Hybrid Clustering Technique to Detect Bone Tumor

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Abstract

The image segmentation technique is considered as one of the most important aspects of processing medical images. CT scanning and MRI (Magnetic Resonance Imaging) are well-known imaging tools in medical image processing. These tools are used for discovering the inner anatomy of the internal organs in a noninvasive manner. Bone cancer is a fatal disease that might target any bone of the body. Thus, the recognition of the cancerous regions in the affected bone is necessary. In this paper, the K-means clustering is used to initialize the cluster centroids of the generated images. This would help the Fuzzy c means to have logically distributed input centroids which has a positive effect on the resulted clusters in terms of the quality of results and time-saving. Three MRI images with various clusters numbers are used in the tests. In addition, morphological operations such as dilation and opening used after the extraction of the fine tumor regions in an effective manner.

Key Words: K-means, Fuzzy C Means, Medical Image, Bone Tumor, Clustering.

DOI Number: 10.14704/nq.2020.18.8.NQ20208 **NeuroQuantology 2020; 18(8):80-85**

Introduction

The number of bones in the adult human-being Skelton equals 213 [1]. The main bones functionalities are supporting for other body's organs, allowing mobility, by fortifying the muscles for an efficient levers impartment, protecting internal structures and body parts, making acidity equilibrium and maintaining the mineral homeostasis, working as storage for the cytokines and growth aspects, and supplying an environment for hematopoiesis in the marrow region [2]. The bone tumor can be defined as abnormal tissue masses residing inside the cells [3]. Two types of bone tumors were discovered. The first is benign (Non-cancerous) while the second is the malignant (Cancerous) [4]. Benign tumors have a very large size and are pressing on the surrounding tissues. After its removal by a medical operation, this kind of tumor is not likely to reoccur. In contrast, malignant tumors have a bigger nucleus that seems to be different from the normal nucleus. Unlike benign tumors, this type of tumor might reoccur [5, 6].

Bone tumors can affect any bone in the skeleton and it can evolve in that particular part of the bone. Benign tumor growth in the bones weakens the bone and destroys healthy tissues [3].

MRI (Magnetic Resonance Imaging) is a technique used for imaging that depends on robust magnetic fields and radio-frequencies to inspect, flaccid tissues, internal body parts, and bones. Unlike the traditional x-ray, the MRI has no exposure to CT or ionizing radiation. The MRI is capable of capturing different types of disorders, such as spinal cord injuries, eye problems, multiple sclerosis, strokes, tumors, and internal ear problems. Moreover, the patients scanned in the MRI are not subject to any renditions.

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Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.
Received: 18 June 2020 **Accepted:** 24 July 2020

MRI might be very helpful in the differential prognosis of benign bone tumors like aneurysmal and simple bone cysts [7].

In this study, the implementation of three segmentation methods to detect and extract bone tumor regions in MRI images of different orientations and methods: clustering K-means, fuzzy c-means, and fuzzy based on K-means.

In this study, the cluster centroids are initialized by the K-means method which is taken as an input to the Fuzzy c means method. Thus, instead of starting the Fuzzy c means randomly, the use of the k-means to initialize the centroids have advantages in terms of the accuracy and the clustering time for clustering the pixels into clusters and all that is accomplished according to the great probability. It is expected that the clustering process would be better than using the Fuzzy c means algorithm alone as was approved by the test results.

K-means Method

Various techniques have been used for image and data classification and segmentation. The k-means method is one of those successful methods used for the clusters by dividing the input data into separate groups called clusters. The datasets are divided into these clusters using the k-means according to their shared features such as the intensity. The k number of the desired number of clusters should be defined in advance. This process incorporates the grouping of data points sharing similar features as one group or cluster, whereas other data points sharing other features from the first clusters are grouped into another group or cluster [8]. K-means' accuracy is subject to the initial selection of the central points which sometimes is called the centroids or seeds. Thus, the k-means is sensitive to the first representation of the initial random structure of the centroids. In order to obtain optimal performance must first be distributed in a certain way [8].

Fuzzy C Means Method

Fuzzy c-means (FCM) this method a groups the input data into separate clusters, still this method is unlike the k-means where the data item belongs to only one class. In FCM the situation is different as this method is soft clustering method that means each data item might belong to more than one cluster at the same time with a varying degree of membership according to a specific membership function. The FCM works on basis of the minimization of the objective function named Jm [9], which is represented in the following equation:

$$J_m = \sum_{i=1}^{n} u_{ij}^{m} \sum_{j=1}^{c} \left\| x_i - c_j \right\|^2 \quad for\ 1 \leq m < \infty \quad (1)$$

Where

uij degree of the membership of

xi the data item belong to some degree to the cluster j

cj is the j th cluster seed

$\left\| \mathrm{x_i} - \mathrm{c_j} \right\|$, is the distance between each designated dataset and its corresponding centroid [9].

Partitioning process of the dataset is accomplished by iteratively minimizing the objective function. In each round the membership values u_{ij} of each data item is updated as well as the clusters centroids cj as shown in the following equations [10].

$$u_{ij} = \frac{\sum_{i=1}^{n} u_{ij}^{m} . x_i}{\sum_{i=1}^{x} x_{ij}^{m}} \quad (2)$$

$$c_j = \frac{1}{\sum_{k=1}^{c} \left[\left\| x_i - c_j \right\| / \left\| x_i - c_k \right\| \right]^{2/(m-1)}} \quad (3)$$

The iterative process of optimization terminates when $\mathrm{MAXij} = \left\{ \left| \mathrm{u_{ij}^{(k+1)}} - \mathrm{u_{ij}^{(k)}} \right| \right\} < \varepsilon$ where ε is a predefined small constant ranging between [0,1], which determines the termination of the optimization.

Hybrid Method Fuzzy based on K-means

In this way, the centers of the final clusters that were reached in a K-means method were adopted and taken as suggested centers for the FCM method instead of the FCM algorithm starting from random centers and then convergence in this way is convergence and reaching the optimal separation in a short time and results of separation resulting from two stages of filtering the image points Attaching them to the clusters they return to and depending on the principle of high probability, it is expected that this process will be more efficient and this is what the results of this work have proven.

Morphological Operations

In image processing [11]. Morphological operators are used due to their robust performance in preserving the shape of a signal, during suppressing the noise [12]. The basic morphological operators are erosion and dilation, opening and closing are two derived operations in terms of erosion and dilation [13]:

1- Opening: The opening means another name for an application "erosion then dilation" this is useful for removing noise the opening is denoted in terms of the primitive operations of dilation and erosion as simply [14]:

$$X^{op}=(X\ominus B)\oplus B \qquad (4)$$

2- Dilation: -the dilation is thickening operation of a binary image by a simple hexagonal structuring element B; therefore; the name "hit" is often applied to this operation. It may be expressed as [15]:

$$X\oplus B=\{x: B_X \cap X\neq\emptyset\} \qquad (5)$$

3- Erosion: the erosion is shrinking and thinning operation, it's used to eliminate noise in the image, but it also reduces the area of the object, It may be expressed in equation [15]:

$$X\ominus B=\{x\backslash B_X \subset X\} \qquad (6)$$

Experimental Data

In this study, three MRI images were adopted to test the performance of the proposed techniques. These images were acquired from local hospitals in Iraq and from the internet. The input images were named image7, image16, image17 for MRI. The experimental images are 106×200 pixels, 174×164pixels, and 541×340 pixels respectively. Figure(1) shows these input images.

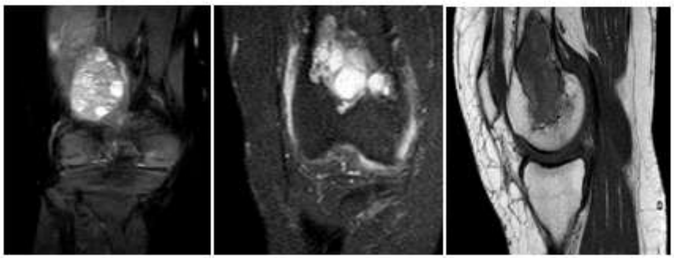

Figure 1. Input MRI bone images

Results and Discussion

The experiments of this study involve applying three techniques were proposed to segment three MRI bone images in order to detect, isolate, and extract tumor regions. The implemented methodologies procedure is illustrated in the block diagram of Figure 2.

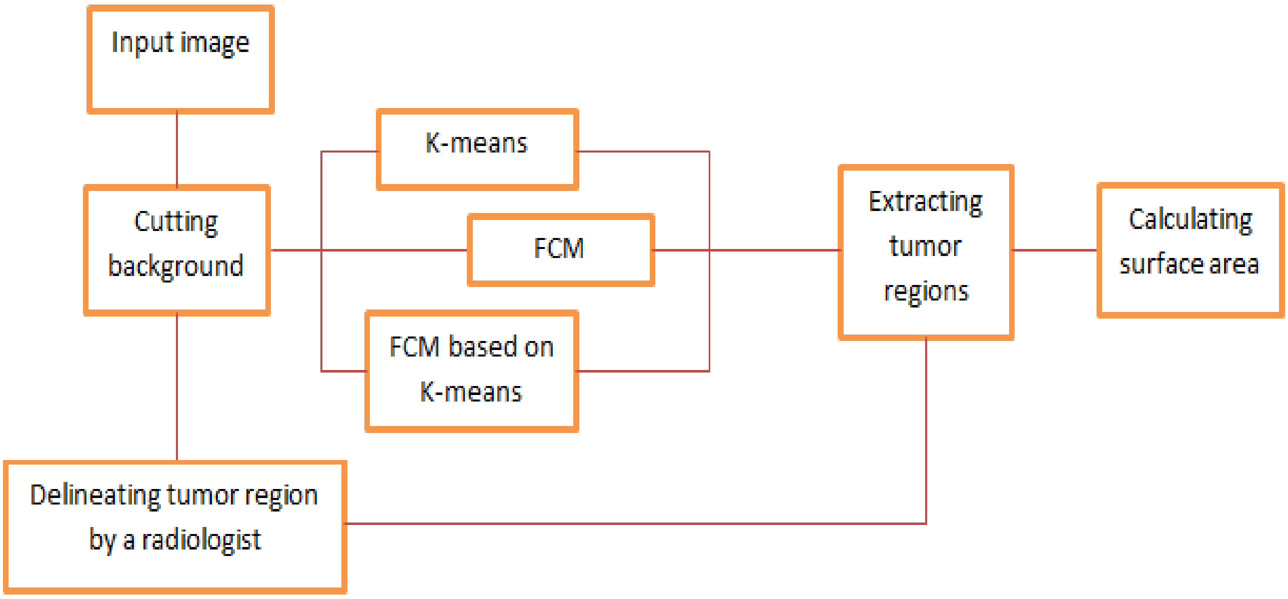

Fig. 2. Block diagram of the implemented procedure

1) K-Means Algorithm

In this step of the work, different number of clusters was tested to segment the input images by the K-means algorithm. It was found that four clusters are the suitable clusters for images bone12 and bone15 images while three clusters are the suitable clusters for bone16. The resultant segmented images for the three images are presented in Figures 3.

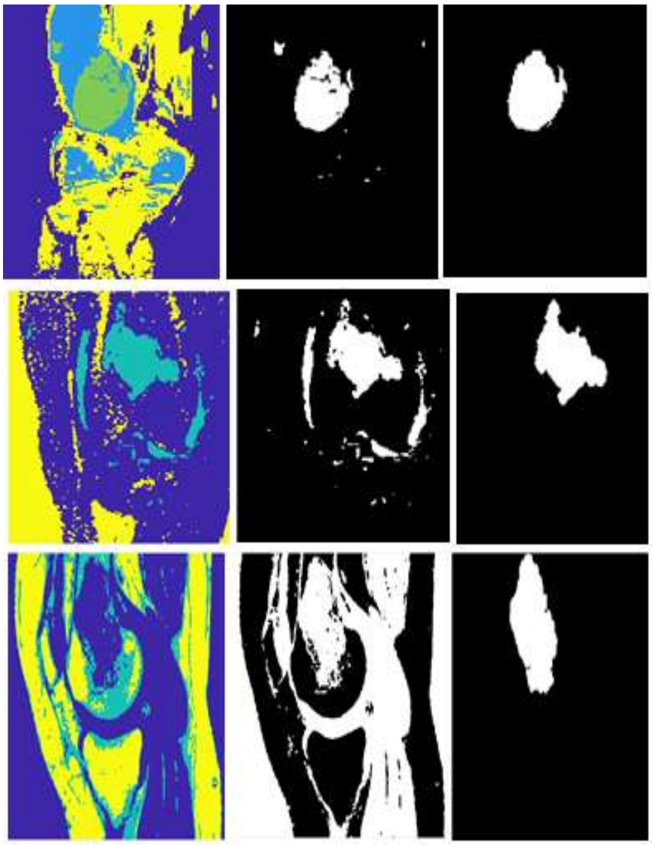

Figure 3. Results of implementing K-means algorithm for MRI images

Figure (3), the first row represents the segmented image, the second row represents the image of the abnormalities cluster and the third row represents the extracted abnormal regions.

2) FCM Algorithm

This algorithm was applied with a different number of clusters to segment bone images. It was found that four clusters is the number of the proper cluster to cluster MRI images into its contents and the resultant segmented images and the corresponding extracted tumor regions are shown in Figures 4.

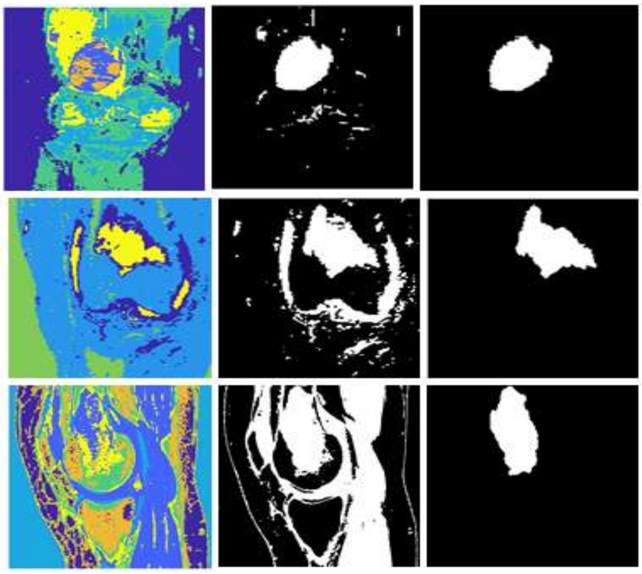

Figure 4. Results of implementing FCM algorithm for MRI images

Figure (4), the first row represents the segmented image, the second row represents the image of the abnormalities cluster and the third row represents the extracted abnormal regions.

3) Hybrid Method FCM based on K-Means

In this hybrid method, K-means segmented images were fed as input images of the FCM algorithm to reduce the long required time of FCM and to test the performance of each of K-means and FCM. The results of this hybrid technique are shown in Figures 5. The first row of in Figures 5 represents the resultant segmented images while the second one shows the abnormal clusters and the third-row represent extracted tumor regions.

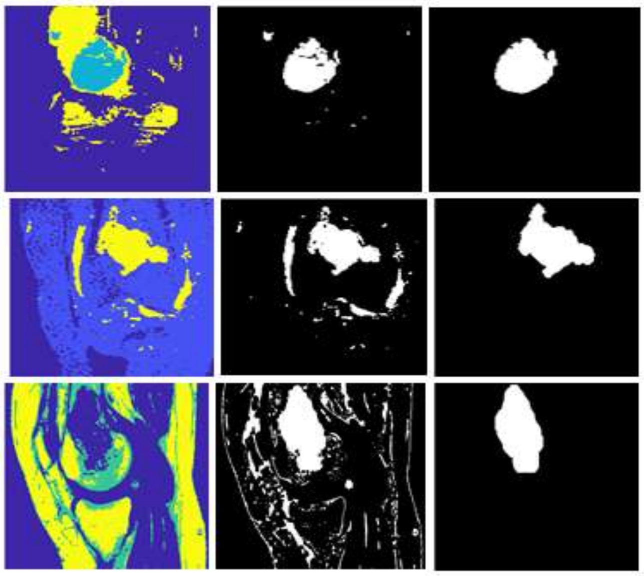

Figure 5. Results of implementing FCM based on K-Means algorithm for MRI images

4) Radiologists Delineation

Through showing the results images the manual delineation to extract the abnormal regions is shown in figure (4).

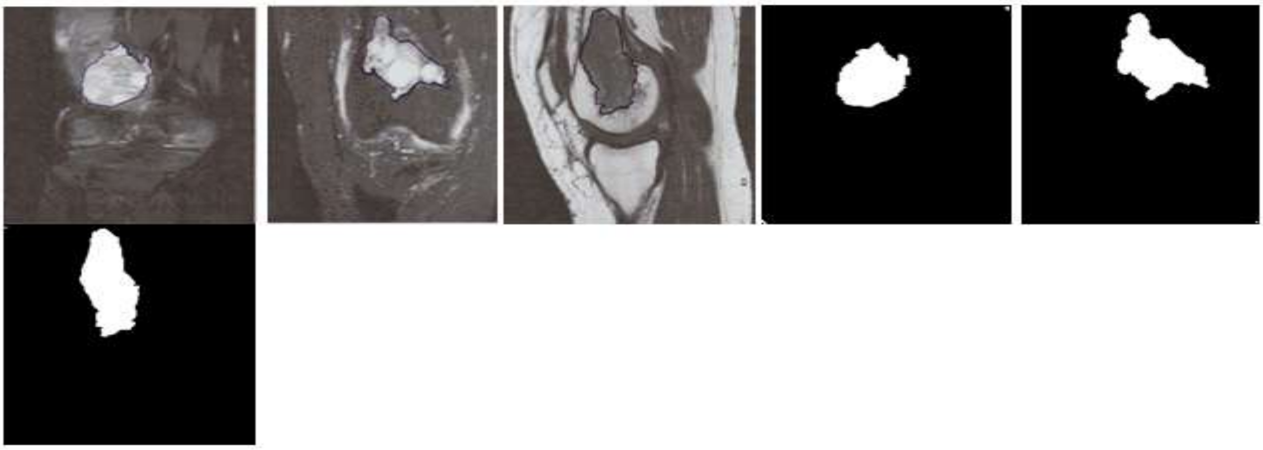

Figure 6. Radiologist delineation of the abnormal region of bone MRI images

Figure 6. The first row represents the original image; the second row represents the extracted abnormal regions images.

Table 1. To calculate the surface area of the tumor region extracted by the method K - means, FCM, and the hybrid method FCM based on k-means by comparing it with the radiologist's area

Image	Surface Area			
	K-Means (pixel)	FCM	FCM based on K-Means	Radiologist (pixel)
Image14	1276	1269	1276	1260
Image16	2165	2167	2152	2166
Image17	13470	13773	13461	13469

Table 2. To calculate the percentage of relative differences

Image	Percent Relative difference%		
	K-Means	FCM	FCM based on K-Means
Image 14	1.2698412698	0.7142857143	1.2698412698
Image 16	0.0461680517	0.0461680517	0.6463527239
Image 17	0.0074244562	0.0296978246	0.0593956493

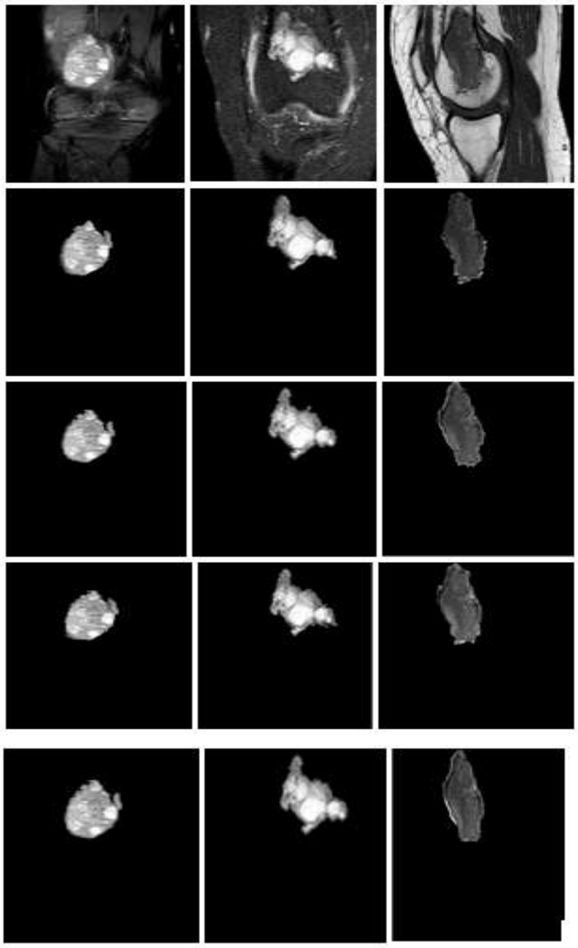

Figure 7. Represent the comparison between the original images in the first row, the second row represents extracted abnormal regions in grey by manual delineation, the third row represents extracted abnormal regions in grey by K-Means algorithm, the fourth row represents the extracted abnormal regions in grey by FCM while the fifth row represents the extracted abnormal regions in grey by FCM based on K-means

Comparison

Through comparison of the results of the tumor region in grey that obtained from the manual delineation of the abnormal region and the tumor region in grey that obtained from applying the K-Means algorithm, FCM, and FCM based on K-means.

Conclusion

In this study, 3 clustering-based methods of image segmentation were used for the detection, isolation, and extraction of the bone tumors using 3 MRI. These images have multiple clusters number. By observing the test results, it is discovered that tumor areas were extracted adequately using the proposed hybrid technique over all three images used in the tests. The use of the k-means-FCM hybrid technique revealed hybrid K-means and the FCM technique emphasizes the goodness performance of each of them and reduces the required elapsed time of the FCM algorithm.

Acknowledgments

Authors wish to express their thanks to Dr. Sabah Jassim Mohammed who works in AL-Askndryh general hospital for his efforts in the delineation of the tumor regions in the adopted MRI and CT scan images.

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