CHAPTER 4

Comparative analysis of filtering methods in fuzzy C-means: Environment for DICOM image segmentation

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4.1 Introduction

Medical image analysis was done using a sequential application of low-level pixel processing and mathematical modeling to develop rule-based systems. During the same period, artificial intelligence was developed in analogy systems. In the 1980s magnetic resonance or computed tomography imaging system has been introduced that encode and decode the output of the images. Digital imaging and communications in medicine (DICOM) has improved the communication mechanism in the medical environment. In products such as CT, MR, X-ray, NM, RT, US, etc., DICOM is used for image storing, printing the information about the patient's condition, and transmitting the correct information about the radiological images. It involves a file format and protocol in communication networks. It is useful for receiving images and patient data in DICOM format. DICOM format has been widely adopted to all medical environments and derivations from the DICOM standard are used into other application areas. DICOM is the basis of digital imaging and communication in nondestructive testing and in security. DICOM data consist of many attributes including information such as name, ID, and image pixel data. A single DICOM object can have only one attribute containing pixel data. Pixel data can be compressed using a variety of standards, including JPEG, JPEG Lossless, JPEG 2000, and Run-length encoding.

Image processing is a rapidly growing field in the academic world that is used with numerous techniques especially in image segmentation and edge detection, which are important for diagnosing the problem or disease. Digital images have been used for getting productive results and data recovery. Spatial changes in MRI are due to the radio frequency coil that will affect the tissue statistics [1]. Medical image segmentation is an essential task in clinical diagnosis. Generally, most of the medical images are the overlapping of the gray scale intensities of various tissues. Medical image data will be uncertain

Generative Adversarial Networks for Image-to-Image Translation
https://doi.org/10.1016/B978-0-12-823519-5.00002-6

due to noise, blurs in recovery, and effects of partial volume from the sensor, which has a low quality of determining. These issues can be resolved by using a fuzzy set which gives the membership function. Hence, fuzzy clustering is a suitable method for the segmentation of medical images. Cluster analysis is a methodology of grouping a data set into groups of indistinguishable individuals. Image segmentation is the process of partitioning image pixels into similar regions. Therefore, clustering algorithms are naturally suitable for image segmentation [2].

The ordinary clustering methods confine all the points of the data set into a single cluster. But fuzzy clustering gives the idea of overlapping the membership in two or more sets. Hence, fuzzy clustering has been widely used in different fields including image segmentation. The fuzzy C-means algorithm has been widely applied in the image processing area including medical image segmentation to classify the major tissues from MRI of the human brain. Furthermore, this algorithm readily meets the scale and shift invariant, then incorporates the multidimensional data [3]. Clustering from the flow of the data is an important task due to the increasing scope of a large amount of data composed over time. Dunn has been developed a fuzzy C-means as a clustering methodology for image segmentation and later it was improved by Bezdek [4, 5].

Due to noise and inhomogeneity, accurate image segmentation is a difficult task in medical images. In the conventional method, the color image is transformed into a gray scale image [6]. For each target class, users prefer training data, and clustering is done for the image using some filters to reduce noise. However, some of the clusters may contain more than one target class. It needs to be partitioned again until getting no such clusters. Since the medical images including ultrasound images such as tomography using X-ray mammography and MRI are represented and saved digitally, the application of image processing methodology has increased tremendously in recent years. Therefore, MRI has been used in many types of research. MRI is an influential tool for detecting unusual changes in various parts of the brain in the initial stage. This tool is a suitable one to acquire brain images with a high contrast level. The recovery parameters of MRI can be modified in order to acquire different gray scale levels for various tissues and types of neuropathology. Though the segmentation of the brain image is a difficult task, it is very important to detect tumors, necrotic tissues, and edema in the diagnostic system. Many methods have been applied for this task namely thresholding, statistical models, region growing, clustering, and active control models. Since the distribution of strain in medical images is very complex in general, the thresholding methodology fails here. Therefore, the extension of thresholding is nothing but region growing needs source from all the regions and facing the corresponding problem to maintain homogeneity as thresholding [6].

The most popular clustering algorithms are expectation-maximization (EM) and fuzzy C-means, which are used for segmentation. The EM method are designed for the distribution of intensity like a normal distribution, which is not suitable for noisy images. But, FCM considers the only intensity of the image and can be used for clustering. The method of unsupervised learning is called clustering, where similar clusters are developed. This method is an objective function-based method and an interesting one. The objective of this method is to divide the observation into as possible as a similar cluster. Likewise, the FCM algorithm is an unsupervised fuzzy clustering algorithm, where the soft partition is possible by getting clusters that partially belong to multiple clusters. These partitions need not be a fuzzy partition as the input may be larger than the data set. But, most of the algorithms generate soft partition, i.e., fuzzy partition. Soft clustering assures the membership degree of all the points in each cluster adding up to one.

In earlier days, computer-aided detection of unusual growth of tissues was motivated by the requirement of obtaining possible accuracy. This process cannot be compared with the recent technologies used, which are digitalized and enable us to observe the volume and location of the unwanted tissues [7]. Since all the objects can have membership in more than one cluster, fuzzy partitions are more adjustable than crisp. FCM clustering uses a simple color feature with adequate information that will efficiently cluster the video frames. Cluster algorithm has been widely used in pattern recognition, data mining, computational biology, and computer vision. Cluster methodology is an unsupervised learning method where the objective is groping elements into clusters with a high level of similarity and the elements in different clusters will have a high level of a degree of dissimilarity. Dissimilarity can be measured using distance, symmetry, curvature, and intensity using the information from the data set [8–10].

FCM clustering is an instrument to categorize the image blocks and provides stepwise detailed searching. Therefore, FCM is a fuzzy classification model where each data is a shaped cluster and identified by a membership degree. Various modifications of FCM clustering have been applied to crisp numbers and only very few of them are extended to noncrisp numbers since it needs complicated equations and tiring calculations. From the data set developing algorithms that can deal with uncertainties is an important task. Automatic generation of type-1 membership functions based on human experts and their perception. This automatic generation can be done by FCM, self-organizing feature map, and robust agglomerative mixture decomposition methods. Image segmentation using type-1 fuzzy sets may give unsatisfactory results and applying type-2 fuzzy sets with more desirable results can solve this issue. Since the secondary grades of type-2 fuzzy sets are equal to one, this set can control the level of uncertainty of data more efficiently than the conventional methods. Here, using interval type-2 fuzzy sets can reduce computational complexity. The clustering procedure for the data under a fuzzy environment is called fuzzy C numbers. These numbers may be considered as normal type fuzzy numbers, triangular, and trapezoidal fuzzy numbers [11–14]. Modeling of membership functions based on similarity decomposition and centroid of clusters is the most important task in fuzzy clustering. In fuzzy cluster analysis, the membership matrix will represent the relationship between the data and it gives a more comprehensive view of the relationships. This membership matrix raises the expressiveness of the cluster analysis. In conventional methods, when the data are equally distanced between representatives, they are assigned to one cluster [15].

4.1.1 Organization of chapter

The remaining part of the work is organized as follows. In Section 4.2, a review of the literature is given for the aim and scope of this work. In Section 4.3, some of the basic concepts are presented for a better understanding of the work. In Section 4.4, image segmentation on the DICOM image is proposed using the FCM clustering algorithm. In Section 4.5, the result and discussion of this work are given. In Section 4.6, we concluded our work in the future direction.

4.2 Related works

Ahmed et al. [1] introduced a new algorithm for fuzzy segmentation on MRI data and calculated inhomogeneities of intensity. They have neutralized the inhomogeneities by their modified fuzzy C-means algorithm which allows the labeling of a pixel by immediate neighborhood. They have also illustrated that the efficiency of their modified algorithm by using synthetic images and MRI data. Yang et al. [2] proposed a new technique called an alternative FCM algorithm for MRI image segmentation to distinguish abnormal and normal tissues in ophthalmology. They have concluded that their proposed algorithm is better than the existing fuzzy C-means algorithm when it detects abnormal tissues depending on a window selection. The extended version of the FCM clustering algorithm has been introduced in Ref. [16] to overcome the issues of noise sensitiveness. Roy et al. [3] studied intensity shading, size of the variable cluster, and smoothness of membership functions of the FCM cluster algorithm in detail and introduced a new parameter called compactness to obtain additional information of the clusters. With that parameter, they have proposed a fuzzy C-means algorithm with variable compactness which is used to analyze major tissues in brain MRIs. Hore et al. [4] exhibited the online fuzzy clustering algorithm to partition large data which may be considered as streaming data. They have concluded that their algorithm offers partitions in large volumes of MRI when clustered all the data at one time. An automatic method is proposed to identify exudates from low contrast digital images of retinopathy patients with nonstretched pupils based on the FCM clustering technique [5]. Balafar [6] introduced a new FCM clustering method which is used to convert the color image into the gray level image by a user-selected training data and decrease the noise by using an anisotropic filter. Suri and Sardana [17] made a prediction of the gold price using the FCM clustering with the help of a known fuzzy membership function based on fuzzy clustering and weighted least square and Takagi-Sugeno model. In 2011, Christ and Parvathi [7] proposed a new technique for the segmentation of medical images using the Silhouette method, Spatial FCM, and hidden Markov random field-based FCM algorithms. Havens et al. [8] analyzed large databases by using three new incremental kernelized FCM algorithms such as rse-Kernelized FCM, sp-Kernelized FCM, and o-Kernelized FCM. They have evaluated the performance of all three algorithms by comparison and recommended rse-Kernelized FCM is suitable for computational problems. Asadi and Charkari [9] have done a video description using FCM clustering with a new keyframe extraction system which is chosen based on maximum membership grade that will produce static video summaries along with high accuracy and low error rate. Pimentel and Souza [10] have been introduced a novel approach to deal with the membership based on the essential information in the entire feature of the image. Biswas et al. [11] confined a fast-geometrical image by using FCM clustering which considers pixel patterns in the column direction of an image block as the classification features and for stepwise precise classification, two-level classification method has been applied.

Recently, Mulyana [12] identified a medical plant using FCM clustering based on a fractal method such as fractal dimension and fractal code which are used to extract the image feature of the 20 variety of medicinal plants for every 30 samples. The experimental result shows that 85.04% and 79.94% fuzzy clustering are based on fractal dimension and fractal code, respectively. Moreno and Lopez [13] explained the progress of a trajectory planning system using fuzzy algorithms and machine vision methods. The system has been controlling the movement of a tele-commanded mobile robot for machine vision techniques and fuzzy algorithms. Hadi et al. [14] have been proposed a vector form of FCM which simplifies the method of FCM clustering applied to fuzzy numbers. Warunsin and Chitsobhuk [18] established the performance of the cyclone identification system using the histogram and used the classification of support vector machines and FCM clustering. Fredo et al. [19] segmented the sub outer layer regions of the brain regions such as corpus callosum (CC) and brain stem (BS) using FCM clustering. They are also recommended that this skeleton can be used to diagnose neural disorders autism automatically. Doganay et al. [20] developed a fully automatic algorithm for lung tissue segmentation using the FCM clustering algorithm. The fast FCM clustering algorithm is used to segment the lung region in two-dimensional high-resolution computer tomography images. Liu et al. [21] presented a fluctuation of the fuzzy local information C-means clustering algorithms which include region-level spatial, spectral, and structural information along with region-level Markov random field model to achieve accuracy to color texture images. Recently, Vani and Anusuya [22] implemented a unique Kannada word recognizer using FCM and vector quantification. To improve the efficiency and speed of FCM, Stetco et al. [15] proposed a fuzzy C-means++ algorithm that obtained a maximum level of occurrences on both artificially generated and real-world data sets. Velmurugan and Naveen [23] have examined the usage of clustering methods and preprocessing methods to forecast the disease in MRI brain images in the medical field. Mohammed et al. [24] introduced the FCM algorithm that takes less time in finding clusters and applied in image segmentation. Kaur and Tulsi [25] have proposed an FCM method to obtain impressive results for complex background images in order to overcome the issue such as failed to compute threshold value when there is no significant change in the gray level of pixels. Heriana [26] had done edge detection on an image using FCM and objective function based on the data distribution of mean and standard deviation values of each of the four magnitude direction values of a pixel that have been calculated based on the objective function. Rai [27] has introduced the idea of detection of soft metaphor by allowing membership values to fuzzy sets which represent varying degrees of metaphoricity. Jebari et al. [28] proposed an automatic genetic FCM algorithm with the uses of newly defined genetic algorithms including a new mutation operator, crossover operator, and tournament selection to develop the number of clusters and to contribute initial centroids. Sivasaravanababu et al. [29] converted the captured RGB image into a gray-scale image and illuminated it by using the technique of image enhancement. Zhang et al. [30] disparate FCM clustering into traditional FCM objectives using a new diversity regularization. The FCM objective has been addressed by an optimization algorithm in order to converge the local optimal solutions with adequate time complexity. Edge detection on DICOM image [31] and image extraction on MRI DICOM image [32] were studied by the use of the MATLAB program under the type-2 fuzzy setting to convert DICOM image into a 2D gray scale image. Jinlin [33] has been introduced a new FCM clustering algorithm based on multiobjective optimization along with fuzzy distance measurement which is used to adjust the weights of the pixel local information to improve the performance and computational time while segmenting images by a different type of noises. Santiago [34] had done mass abnormality segmentation and categorization modified FCM using histogram and binary decision tree. The importance of preprocessing and fuzzy methods has been highlighted for the segmentation and classification of mammographic image processing.

Torra [35] has studied and analyzed the effect of the parameter m which corresponds to the degree of fuzziness of the solution acquired from the unsupervised FCM algorithm. Umoren et al. [36] refined an isolated diagnostic system using the FCM algorithm and shown that ophthalmic pathological results obtained from FCM are faster and reliably clustering. Srivastava et al. [37] analyzed the image using the FCM algorithm by carrying out the apportionment procedure in which the image is considered as an object and subdivided into the class of images to overcome noise sensitivity. Tolentino et al. [38] have proposed a new technique for the measurement of the distance to rectify the issues of FCM incorporating trigonometric functions and Manhattan distance calculation on speed and accuracy. Vernanda et al. [39] focused on the controversy involved in students' data that continue to colleges introduced graduate-school clustering using FCM. Borthakur et al. [40] identified suitable metrices from heart rate variability analysis for sonification. They have also investigated the use of the auditory display in aiding the analysis of heart rate variability leveraged by unsupervised machine learning techniques. Katircioglu et al. [41] determined Denim fabric's measurement of the influence of air using the FCM algorithm. The fabric samples are analyzed by a microscope to count the bright areas of the pixels and images are improved by image processing. Gan has [42] proposed safe semisupervised FCM clustering and introduced MinMax FCM to swamp the issues such as wrongly labeled samples which are carefully examined by constraining the corresponding predictions to be those yielded by unsupervised clustering.

However, the realm of image segmentation on the DICOM image of the patient's MRI has not been studied yet in the literature so far. Hence, it is still open to many possibilities for innovative research work especially in the context of FCM clustering. Hence, in this chapter, we have studied and analyzed the performance of a fuzzy C-means clustering (FCMC) algorithm along with different image filtering methods based on digital imaging and communications in medicine (DICOM) data set. The significance of this study is to the lower false positive rate and the intrusion detection is a high rate. For this purpose, the DICOM color images are first converted to gray scale and applied various filters to reduce the noise error.

4.3 Methodology

4.3.1 Proposed algorithm

In this section, edge detection is done on the DICOM image of a magnetic resonance imaging (MRI) patient using the fuzzy C-means clustering (FCMC) algorithm.

Algorithm 4.1: Fuzzy C-means clustering algorithm

1. Convert CT scan files to DICOM through *mri=flipdim(mri,1)*;
2. Import the background image and show it on the axes through *bg=imread('background.png')*;
3. Prevent plotting over the background and turn the axis off
  | making sure the background is behind all the other uicontrols;
4. Covert RGB to Green Channel Complement through *GIm=imcomplement*(*green*);
5. Contrast Limited Adaptive Histogram Equalization
6. Structuring Element through *se=strel*(*'ball',8,8*);
  | Morphological Open through *gopen=imopen*(*HIm,se*);
7. Remove Optic Disk using
  | *godisk=HIm - gopen 2D*
  | *Median Filter medfilt=imguidedfilter(godisk,'DegreeOfSmoothing',1);*
8. Segmentation Using Fuzzy C-means through
  | *ffcm1=*([*'The 1st Cluster=' num2str*(*ccc1*)]);
  | *ffcm2=*([*'The 2nd Cluster=' num2str*(*ccc2*)]);
9. Using edge detection detect the edge through
  | *SegmentedImage=get*(*LTproject.segmented_image,'Userdata'*).

4.3.2 Evaluation metrics

The fuzzy C-means clustering [3] is the solution of the energy function and is defined mathematically as

$$J_{\mathrm{FCM}} = \sum\nolimits_{i \in \mho} \sum\nolimits_{j=1} u_{ij}^{p} \left(y_i - v_j\right)^2 \tag{4.1}$$

where y_i is the intensity of the observed image at the ith pixel, C is the number of classes, v_j is the centroid of the class, $\mho$ is the domain of the image, and u_{ij} is the membership (nonnegative) function of the ith pixel for the jth class and $\sum_{j=1}^{C} u_{ij} = 1, \forall i \in \mho$. The parameter p is the weighting exponent where $p > 1$. If $p = 1$, then FCM becomes hard K-means algorithm with binary values as the member functions. The membership function and the center of the cluster is defined by

$$u_{ij} = \frac{1}{\sum\nolimits_{k=1}^{m} \left[\frac{d\left(y_i, \varphi_j\right)}{d\left(y_i, \varphi_k\right)} \right]^{\frac{2}{m-1}}} \tag{4.2}$$

$$v_j = \frac{\sum\nolimits_{k=1}^{m} \left(u_{ij}\right)^f y_i}{\sum\nolimits_{k=1}^{n} \left(u_{ij}\right)^f}$$

where f is the degrees of freedom.

$$\text{Accuracy} = \frac{N_{\text{True Positive}} + N_{\text{True Negative}}}{N_{\text{True Positive}} + N_{\text{True Negative}} + N_{\text{False Positive}} + N_{\text{False Negative}}} \tag{4.3}$$

Precision is expressed as

$$\text{Precision} = \frac{N_{\text{True Positive}}}{N_{\text{True Positive}} + N_{\text{False Positive}}} \tag{4.4}$$

Eq. (4.5) shows that the harmonic mean between precision and sensitivity is given by

$$\text{Harmonic mean} = \frac{2 \times N_{\text{True Positive}}}{2 \times N_{\text{True Positive}} + N_{\text{False Positive}} + N_{\text{False Negative}}} \tag{4.5}$$

4.3.3 Morphological operations

A medium filter can do removing noise from an image effectively. It is a classical preprocessing step to make the results better of later processing like edge detection. Under some conditions, this filter extracts edges during noise reduction. Hence, this filter has been used in digital image processing widely [24].

4.3.3.1 2D median filter

2D filter is a technique of nonlinear digital filtering which is used for the removal of noise from an image. Removing noise from an image is a preprocessing step of ensuing processing like edge detection. This filter extracts edges during noise reduction and hence it has been widely used in image processing and signal processing as well.

4.3.3.2 Imguided filter

The function of the Imguided filter enforces edge preserving on an image smoothly using a guidance image that is the content of a second image. This guided image can be a different version of the image or an entirely different image. Guided image filtering is a region of operation where the statistics is a region in the parallel dimensional neighborhood is the guided image. This takes place while measuring the value of the output pixel. The structure of the guidance image and the image to be filtered are the same when both are the same. If they are different, structures in the guidance image will impact the filtered image.

4.3.3.3 Imfilter

The function of Imfilter calculates the value of each output pixel using double-precision, floating-point arithmetic. Using the Imfilter toolbox, images can be filtered using convolution or correlation. It handles types of data using the rules of arithmetic saturation and the output image has a similar data type as the input image. If the result exceeds the type of data, this filter truncates the result to the allowed range. If the data type is an integer, then this filter rounds fractional values. Using this truncation behavior, the image can be converted to various types of data before calling Imfilter. If the input image is of class double, then the output will be negative values.

4.3.3.4 Wiener 2 filtering

It is two-dimensional noise-removal filtering and it is a linear filter. This filter adapts itself according to the variance of the local image. If the variance is large, then this filter performs in a smooth way. While the variance is small this filter carries out very smoothly. This adaptive filter has been used widely for preserving edges and of the image and other parts as well. This filter also manages the preliminary calculations and enforces the input image.

4.3.3.5 Gaussian filter

It is a linear filter. It is used to reduce the noise and it is alone will blur edges and low contrast. It is faster than other filters. Imadjust is not necessary for this filter.

4.3.4 Research design

Fig. 4.1 depicts the methodology used for image segmentation on DICOM using FCM.

Based on Fig. 4.1, DICOM image segmentation begins with the DICOM image read.

4.4 Experimental analysis

The proposed methods are implemented in MATLAB 2015a environment. The DICOM files are in the montage shown in Fig. 4.2.

We choose the slide with the best view as in Fig. 4.2 for full image purpose in Fig. 4.3.

The data set used in this chapter is sourced from the digital imaging and communications in medicine (DICOM) database for brain images. The color type of the image is gray scale and the modality is computed tomography. The study description is facial bone from 50-year-old female. The thickness of the slice is 4. Fig. 4.3 shows an excerpt of the DICOM data set. Medical imaging is useful in convolution models for image segmentation. Medical image segmentation data sets are limited, and annotated data is available for training. While surgery is one of the treatment for brain tumors, radiation and chemotherapy may be used to slow the growth of tumors that cannot be physically removed. Magnetic resonance imaging (MRI) furnishes elaborated images of the brain and is also common test used to diagnose brain tumors. All the more, brain tumor segmentation

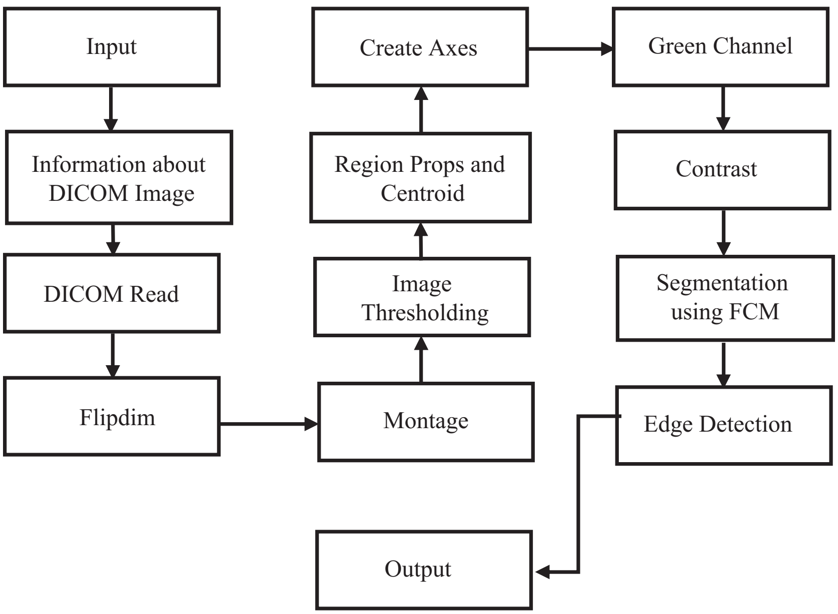

Fig. 4.1 DICOM image segmentation using FCM.

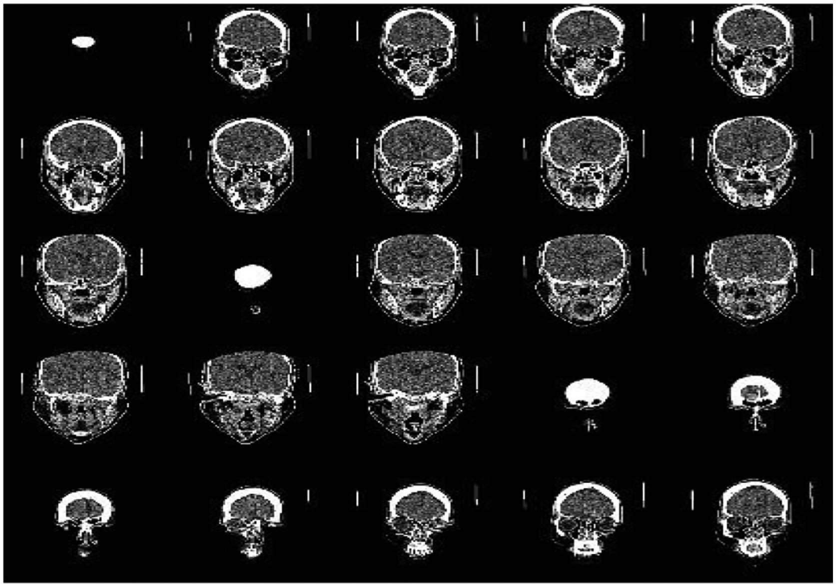

Fig. 4.2 Montage of the DICOM File.

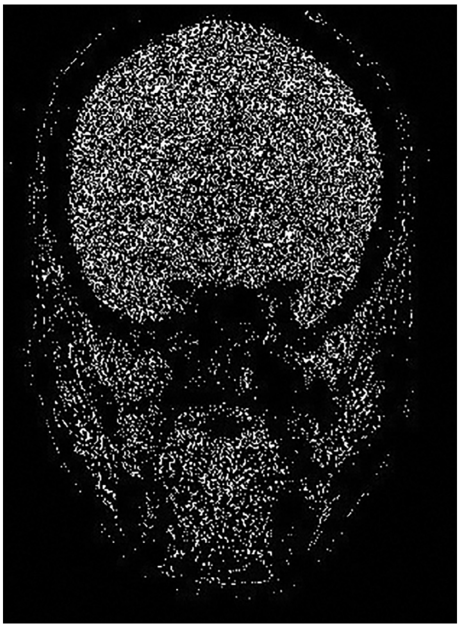

Fig. 4.3 Image with the best view.

from MR images can have a great impact on improved diagnostics, growth rate prediction, and treatment planning. Some tumors can be easily segmented, others were difficult to identify locate/diagnose. These tumors are often circulated, poorly contrasted, and extend tentacle-like structures that make them difficult to segment. Another primal difficulty with segmenting brain tumors is that they can appear in any shape, size, and anywhere in the brain. Brain is typically made of three layers of tissues: white matter, gray matter, and cerebrospinal fluid. Brain tumor segmentation aims to detect the location and extension of the tumor regions. This is done by identifying abnormal areas from normal tissue. Borders of abnormal tissues are often fuzzy and hard to distinguish from healthy tissues.

4.5 Performance analysis

Here, the performance of the entire process of image segmentation on the DICOM image using FCM has been described clearly in Fig. 4.4. Information on the physical object is known as 3D presentation states (3DPR) that is nominated for storing all parameters and relevant information of 3D visualization. The main purpose of 3DPR is allowing the storage and distribution of the presentation of an image in 2DPR, it can be applied to volume data via 3DPR. Thus, the experiment is to develop a systematic and DICOM-conformant parameterization of 3D visualization. This corresponds to parameterizing all procedures of 3D medical visualization and storing all necessary parameters and data in a 3DPR object. Then, the 3DPR object can be used to rerun all the procedures automatically to regenerate the 3D visualization. The procedures to be parameterized are preprocessing, segmentation, and postprocessing. Instead of storing the segmentation parameters, segmented voxel data can be stored using lossless compression. Using diverse test cases, various compression methods are used.

Clear visibility of the image has been obtained using a green channel image with high contrast as shown in Fig. 4.4. In the denoising process, the main disadvantage of the existing methods is the behavior of over amplifying in the relatively homogenous region of an image. To overcome this disadvantage, we used contrast limited adaptive histogram equalization as shown in Fig. 4.4. Removing noise from an image can be done effectively using the median filter. It is a classical preprocessing step to make the results better of later processing like edge detection. Under some conditions, this filter extracts edges during noise reduction. Hence this filter has been used in digital image processing as shown in Fig. 4.4. In this part, using the morphological open and remove the disk, the image has been structured using a 2D median filter and removed background and image adjustment as shown in Fig. 4.4. The background and image adjustment have been done. Using edge detection segmented images have detected the edge.

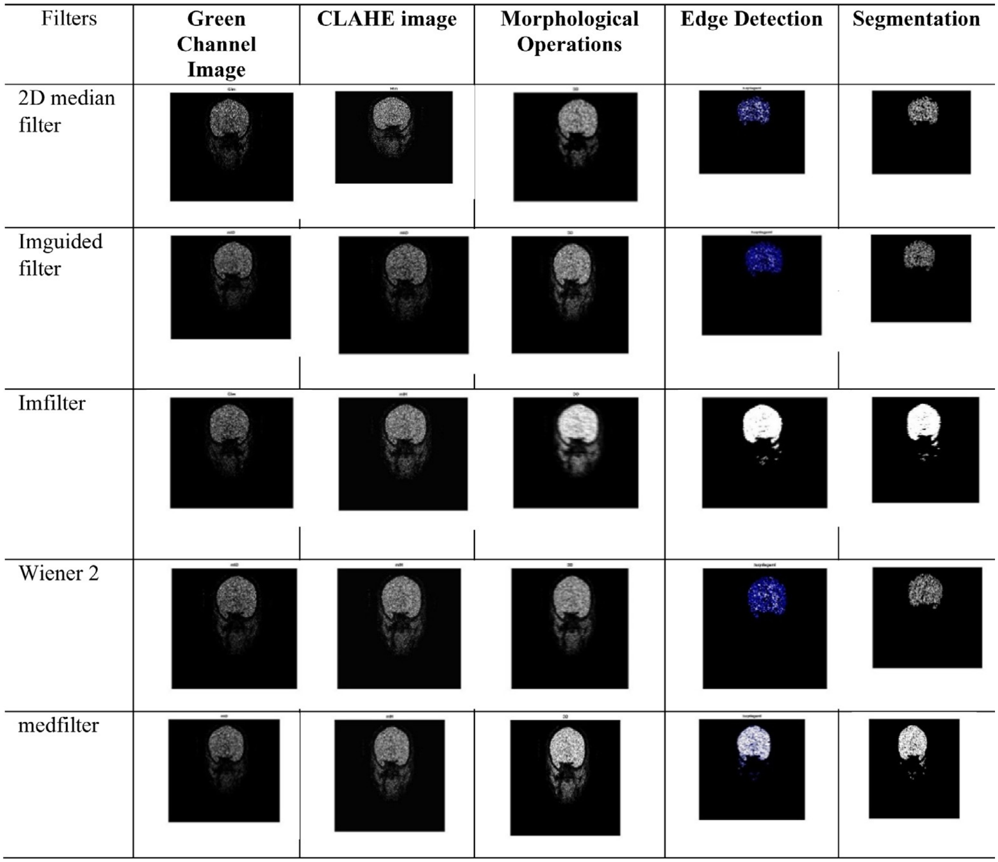

Fig. 4.4 Different filter segmentation.

4.6 Results and discussion

In the proposed system, 2D median filter is found to be the best filter to extract the image from DICOM information. The classification output of the experiment reveals that the accuracy of the image extraction is 97%, 5% sensitivity, 99% specification, 12% PPV, and 7% harmonic mean of precision and sensitivity. The classification outputs are shown in Table 4.1 and Fig. 4.5.

The classification output of the experiment reveals that the accuracy of the image extraction through 2D median filter is 97%, Imguided is 94%, Imfilter is 96%, wiener2 is 96%, and Medfilters is 96%. In the proposed system, 2D median filter is one of the best filters to extract the image from DICOM information for accuracy.

The classification output of the experiment reveals that, in Fig. 4.6, the sensitivity of the image extraction through a 2D median filter is 4%, Imguided is 23%, Imfilter is 4%,

Table 4.1 Classification outputs.

Filters	Accuracy	Sensitivity	Specificity	FPR	PPV	Harmonic mean
2D median	0.9771	0.1418	0.9858	0.0192	0.1363	0.1734
Imguided	0.9431	0.2314	0.9568	0.0432	0.0933	0.1330
Imfilter	0.9662	0.0468	0.9848	0.0022	0.1174	0.0649
Wiener 2	0.9684	0.0996	0.9783	0.0117	0.1168	0.1236
medfilter	0.9618	0.1354	0.9794	0.0106	0.1125	0.1654

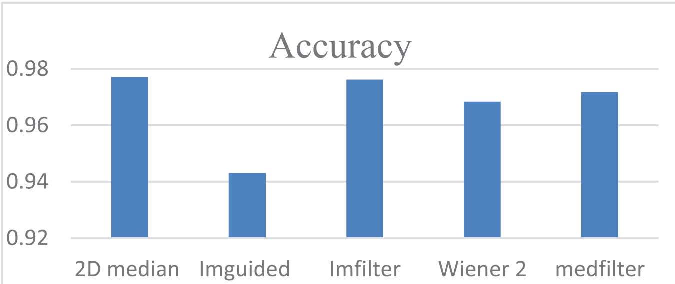

Fig. 4.5 Accuracy comparison of all filters.

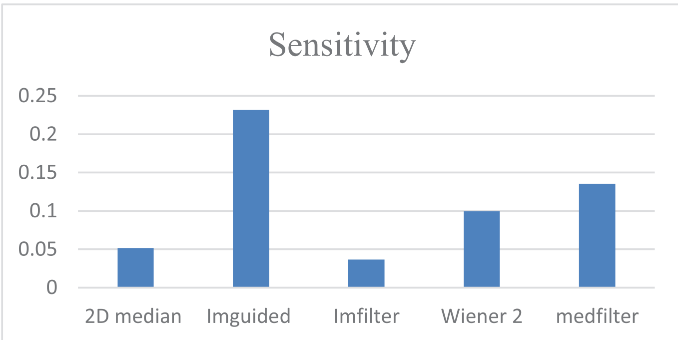

Fig. 4.6 Sensitivity comparison for all filters.

wiener2 is 9%, and Medfilters is 13%. In the proposed system, 2D median filter and Imfilter are the same percentages of sensitivity.

Fig. 4.7 the classification output of the experiment reveals that the specificity of the image extraction through a 2D median filter is 98%, Imguided is 23%, Imfilter is 4%, wiener2 is 9%, and Medfilters is 13%. In the proposed system, 2D median filter and Imfilter are the same percentages of specificity.

Fig. 4.8 reveals that the specificity of the image extraction through 2D median filter is 0%, Imguided is 4%, Imfilter is 0%, wiener2 is 0%, and Medfilters is 0%.

Fig. 4.7 Specificity comparison of all filters.

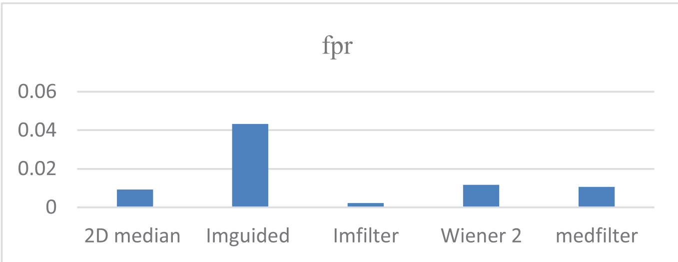

Fig. 4.8 FPR comparison for all filters.

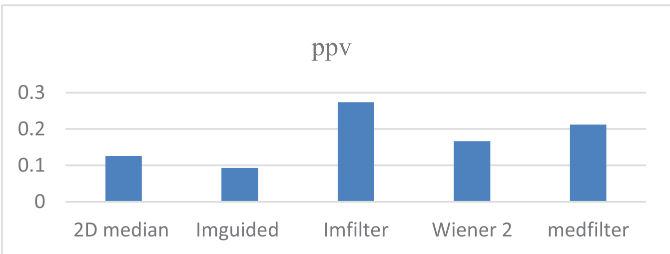

Fig. 4.9 PPV comparison for all filters.

Fig. 4.9 is the classification output of the experiment which reveals that the PPV of the image extraction through 2D median filter is 12%, Imguided is 9%, Imfilter is 27%, wiener2 is 16%, and Medfilters is 21%.

Fig. 4.10, the classification output of the experiment reveals that the harmonic of the image extraction through 2D median filter is 7%, Imguided is 13%, Imfilter is 6%, wiener2 is 12%, and Medfilters is 16%.

The classification output of the experiment reveals that the accuracy of the image extraction is 97%, 5% sensitivity, 99% specification, 12% PPV, and 7% harmonic mean

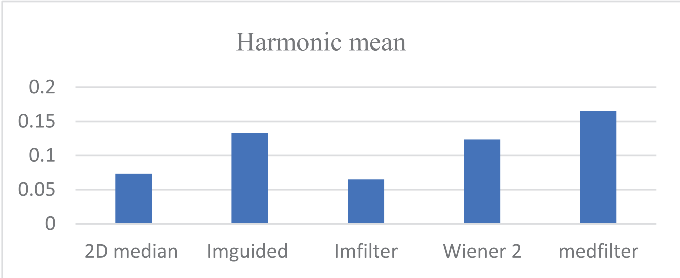

Fig. 4.10 Harmonic comparison for all filters.

of precision and sensitivity. In the proposed system, 2D median filter is one of the best filters to extract the image from DICOM information.

4.7 Conclusion

Most of the trials fail to segment the images due to noise, inequality of content, less contrast, and inhomogeneity of the image that is to be segmented. Because of these reasons, it is required to follow these methods for reducing error. The procedure of separation of a digital image into numerous segments is called image segmentation. This process aims to facilitate the portrayal of the image into more meaningful and make it easier to determine or analyze. Using this method, one can locate the objects, curves, and lines in images. In this way, each pixel would be labeled in an image where the pixels with the same label contribute secure characteristics. Hence, in this way image segmentation is very useful in digital image processing. In this chapter, image segmentation has been done on the DICOM image of a patient's MRI. It has been observed that it takes very little memory space to save the file. Further, the process may be extended to neutrosophic and plithogenic environments.

Acknowledgment

This research is supported by Universiti Tun Hussein Onn Malaysia, Malaysia under GPPS Vote No: H346.

References

[1] M.N. Ahmed, S.M. Yamany, N. Mohamed, A.A. Farag, T. Moriarty, A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data, IEEE Trans. Med. Imaging 21 (3) (2002) 193–199.
[2] M.S. Yang, Y.J. Hu, K.C.R. Lin, C.C.L. Lin, Segmentation techniques for tissue differentiation in MRI of ophthalmology using fuzzy clustering algorithms, Magn. Reson. Imaging 20 (2002) 173–179.
[3] S. Roy, H. Agarwal, A. Carass, Y. Bai, D.L. Pham, J.L. Prince, Fuzzy c-means with variable compactness, in: IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2008, pp. 452–2455, https://doi.org/10.1109/isbi.2008.4541030.