy C-means is used for the segmentation process. Hu moments are 7 nonlinear combinations of normalized central moments that are invariant. The methodology is applied on a data set of 155 tumor and 97 normal brain MRI images and Hu moment features are extracted. The entropy of the Curvelet reconstructed image is high, whereas FCM segmented image has low. Hence it is known that the obtained segmented image is much optimized.

***IndexTerms* – Fast Discrete Curvelet Transform, Fast Fuzzy C-means, Hu moments.**

I. INTRODUCTION

Medical imaging is undergoing a remarkable rise and is a multidisciplinary field of study with expertise in engineering science, implementation mathematics, computer science, statistics, physics, medicine, and biology. The modern world employs a variety of medical imaging modalities to aid in the diagnosis and analysis of diseases in the human body. Computer-aided diagnostic image processing has become an important part of the clinical routine. As the use of medical images grows, a huge amount of data accumulates in storage and is staggering worldwide [1]. Therefore, extensive data storage facilities are required to store image data for further analysis. For the purpose of data storage, images can be transformed into a set of features which can be used for image recognition, retrieval, pattern recognition etc., therefore, feature extraction becomes an important step in any research area. [2]

Images can be described by two types of features, local features – that maps to contours of shape, global features – represent regions of the shape. Some of the contour-based shape descriptors are wavelets, curvelets and region-based shape descriptors are geometric moments, moment invariants [3]. Curvelet transform, a local feature enables near-optimal, non-adaptive sparse representation of objects with edges. Hu moments, a global feature are translational, rotational, and scale invariant that have been widely used for object shape recognition. In this paper, a novel feature extraction method combining Curvelet and Hu moments is proposed. Combining these two systems gives better results in features. Curvelets reconstructs the images with more defined curved edges, which aids for segmentation. Hu moments features upon segmentation gives optimized and good results further which can be used for feature matching.

II. THEORETICAL BACKGROUND

2.1 Image Transforms

The process of transferring an image in some way from one expression space to another is called Image Transform. The geometry of the new image may differ from that of the original image, or it may incorporate newly derived information. Image transforms are commonly used to express images more efficiently, compress images, and enhance or show particular information of interest. The transformation matrix can be used to perform geometric transformations on position vectors, color transformations on color vectors, 3-D to 2-D projections, and so on. A matrix used in image processing to accomplish linear transformation.

If F is the NxN image matrix and T is the result of the NxN transform, then,

$$T = AFA \quad \text{……………………………………………} \quad Eq(2.1)$$

where A is a symmetric transformation matrix of NxN dimensions. To obtain the inverse transform, the two sides of the preceding equation are multiplied by an inverse transform matrix B, respectively.

BTB = BAFAB ………………………………….. Eq(2.2)

If B = A-1 then,

F = BTB …………………………………...…. Eq(2.3)

The original image matrix is obtained.

2.2 Curvelet Transform

The Curvelet transform is an extension of wavelet transform, aimed at dealing interesting phenomena that occur along the curved edges in 2D images. They are the high dimensional generalization of the wavelets. Curvelets are designed to display images at different scales and different orientations, having time-frequency localization properties of wavelets but also show a very high degree of directionality and anisotropy, and its singularities can be well approximated with very few coefficients.

Curvelets were developed to overcome the limitations of wavelets. The characteristics of Curvelet transform are [4]:

1. Anisotropic scaling principle.
2. Multi-scale geometric transform.
3. Special micro local features.

Curvelet transform was developed in two generations.

The first generation of the Curvelet transform is called Continuous Curvelet Transform, where it used a complex algorithm of Ridgelet transform of an image. The algorithm was modified in 2003 due to its slow performance. Thus, to increase the speed and reduce the redundancy of the transform, the use of the Ridgelet transform was eliminated [5]

The second generation curvelet transform is called Fast Discrete Curvelet Transform (FDCT). FDCT is available in two methods for implementation namely, the **Unequally Spaced Fast Fourier Transform (USFFT)** and the **Wrapping-based**. Both methods give the same output, but the wrapping method is faster to implement. Hence Wrapping based method is selected for our study [6] [7].

The new version (wrapping-based) of the curvelet transform based on Fourier sampling accepts a 2D picture as input in the form of a Cartesian array f [m, n], where $0 \le m < M$, $0 \le n < N$ are the array dimensions. The outputs, as shown in Eq (2.4), will be a set of curvelet coefficients $c^D(j, l, k_1, k_2)$ indexed by a scale *j*, an orientation *l*, and spatial position parameters k_1 and k_2. [5]

$$c^D(j,l,k_1,k_2) = \sum_{\substack{0\le m<M \\ 0\le n<N}} f[m,n]\varphi^D_{j,l,k_1,k_2}[m,n] \dots\dots\dots\dots\dots\dots Eq\ (2.4)$$

Each φ^D_{j,l,k_1,k_2} is a digital curvelet waveform, superscript D stands for "digital." These approach implementations are the effective parabolic scaling law on the subbands in the frequency domain to capture curved edges within an image in more effective way. Curvelet transform is typically applied in the frequency domain to attain a higher level of efficiency. This signifies that the image is subjected to a 2D FFT. The "wedge" is created for each scale and orientation; the result is then wrapped around the origin, and 2D IFFT is performed, resulting in discrete curvelet coefficients.

Curvelet transform = IFFT [FFT(Curvelet) × FFT_Image]………… Eq (2.5)

2.3 Fast Fuzzy C-Means

Two prominent image segmentation techniques are c-means and fuzzy c-means clustering. While their implementation is simple, if done incorrectly, it will result in significant cost in memory consumption and time. Although these flaws can be overlooked in small 2D photos, they become increasingly obvious in large 3D datasets. The goal of this proposal is to provide an efficient implementation of these techniques for segmenting N-dimensional grayscale images. During the clustering procedure, the histogram of image intensities is used instead of the raw image data to increase computational efficiency.

2.4 Image Moments

Moments are scalar values used to characterise and capture the key characteristics of a function. Image moments and moment invariants are important elements in object recognition and shape analysis. Moments are technically defined as function "projections" onto a polynomial base.

General moment M_pq^((f)) of an image f (x, y), where p, q are non-negative integers and r = p + q is called the order of the moment, defined as

$$M^{(f)}_{pq} = \iint_D p_{pq}(x,y)\, f(x,y)dx\, dy \quad \dots\dots\dots..(2.6)$$

$$Z^p_{nm} = \int_0^1\int_0^{2\pi} h_{nm}(r,\theta)f(r,\theta)r\, dr\, d\theta \dots\dots\dots..(2.7)$$

Eq(2.6) represents Cartesian Co-ordinates and Eq(2.7) represents Polar Co-ordinates.

2.5 Hu Moments

Hu moment uses central moment. This is basically the same as the moment just described, except that the x and y values used in the formula are shifted by the mean value.

The invariant features can be achieved using central moments, which are defined as in equation (2.8)

$$\mu_{pq} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(x-\bar{x})^p\,(y-\bar{y})^q\, f(x,y)dxdy \quad \dots\dots\dots.Eq\ (2.8)$$

Where,

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad , \quad \bar{y} = \frac{m_{01}}{m_{00}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . Eq(2.9)$$

Based on central moments, Hu introduced seven moment invariants

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \mu_{03})^2$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \mu_{03})^2$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})\ (\eta_{21} + \eta_{03})\ [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

……………………………. Eqs(2.10)

The obtained features are normalized using eq (2.11)

$$f_{norm} = \begin{cases} 0 & \text{If } f \leq fmin \\ \frac{f - fmin}{fmax - fmin} & \text{If } fmin < f < fmax \\ 1 & \text{If } f \geq fmax \end{cases} \quad \dots\dots\dots\dots .Eq(2.11)$$

III. METHODOLOGY

The input image is read in the matlab. A wrapping-based curvelet transform is used, with computing Fast Fourier Transform. A curvelet is obtained at a given orientation "n" and scale "s" by dividing the frequency interval into digital corona tiles. Each corona tile is translated by multiplying the polar wedge by the Fourier samples. Wrapping a parallelogram generated by a tile around a rectangle at the origin. The inverse FFT is applied to the collection of curvelet coefficients and total the curvelet array. The curvelet transform image is reconstructed using these co-efficients. The Fast fuzzy C-means approach for image segmentation which seeks to provide efficient implementations of these algorithms for segmenting N-dimensional grayscale images. It used image intensity histograms instead of raw image data during the clustering phase as it improves computational performance. The central moments are calculated (eq 2.8), and using this Hu moments are obtained by eqs (2.10). These Hu moments are normalized using eq (2.11). The normalized Hu moments are stored as H0, H1, H2, H3, H4, H5, H6.

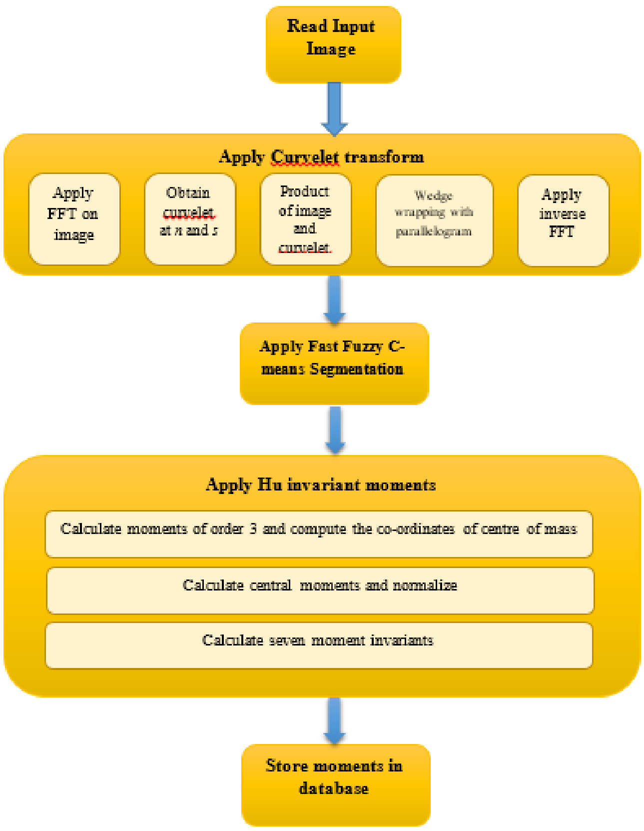
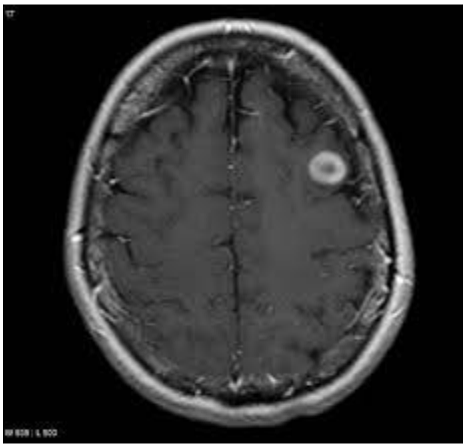
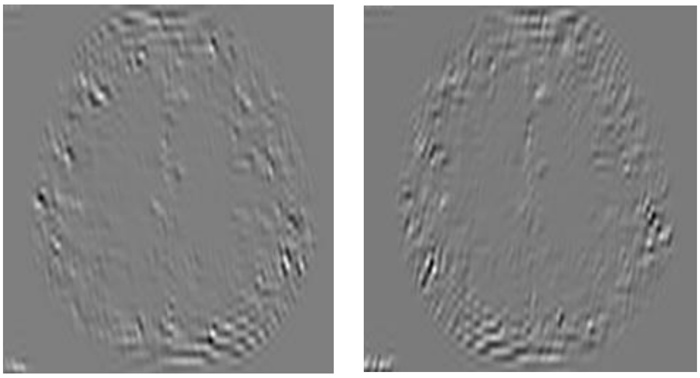


Figure 3.1: Block Diagram

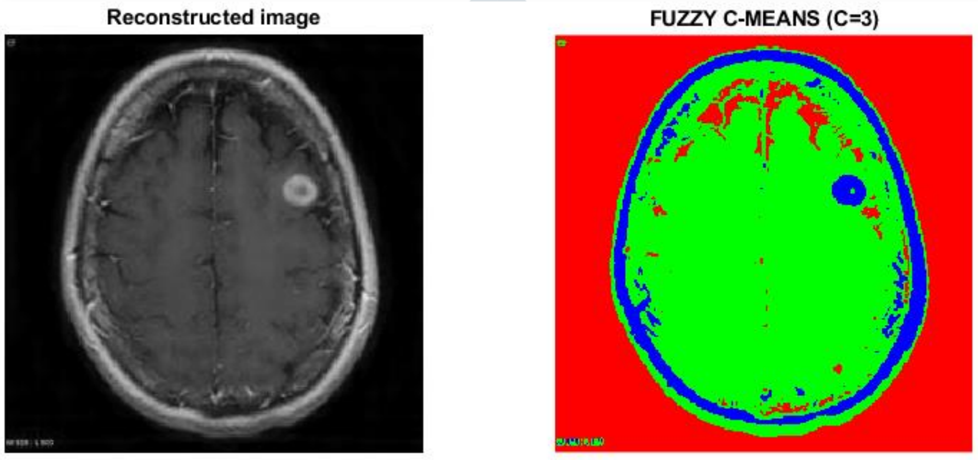
IV. RESULTS AND DISCUSSION



(a)



(b)



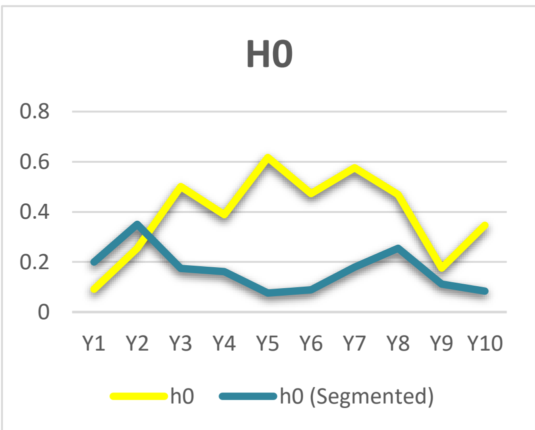
(c)

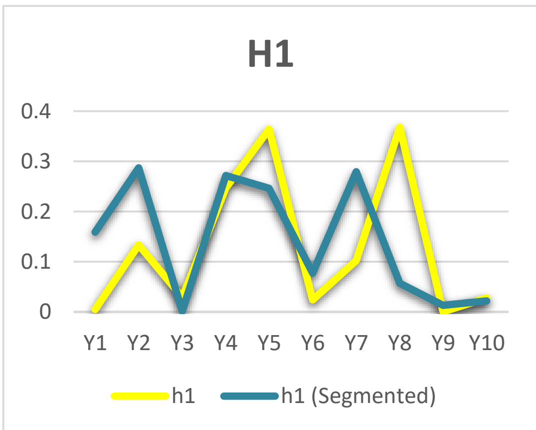
Figure 4.1 (a) Input image (b) Curvelet co-efficients (c) Curvelet reconstructed and Fast Fuzzy C means segmented image

For the shape feature extraction, Hu moments are applied. The comparison is done by applying the Hu moments at three stages namely:

1. Original image
2. Curvelet transform reconstructed image
3. Segmented image

It is observed that the Hu moments have same values for both original and Curvelet reconstructed image.





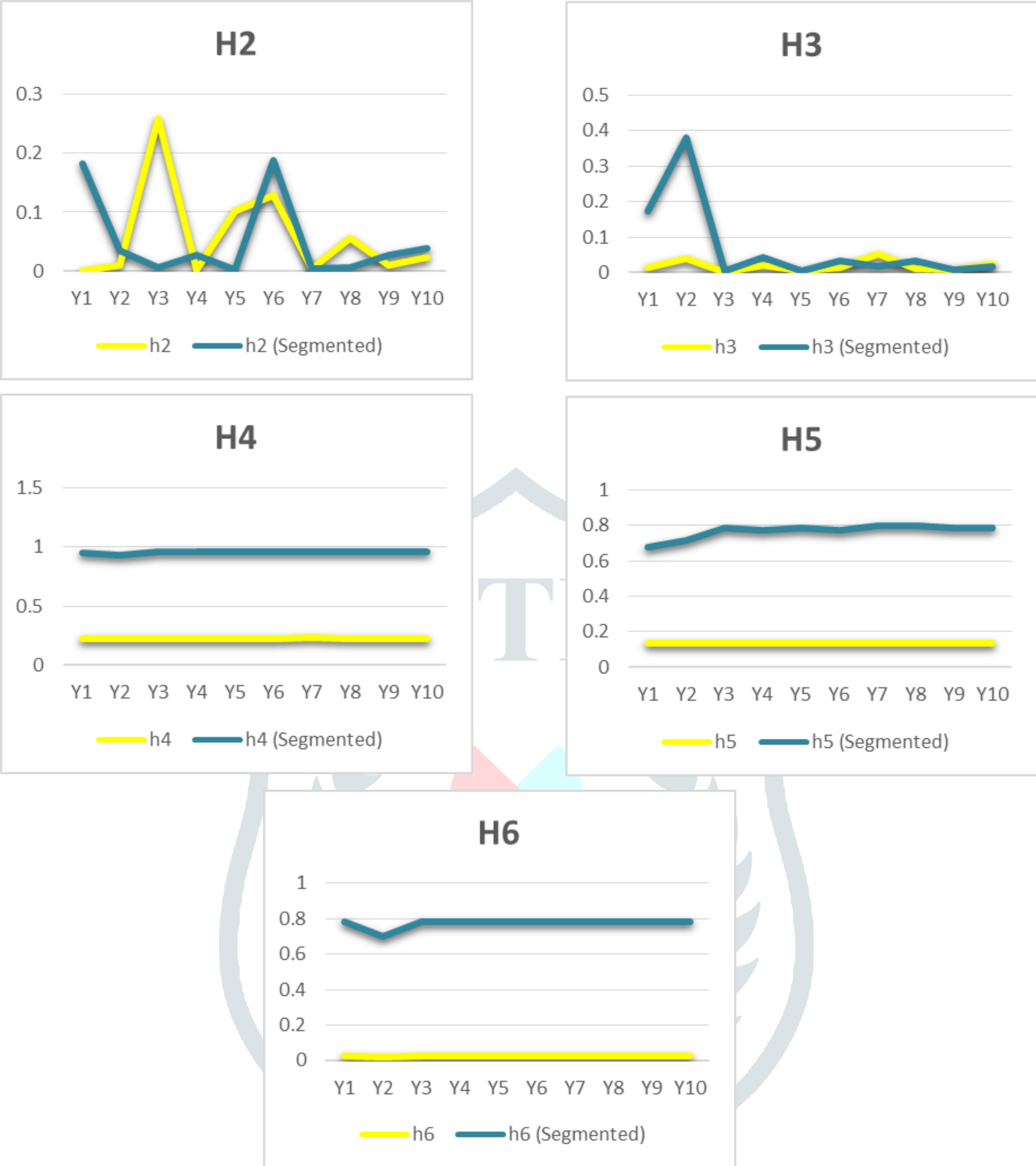


Figure 4.2 Normalized Hu moments

After the extraction of the features, entropy is calculated.

	Original	Curvelet	FCM
Y1	6.901447	7.184039	1.359455
Y2	5.979	6.6028	1.469473
Y3	5.8603	6.5285	1.452013
Y4	5.7861	6.4597	1.257739
Y5	5.0511	6.0936	1.231108
Y6	6.3145	6.7505	1.231108
Y7	5.842	6.7772	1.122502
Y8	5.9482	6.2028	1.122502
Y9	6.9422	7.6191	1.434305
Y10	6.5907	7.1506	1.335838

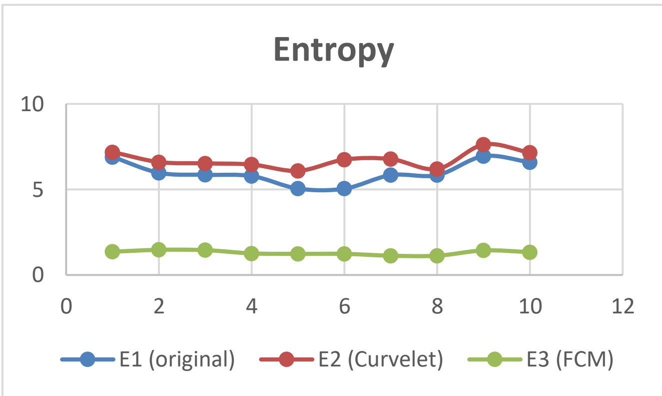


Figure: 4.3 Graphical representation of entropy

Table 4.1: Entropy comparison

Conclusion

The images are first subjected to the Curvelet transform (FDCT), a wrapping-based approach. Curvelets use sparse representation, which chooses and reconstructs the most prominent values, and have higher dimensionality than wavelets. Curvelet co-efficients are derived after implementing the Curvelet transform in frequency domain. Inverse FFT is applied on the co-efficients and the image is reconstructed. Fast FCM segmentation is applied on the reconstructed image for segmentation. On the segmented image Hu moments are obtained which is a good shape descriptor. For the purpose of this study, Hu moments is applied on original image, Curvelet reconstructed image and the segmented and the moments are normalized. It is observed that the Hu moments are invariant after the application of Curvelet transform, as the values for original image and reconstructed image is found to be same. The entropy of the images are calculated and are plotted. The entropy of the Curvelet reconstructed image is high, whereas FCM segmented image is low. As a result, the generated segmented image is highly optimized.

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