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MRI BRAIN IMAGE SEGMENTATION USING GENERALIZED FUZZY C-MEANS ALGORITHM

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ABSTRACT – Medical images are widely used to plan further treatment for the patient. However the images sometimes are corrupted with a noise which normally exists or occurs during storage or while transferring the image. Therefore the need to enhance the image is crucial in order to improve the image quality. Segmentation technique for Magnetic Resonance Imaging (MRI) of the brain is one of the method used by radiographer to detect any abnormality happened specifically for brain. The method is used to identify important regions in brain such as white matter (WM), grey matter (GM) and cerebrospinal fluid spaces (CSF). The clustering method known as Generalized Fuzzy C-means (GFCM) is proposed to be used in this project as a tool to classify the three regions. The results are then compared with fuzzy C-means clustering (FCM) and adaptive Fuzzy C-means (AFKM).The segmented image is analyzed both qualitative and quantitative. The proposed method provides better visual quality of the image and minimum Mean Square Error.

Key Words: Image Processing, Image Segmentation, Brain MRI image, Clustering.

1. INTRODUCTION

Medical imaging is the technique used to create images of the human body (or parts and functionthereof) for clinical purposes which are followed by medical procedures seeking to reveal, diagnose, or examine disease or medical science including the study of normal anatomy and physiology. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred as medical imaging, but ratherare a part of pathology.

Many of the techniques developed for medical imaging also have scientific and industrial applications. Medical imaging is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. In this restricted sense, medical imaging can be seen as the solution of mathematical inverse problems. This means that cause (the properties of living tissue) is inferred from effect (the observed signal). In the case of ultra sonography the probe consists of ultrasonic pressure waves and echoes inside the tissue show the internal structure. In the case of projectionradiography, the probe is X-ray radiation which is absorbed at different rates in different tissue types such as bone, muscle and fat. The term noninvasive is a term based on the fact that following medical imaging modalities do not penetrate the skin physically. But on the electromagnetic and radiation

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level, they are quite invasive. From the high energy photons in X-Ray Computed Tomography, to the Tesla coils of an MRI device, these modalities alter the physical and chemical environment of the body in order to obtain the data. Finally, these may lead to inconveniences in making decision [1]. Many segmentation methods have been introduced in the literature [2]. In digital image processing, segmentation refers to the process of splitting observe image data to a serial of non-overlapping important homogeneous region [3]. Clustering algorithm is one of the processes in segmentation. In the analysis of medical images for computer-aided diagnosis and therapy, a preliminary processing task often required is segmentation [3, 4]. Besides that, by using computer aided, image processing can be applying image reconstruction. It is very important to medical field because radiologist can identify the abnormality happen at the brain. Since radiologist can determine abnormality in the patient brain, they can give the best treatment for the patient.

2. METHODOLOGY

Segmentation via clustering can also be used to detect the three regions at the brain image. Magnetic Resonance Image (MRI) of brain is one of medical imaging tools used to detect abnormality in brain. From the MRI brain images, the radiologist normally interested to look for three significant regions. The three regions are white matter (WM), grey matter(GM) and cerebrospinal fluid spaces (CSF). Figure 1 shown three regions of normal MRI brain image. The precise measurement of these three regions is important for quantitative pathological analyses and so becomes a goal of lots of method for segmenting MRI brain image data.

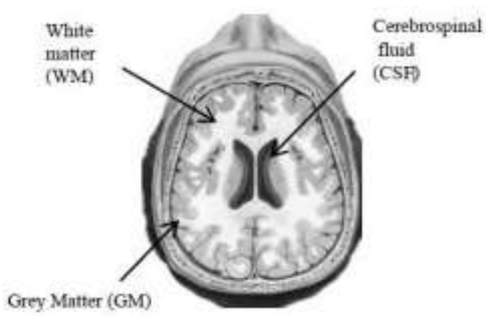


Figure 1: The normal brain MRI image

In this paper segmentation via clustering method named Generalized Fuzzy C-means (GFCM) clustering is used to segment the MRI brain image into three different regions. The GFCM method is proposed to prove that it can classify and segment the MRI brain image better than conventional method. AFKM clustering algorithm [5] is combination of KM, MKM and FCM clustering. The features of GFCM are to provide a better and more adaptive clustering process. The remaining of the paper presents about GFCM clustering algorithm is proposed. Besides that, the comparison detail of qualitative and quantitative also presented [6].

In medical field, Medical Resonance Image (MRI) is one of the methods used to detect abnormalities in human body. The clustering

definition cluster centers by iteratively regulating their locations and minimizing an objective function as K-Means (KM) algorithm. The advantage of FCM is that, it allows more flexibility when dealing with multiple clusters by introducing multiple fuzzy membership grades.

2.2 Adaptive Fuzzy K Means (AFKM) clustering Algorithm

AFKM method is recommended to be used to process MRI images [7]. The AFKM is combination of fundamental theories of conventional K-means and MKM clustering algorithm (i.e., assigning each data to its closet centre or cluster) and the conventional Fuzzy C-means (FCM) clustering algorithm (i.e., allows the data to belong to two or more clusters or centres) [8]. The objective function of AFKM is calculated using the equation

$$J = \sum_{k=1}^{n} \sum_{t=1}^{N} (M_{kt}^{m})\ (\mathrm{v_t} - \mathrm{c_k})^2 \tag{1}$$

Where $\mathrm{M_{kt}^{m}}$the fuzzy membership function and m is is the fuzziness exponent. The degree of being in a certain cluster is related to the inverse of the distance to the cluster. The new position for each centroid is calculated using the equation:

$$C_k = \frac{\sum_{t=1}^{N} (\mathrm{M_{kt}^{m}})\mathrm{v_t}}{\sum^{N} (\mathrm{M^{m}})}$$

algorithm for image segmentation was introduced to the MRI images in order to segment the image. Inthis paper, a new method of clustering algorithm based segmentation known as technique is recommended. The segmentation technique used to be implemented medical image like MRI. It use to exquisite soft tissue contrast between normal tissue and pathologic tissue. The proposed method for this paper is then comparing with conventional method known as Fuzzy C-means (FCM), Adaptive Fuzzy k means (AFKM) and Enhanced Adaptive Fuzzy k means (GFCM).

2.1 Fuzzy C-means (FCM) clustering Algorithm

Bezdek Fuzzy C-means (FCM) algorithm is one of the most commonly used clustering algorithms. FCM clustering is constructed based on the same idea of

$t=1 \quad kt$

(2)

The AFKM algorithm improved the clustering with the introduction of belongingness concept where it measures the degree relationship between centre and its members. The degree of belongingness is calculated as

$$B_k = \frac{C_k}{M_{kt}^{m}} \qquad (3)$$

The objective is to minimize the objective function from equation (1). The process is repeated iteratively until the center is no longer moved all data have been considered.

2.3 Enhanced Adaptive K-means (EK-MEAN) clustering Algorithm

Using standard algorithm for k mean clustering, affected region was not extracted properly. To improve its performance, morphological opening-by-reconstruction operation is applied on the output of k-mean clustering algorithm. The idea of opening-by-reconstruction is taken from marker controlled watershed algorithm, which uses both opening and closing-by-reconstruction followed by watershed segmentation. Morphological reconstruction processes one image, called the marker, based on the characteristics of another image, called the mask. The high-points, or peaks, in the marker image specify where processing begins. The processing continues until the image values stop changing. Morphological reconstruction can be thought of conceptually as repeated dilations of the marker image until the contour of the marker image fits under the mask image. In this way, the peaks in the marker image "spread out", or dilate [9]. The characteristics of the marker image determine the processing performed in morphological reconstruction. The peaks in the marker image should identify the location of objects in the mask image that we want to emphasize. Opening-by-Reconstruction is more efficient than standard opening and closing at removing small blemishes without affecting the overall shapes of the objects [10].

2.3.1 EAK -Means Algorithm

This algorithm is a fully automatic way to cluster an input Color or gray image using k-means principle, but here you do not need to specify number of clusters or any initial seed value to start iteration, this algorithm automatically finds number of cluster and cluster center iteratively. It is a very fast implementation of clustering an image without knowing number of clusters.

(a) Cluster a Gray (single channel (0-255)) or Color image (3 channels (0-255)) as in k-means.
(b) Not need to be specifying number of cluster for clustering.
(c) Very Fast implementation.
(d) Very Easy to understand.
(e) Easy to modify the code according to your requirements.
(f) No use of any Image Processing Tool Function.
(g) This code uses same principle as in k-means, but here you do not need to define number of clusters.
(h) You can use this code to estimate the number of clusters(colors) present in image, this code may not be segment all images as you want, so post processing of clustered image is suggested.

Algorithm Steps follows as:

(i) The K-mean algorithm to cluster the image pixels. Then mark the desired cluster.
(ii) The Morphological opening-by-reconstruction operation on desired cluster.
(iii) Choose suitable structuring element, Structural Element and apply erosion operation to remove background pixels from boundary
(iv) Reconstruct the marker image.
(v) Apply dilation operation by adding pixels of object boundaries.
(vi) By using regional maxima, the cavity of abnormal area will be highlighted. The performance of this algorithm depends on choice of Structural Element.

3. RESULTS AND DISCUSSION

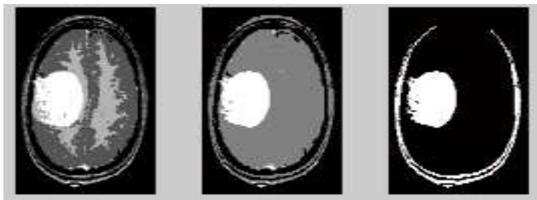
From these images, the performance analysis of qualitative and quantitative are implemented. The qualitative analysis depends on the human visual. Human visual can interpret the images based on capability and segmentation algorithm of conventional method like FCM, AFKM and the new method proposed which is GFCM. It can detect the region of interest like GM, WM and CSF. For quantitative analysis, it refers to the performance of segmentation of the image. It produces by proposed algorithm. The conventional algorithm will compared with a new proposed algorithm. The result of quantitative analysis taken based on three evaluation functions.

The three functions of quantitative analysis are F (I), F' (I) and Q (I). The image size can calculate from N x M. For evaluation of the cluster, the mean squared error (MSE) is the one most fundamental benchmark. Besides that, these functions related more to the visual judgment. For the better result of segmentation, AFKM values of F (I), F' (I) and Q (I) are smaller than FCM values. Both of result of qualitative and quantitative will be presented.

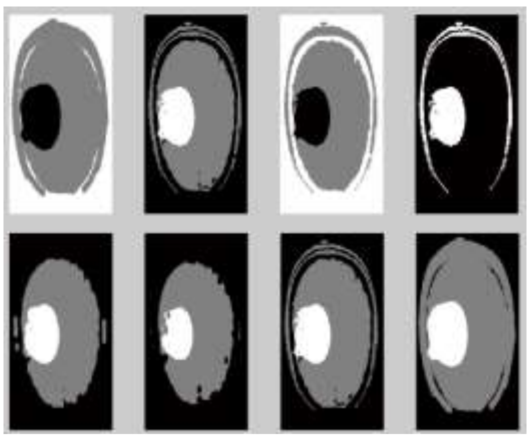
3.1 Qualitative Analysis

For the result in qualitative analysis, six images are used. Qualitative analysis is to examine usually whether the resultant image is good or not. The performance is examined visually in qualitative analysis. The segmentation performances are compared with conventional methods of FCM, AFKM and new method proposed of GFCM. Clustering algorithm used in this paper is to segment the MRI brain image into here regions i.e. the GM, WM and CSF, therefore the clustering algorithm is chosen to have three clusters. The result is then compared with FCM and AFKM algorithm. From the result shown in Figures 2 to 4, it can be observed that quality of image is not perfect compared to the AFKM method. The weakness of FCM method is it over segment the image which leads to image become too bright. But using AFKM, it can segment the image clearly and the region of interest is sharper.

(a)

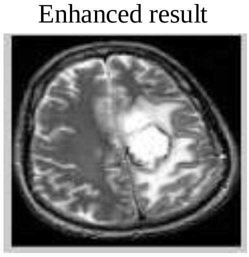


(b) (c) (d)

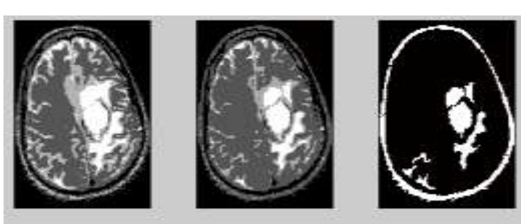


(e)

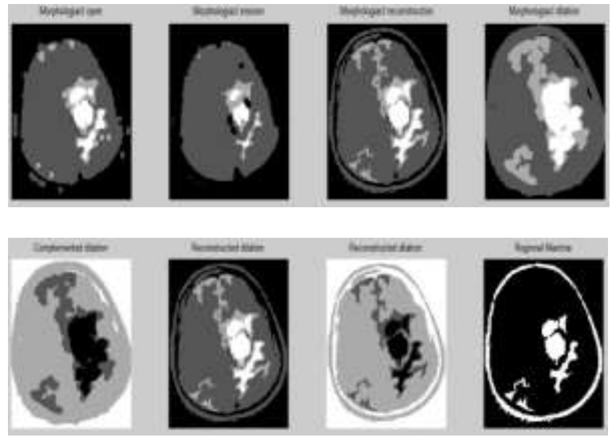
Figure 2: The MRI Image 1 of segmentation image with three clusters:
(a) Original image (b) FCM (c) AFKM (d) GFCM (e) Enhanced result



(a)

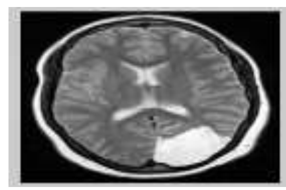


(b) (c) (d)



(e)

Figure 3: The MRI Image 2 of segmentation image with three clusters
(a) Original image (b) FCM (c) AFKM (d) GFCM (e) Enhanced result



(a)

(b) (c) (d)

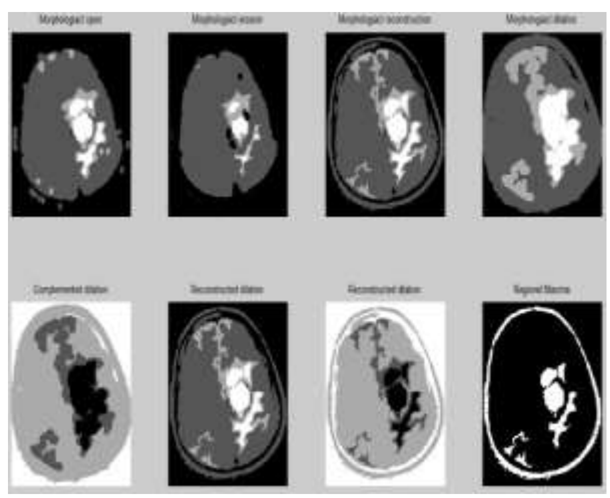


Figure 4: The MRI Image 3 of egmentation image with three clusters (a) Original image (b) FCM (c) AFKM (d) GFCM (e) Enhanced results

After implementing GFCM algorithm, the image looks clearly in the visual compared to the conventional method of FCM and GFCM. By FCM, the MRI brain image is brighter compared to AFKM. It happens because the FCM have over segment of the image. It can give effect on segmentation and three regions cannot be detected clearly. The images of GFCM become sharper and clearer.

3.2 Quantitative Analysis

The analysis of quantitative is evaluated based on the three benchmark functions. The analysis also evaluates by fundamental benchmark is mean squared error (MSE).The quantitative analysis is to support the qualitative. The result of quantitative analysis show in Tables I to IV. These tables summarize the segmentation of the quantitative estimation. All the result gets from a comparison of FCM, AFKM and GFCM clustering method. From the comparison, new method of GFCM produces the better result compared to conventional method of FCM and AFKM. The new method proposed of GFCM produces the smaller values of all MSE, F (I), F' (I) and Q (I) analysis. So; it can be conclude the GFCM method is successful segmentation. It is because GFCM can detect the three regions at MRI brain. In addition, the proposed GFCM manages to segment the image successfully with less noisy pixel. Generally, these interpretations specify that the AFKM might be a better methodology in terms of image segmentation application.

Image quality assessment is an important but difficult issue in image processing application such as compression. For a long time, mean square error (MSE) are widely used to measure the degree of image distortion because they can represent the overall gray-value contained in the entire image. With MSE only gray value differences between corresponding pixels of the original and the distorted version are considered. Pixels are treated as being independent of their neighbors. Although MSE its merits and is widely accepted in image processing research, it only measures gray-level difference between pixels of the ideal and the distorted images without considering correlation between the neighboring pixels. Distorted images with equal MSE may have significantly different visual quality.

A human observer always views an image as an entirely, rather than just a collection of isolated pixels, therefore correlation between neighboring pixels play a role in the subjective judgment of image quality. For evaluation of the cluster quality, the most fundamental benchmark is the mean squared error (MSE) which is defined as

$$MSE = \frac{1}{N} \sum_{j=1}^{M} \sum_{i=1} (x_i - c_j)^2 \qquad (4)$$

Let i and j be the original and the distorted images respectively, sized M* N.

To appraise the performance of the algorithms more objectively, the following three evaluation functions F (I), F' (I) and Q (I) are employed

Evaluation Function I- F (I)

$$F(I) = \frac{1}{1000\ (N*M)} \sqrt{R} \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \qquad (5)$$

where I is the segmented image, N* M is the image size. R is the number of regions of the segmented image, A_i is the area of i^{th} region, e_i is the average colour error of the i^{th} region. The smaller the values of F (I), the better are the segmentation results.

Evaluation Function II- F' (I)

$$F'(I) = \frac{1}{1000\ (N*M)} \sqrt{\sum_{A=1}^{Max} (A)} \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \qquad (6)$$

where I is the segmented image, N* M is the image size. R (A) is the number of regions having exactly area A. Max is the area of the largest region in the segmented image, A_i is the area of i^{th} region, e_i is the average colour error of the i^{th} region. The smaller the values of F'(I), the better are the segmentation results.

Evaluation Function III- Q (I)

$$(I) = \frac{1}{1000\ (N*M)} \sqrt{R} \sum_{i=1}^{R} \frac{e_i^2}{1+\log A_i} + \left(\frac{R(A_i)}{A_i}\right)^2 \qquad (7)$$

where I is the segmented image, N* M is the image size. R is the number of regions of the segmented image, A_i is the area of i^{th} region, e_i is the average colour error of the i^{th} region. While $\sqrt{A_i}$ has been replaced with $(1 + \log A_i)$ to obtain a stronger penalization of non-homogeneous regions. In any case the denominators A_i drastically forces the term $\frac{R(A_i)}{A_i}$ to near zero for large regions; and lets it grow for small regions. The functions F' (I) and Q (I) are improvements over F (I) and correspond more closely to the visual judgment than F (I). The computational results are presented in the Table II, III and IV.

Table I
MSE Evaluation of quantitative

Images	FCM	AFKM	GFCM
MRI Image 1	11861	528.9	2.4241
MRI Image 2	13577	428.49	3.5214
MRI Image 3	13228	460.79	3.5752

Table II
F (I) Evaluation of quantitative

Images	FCM	AFKM	GFCM
MRI Image 1	2.2955e+09	4.3929e+09	5.463e+10
MRI Image 2	2.4496e+10	6.1764e+10	2.3933e+11
MRI Image 3	3.3686e+09	8.2529e+09	2.207e+10

Table III
F' (I) Evaluation of quantitative

Images	FCM	AFKM	GFCM
MRI Image 1	0.00030858	0.00059057	0.00069188
MRI Image 2	0.00045284	0.0011095	0.0029695
MRI Image 3	0.0032929	0.0083037	0.032237

Table IV
Q (I) Evaluation of quantitative

Images	FCM	AFKM	GFCM
MRI Image 1	.4243e-10	2.1669e-09	02196e-09
MRI Image 2	.1119e-09	5.3871e-08	1.7131e-05
MRI Image 3	.5767e-10	5.7694e-09	4.3847e-07

By using FCM, the image is unclear. It is because the image becomes bright and does not meet the criteria of segmentation. But when AFKM method applied, the images are sharp and the segment of WM, GM and CSF are correctly. From the resultant images, a new method proposed of GFCM can give better performance of segmentation technique compared the conventional method of FCM and AFKM by evaluation of minimum mean square error (MSE).

The time complexity of an algorithm quantifies the amount of time taken by an algorithm to run as a function of the length of the string representing the input MRI Image. From the obtained results GFCM requires more computation time than FCM because of the fuzzy measures calculations involvement in the algorithm.

The Fuzzy C-means clustering can avoid local minima is partly positive. For low-dimensional data, local minima can vanish by a suitable choice of the images taken. For high-dimensional data, additional local minima can be introduced. The choice of the images can be cucial for the avoidance of local minima. How to choose an appropriate pixel value for the image will be investigated in a future work.

4. CONCLUSION

The performance of K-mean and proposed enhanced K-mean algorithm was evaluated on number of MRI brain images to segment affected region. The novelty of the method is simplicity. Both qualitative as well as quantitative results are in the favor of enhanced k-mean clustering algorithm. The proposed algorithm is better than the Adaptive C-Means Clustering Algorithm for brain image segmentation, the validity measure of nearly all the images has been better than the adaptive K-Means clustering algorithm, the adaptive K-means algorithm uses user defined number of cluster which use to cause noisy image, but in the proposed algorithm, it uses the method for determining the number of optimal cluster. It also removes the problem of empty clusters problem from Adaptive C-Means clustering algorithm where there was issue that if no pixel is assigned to a cluster then that cluster remains empty. This algorithm has been implemented in Matlab. Experimental results obtained from this algorithm are satisfactory, giving better clusters and better segmented image than the adaptive K Means clustering algorithm.

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