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Using Global Optimization Techniques to Segmentation of Magnetic Resonance Images (MRI)

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Abstract
The Otsu method is one of the segmentation methods that work by finding an appropriate threshold to segment the image. This paper focuses to improve this method by using global optimization precisely the filled function method. The proposed method has been applied to various MRI images, revealing that a segmentation time was reduced by 80% as an approximate percentage. Then applying the single peak quality value MRI segmentation assessment criteria including power-to-noise ratio (PSNR), mean square error (MSE), and signal-to-noise ratio (SNR), appears to result shows the proposed method took a shorter period than the Otsu approach. Then we hybridized the proposed method with K-means cluster and fuzzy c-means methods. The calculating results with the same above criteria show an improvement in image segmentation by hybrid k-means and fuzzy c-means methods of the proposed method in comparison with the traditional methods.

1. Introduction

Segmentation of images is regarded as one of the most essential steps needed for the research of image processing [1; 2] . Separating an image into distinguished, homogeneous pieces which have no overlap advancing analysis of image [3]. Segmentation of images is crucial for a wide range of computer applications, including robotic vision, medical imaging, pattern recognition, biomedical image processing, and others. Segmentation of images algorithms have been developed according to the base-region, base-edge, clustering of base-feature methods, and base-threshold. When compared to other methods, segmentation of threshold-based is regarded to be better due to its accuracy, speed, low storage requirements and simplicity [4]. In this research, the segmentation is improved by the Otsu method with global optimization by using the filled function, and then the softness is hybridized with the method and method.

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2. Otsu algorithm

Japanese researchers proposed the Otsu technique, picture system segmentation with global threshold binarization, in 1979. The thresholding for this approach is the greatest interclass between the image, background, and target contrast. Based on the same criteria, Otsu's technique is well-known for its higher variation between groups. It distinguishes between a background picture and a foreground image using grayscale attributes. When the optimum threshold is chosen, the difference between two segments is higher [5].

Where:

$\boldsymbol{w_b}(\mathrm{t})=\sum_{\mathrm{i=1}}^{\mathrm{t}} \boldsymbol{P(i)}$	(1)	Weight, Background
$\boldsymbol{w_f}(\mathrm{t})=\sum_{\mathrm{i=t+1}}^{\mathrm{l}} \boldsymbol{P(i)}$	(2)	Weight, Foreground
$\mu_b(\mathbf{t}) = \frac{\sum_{\mathrm{i=1}}^{\mathrm{t}} \mathrm{i} * P(i)}{w_b(\mathrm{t})}$	(3)	Mean, Background
$\mu_f(\mathbf{t}) = \frac{\sum_{\mathrm{i=t+1}}^{\mathrm{l}} \mathrm{i} * P(i)}{w_f(\mathrm{t})}$	(4)	Mean, Foreground
$\boldsymbol{\sigma_b^2}(\mathbf{t}) = \frac{\sum_{\mathrm{i=1}}^{t} (i-\mu_b(\mathrm{t}))^2 * P(i)}{w_b(\mathrm{t})}$	(5)	Variance, Background
$\boldsymbol{\sigma_f^2}(\mathbf{t}) = \frac{\sum_{\mathrm{i=t+1}}^{l} (i-\mu_f(\mathrm{t}))^2 * P(i)}{w_f(\mathrm{t})}$	(6)	Variance, Foreground
$\boldsymbol{\sigma_{\mathrm{B}}^2} = \boldsymbol{w_b w_f}(\mu_b - \mu_f)^2$	(7)	Between class variance

3. Polynomial function

The function that is cubic, quadratic or quartic the following here are a few instances polynomial norm definition and structure. are provided [6; 7].

$$A_m\ (k)\ = A_1 k\ +\ A_0\ + \ldots + A_{m-1}\ k^{n-1}\ +\ A_m\ k^m \qquad (8)$$

where m, m-1, m-2, ...0 are the powers of k and A_1, A_0 ,..., $\mathrm{A_m}$, $\mathrm{A_{m-1}}$ are the coefficients of $\mathrm{A}_m\ (k)$, all m's are positive integers. Just determine the coefficients for Equation (8) [8].

4. Optimization of global

Optimization of global problems are used to generate several real-world scenarios challenges in computer science, economics, engineering, and other areas. As an example:

$$\underset{k \in \omega}{\text{minimum}}\ \ M(k) \qquad (9)$$

where $M(\mathrm{k})$ is a measurable function and ꞷ ∈ R   is domain [9]. Including bound and branch methods [10] and algorithms of covering, include curve of space filling approaches[11; 12], A variety of strategies can be used to solve global optimization problems. Other techniques [13; 14]. While they converge relatively slowly, these techniques guarantee the solution. The auxiliary function approach is one among the most popular important deterministic techniques approaches. This strategy is generated with the use of deterministic search algorithms to be able to convert from the current local minimizer to a better one. Including the Global Descent Method,

method Tunneling [15;16;17; 18], and a method filled function, there are several methods to express the auxiliary function.

4.1. Filled Function Method

In minimizer local (minl), It was referred to as the goal function's function filled. M(k). m_n, if a function auxiliary $\mathrm{M}(\mathrm{m}, \mathrm{m}_n)$ meets criteria below

- The function $\mathrm{M}(\mathrm{m}, \mathrm{m}_n)$ local maximizer (maxl) m_n,
- The function $\mathrm{M}(\mathrm{m}, \mathrm{m}_n)$ must not steadfast places at B1 = { m ∈ ꞷ | $\mathrm{M}(\mathrm{k}) \geq \mathrm{M}(\mathrm{m}_n), m \neq \mathrm{m}_n$ },
- The function $\mathrm{M}(\mathrm{m}, \mathrm{m}_n)$, has maintained a consistent position at B2 = { m | $M(m) < M(\mathrm{m}_n)$ m∈ ꞷ} region, if m_n is not has minimizer global (ming) for function $M(m)$

Addressed as (global optimization) in a local of single minimizer, the first function was suggested in 1987 by authors Ge and Qin, filled with two parameters. Including systems of Nonlinear Equations[19], optimization problems constrained, non-Smooth problems [20; 21], and others [22; 23], Since then, several notable r

esearch have been conducted in order to broaden the applicability of filled functions to different sorts of challenges. Recently, the production of the following auxiliary function or filled function approaches was developed [24; 25].

5. K-means method

The K-Means clustering algorithm separates n items into k groups, with each item being a member of the cluster with the closest mean. This approach yields precisely k unique clusters with the maximum distinction achievable. The best number of clusters k that results in the largest separation (distance) is unknown in advance and must be determined using data. Squared error function clustering, often known as K-Means clustering, aims to reduce total intra-cluster variation [26; 27]:

$$\mathrm{J} = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (10)$$

j: Objective Function, k: Number of clusters, n: Number of cases, i: case I, c_j: centroid for cluster j, $\left\| x_i^{(j)} - c_j \right\|^2$: Distance function.

5.1. K-means Algorithm

- Divides the data into k groups, where k is an integer.
- Select k locations at random to act as cluster centers.
- Assign items to the cluster center that is closest to them using the distance function.
- Determine the centroid or mean of each cluster's components.
- Repeat steps 3,4 until each cluster receives the same number of points in subsequent rounds.

6. Fuzzy c-means method

Based on the distance between the center of the cluster and the data point, this approach assigns membership to each data point that is linked to a cluster center. The closer the data is to the cluster center, the more likely it belongs there. Clearly, each data point's total membership should equal one. Membership and cluster centers are updated after each iteration using the following formula [28; 29]:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(2/m-1)}} \qquad (11)$$

$$v_i = \frac{(\sum_{i=1}^{n}(\mu_{ij})^m x_i)}{(\sum_{i=1}^{n}(\mu_{ij})^m x_i)} \qquad \forall j = 1,2,\ldots,n \qquad (12)$$

' n ' represents the quantity of data points, ' m ' is representative of fuzziness index (m) in [1], ' ij ' denotes the data's membership in the j cluster center, the letter ' vj ' stands for the j cluster center, the letter ' c ' stands in terms of the number of clusters centers, and' dij ' denotes the distance between i data and j cluster center.

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c} ((\mu_{ij})^m ||x_i - v_j||^2 \qquad (13)$$

distance between i data point and the j cluster center is denoted by '||xi - vj||'.

Fuzzy c-means algorithm:

- Choose 'c' centers of cluster at random.
- Using the membership of fuzzy ' μij,' compute:

$$\mu_{c_i}(x) = \frac{1}{\sum_{j=1}^{k}\left[\frac{||x-v_i||^2}{||x-v_i||^2}\right]^{\frac{1}{m-1}}} \quad , \ 1 \le i \le k, x \in X$$

- Calculate the fuzzy centers 'vj' as follows:

$$v_i = \frac{\sum_{x \in X} \mu_{c_i}(x)^m x}{\sum_{x \in X}^{n} \mu_{c_i}(x)^m} \quad 1 \le i \le k$$

7. Proposed Algorithm

To segment medical images prepared with various equipment. In this research, we will develop the Otsu method segmentation and improve it by global optimization, specifically the filled function, and with the following steps:

7.1. Otsu_FFM algorithm

Step1 An MRI picture is used as input.
Step2 Create a grayscale picture representation.
Step3 Apply the histogram to the MRI picture.
Step4 Using the Otsu approach, calculate the threshold.
Step5 Using a polynomial function, convert the threshold from discrete to curve fitting.
Step6 Using the Filled Function Method, find the optimal threshold.
Step7 Image segmentation.

7.2. Research methodology

First, we use our suggested method in [30] which boils down to the following steps:

- To get the **weight of background**, we utilize an equation (1) **.**
- To get the **weight of foreground**, we utilize an equation (2) **.**
- To get the **mean of background**, we utilize an equation (3) **.**
- To get the **mean of foreword**, we utilize an equation (4) **.**
- To get the variance **of background**, we utilize an equation (5) **.**
- To get the **variance of foreword**, we utilize an equation (6) **.**
- To get the **between class variance**, we utilize an equation (7) **.**

After these steps, we have obtained the threshold by Otsu method, which we will segment the image with. For the purpose of improving this threshold, we will use the filled function that will find the best possible threshold for segmentation of the image and at the level of global optimization using the equation

$$F(x, x_k^*) = \frac{1}{\alpha + \|x - x_k^*\|^2} h(P_n^*(x) - P_n^*(x_k^*)) \qquad (14)$$

After these steps we have obtained an improved segmentation method and we will hybridize it with a method K-means cluster according to the following steps:

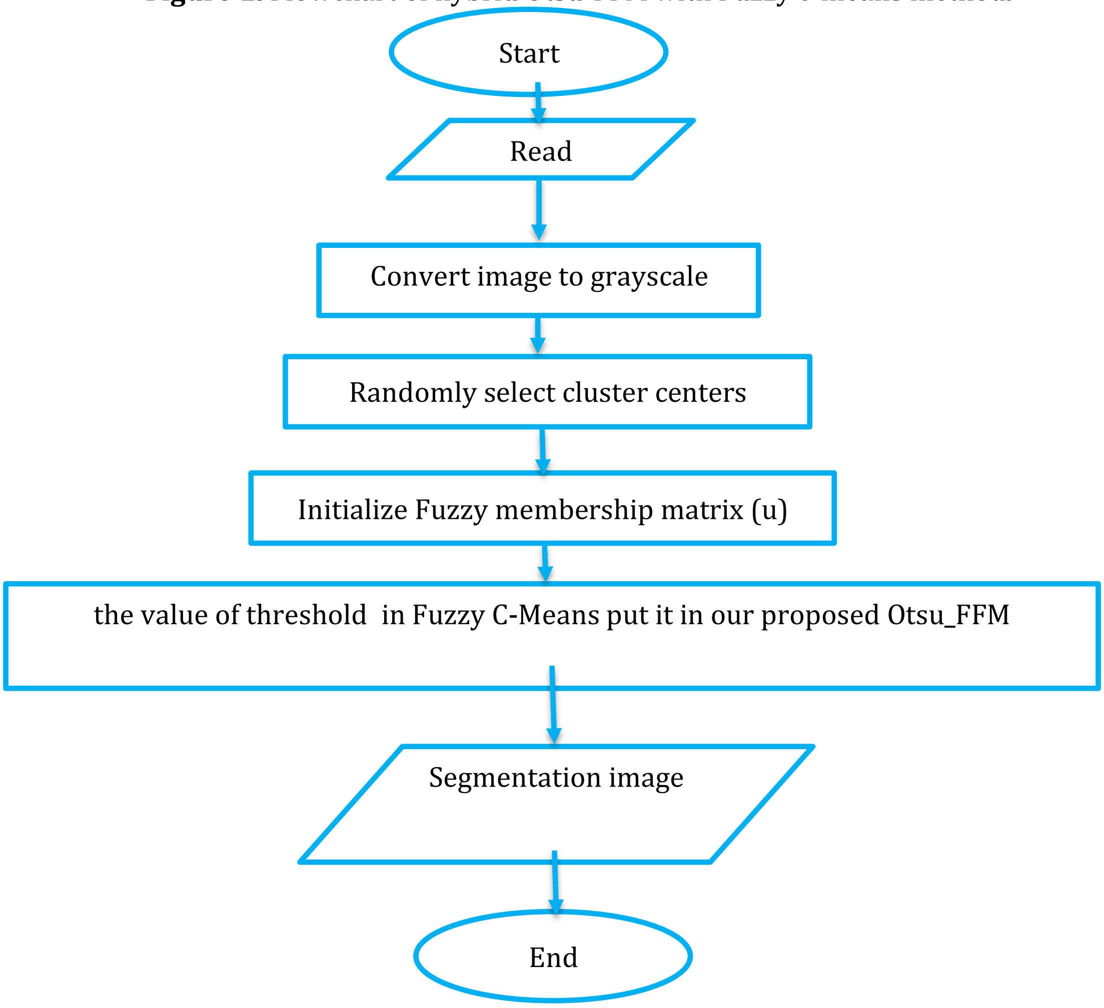
7.3. Hybrid Algorithm (Otsu_FFM with K-means Algorithm)

The algorithm divides the information into k groups, where k is a fixed number.

- Select k locations at random as cluster centers.
- Assign items to the cluster center that is closest to them using the distance function.
- Use the suggested Otsu_FFM's threshold value as the centroid value.
- Segment apart the image.

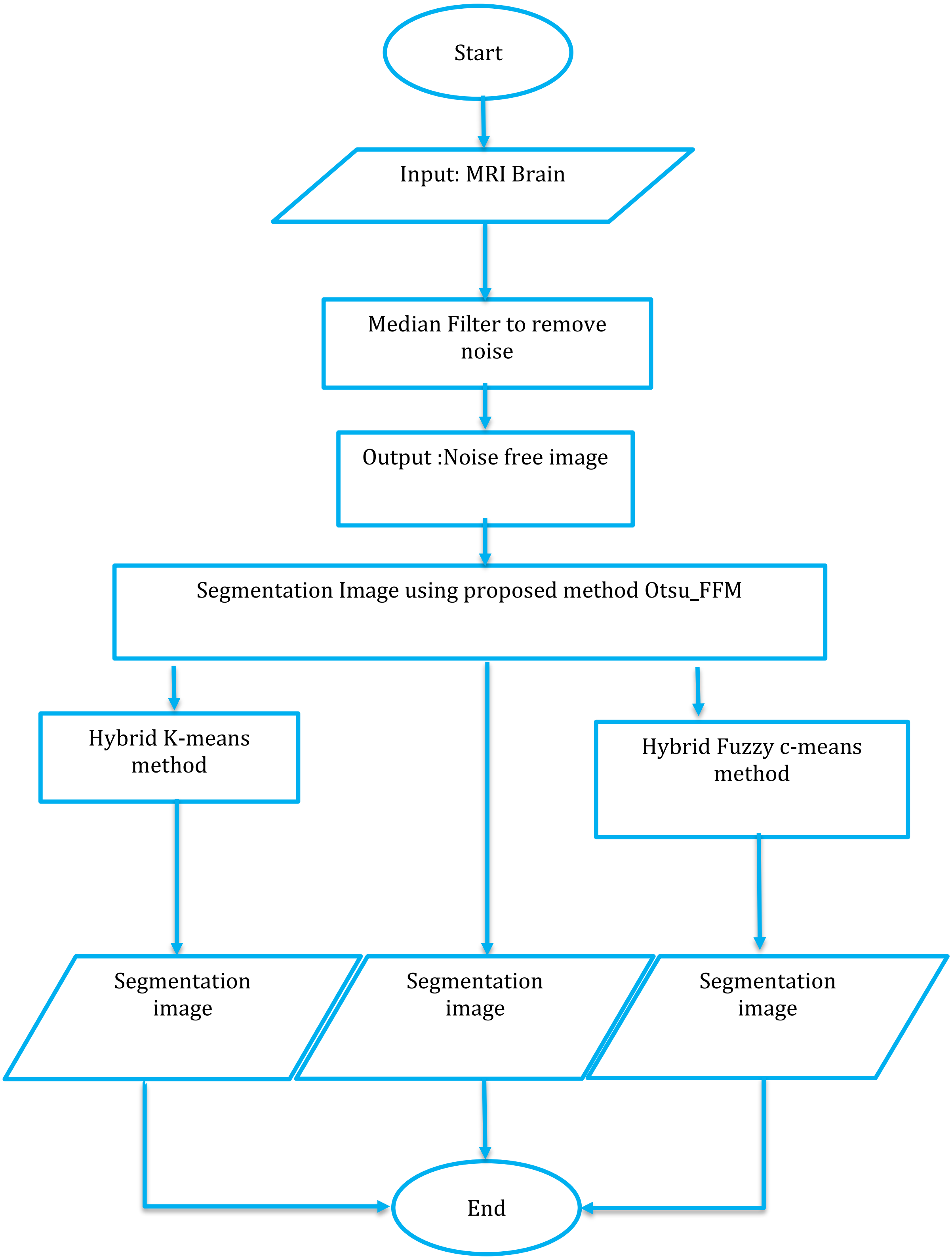
After determining the threshold value using our proposed method, we hybridize the Fuzzy C-Means traditional method by finding the threshold in Fuzzy C-Means traditional method and put it in our proposed method Otsu-FFM, then we will obtain segmentation of the images in an improved way, which is our proposed method as shown in the flowchart.

Figure 1. Flowchart of hybrid Otsu-FFM with Fuzzy c-means method.



We can summarize our Methodology in this flowchart.

Figure 2. Flowchart of our Methodology



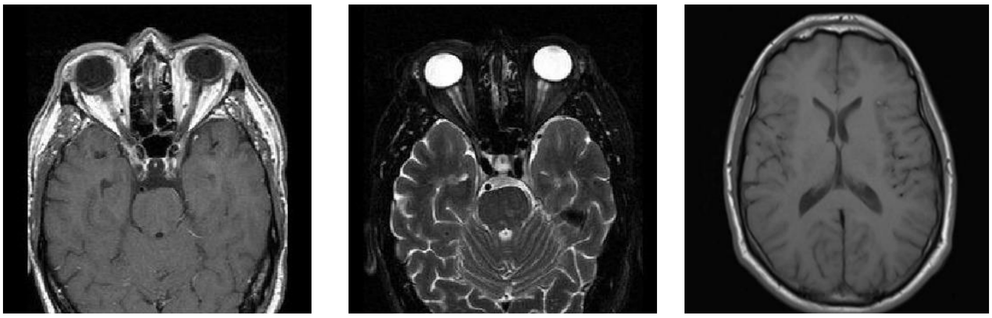
8. Experimental results

We use a variety of medical picture types as test data as MRI images. All tests carried using MATLAB 10 (2020). In order to evaluate the effectiveness of the proposed system, four factors are used to evaluate the performance:

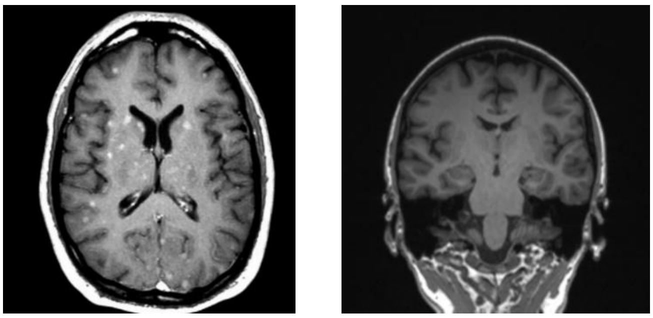
- MSE: Mean Square Error expressed in decibels.
- Peak Signal to noise ratio (PSNR) expressed in decibels.
- Signal to noise ratio (SNR) expressed in decibels.
- Run Time expressed in second.

The results of the image segmentation technique are first examined by computing comparison ratios, and their results are then contrasted using the above-mentioned factors.

Figure 3. Original MIR images from dataset



(A) (B) (C)



(D) (E)

The values of the quality standards (see Figure 8) for the image MRI (see Figure 6). that have been segmented by our proposed method, as well as segmented by the proposed traditional and hybrid methods, are shown as follows:

- PSNR (The higher its value, the better the quality)
    - Between proposed method Otsu_FFM and Otsu traditionally:

      PSNR for proposed method Otsu_FFM more than Otsu tradition which leads to the fact that our proposed method is the most efficient compared to the traditional Otsu method.

- Between K-means and Hybrid Otsu-FFM-Kmeans:

  PSNR for K-means less than Hybrid Otsu-FFM-Kmeans , which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional K-means method.

- Between Fuzzy C-means and Hybrid Otsu-FFM-Fuzzy C-means:

  PSNR for Fuzzy C-means less than Hybrid Otsu-FFM-Fuzzy C-means, which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional Fuzzy C-means method.

- SNR (The higher its value, the better the quality)
  - Between proposed method Otsu_FFM and Otsu traditionally:

    SNR for proposed method Otsu_FFM more than Otsu tradition which leads to the fact that our proposed method is the most efficient compared to the traditional Otsu method.

  - Between K-means and Hybrid Otsu-FFM-Kmeans:

    SNR for K-means less than Hybrid Otsu-FFM-Kmeans , which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional K-means method.

  - Between Fuzzy C-means and Hybrid Otsu-FFM-Fuzzy C-means:

    SNR for Fuzzy C-means less than Hybrid Otsu-FFM-Fuzzy C-means, which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional Fuzzy C-means method.

- MSE (The lower its value, the better the quality)
  - Between proposed method Otsu_FFM and Otsu traditionally:

    MSE for proposed method Otsu_FFM less than Otsu tradition which leads to the fact that our proposed method is the most efficient compared to the traditional Otsu method.

  - Between K-means and Hybrid Otsu-FFM-Kmeans:

    MSE for K-means more than Hybrid Otsu-FFM-Kmeans , which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional K-means method.

  - Between Fuzzy C-means and Hybrid Otsu-FFM-Fuzzy C-means:

    MSE for Fuzzy C-means more than Hybrid Otsu-FFM-Fuzzy C-means, which leads to the fact that our proposed method of hybridization is the most efficient compared to the traditional Fuzzy C-means method.

- Run Time for proposed method Otsu_FFM compared to the all methods which leads to the fact that our proposed method is the fastest implementation.

Figure 4. Image segmentation (image (A)) using proposed methods

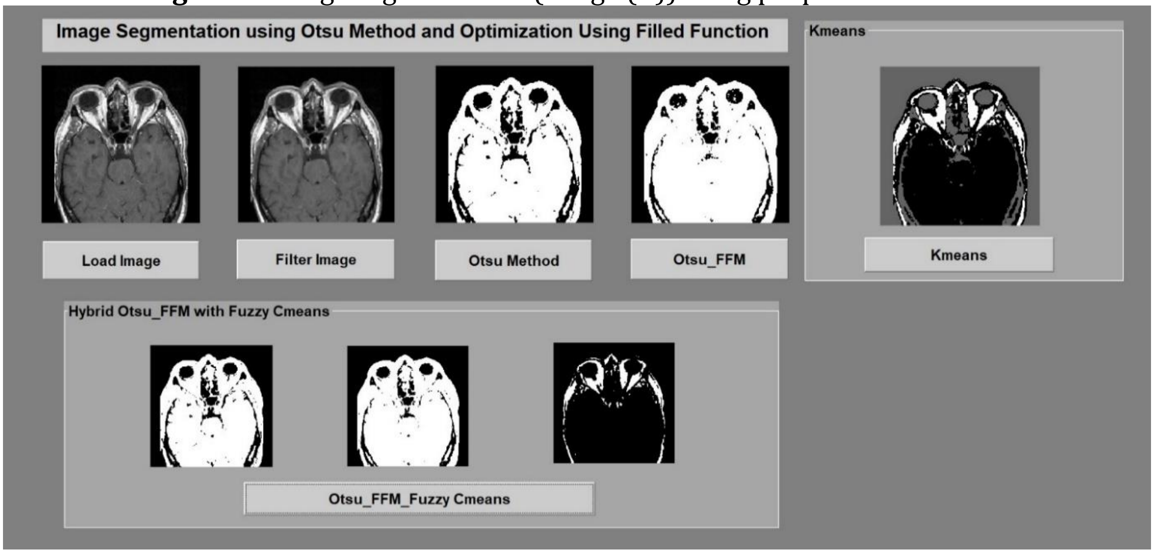
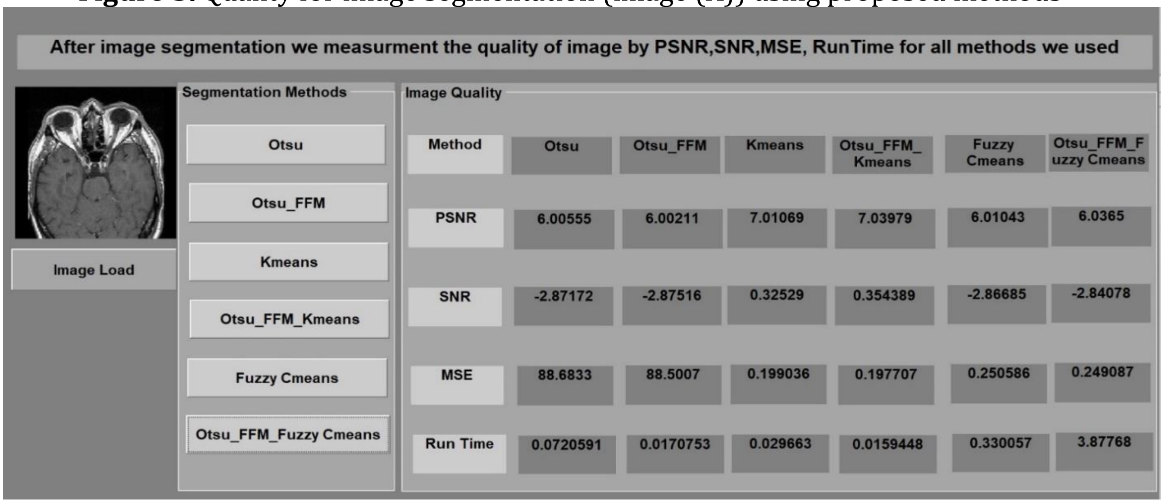


Figure 5. Quality for image segmentation (image (A)) using proposed methods



Method	Otsu	Otsu_FFM	Kmeans	Otsu_FFM_ Kmeans	Fuzzy Cmeans	Otsu_FFM_F uzzy Cmeans
PSNR	6.00555	6.00211	7.01069	7.03979	6.01043	6.0365
SNR	-2.87172	-2.87516	0.32529	0.354389	-2.86685	-2.84078
MSE	88.6833	88.5007	0.199036	0.197707	0.250586	0.249087
Run Time	0.0720591	0.0170753	0.029663	0.0159448	0.330057	3.87768

Figure 6. image segmentation (image (B)) using proposed methods

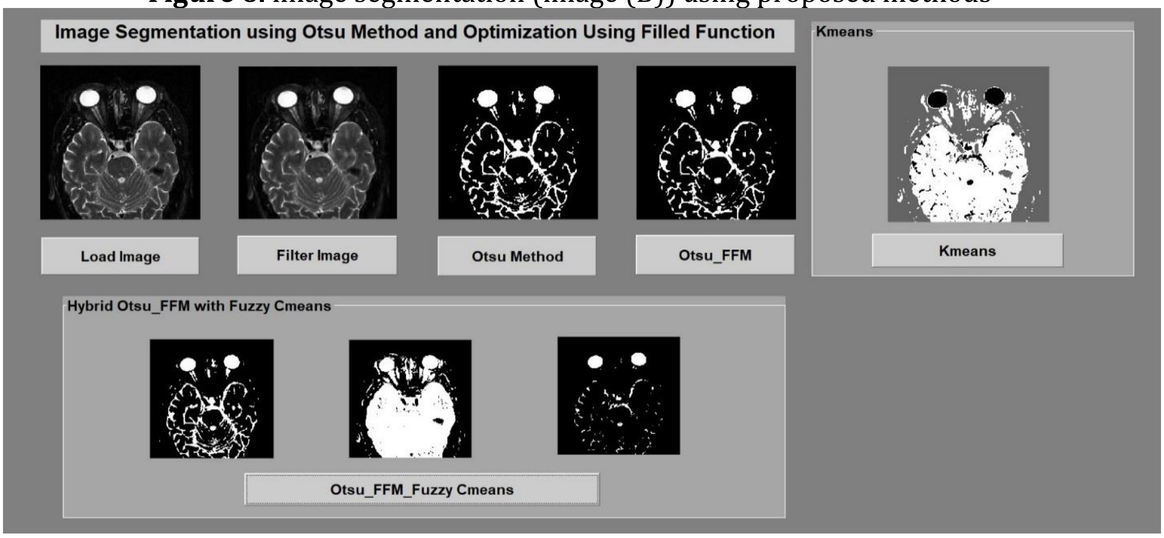


Figure 7. Quality for image segmentation (image (B)) using proposed methods

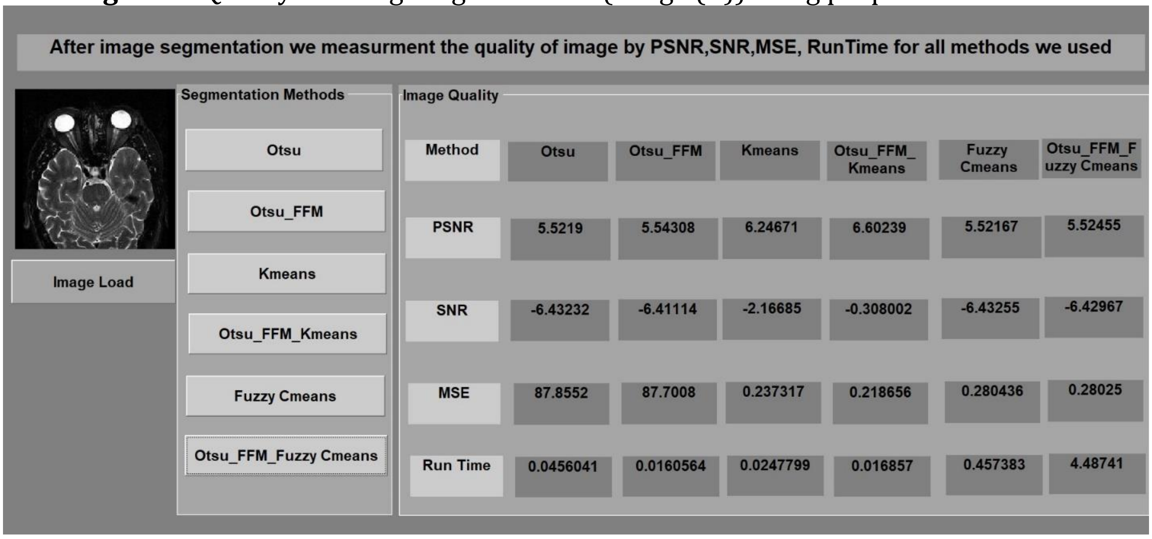


Figure 8. image segmentation (image (C)) using proposed methods

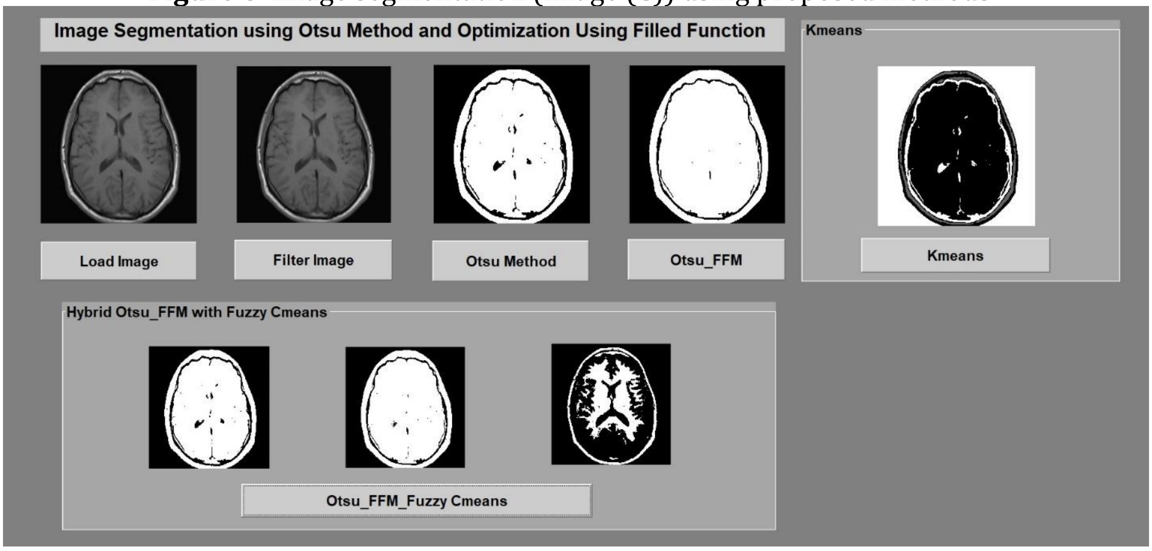


Figure 9. Quality for image segmentation (image (C)) using proposed methods

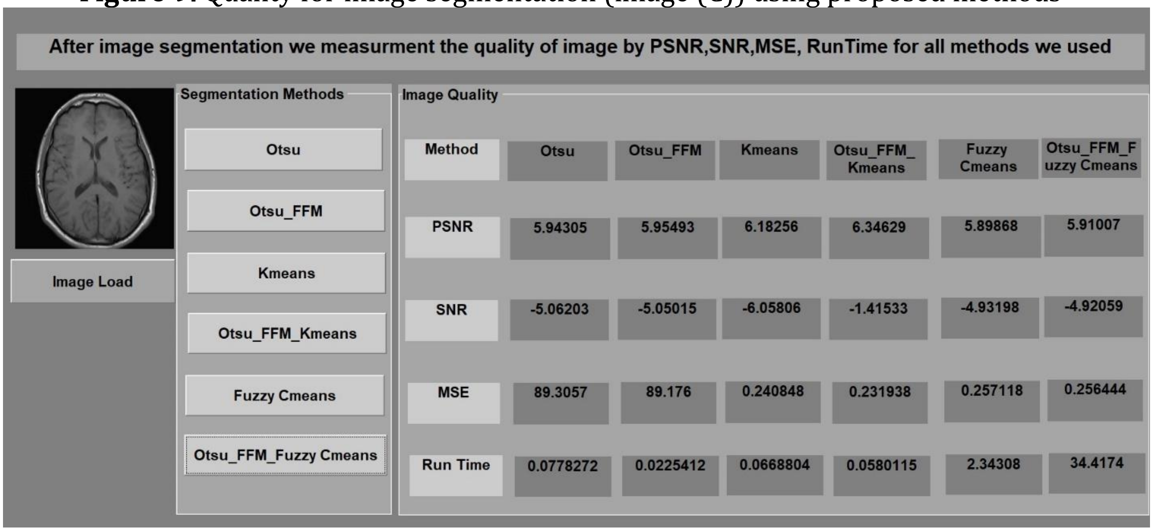


Figure 10. image segmentation (image (D)) using proposed methods

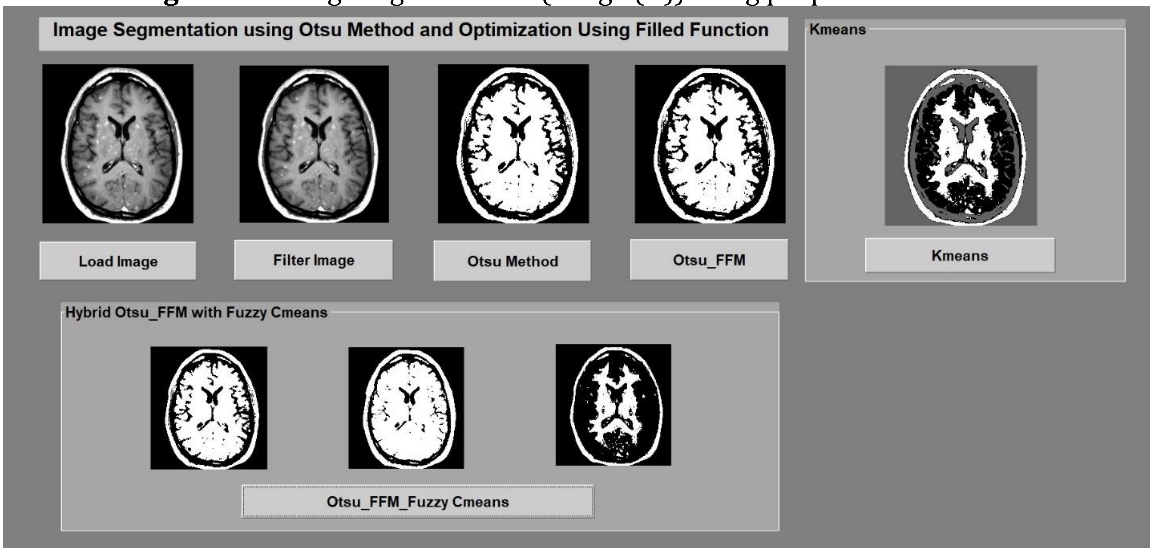


Figure 11. Quality for image segmentation (image (D)) using proposed methods

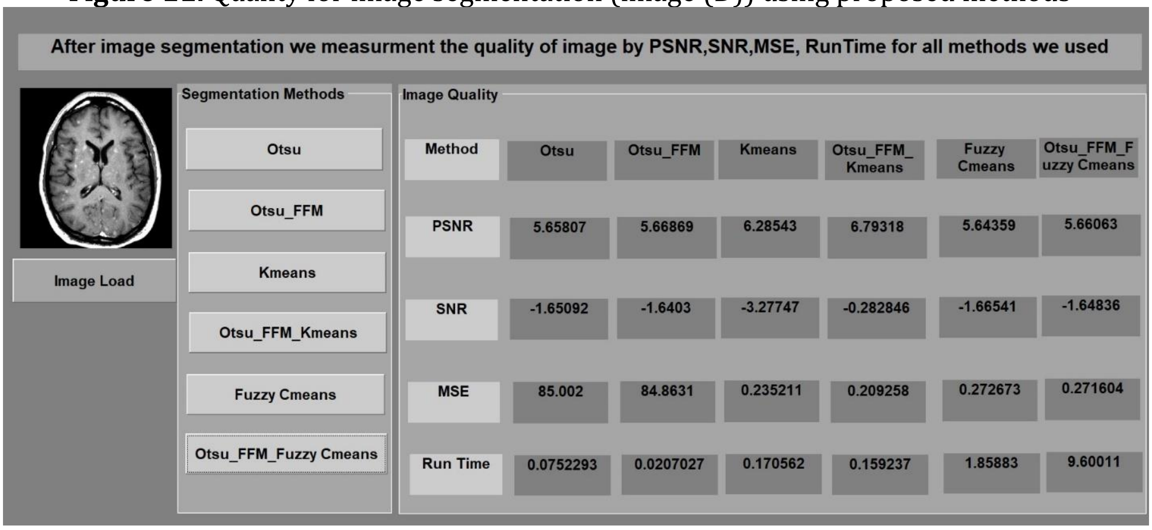


Figure 12. image segmentation (image (E)) using proposed methods

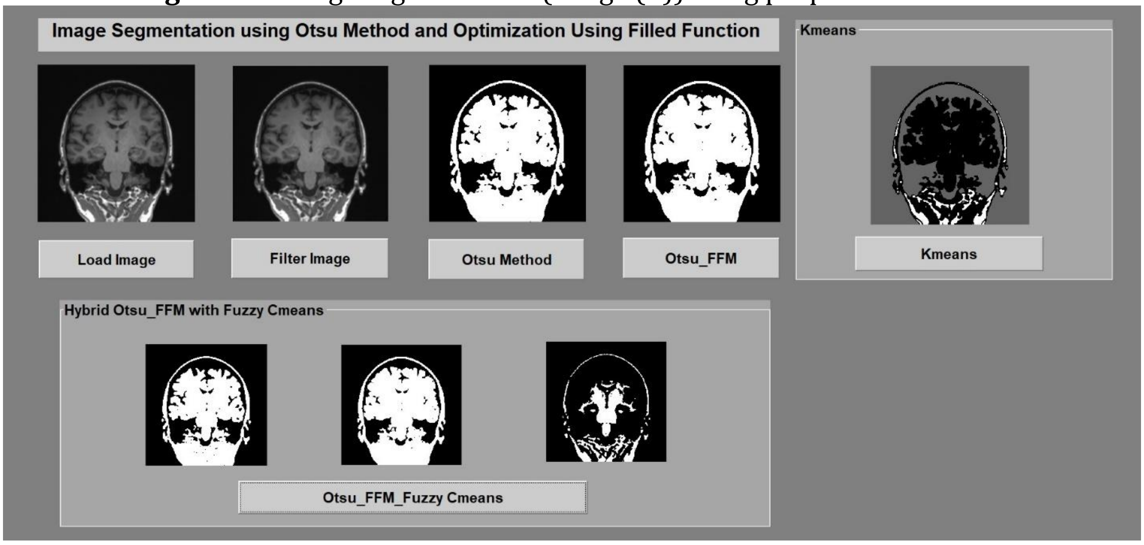
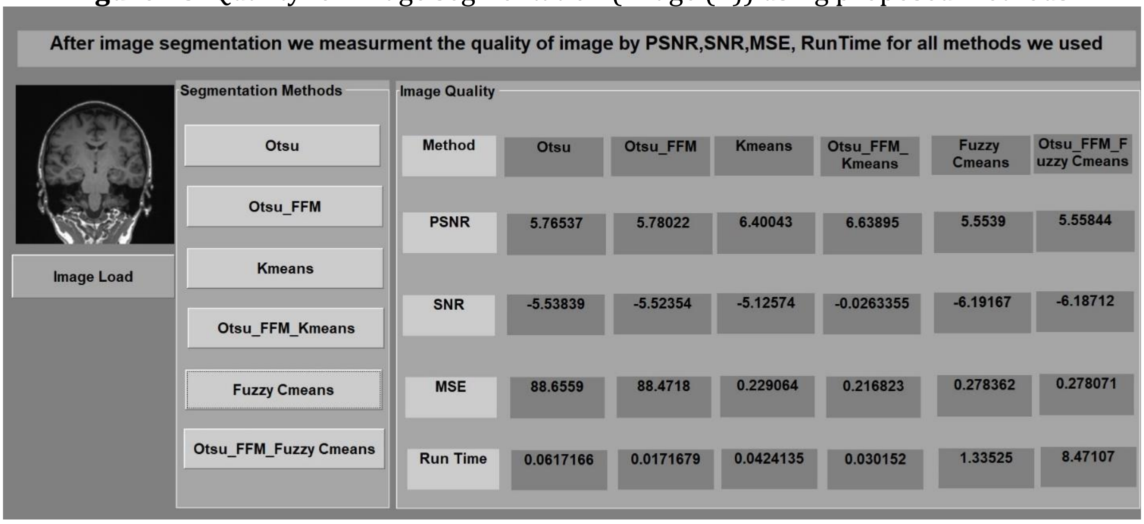


Figure 13. Quality for image segmentation (image (E)) using proposed methods



9. Conclusion

In this study, I applied the image segmentation method by optimizing the traditional Otsu method using mass optimization, specifically the filled function. Then we hybridized it with the k-means method and Fuzzy c-means method. A comparison of the results was made, and the following was obtained:

The proposed method of image segmentation was implemented on medical images. The results proved that the suggested technique can segment pictures more correctly and fast than previous ways, as shown in Figure 8. The effectiveness of our suggested method the mean difference between the generated picture following segmentation and image ratio of noise (PSNR) were calculated. We'll go with 0.7. (MSE) noise becomes smaller than the recommended standard MSE technique Otsu-FFM = 88.5007, the traditional MSE method Otsu = 88.6833 and the traditional MSE K-means = 0.199036, Otsu-FFM-K-means=0.197707 and the traditional MSE Fuzzy C-means = 0.250586, Otsu-FFM-Fuzzy C-means=0.249087. It has the first image was processed in 0.0170753 seconds, which is rather faster when compared to other algorithms. Our approach can identify tumor locations but cannot properly diagnose the condition. Because this method outperforms others in terms of segmentation speed and threshold determinism, it has the potential to be developed as a model for machine learning and an AI (artificial intelligence) algorithm to help in illness categorization in the future.

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