International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2018 IJSRCSEIT | Volume 3 | Issue 1 | ISSN : 2456-3307

Segmentation of Brain Tumor Images using Hybrid Clustering Technique

C. Kuyin*[1], M. Poornima[2], S. Sweetline[3]

[*1]Assistant Professor, Department of Commerce with Computer Applications, Jayaraj Annapackiam College for Women (Autonomous), Periyakulam, Tamilnadu, India

[2]Assistant Professor, Department of Commerce with Computer Applications, Jayaraj Annapackiam College for Women (Autonomous), Periyakulam, Tamilnadu, India

[3]Student, II B.Com (CA), Department of Commerce with Computer Applications, Jayaraj Annapackiam College for Women (Autonomous), Periyakulam, Tamilnadu, India

ABSTRACT

Image segmentation refers to the process of partitioning an image into mutually exclu-sive regions. It can be considered as the most essential and crucial process for facilitating the delin-eation, characterization, and visualization of regions of interest in any medical image. Despite intensive research, segmentation remains a challenging problem due to the diverse image content, cluttered objects, occlusion, image noise, non-uniform object texture, and other factors. There are many algorithms and techniques available for image segmentation but still there needs to develop an efficient, fast technique of medical image segmentation. This paper presents an efficient image segmentation approach using K-means clustering technique integrated with Fuzzy C-means algorithm. It is followed by thresholding and level set segmen-tation stages to provide an accurate brain tumor detection. The proposed technique can get benefits of the K-means clustering for image segmentation in the aspects of minimal computation time. In addition, it can get advantages of the Fuzzy C-means in the aspects of accuracy. The performance of the proposed image segmentation approach was evaluated by comparing it with some state of the art segmentation algorithms in case of accuracy, processing time, and performance. The accuracy was evaluated by comparing the results with the ground truth of each processed image. The exper-imental results clarify the effectiveness of our proposed approach to deal with a higher number of segmentation problems via improving the segmentation quality and accuracy in minimal execution time.

Keywords : Medical image segmentation; Brain tumor segmentation; K-means clustering; Fuzzy C-means; Expectation Maximization

I. INTRODUCTION

Image segmentation refers to the process of partitioning a digital image into multiple regions. The goal of segmentation is to change the representation of an image to be more meaningful and easier to analyze. It is used in order to locate objects and boundaries in images. The result of image segmentation occurs as a set of regions that collectively covers the entire image. Therefore, medical image segmentation plays a significant role in clinical diagnosis. It can be considered as a difficult problem because medical images commonly have poor contrasts, different types of noise, and missing or diffusive boundaries. The anatomy of the brain can be scanned by Magnetic Resonance Imaging (MRI) scan or computed tomography (CT) scan. The MRI scan is more comfortable than CT scan for diagnosis. It is not affect the human body because it does not use any radiation. It is based on the magnetic field and radio waves. On the other hand, brain tumor is one of the leading causes of death among people. It is evidence that the chance of survival can be increased if the tumor is detected correctly at its early stage. In most cases, the physician gives the treatment for the strokes rather than the treatment for the tumor. Therefore, detection of the tumor is essential for the treatment. The life-time of the person who affected by the brain tumor will increase if it is detected early. Thus, there is a need for an efficient medical image segmentation method with some preferred properties such as minimum user interaction, fast computation, accurate, and robust segmentation results.

Image segmentation algorithms are based on one of the two fundamental properties of image intensity values: discontinuity and similarity. In the formal category, the segmentation approach is based on partitioning the processed image based on changes in intensity, such as edges and corners. The second one is based on partitioning an image into regions that are similar due to a set of predefined criteria. Therefore, there are many segmentation techniques which can be broadly used, such as histogram based methods, edge-based methods, artificial neural network based segmentation methods, physical model based approaches, region-based methods (region splitting, growing, and merging), and clustering methods (Fuzzy C-means clustering, K-means clustering, Mean Shift, and Expectation Maximization).

There are many challenging issues to image segmentation like development of a unified approach that can be applied to all types of images and applications. Even, the selection of an appropriate technique for a particular kind of image is a difficult problem. Thus, there is no universal accepted method for image segmentation. So, it remains a challenging problem in image processing and computer vision fields.

II. RELATED WORK

Medical image segmentation is considered as a hot research topic. Several researchers have suggested various methodologies and algorithms for image segmentation. For example, Bandhyopadhyay and Paul proposed a brain tumor segmentation method based on K-means clustering technique. The method consists of three steps: K-means algorithm based segmentation, local standard deviation guided grid based coarse grain localization, and local standard deviation guided grid based fine grain localization. The extraction of the brain tumor region from the processed image requires the segmentation of the brain MRI images to two segments. One segment contains the normal brain cells consisting of Grey Matter (GM), White Matter (WM), and the Cerebral Spinal Fluid (CSF). The second segment contains the tumor cells of the brain. The segmentation technique is constraint by the fact that the images need to be of adjacent imaging layer. The image fusion method gave a good result in fusing multiple images. In particular cases, it resulted in the loss of intensity. Moreover, it also ignored the finer anatomic details, such as twists and turns in the boundary of the tumor or overlapping region of gray and white matters in the brain.

Meena and Raja proposed an approach of Spatial Fuzzy C-means (PET-SFCM) clustering algorithm on Positron Emission Tomography (PET) scan image datasets. The algorithm is joining the spatial neighborhood information with classical FCM and updating the objective function of each cluster. Spatial relationship of neighboring pixel is an aid of image segmentation. These neighboring pixels are highly renovated the same feature data. In spatial domain, the member-ships of the neighbor centered are specified to obtain the cluster distribution statistics. They calculated the weighting function based on these statistics and applied into the member-ship function. Their algorithm is tested on data collection of patients with Alzheimer's disease. They did not calculate objective based quality assessment that could analyze images and did not report their quality without human involvement.

Glavan and Holban proposed system that using a convolution neural network (CNN) as pixel classifier for the segmentation process of some X-ray images. The system analyzes each pixel from the image and tries to classify them into two classes: bone and non-bone. They attempted to separate the bone tissue area from the rest of the image. Their CNN obtained the best results in contrast to other configurations. For ensuring a minimum training time of the network, they used only the interest areas from an image. Their method recognized the significant bone areas, but the problems appeared when the bone area presented irregularities and take more execution time in training.

Tatiraju and Mehta introduced image segmentation using K-means clustering, Expectation Maximization (EM), and Normalized Cuts (NC). They analyzed the two former unsupervised learning algorithms and compared them with a graph-based algorithm, the Normalized Cut algorithm. They applied the partitioning algorithm to gray-scaled images with varying value of k (number of clusters). For smaller values of k, the K-means and EM algorithms give good results. For larger values of k, the segmentation is very coarse; many clusters appear in the images at discrete places. The NCuts algorithm gave good results for larger value of k, but it takes a long time.

III. THE PROPOSED MEDICAL IMAGE SEGMENTATION SYSTEM

There are some medical image segmentation systems which use K-means algorithm for detecting mass tumor in brain. The K-means algorithm is fast and simple to run on large datasets, but it suffers from incomplete detection of tumor, mainly if it is a malignant tumor. On the other hand, other systems use Fuzzy C-means algorithm because it retains the more information of

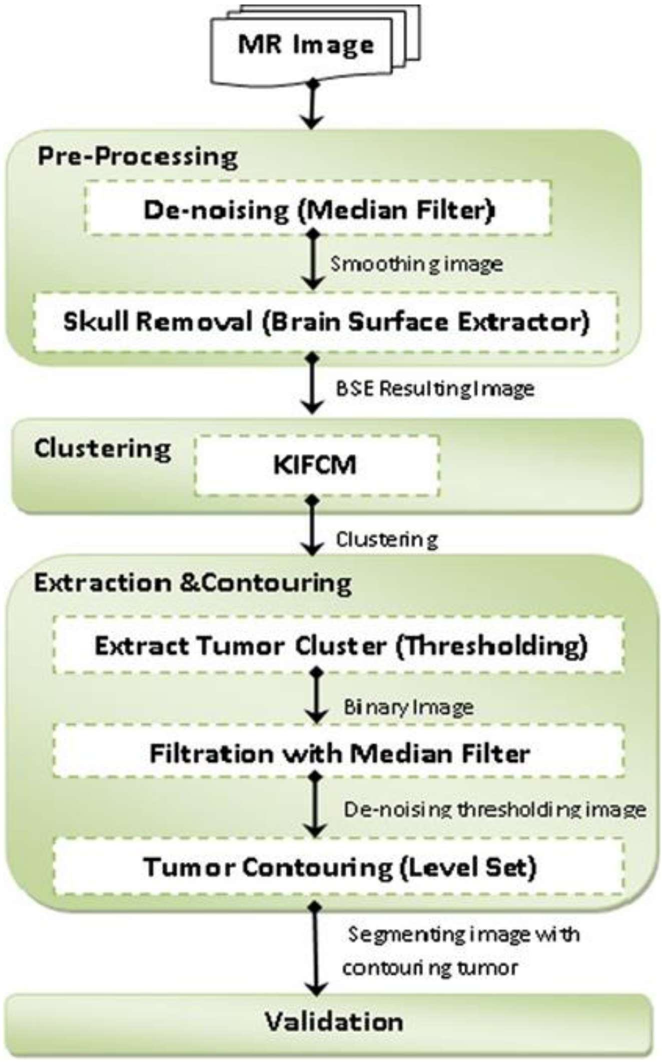


Figure 1. The framework of the proposed image segmentation system.

the original image to detect malignant tumor cells accurately compared to the K-means. These systems are sensitive to noise and outliers, and they take long execution time.

In our proposed medical segmentation system, we get benefits from the last two algorithms. As shown in Fig. 1, the pro-posed medical image segmentation system consists of four stages: preprocessing, clustering, tumor extraction and contouring, and validation stages. The main idea of doing the integration is to reduce the number of iterations done by initializing the right cluster centers to Fuzzy C-means clustering techniques that, of course, minimizes execution time and give qualitative results. The results of our experiments clarified that our hybrid clustering method (KIFCM) can detect a tumor that cannot be detected by Fuzzy C-means with less execution time. The main stages of the proposed system will be discussed in more detail in the subsequent sections.

A. Pre-processing stage

This phase is implemented by applying a series of initial processing procedures on the image before any special purposes processing. It improves the image quality and removes the noise. Since, the brain images are more sensitive than other medical images; they should be of minimum noise and maximum quality. Therefore, this stage consists of the following two sub-stages:

1) De-noising: MRI images are usually corrupted by disturbances like Gaussian and Poisson noise. The vast majority of the de-noising algorithms assume additive white Gaussian noise. There are some algorithms that designed for Gaussian noise elimination, such as edge preserving bilateral filter, total variation, and non-local means. In this paper, we used median filter. Median filtering is a nonlinear filter that is used as an effective method for removing noise while preserving edges. It works by moving pixel by pixel through the image, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the "window," which slides pixel by pixel over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. Image processing researchers commonly assert that median filtering is better than linear filtering for removing noise in the presence of edges. The output of this sub-step in preprocessing is the free noising MRI image.

2) Skull removal: Image background does not usually contain any useful information but increase the processing time. Therefore, removing background, skull, scalp, eyes, and all structures that are not in the interest decrease the amount of the memory used and increased the processing speed. Skull removed is done by using BSE (brain surface extractor) algorithm. The BSE algorithm is used only with MRI images. It filters the image to remove irregularities, detects edges in the image, and performs morphological erosions and brain isolation. It also performs surface cleanup and image masking. The output of this sub step is the free noising MRI image contains only the human brain.

B. Clustering stage

By de-noising the MRI image and removing skulls, the images are fed to KIFCM technique by initializing cluster numbers k, max iterations, and termination parameter.

Then, assign each point to the nearest cluster center based on a minimum distance by checking the distance between the point and the cluster centers then re-compute the new cluster centers. It repeats until some convergence criterion is met.

On the other hand, there are some points scattered and far away from any cluster center. Therefore, the resulting new cluster centers, the clustered points, and the scattered points can be entered in the same time to the looping step that calculates the new distances and clustering the points due to membership value. Then, the membership and means values are updated with determining the condition of closing.

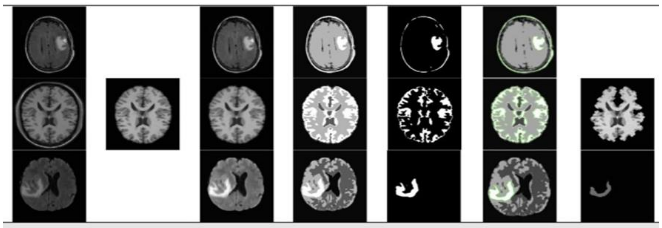
This looping step takes less number of iterations than the random selection because the initial centers of the clusters were not randomly chosen which saves time and effort. Although, the points were reclustered due to its membership. There is no inference between points in their clusters, because there is no huge change done by the reclustering process. The output of the technique is the clustering image, execution time, and iteration numbers that are recorded to compare with other clustering methods. In this stage, we make a hybrid clustering method based on hard and soft clusterings. The hard clustering technique put each point to belong to only closest cluster. Whereas, the soft clustering technique gives every point a degree of membership, rather than belonging wholly to just one cluster.

C. Extraction and contouring stage

In this stage, we used two segmentation methods: thresholding and active contour level set methods:

1) Thresholding segmentation: It is intensity-based segmentation. Thresholding or image binarization is one of the important techniques in image processing and computer vision. It is used to extract the object from the back-ground. The segmented image, which is obtained by thresholding, has the advantages of smaller storage space, fast processing speed, and ease of manipulation, compared with gray level image which usually contains a large number of gray levels (maximum 256 levels). The output of this step is the segmenting image with dark background and lighting tumor area.
2) Active contour by level set: Active contours have been used for image segmentation and boundary tracking since the first introduction of snakes by Kass et al. The basic idea is to start with initial boundary shapes represented in a form of closed curves, i.e. con-tours, and iteratively modify them by applying shrink/ expansion operations according to the constraints. The used active contour method show robust segmentation capabilities in medical images where traditional segmen-tation methods show poor performance. An advantage of the active contours as an image segmentation method is that they partition an image into sub-regions with con-tinuous boundaries. While the edge detectors based on the threshold or local filtering, it often results in discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. Depending on the implementation scheme, active contours can use various properties used for other segmentation methods such as edges, statistics, and texture. Level set algorithm is demonstrated in details by Lee.

The clustering image is entered to the binarization process using inverse thresholding method with iteration number equals 3. The noise of the image is removed by using the median filter that eliminates the small regions that are far away from the tumor cluster. We can consider this step as a post-processing step in our system. Of course, these two steps can be converted to one step if the classical FCM is used which user can enter the cluster to be a threshold or appeared only in image. In our proposed technique, we get rid of user inter-action that may be true or false. After that, the thresholding image with the lighting tumor cluster is fed to the level set. Level set contours the tumor area of the thresholding image on the original image. The output of this step is the thresholding image and original free noising image with contouring tumor area. The tumor area can be calculated by computing the white pixels of total pixels of the image.



D. Validation stage

In validation stage, the segmented images by KIFCM were compared to the ground truth in cases of the third data set as illustrated in experimental results. It compared to the typical images as in the second data set, but the first one does not have any ground truth. The results were evaluated by performance matrix that contains the precision and recall. Precision is the correct segmentation that refers to the percentage of true positive. In other words, it is the number of pixels that belong to a cluster and is segmented into that cluster. Recall, or sensitivity is defined as the number of the true positives divided by the total number of elements that belong to the positive cluster.

IV. CONCLUSION

Image segmentation plays a significant role in medical image. In the field of medical diagnosis, an extensive diversity of imaging techniques is available presently, such as CT and MRI. MRI is the most effectively image model used for diagnostic image examination for brain tumor. The MRI scan is more comfortable than CT scan for diagnosis. On the other hand, K-mean algorithm can detect a brain tumor faster than Fuzzy C-means, but Fuzzy C-means can predict tumor cells accurately. Original Fuzzy C-means algorithm fails to segment image corrupted by noise, outliers, and other imaging artifacts. Therefore, we developed a new approach that integrates the K-means clustering algorithm with the Fuzzy C-means algorithm to detect brain tumor accurately and in minimal execution time. Our framework consists of four stages: pre-processing (de-noising and skull removal), clustering (integration of K-means and Fuzzy C-means), extraction and contouring (thresholding and level set), and validation stages.

V. REFERENCES

[1] Christe SA, Malathy K, Kandaswamy A. Improved hybrid segmentation of brain MRI tissue and tumor using statistical features. ICTACT J Image Video Process 2010;1(1):34-49.

[2] Bandhyopadhyay SK, Paul TU. Automatic segmentation of brain tumour from multiple images of brain MRI. Int J Appl Innovat Eng Manage (IJAIEM) 2013;2(1):240-8.

[3] Patel J, Doshi K. A study of segmentation methods for detection of tumor in brain MRI. Adv Electron Electr Eng 2014;4(3):279-84.

[4] Dass R, Priyanka, Devi S. Image segmentation techniques. Int J Electron Commun Technol 2012;3(1):66-70.

[5] Tatiraju S, Mehta A. Image Segmentation using k means clustering, EM and normalized Cuts, University Of California Irvine, technical report.