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A SEMI-AUTOMATIC BRAIN TUMOR SEGMENTATION

[1]Shibin Tomy Mathew, [2]Dr. AmitGarg

[1]Departments of Electronics & Communication Engineering

Ajay Kumar Garg Engineering College, Ghaziabad

Email:shibintomy@gmail.com

[2]Departments of Electronics & Communication Engineering

Ajay Kumar Garg Engineering College, Ghaziabad

Email:amitstp@gmail.com

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Abstract

Brain tumor segmentation based on magnetic resonance imaging (MRI) has gained a lot of interest in the recent years as MRI provides non-invasive images of the tumor and better soft tissue contrast. Image segmentation of the MRI image of the tumor helps to isolate the tumor tissue from the normal brain tissue. In this paper, a new semi-automatic brain tumor segmentation method for MRI images is presented. The proposed technique include a filtering and skull stripping based preprocessing stage to enhance the quality of the MRI images, a fast bounding box (FBB) detection algorithm to locate the tumor and a kernel based fuzzy c-means approach for the segmentation of the tumor. For better segmentation performance, a Graph Cut algorithm is also included in the technique as a co-segmentation process for clearer visualization of the tumor. Experiments have been performed on a set of clinical MRI images using Matlab R2017b. The performance of the proposed method along with two other methods viz. Fuzzy C-means (FCM) and kernel based fuzzy c-means algorithm (KFCM) are evaluated and compared on the basis of performance parameters such as Accuracy, Sensitivity and Specificity. Experimental results reveal that the proposed method is highly efficient in comparison to the other methods for brain tumor segmentation.

Key words: MRI images, Brain, Tumor.

1. Introduction

In every portion of the body, the tumor is the unchecked development of cancer cells. Tumors are of multiple forms that have common characteristics . A brain tumor describes a collection of irregular cells that uncontrollably replicate in the brain. Brain cancers are commonly known as the benign brain and metastatic brain tumors. They start in the brain and tend to remain in the brain and then begin to spread to the brain like a cancer elsewhere in the body.

There are two types of brain tumor: benign and malignant[1]. The benign brain tumor is structurally standardized and does not produce infected cells (cancer). They are less aggressive, gradually developed, and sometimes stay separated from the developing brain's natural tissues. These will not travel to other brain areas or certain parts of the human body and are usually harder to remove through surgery whereas malignant brain tumors are structurally non-uniform and include cancer cells. These are not necessarily easy to differentiate from the normal tissues around them. This is also often impossible to eliminate them absolutely without affecting the brain tissues around them. The WHO has issued the classification scheme. It classifies brain tumors in category I to IV. Category I and II are generally benign brain tumors (low grades); category III and grade IV are malignant (high-grade) brain tumors. Brain tumor severely affects human lives. Earlier diagnosis and care have been a must, like surgery, radiation therapy, or chemotherapy.

The development of the MRI method plays a vital part in identifying brain tumor cases and has a significant effect on the treatment of patients. Modern medical imaging producing technologies, such as X-ray, computed tomography (CT), and magnetic resonance imaging (MRI), shows the detailed brain tumors, but also

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improve clinical doctors to study the of brain tumors for planning a better treatment [1]. Registered doctors perform a significant part in brain tumor assessment. When a brain tumor is clinically detected, the location, size, and connection to the underlying structures must be evaluated by radiological evaluation. Such knowledge is significant and crucial for determining between the different treatment types, such as surgery, radiation, and chemical therapy[1]. The detection of brain tumors using MRI techniques is one of the main problems in the divisions of radiology.

MRI is a modality to offer useful knowledge on the type, the scale, and location of tumors without subjecting the patient to a high degree of ionization[2]. MRI attracts more and more attention to diagnosing brain tumors in the clinical field[3]. A large magnet, radio waves, and a computer are used in an MRI scan to create a detailed cross-cutting picture of the internal structures and organs. MRI is increasingly attracting attention to the diagnosis of brain tumors in the medical field. Images of various MRI sequences are used to diagnose and delineate the tumor. These sequence images include T1 weighted MRIs (T1w), T1 weighted MRIs with contrast enhancement, T-2 weighted MRIs (T2w), Proton density-weighted MRIs (PDW), FLAIR, and more [4].

Methods of brain tumor segmentation can be categorized according to the degree of human interaction necessary for image segmentation. The segmentation strategies are typically listed as manually, semi-automatically and entirely automatically [5]. Through manual segmentation, the doctors identify tumors themselves utilizing their pathology training and understanding. When more brain tumor images appear, the manual segmentation of the multiple areas of the brain tumor is a time-consuming and error-prone job for them, and outcomes are low. For semi-automatic and completely automated segmentation systems, manual segmentation results is considered for comparison. Semi-automatic segmentation combines human and computer interface results to determine segmentation. The segmentation of semi-automatic brain tumors comprises of doctors and computer. The doctors will enter some criteria and is responsible for interpreting the visual input and supplying the computer with suggestions. A completely automated segmentation system decides the segmentation without human contact with the aid computers. Clinically, semi-automatically operated approaches with the least user interference are more appropriate.

Many segmentation methods for segmenting the tumor from the MRI images are present in the literature. The brain tumor segmentation thresholding approach is one of the most natural and most potent segmentation techniques. It is often used to complicated segment images such as those of the brain MRI as the preprocessing phase due to their incapacity to use all the necessary image detail. Ilhan proposed in 2017[6] a method utilizing the morphological process, subtraction of pixels, threshold segmentation, and picture filtration techniques for consistent pictures of the head, spine, and tumor. Y. Feng, a multi-scale 3D Otsu threshold algorithm for the segmentation of medical images, was published in 2017[7]. Roy suggested an underlying skull stripping algorithm in 2015[8] focused on brain morphology and picture strength features. They used the level of adaptive sensitivity and morphological operations to improve MRI representations in the brain. In 2009 Park[9] introduced an algorithm with three steps; firstly, through histogram analysis, the context voxels were omitted; secondly, morphological operations were implemented, and 2D regional algorithm was finally used. Saha,[10] suggested an indirect segmentation strategy in 2011 that uses a collection of input MR slices to provide data as a subset of MR-slices like axis-parallel boxes that separate the tumors. It presents a detection method that looks for the most different region in an axial view, the MR section, between the left and right half of the brain. In 2012, Tao and Mrinal suggested a fully automated segmentation strategy for brain tumors that involves a preprocessing of FCM (Float C-Means), a fast bounding box (FBB) for tumor position detection, and a modern dynamic snake using the updated hausdorff distance (MHD) to finalize tumor extraction. In 2015, Parveen [12] proposed the hybrid technology for brain tumor prevision, based on the support vector machine (SVM) and the fuzzy c-means (FCM). The streak of the skull enhances the images. Clustering of Fuzzy c-means (FCM) is used for picture segmentation, gray grade running length (GLRLM) matrix is used for the extraction of structure, and the help method of a vector (SVM) system is used in the classification of brain MRI pictures. Sheela[13] suggested automated segmentation of the brain tumor by utilizing the Greedy Snake Paradigm and Fuzzy c-means optimization in 2019. Initially, this method uses morphology in the picture. The greedy serpent model estimates the new borders of the tumor and optimizes the inaccurate boundaries using the Fuzzy c-means algorithm to ensure accurate segmentation. Ahmed et al [14] suggested in

2002 an addition to the normal FCM objective feature to resolve the strength of brain MR picture inhomogeneity. Zhang et al[15] proposed a new algorithm in 2004 for fluctuating MRI data segmentation. “The algorithm proposed was realized by changing the objective function of the conventional c-media (FCM) algorithm using a distance metric induced by the kernel and a space penalty for the membership functions.” It was accomplished because the initial Euclidean distance in the FCM was replaced by a kernel-induced distance and subsequently by a kernel-based c-mean (KFCM) algorithm. If noise and other artifacts are present, the presented algorithm is more effective than the standard algorithm. Graphs Cut is a common graph-based segmentation used in MRI images to classify brain tumors. Boykov and Jolly[16] proposed an interactive graph cut segmentation technique. In order to have hard constraints for segmentation, the user had to label those pixels as target or context.

The outline of the paper is as follows

Section 1 describes the preprocessing of MRI image.

Section 2 describes the segmentation using KFCM.

Section 3 describes the graph cut segmentation algorithm.

2. Proposed method

The flow chart for the proposed segmentation method is shown in Fig. 1**.**The different processes used in the proposed method are described here for the purpose of illustration which is as follows-

Preprocessing

In this work, clinical brain MRI images have been gathered from Internet Brain Segmentation Repository (IBSR) [17]. For the most part the pictures got from the dataset are not suitable for examination because of different sorts of noises and artifact present in the pictures. The proposed preprocessing utilized in this work incorporates two stages i.e. denoising and skull stripping.

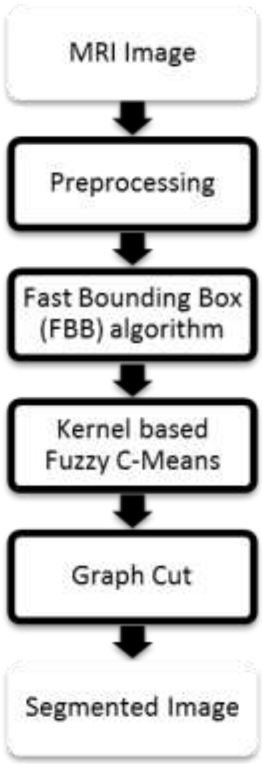


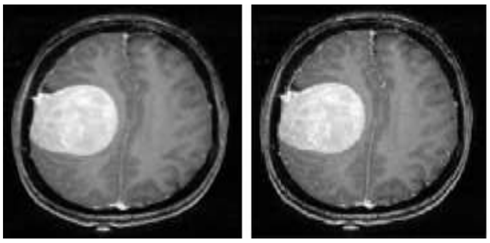
Fig.1. Flowchart of proposed segmentation method

Denoising

A median filter [18] is utilized to remove noise from the MRI brain images. It is a nonlinear digital filtering procedure utilized strategy to safeguard the edges of MRI images while denoising. This filter works by replacing the image pixels value by median of its neighborhood pixels lying within the mask used for median filtering. Fig 2(a) shows an MRI image taken from IBSR dataset and Fig 2(b) presents the corresponding filtered output image using median filter

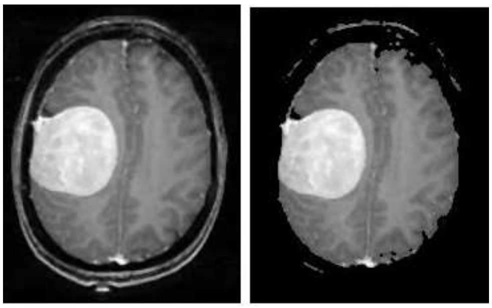
Skull Stripping

Unwanted tissues, including the skull and the skin and muscles, are extracted from picture MR using skull stripping[19]. This is a very significant step as it reduces code difficulty and time in the segmentation process. This approach utilizes morphological degradation and dilation to extract the skull from the area of the brain. Image. 3(a) displays the picture, and Fig after denoising 3(b) shows the skull stripping graphic.



(a) (b)

Fig. 2.(a) Original image (b) Filtered image.



(a) (b)

Fig. 3. [a] Filtered image [b] Skull stripped image

Fast Bounding Box (FBB) Algorithm

The Fast Boundingbox (FBB) algorithm [19] is utilized to find the area of interest or tumor in the preprocessed picture. The input MRI segments the image into equal parts one half is treated as test picture and another as reference picture. To discover the divergence for finding the tumor, a novel score work or a Bhattacharya Coefficient (BC) is employed that can search rapidly in both horizontal and vertical direction of brain region. The Bhattacharya Coefficient is a similarity measurement to detect the rectangle between two normal histogram of gray scale intensity. Fig. 4 shows the location of

the region of interest using the fast bounding box algorithm.

Kernel Based Fuzzy C-Means Algorithm

The standard Fuzzy C-means (FCM) objective function [15] for partitioning a dataset $\{x_k\}_{k=1}^{N}$ into c clusters is given by

$$\boldsymbol{J_{fcm} = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{m} \|x_k - v_i\|^2} \qquad \textbf{(1)}$$

Where $\{v_i\}_{i=1}^{c}$ are the centers of the clusters and the array are $\{u_{ik}\}(= U)$ represents a partition matrix.

It uses the reliable Euclidean distance and is immune to noise, the key restriction of the regular FCM algorithm. The number of clusters must be defined in advance.

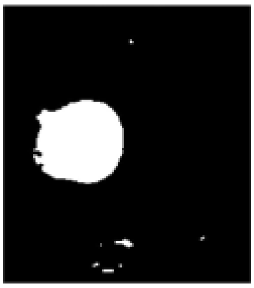


Fig. 4. Locating the region of interest using FBB algorithm

In KFCM,the focal point of the clusters in the kernal space is planned from either the first information space or the component space.

The objective function can be modified as:

$$J_{kfcm} = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{m} \|\varphi(x_k) - \varphi(v_i)\|^2 \quad \textbf{(2)}$$

KFCM gives adaptability to portion work choice and offers a clever thought for joining diverse data from different sources in the part space. This adaptability incredibly causes us in clustering based segmentation because of obtaining of image object from various sources.Fig. 5 shows the segmented tumor using KFCM

Graph Cut Algorithm

Graph Cut [16] is a semi-user interface segmentation strategy that we can use to segment an image into elements that is foreground and background. Graph cut segmentation does not require initialization. It can highlight edges on the image, called, scribbles to identify what is necessary in the image.Itcan also refine the segmentation by drawing more scribbles on the image until we are satisfied with the result.

The Graph Cut method utilize graph theory to brain MRI image to achieve faster tumor segmentation. The technique develops a graph of the image where each object of the image is a node connected by weighted edges. Fig. 6(a) shows the tumor segmented using KFCM algorithm. Fig. 6(b) and Fig. 6(c) shows the process of segmenting the tumor using Graph Cut algorithm. Fig. 6(d) shows the final segmented tumor.

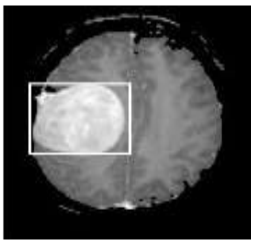
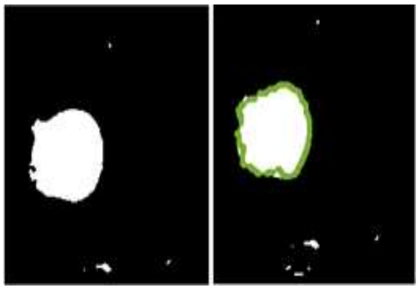
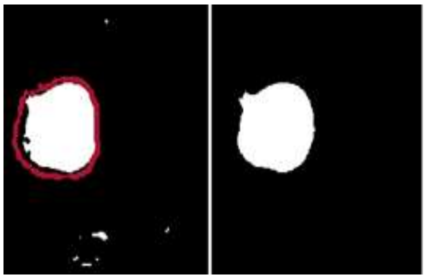


Fig. 5.Segmented tumor KFCM



(a) (b)



(c) (d)

Fig. 7. Process of Graph Cut segmentation (a) KFCM Segmented (b) Identifying the foreground region (c) Identifying the background region (d) Segmented Tumor

The detailed description of the proposed is given below:

Step 1: Take the MR image.

Step 2: Apply median filtering on the MR image.

Step 3: Apply skull stripping procedure on the filtered image.

Step4: Initialize the Fast Bounding Box algorithm to locate the tumor region.

Step 5: Apply the Kernel based Fuzzy clustering algorithm**.**

Step 6: Apply the Graph Cut Algorithm on the segmented image**.**

3. Materials and Performance Analysis

The data collection was derived from the Internet Brain Segmentation Repository (IBSR) [17]. The proposed method was simulated using the MATLAB (2017a) software in an Intel center i7 CPU 1.80 GHz with 8GB RAM PC.

Accuracy, sensitivity and specificity are the evaluation standards that are calculated to represent the efficiency of proposed technique for comparing with other similar algorithms.

Accuracy quantifies the efficiency of segmentation algorithm. It is calculated by

$$\textbf{Accuracy}=\frac{TP+FN}{TP+TN+FP+FN}*100 \qquad \textbf{(3)}$$

where True Positive represents the number of samples that confirm the presence of tumor from the proposed algorithm decision and the ground truth label; True Negative represents the number of samples where both the proposed algorithm decision and the ground truth label confirm the absence of tumor; False Positive and False Negative are the number of samples where the decisions mismatch.

Sensitivity represents the exactness of an algorithm to segment tumor region. It is calculated by

$$\textbf{Sensitivity}= \frac{TP}{TP+FN} * 100 \quad (4)$$

Specificity denotes the ability of an algorithm to segment normal tissue in an image. It is calculated by

$$\textbf{Specificity} = \frac{TN}{TN+FP} * 100 \quad (5)$$

4. Experimental Results

For evaluating the effectiveness of the proposed technique and other techniques, experiments were conducted on a set of 50 MRI images obtained from ISBR. Results for the proposed techniques and compared techniques are presented quantitatively based on evaluation parameters accuracy, sensitivity and specificity. Also the qualitative evaluation is done by visualizing the different images segmented using the proposed method and other methods.

For quantitative analysis a set of 50 MRI images is used for the purpose of experimentation out of which 3 images are shown here for the purpose of illustration.

Fig. 8(a) presents the quantitative comparison among proposed method and other two methods based on evaluation metric accuracy. Value of accuracy metric for all the imagesobtained from FCM method is represented as blue colour, from KFCM method is represented as red colour and for the proposed method is presented as green colour. It is to be noted from Fig. 8(a) that highest value of accuracy metric is achieved using the proposed method in case of all the three images. KFCM shows the moderate values of accuracy metric while FCM provides the lowest value of accuracy metric for all the three images. Fig. 8(b) presents the quantitative comparison among proposed method and other two methods based on evaluation metric specificity. Value of specificity metric for all the images obtained from FCM method is represented as blue colour, from KFCM method is represented as red colour and for the proposed method is presented as green colour. It is to be noted from Fig. 8(b) that highest value of specificity metric is achieved using the proposed method in case of all the three images. KFCM shows the moderate values of accuracy metric while FCM provides the lowest value of accuracy metric for all the three images. Fig. 8(c) presents the quantitative comparison among proposed method and other two methods based on evaluation metric sensitivity. Value of sensitivity metric for all the images obtained from FCM method is represented as blue colour, from KFCM method is represented as red colourand for the proposed method is presented as green colour. It is to be noted from Fig. 8(c) that highest value of sensitivity metric is achieved using the proposed method in case of all the three images. KFCM shows the moderate values of accuracy metric while FCM provides the lowest value of sensitivity metric for all the three images.

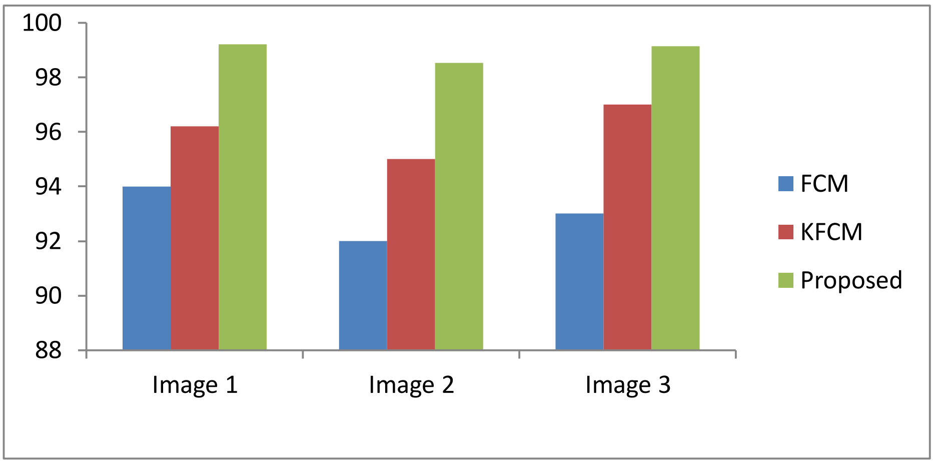


Fig.8(a) Quantitative comparison with different clustering algorithms using accuracy metric

Qualitative analysis is also done in this work for visual quality evaluation. Fig. 9(a) &10(a) shows clinical MRI images. Fig. 9(b) &10(b) depicts the tumor segmented images obtained using the FCM algorithm and Fig. 9(c) & 10(c) present the images using KFCM algorithm. Fig. 9(d) & 10 (d) shows the segmented tumor images obtained using the proposed method.

From the obtained results of all the methods it is to be noted by visual quality inspection that segmented tumor images obtained using the proposed method is of superior quality than other segmented images obtained using other methods. The boundaries of the segmented region obtained using proposed method is more sharp and clear as compared to the segmented images obtained using FCM and KFCM wherein boundaries are not sharp and clear. The worst performance is shown by FCM algorithm**.**

5. Conclusion

In this paper, utilizing MRI images, segmentation of brain tumor tissues from the ordinary tissues is done without using priori data. MRI information and dataset of the brain tumor from the IBSR dataset have been utilized in helping this investigation. A preprocessing algorithm was used to boost the signal to noise (SNR) ratio and to remove the impact of undesirable noises. A skull stripping algorithm was utilized to remove the skull and undesirable artifacts from the MRI picture. A fast bounding box algorithm was also used to identify the region of interest. Besides this a kernel based fuzzy c- means clustering approach was also used to segment the tumor. For getting the better segmentation performance a graph cut algorithm was also used. The experimental findings indicate that the above process increases accuracy and fast segmentation and provides demarcation of the tumor. The experimental new approach revealed we have achieved 99.66% accuracy.. It indicates the effectiveness of the procedure suggested to segment the tumor from natural brain tissues.

6. Acknowledgment

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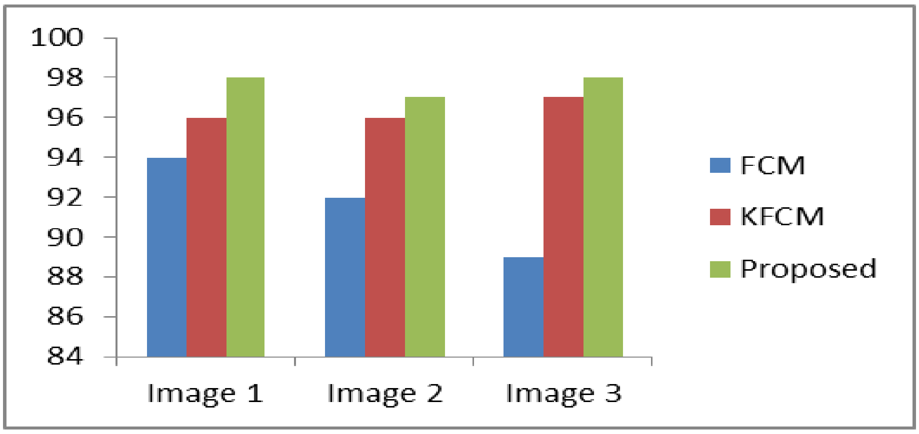

Fig.8(b) Quantitative comparison with different clustering algorithms using specificity metric.

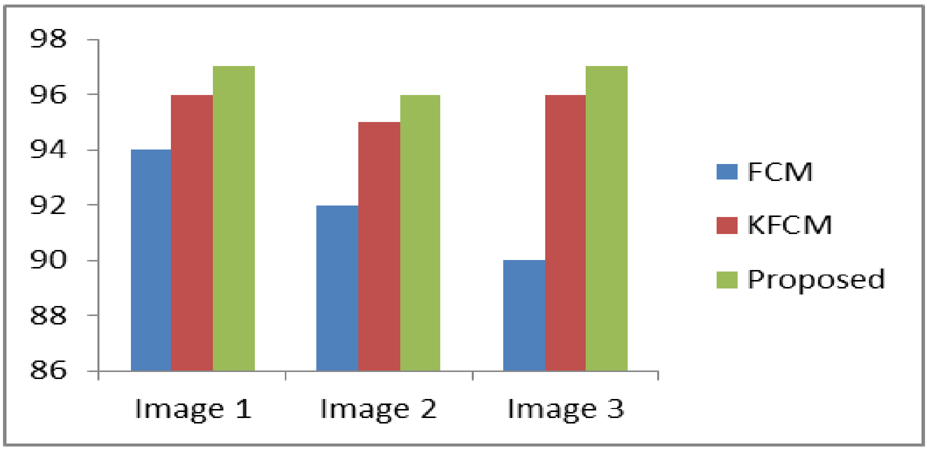

Fig.8(c) Quantitative comparison with different clustering algorithms using sensitivity metric.

(a) (b) (c) (d)

Fig. 9 Comparison of various segmentation methods (a) Sample MRI image (b) FCM (c) KFCM (d) Proposed algorithm

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