

Multil-Kernels Integration for FCM Algorithm for Medical Image Segmentation using Histogram Analisis

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Abstract

This paper suggests a new process for medical image segmentation using the mixing of two different multi-kernels with spatial information in Fuzzy C-Means algorithm. In literature, it has proved that the multi-kernels outperform the single kernels. In this paper, the integration of two hyperbolic tangent kernels and two Gaussian kernels are used in the proposed algorithm for clustering of images. The presentation of the proposed algorithm is tested on Open Access Series of Imaging Studies (OASIS) MRI image data base. Also, the histogram psychiatry of MRI images are take place in this manuscript. The evaluation is tested in terms of V_{pc} , V_{pe} and Silhouette Value. The results after examination, the proposed method shows a significant enhancement as compared to other existing methods in terms of V_{pc} , V_{pe} and Silhouette Value under different Gaussian noises.

Keywords: FCM, Fuzzy, Multi-Gaussian Kernal, Multi-Hyperbolic Tangent Function, Multiple-Kernal, Segmentation

1. Introduction

In image processing and computer vision, medical image segmentation is an energetic research area¹. The procedure of clustering the image into non-overlaped, steady regions is called the image segmentation. These regions are indistinguishable with respect to some features like texture, color, shape, intensity etc. Based on the features, the process of segmentation is alienated into four groups: clustering (*intensity*), thresholding (*intensity*), region extraction (*color or texture*) and edge detection (*texture*).

In literature, several techniques are obtainable for medical image segmentation. The before available literature on segmentation methods are: thresholding techniques², clustering techniques³, classifiers based techniques⁴, region mounting techniques⁵, Artificial Neural Networks (ANNs) based techniques⁶, Markov Random Field (MRF)⁷ models atlas-guided techniques etc. Amongst the above discussed methods, the clustering based techniques show an importance in medical imaging research.

Clustering is a process for classifying patterns or objects in such a way that samples of the same cluster are more analogous to one another than samples belonging to other clusters. There are two main clustering approaches: the hard clustering technique and the fuzzy clustering technique. MacQueen⁸ has proposed the k-means clustering algorithm. The k-means is one of the hard clustering technique. The customary hard clustering techniques classify every position of the minutes set just to one cluster. As an effect, the consequences are often very crispy, i.e., in image clustering every pixel of the image goes to one cluster. However, in many real situations, issues such as limited spatial resolution, abridged contrast, partly cover intensities, noise and intensity in homogeneities decrease the efficiency of hard (crusty) clustering techniques. Fuzzy set theory⁹ has bring in the idea of unfinished membership, explained by a membership function. Fuzzy clustering, as a soft segmentation technique, has been extensively analized and effectively applied in image segmentation and clustering¹⁰⁻¹⁹. Among the fuzzy clustering techniques,

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Fuzzy C-Means (FCM) algorithm¹⁰ is the generally well-liked technique which is used in image segmentation due to its robust features for uncertainty and can keep much more information as compared to hard segmentation techniques¹¹. While the standard FCM algorithm works fit on most noise-free images, it is very aware to noise and other imaging artifacts, because it does not consider any data about spatial background.

Panas and Toliás¹² developed a fuzzy rule-based scheme called the ruled-based neighborhood enhancement system region to impose spatial constraints by post processing the Fuzzy C-Means clustering results. Noordam et al.¹³ proposed a Geometrically Guided FCM (GG-FCM) algorithm a semi-supervised Fuzzy C-Means CM method, where a geometrical condition is used determined by taking into account the local neighbourhood of each pixel. Pham¹⁴ modified the FCM objective values by including spatial values on the membership functions. The punishment term leads to an iterative algorithm, which is extremely comparable to the original FCM and allows the estimation of spatially flat membership functions. Ahmed et al.¹⁵ proposed the Fuzzy C-Means with spatial constraints (FCM_S) where the objective function of the typical Fuzzy C-Mean is modified in order to compensate the intensity in uniformity and authorize the labeling of a pixel to be effected by the labels in its region.

Chen and Zhang¹⁶ proposed Fuzzy C-Means with spatial constraints 1 and constraints 2 (FCM_S1 and 2), two variants of FCM_S algorithm in order to reduce the computational difficulty. These two techniques introduced the further mean and median-filtered image, respectively, which can be planned in advance, to change the region term of FCM_S. Thus, the performance times of both FCM_S1 and FCM_S2 are significantly reduced. advance, they have enhanced the FCM_S objective function to more likely reveal intrinsic non-Euclidean structures in data and more robustness to noise. They after that replace the Euclidean frostiness by a kernel-induced distance and proposed kernel versions of Fuzzy C-Means constraints with spatial constraints also known as KFCM_S1 and S2 and KFCM_S2¹⁶.

Szilagyí et al.¹⁷ proposed the Enhanced Fuzzy C-Means (EnFCM) algorithm to accelerate the image segmentation process. The structure of the proposed algorithm is different from that of FCM_S and its variants. First, a linearly-weighted sum image is created from both original image and all pixel's local region standard gray scales.

Then clustering is performed on the basis of the gray scale histogram instead of pixels of the summed image. Since, the number of gray scales in an image is typically much of the summed image. Since the number of gray levels in an image is generally much smaller than the number of its pixels, the computational time of proposed algorithm is reduced.

Cai et al.²⁰ planned the Fast Generalized Fuzzy C-Means algorithm (FGFCM) which uses the spatial in order also recognized as the intensity of the local pixel region and the number of gray scales in an image. This method forms a nonlinearly-weighted sum image from both original image and its local spatial and gray scale region. The computational obscurity of proposed algorithm is very little, because clustering is carried out on the basis of the gray scale histogram. The greatness of the segmented image is well enhanced. Yang and Tsai²¹ proposed the Gaussian Kernel based FCM (GKFCM) for medical image segmentation. The proposed algorithm becomes a comprehensive type of KFCM_S1 and S2 and algorithms and presents with more competence and robustness. Chen et al.²² have proposed the Multiple-Kernel Fuzzy C-Means (MKFCM) for image-segmentation troubles. They have used the linear arrangement of multiple kernels as complex kernel.

Kannan et al.²³ proposed the Hyperbolic Tangent Fuzzy C-Means (HTFCM) base image segmentation for breast images. They contain use the hyper tangent function as objective function in position of unique Euclidean distance on characteristic space. Venu et al.²⁴ proposed the segmentation algorithm (HGFCM) which integrates the hyper tangent and Gaussian kernel functions for MRI image segmentation.

The association of the paper is given as follows. section 1 presents the literature and connected work of proposed clustering algorithms. The various methods which are available for cluster based segmentations are given in section 2. section 3 presents the evaluation events and dataset used in this paper. The new results and discussions are given in section 4. Conclusions are derived in section 5.

2. Methods

2.1 FCM Algorithm

FCM clustering technique is a generalization of the hard C-Means algorithm yields extremely superior results in

an image region clustering and object categorization. As in hard k-means algorithm, Fuzzy C-Means algorithm is based on the minimization of a normal function.

Let a matrix of n data elements, each of size s (s1) is represented as $X = (x_1, x_2, \dots, x_n)$. FCM generates the clustering by iteratively minimize the objective function given in Equation 1.

Objective function:
$$O_m(U, C) = \sum_{i=1}^c \sum_{j=1}^n U_{ij}^m D^2(x_j, C_i) \quad (1)$$

Constraint:
$$\sum_{i=1}^c U_{ij} = 1; \quad \forall j \quad (2)$$

Where, U_{ij} is membership of the j^{th} data in the i^{th} cluster C_i , m is fuzziness of the system $m=2$ and D is the distance between the cluster center and pixel.

Algorithm

The algorithm for the Fuzzy C-Means based clustering is given below.

Input: Raw image; Output: Segmented image;

Step 1: Randomly initialize the ($c = 3$ clusters) cluster centers C_i .

Step 2: The distance D between the cluster center and pixel is calculated by using Equation 3.

$$D_2(x_j, C_i) = \|x_j - C_i\|_2 \quad (3)$$

Step 3: The membership values are calculated by using Equation 4.

$$U_{ij} = \frac{(D(x_j, C_i))^{-1/(m-1)}}{\sum_{k=1}^c (D(x_j, C_k))^{-1/(m-1)}} \quad (4)$$

Step 4: Update the cluster centers.

$$C_i = \frac{\sum_{j=1}^n U_{ij}^m x_j}{\sum_{j=1}^n U_{ij}^m} \quad (5)$$

- The iterative process starts:
 1. Update the U_{ij} by using Equation 4.
 2. Update the C_i by using Equation 5.
 3. Update the D using Equation 3.
 4. If $|C_{new} - C_{old}| > \epsilon$, ($\epsilon = 0.001$) then go to step1
 5. Else stop

Assign every pixel to a precise cluster for which the membership value is maximal.

2.2 KFCM Algorithm

Kernel based FCM algorithm and its objective function are given below:

Objective function:
$$O_m(U, C) = \sum_{i=1}^c \sum_{j=1}^n U_{ij}^m (1 - K(x_j, C_i))$$

Thus, the revise equations for the essential conditions for minimizing $O_m(U, C)$ are given below:

$$C_i = \frac{\sum_{j=1}^n U_{ij}^m K(x_j, C_i) x_j}{\sum_{j=1}^n U_{ij}^m K(x_j, C_i)}; \quad i = 1, 2, \dots, C \quad (6)$$

$$U_{ij} = \frac{(1 - K(x_j, C_i))^{-1/(m-1)}}{\sum_{k=1}^c (1 - K(x_j, C_k))^{-1/(m-1)}}; \quad j = 1, 2, \dots, n \quad (7)$$

We recognize the necessary surroundings for minimizing $O_m(U, C)$ are revise Equations 6 and 7 only when the kernel function K is selected to be the Gaussian function with $K(x_j - C_i) = \exp(-\|x_j - C_i\|^2 / \sigma^2)$. Different kernels can be selected by replacing the Euclidean distance for different environment. However, a Gaussian kernel is appropriate for clustering in which it can fundamentally make the essential conditions. The above planned KFCM algorithm is very sensitive to the noise conditions. To solve this difficulty Chen and Zhang¹⁶ have introduced the KFCM_S1 and KFCM_S2 techniques which are utilize the spatial data by bring a parameter.

2.3 GKFCM Algorithm

Yang and Tsai²¹ proposed the Gaussian kernel based FCM for medical image segmentation. The proposed GKFCM algorithm becomes a widespread type of FCM, KFCM_S1 and KFCM_S2 algorithms and presents with more efficiency and robustness. It is mentioned that the parameter α is used to manage the effect of the neighbors for adjusting the spatial bias alteration term. In fact, the parameter α greatly affects the clustering results of KFCM_S1 and KFCM_S2 techniques. Intuitively, it would be appropriate if we can correct each spatial bias change term independently for every cluster i . That is, the in general parameter α is better replaced with $\hat{\eta}_i$, that is connected to each cluster i . In this sense, Yang and Tsai²¹ considered the customized objective function $O_m^G(U, C)$ with the following constraints.

$$O_m^G(U, C) = \sum_{i=1}^c \sum_{j=1}^n U_{ij}^m (1 - K(x_j, C_i)) + \sum_{i=1}^c \sum_{j=1}^n \eta_i U_{ij}^m (1 - K(\bar{x}_j, C_i)) \quad (8)$$

where $K(x_j, C_i) = \exp(-\|x_j - C_i\|^2 / \sigma^2)$, \bar{x}_j is the mean of the neighbor pixels, σ^2 is the variance of the total image.

$$C_i = \frac{\sum_{j=1}^n U_{ij}^m (K(x_j, C_i)x_j + \eta_i K(\bar{x}_j, C_i)\bar{x}_j)}{\sum_{j=1}^n U_{ij}^m (K(x_j, C_i) + \eta_i K(\bar{x}_j, C_i))}; i = 1, 2, \dots, C \quad (9)$$

$$U_{ij} = \frac{((1 - K(x_j, C_i)) + \eta_i (1 - K(\bar{x}_j, C_i)))^{-1/(m-1)}}{\sum_{k=1}^c ((1 - K(x_j, C_k)) + \eta_i (1 - K(\bar{x}_j, C_k)))^{-1/(m-1)}}; i = 1, 2, \dots, C; j = 1, 2, \dots, n \quad (10)$$

2.4 Multi-Hyperbolic Tangent and Multi-Gaussian Kernels for FCM (MHMGFCM)

The ideas which are presented in HGTFM²⁴ and GKFCM²¹ are aggravated us to propose the MHMGFCM_S1 and MHMGFCM_S2. The considered hyperbolic tangent function²³ is given below:

$$H(x_j, C_i) = 1 - \tanh(-\|x_j - C_i\|^2 / \sigma^2) \quad (11)$$

where, σ^2 is the user distinct function.

The presentation of the segmentation algorithm varies with the σ^2 values. Hence, it is required to fix the suitable value for σ^2 .

In this proposed paper, we deem the value of σ^2 with the variance of the nearby P neighbors of radius R form the center pixel x_j .

$$\sigma^2 = \sum_{j=1}^P \|x_j - \bar{x}\|^2 / P \quad (12)$$

where,

$$\bar{x} = \sum_{j=1}^P x_j / P.$$

The objective function which is used in this manuscript for MHMGFCM_S1 and MHMGFCM_S2 is given in Equation 13.

where, \bar{x}_j is the mean and median for MHMGFCM_S1 and S2.

$$O_m^H(U, C) = \sum_{i=1}^c \sum_{j=1}^n U_{ij}^m (1 - H_1(x_j, C_i))(1 - H_2(x_j, C_i))(1 - K_1(x_j, C_i))(1 - K_2(x_j, C_i)) \quad (13)$$

$$U_{ij} = \frac{((1 - H_1(x_j, C_i))(1 - H_2(x_j, C_i))(1 - K_1(x_j, C_i))(1 - K_2(x_j, C_i)))^{-1/(m-1)}}{\sum_{k=1}^c ((1 - H_1(x_j, C_k))(1 - H_2(x_j, C_k))(1 - K_1(x_j, C_k))(1 - K_2(x_j, C_k)))^{-1/(m-1)}}; i = 1, 2, \dots, C; j = 1, 2, \dots, n \quad (14)$$

$$C_i = \frac{\sum_{j=1}^n U_{ij}^m ((K_1(x_j, C_i)K_2(x_j, C_i)H_1(x_j, C_i)H_2(x_j, C_i))x_j)}{\sum_{j=1}^n U_{ij}^m (K_1(x_j, C_i)K_2(x_j, C_i)H_1(x_j, C_i)H_2(x_j, C_i))}; i = 1, 2, \dots, C \quad (15)$$

MHMGFCM Algorithm

Input: Raw image; Output: Segmented image;

Step 1: Arbitrarily initialize the cluster centers $C_i (c = 3$ clusters)

Step 2: Membership values computation using Equation 14.

Step 3: Cluster centers updating using Equation 15.

- The iterative procedure starts:
 1. Membership values updating U_{ij} using Equation 14.
 2. Update the cluster centers C_i by using Equation 15.
 3. If $|C_{new} - C_{old}| > \xi$; ($\xi = 0.001$) then go to step 1
 4. Else stop
- give each pixel to a exact cluster for which the membership importance is maximal

Two types of cluster validity functions, fuzzy partition and feature structure, are frequently used to calculate the presentation of clustering. The representative functions for the fuzzy separation are partition coefficient V_{pc} ²⁸ and partition entropy V_{pe} ²⁹. They are defined as:

$$V_{pc} = \frac{1}{n} \sum_{j=1}^n \sum_{i=1}^c U_{ji}^2 \quad (16)$$

$$V_{pe} = \frac{1}{n} \sum_{j=1}^n \sum_{c=1}^c e^{\log u_{ji} (\log u_{ji})} \quad (17)$$

3. MR Imaging Data Base

The Open Access Series of Imaging Studies (OASIS)²⁷ is a series of magnetic resonance imaging (MRI) data which is openly obtainable for study reason. This data consists of a cross-sectional composed works of 442 subjects aged 18 to 94 years. The MRI gaining facts are given in Table 1. The appearance of the proposed method is tested in terms of V_{pc} , V_{pe} and Silhouette value. Figure 1 illustrates the sample images selected for testing.

Table 1. MR Imaging data processing²⁷

Sequence	MP-RAGE
Repletion Time (m sec)	9.7
Eco Time (m sec)	4.0
Flip Angle (o)	10
Inverse Time (m sec)	20
Difference in Time (m sec)	200
Orientation	Sagittal
Thickness, Gap (mm)	1.25, 0
Resolution (Pixels)	176×208(1×1 mm)

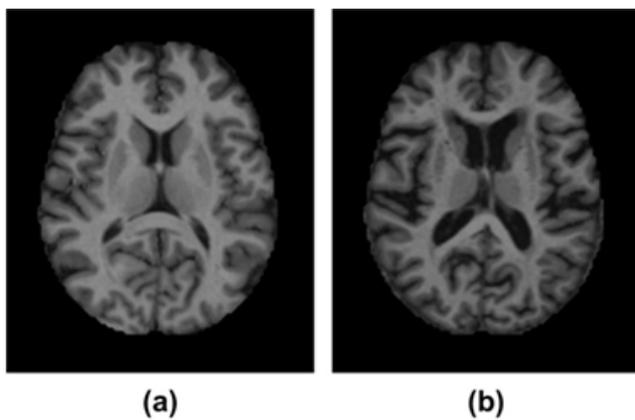


Figure 1. MRI brain images used for segmentation.

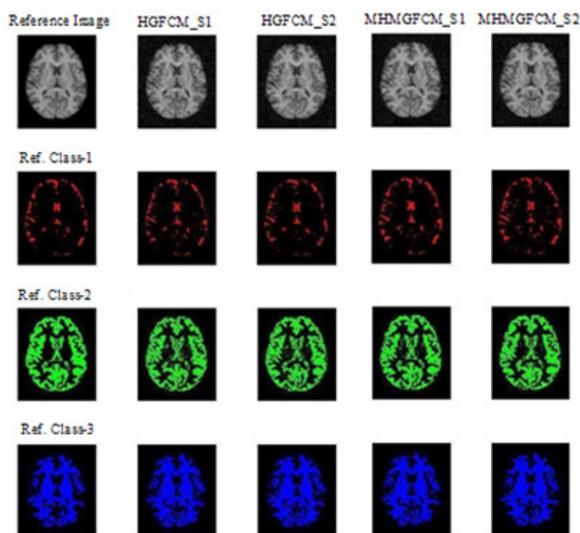


Figure 2. Assessment of proposed MHMGFCM_S1 and S2 Algorithms at 5% Gaussian Noise.

4. Experimental Results and Discussion

In order to confirm the efficiency of the proposed

algorithm, experiments were conducted on brain MRIs²⁷. The presentation of the proposed algorithm is compared with the other existing FCM variant methods in terms of V_{pc} , V_{pe} and Silhouette Value.

Table 2. Estimation of different methods in terms of V_{pc} with 10% Gaussian noise

Method	Image (a)	Image (b)	Image (c)	Image (d)	Image (e)	Image (f)	Image (g)
HGF- CM-S1	0.481	0.511	0.581	0.531	0.631	0.571	0.901
HGF- CM-S2	0.491	0.511	0.691	0.701	0.691	0.691	0.821
MHMG- FCM_S1	0.860	0.840	0.76	0.810	0.74	0.790	0.960
MHMG- FCM_S2	0.875	0.735	0.815	0.855	0.755	0.835	0.985

Table 3. Estimation of different methods in terms V_{pe} with 10% Gaussian noise

Noise intensity	Image (a)	Image (b)	Image (c)	Image (d)	Image (e)	Image (f)	Image (g)
HGF- CM-S1	0.450	0.499	0.329	0.589	0.129	0.199	0.119
HGF- CM-S2	0.279	0.299	0.259	0.179	0.089	0.279	0.049
MHMG- FCM_S1	0.105	0.165	0.105	0.065	0.045	0.045	0.005
MHMG- FCM_S2	0.095	0.115	0.075	0.005	0.015	0.035	-0.025

Table 4. Estimation of different methods in terms of Silhouette value with 10% Gaussian noise

Noise intensity	Image (a)	Image (b)	Image (c)	Image (d)	Image (e)	Image (f)	Image (g)
HGF- CM-S1	0.591	0.511	0.691	0.691	0.851	0.651	0.654
HGF- CM-S2	0.551	0.661	0.811	0.831	0.751	0.791	0.841
MHMG- FCM_S1	0.995	0.985	0.895	0.835	0.845	0.915	0.975
MHMG- FCM_S2	0.875	0.765	0.765	0.875	0.795	0.945	0.987

Figure 2 illustrates the cluster segmentation results of the proposed method and other existing methods with the 5% Gaussian noise on Image (a) of OASIS-MR Imaging data base. The performance of the proposed methods (MHMGFCM_S1 and MHMGFCM_S2) is compared with the HGFCM_S1 and HGFCM_S2. Tables 2 to 4 show the segmentation performance in terms V_{pc} , V_{pe} and Silhouette Value on Image (a) and Image (b) respectively

under different Gaussian noise conditions. From Figure 2 and Tables 2 to 4, it is clear that the proposed method outperforms the other existing algorithms in terms of V_{pc} , V_{pe} and Silhouette Value.

4.1 Histogram of MRI Brain Image Analysis

The histogram of a digital image with gray levels in the range $[0, L-1]$ is a discrete function $h(r_k) = n_k$, where r_k is the k th gray level and n_k is the number of pixels in the image having gray level r_k . It is general observe to normalize a histogram by separating each of its values by the total number of pixels in the image, denoted by n . Thus a normalized histogram is given by $p(r_k) = n_k/n$, for $k = 0, 1, \dots, L-1$. $P(r_k)$ gives an approximation of the probability of occurrence of gray level r_k . Note that the sum of all apparatus of a normalized histogram is equal to 1. Histogram exploitation can be used successfully for image enhancement, image compression and segmentation.

A histogram uses a bar graph to shape the occurrences of each gray level nearby in an image. Figure 3 shows Histogram of Normal Brain Image. The horizontal axis is the gray-level values. It begins at zero and goes to the number of gray levels (256 in this example). Each vertical bar represents the number of times the consequent gray level occurred in the image. In Figure 3 the bars “peak” at about 120 and 150 representative that these gray levels occur most frequently in the image.

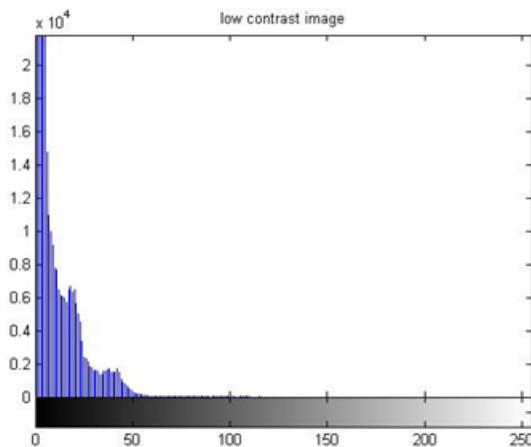


Figure 3. Histogram of normal brain image.

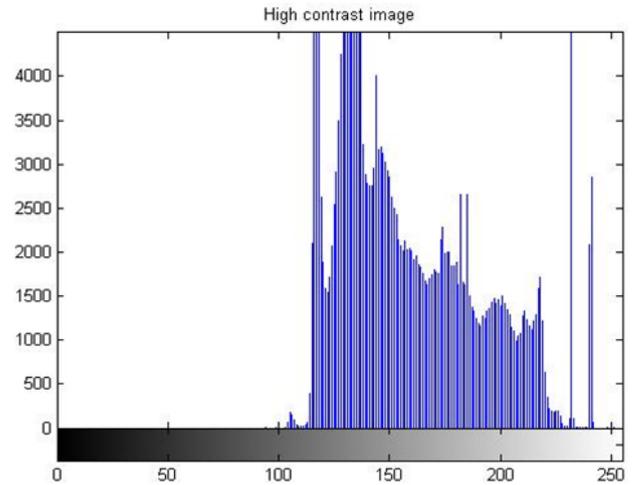


Figure 5. High contrast image.

Amongst other uses, histograms be able to specify whether or not an image was scanned accurately. Figure 4 shows a histogram of an image that was poorly scanned. The gray levels are group together at the dark end of the histogram. This histogram indicate poor contrast. When produced from a normal image, it indicate inappropriate scanning. The scanned image will look like a TV picture with the brightness and contrast turned down.

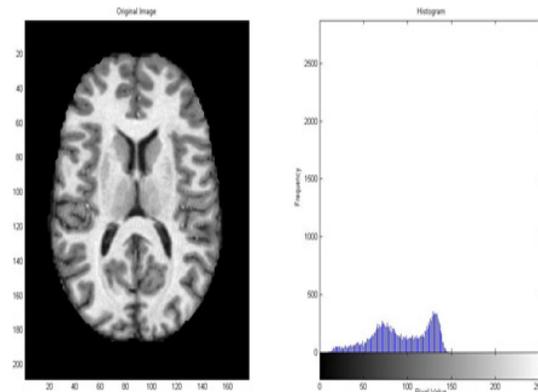


Figure 4. Low contrast image.

Figure 5 shows the image with its histogram. The gray levels in the histogram make transversely most of the scale, representative that this image was scanned with high-quality contrast. The pixel values are located at high end of the intensity.

5. Conclusion

The new algorithms for MHMGFCM_S1 and MHMGFCM_S2 based on image segmentation with spatial information, partition coefficient V_{pc} , partition entropy V_{pe} and Silhouette Value terms are proposed in this paper. The algorithms which are increasing the performance and decreasing the computational complexity. The algorithms utilizes the multi-hyperbolic tangent function and multi-Gaussian kernels, these validity functions is that the partition with less fuzziness and better performance. As a result, the best clustering is achieved when the value V_{pc} is maximum and V_{pe} is minimum.

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