

COMPARISON OF HYBRID SEGMENTATION METHODS FOR DETECTION OF BRAIN TUMOR IN MRI

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Abstract - This paper reviews the comparative analysis of medical image segmentation techniques for segmenting tumor from MRI images to clearly determine brain tumours and help the physician make a better diagnosis. Brain tumors are the leading cause of cancer death in children under the age of 20. The brain tumor segmentation is a challenging and complex task. In recent years segmentation problems have been attracted interest and ongoing research. In this paper comparative study of hybrid segmentation techniques like K-means, PSO-K means, Firefly-K means, Seg-UNet architecture were carried out and found that hybrid Seg-UNet can provide better output of original image and visual observation of tumors. This hybrid method achieves 99.2% segmentation accuracy with sensitivity 96% and specificity 94%. The results showed that hybrid methods provide a significant contribution to help the physicians in Magnetic resonance brain image tumor detection.

Keywords: Segmentation, K-means, PSO-K means, Seg-Unet, segmentation accuracy

I. INTRODUCTION

The image acquired by the acquisition device is susceptible by the environment. The restoration of images tries to minimize the effects of these degradations by means of a filter (Elsherif 2001; Zong 1996). Therefore, a fundamental problem in the image processing is the improvement of their quality through the reduction of the noise. A great variety of techniques dedicated to carry out this task exist. Each of them depends on the types of the noise in images. The image acquired by the acquisition device is susceptible by the environment. The restoration of images tries to minimize the effects of these degradations by means of a filter (Elsherif 2001; Zong 1996). Therefore, a fundamental problem in the image processing is the improvement of their quality through the reduction of the noise. A great variety of techniques dedicated to carry out this task exist. Each of them depends on the types of the noise in images. The image acquired by the acquisition device is susceptible by the environment. The restoration of images tries to minimize the effects of these degradations by means of a filter (Elsherif 2001; Zong 1996). Therefore, a fundamental problem in the image processing is the improvement of their quality through the reduction of the noise. A great variety of techniques dedicated to carry out this task exist. Each of them depends on the types of the noise in images.

The segmentation of the brain tumor image is to extract one or more Regions of Interests (ROIs) from the background after pre-processing. The principle goal of segmentation is to partition an image

into homogenous regions (spatially connected groups of pixels called classes or subsets) with respect to one or more characteristics or features, such that the union of any two neighboring regions yields a heterogeneous. Castleman defines image segmentation as a process that partitions a digital image into disjoint (non-overlapping) regions. The level of this subdivision into disjoint regions depends on the problem being solved. General image segmentation algorithms for intensity images are based on one or two basic properties of intensity values: discontinuity and similarity. The first approach is to partition an image based on abrupt changes in intensity, where the principal areas of interest are the detection of the boundaries between objects within an image. The second is a region approach, which assigns each pixel to a particular object [1] (Gonzalez and Woods 2008). Accurate segmentation of the brain tumor region is an important prerequisite in the computer-assisted analysis of MRI brain tumor images. The goal is to exclude the background from the further processing. The segmentation algorithm should identify the tumor region independently of the digitization system, the orientation of the breast in the image, image artifacts and other image characteristics.

Segmentation of brain MRI is a challenging problem that has received an enormous amount of attention by various researchers. MR Brain tumor image segmentation can help to identify regions like gray matter, white matter and cerebrospinal fluid and tumor for functional visualization in the diagnosis of diseases like stroke and cancer. Brain segmentation research has increased in importance over the last decade. It is difficult to perform the brain MR image segmentation manually as there are several challenges associated with it. Radiologist and medical experts spend plenty of time for manually segmenting the brain MR images, and this is a non-repeatable task. In view of this, an automatic segmentation of the brain MR images is needed to correctly segment the tissues of the brain in a shorter time span. The accurate segmentation is crucial as otherwise the wrong identification of disease can lead to serious negative consequences.

Automatic detection and segmentation of brain tumor from brain MR images offer a mechanism for overcoming the tedium involved in the manual segmentation of large datasets. It also promises reproducibility which is affected by inter and intra observer variability. However, automated systems have significant problems to achieve these objectives. The major problems are that pixel intensities violate the independent and identically distributed assumption within and between images due to the nature of brain MR images, and the presence of a significant amount of artifacts and intensity inhomogeneity in MR images. Therefore, the automated method must consider these problems to achieve reproducible segmentation results and developing clinically accepted automated methods remains an active research area. Hence, the importance of having effective tools for grouping and recognizing different anatomical tissues, structures is growing with the improvement of the medical imaging systems.

Several methods are employed for MR brain image segmentation such as clustering methods, thresholding method, classifier, region growing, deformable model and markov random model etc. The present research has mainly focused attention on clustering methods, because it is widely used in biomedical applications particularly for brain tumor detection in abnormal magnetic resonance images. It is one of the widely used image segmentation techniques which classify the samples belonging to different groups [2] (Kao et al 2008). Many techniques have been proposed to automate the brain tumor detection and some notable methods are reviewed in the following sections.

II.K-means Clustering Algorithm

K-Means algorithm (Kanungo et al 2002) is one of the unsupervised clustering algorithm due to its efficiency and simplicity in clustering large data sets. In traditional K-Means algorithm the numbers of clusters is defined and are initialized apriori. Next, k cluster centers are randomly chosen. Euclidean distance is generally considered to determine the distance between data objects and the cluster center. The distance between the each data point to each cluster centers are calculated. The data point is moved to particular cluster which has the shortest distance. The centroid is then re-estimated. Again each data point is compared with all the centroids. The process continuous and at the end of loop, k-centroids change their point step by step until the centroids do not move any more. This algorithm works on basis of minimizing squared error function. The K-Means algorithm always converges to a local minimum. Local minimum found depends on the initial cluster centroids. K-means clustering algorithm is summarized as,

2. Repeat

a) For each data vector, assign the vector to the class with the closest centroid vector, where the distance to the centroid is determined using,

$$d(z_p, m_j) = \sqrt{\sum_{k=1}^{N_d} (z_{pk} - m_{jk})^2} \quad (i) \quad (1)$$

where z_p denotes the Pth data vector, m_j denotes the centroid vector of cluster j and k subscripts the number of features of each centroid vector

b) Recalculate the cluster centroid vectors, using,

$$v_j = \frac{1}{n_j} \sum_{v_d \in c_j} i_j \quad (ii) \quad (2)$$

where n_j denotes the number of data vectors in cluster j, v_j stands for the centroid vector and c_j is the subset of data vectors that form cluster j ,until a stopping criterion is satisfied.

The K-means clustering process can be stopped when any one of the following criteria are satisfied: when the maximum number of iterations has been exceeded, when there is little change in the centroid vectors over a number of iterations or when there are no cluster membership changes. The diagrammatic representation of the K-means algorithm and its flow is shown

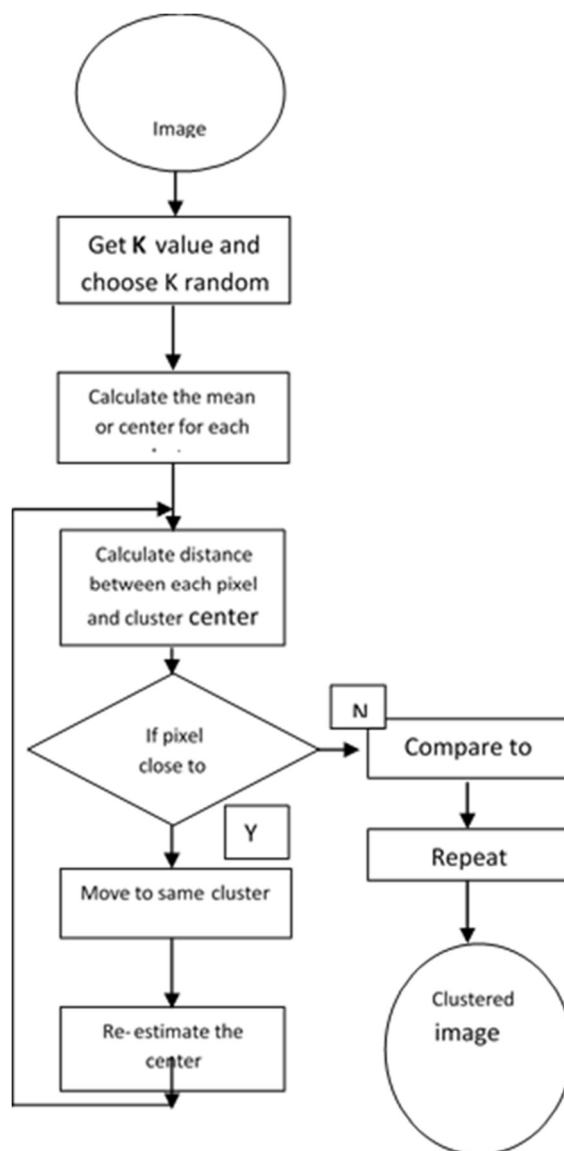


Figure 1 Flow chart of K-means Algorithm

III. PSO-K means clustering Algorithm

Hybrid evolutionary optimization algorithm is proposed based on PSO and K-means [4] is applied for brain tumor segmentation. Hybrid system mix different methods and make them work together to achieve a solution better than the one possible by using a single method for the same problem (Xiaohui Cui et al 2005). Here, to overcome the K-means shortcomings, the hybrid evolutionary algorithm is used to solve the clustering problem. To use the advantages of the K-means algorithm in the proposed algorithm, the output of PSO algorithm was considered as the initial state of K-means. Starting with a randomly initialized population, each particle in PSO flies through the searching space and remembers the best position it has seen. Members of a swarm communicate good positions to each other and dynamically adjust their own position and velocity based on these good positions. The velocity adjustment is based upon the historical behaviors of the particles themselves as well as their neighbors. In this way, the particles tend to fly towards better and better

searching areas over the searching process and find the optimal cluster centers. The last gbest value is considered as the initial solution for the K-means algorithm. .

Hybrid firefly-K means

Firefly Algorithm is a highhanded method to PSO in terms of both efficiency[6] and success rate but the drawback of firefly algorithm is that the firefly traps into several local optima due to unchanged parameter during iterations. In the standard Firefly Algorithm, firefly 'i' movement is attracted to the most attractive best solution. Thus if there was no local best in each firefly's neighborhood, they move towards the best solution and make better position for each firefly for the next iteration and thus get closer to the global best. After obtaining optimal cluster centers i.e global best, the K-means algorithm is initialized with this center. The K-means is then used to cluster the objects.

IV Seg-UNet Architecture

Seg-UNet[6] is hybridization architecture of SegNet5 and U-Net architecture, which are widely used for segmentation of the brain tumor image. Seg-UNet is a semantic segmentation based on SegNet and UNet .This architecture is encoder-decoder model. In this work input is a scaled-down the tumor region in an MR image with width W and height H. The Seg-UNet takes brain tumor input of size $256 \times 256 \times 3$, 32 convolution filters of size 3×3 are used to convolve across the input to extract feature map of size $256 \times 256 \times 32$. Further down sample the feature map size to $128 \times 128 \times 32$. In the second convolution block, convolutional layers of the same filter size are used on the output of the previous layer and reduce the third dimension to 64, it becomes $128 \times 128 \times 64$ and then dimensions reduce to $64 \times 64 \times 128$. In third convolution blocks, furthermore, it is down sampled to $32 \times 32 \times 256$. In the fourth convolution blocks, the feature map size is reduced to half and then down sample to $16 \times 16 \times 512$.. It observed that the last dimension (depth) cannot be increased anymore, as the feature becomes very small and difficult to differentiate among them. Therefore, going deeper may not be useful and it will lead to unnecessarily higher computational time. An up sampling path or decoder scales up to the feature map dimension of lower resolution to a higher resolution to get back the original input resolution, this will preserve correct boundary delineation of the tumors.

V. SEGMENTATION PERFORMANCE MEASURES

A. Sensitivity

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \times 100$$

where, TP is the number of True Positives; FP is the number of False Positives; TN, the number of true negatives; FN, the number of False Negatives

B. Specificity

$$\text{Specificity (\%)} = \frac{TN}{FP+TN} \times 100$$

where, TP is the number of True Positives; FP is the number of False Positives; TN, the number of true negatives; FN, the number of False Negatives

$$\text{C. accuracy (\%)} = \frac{TP+TN}{TP+FP+FN+TN}$$

VI RESULTS AND DISCUSSIONS

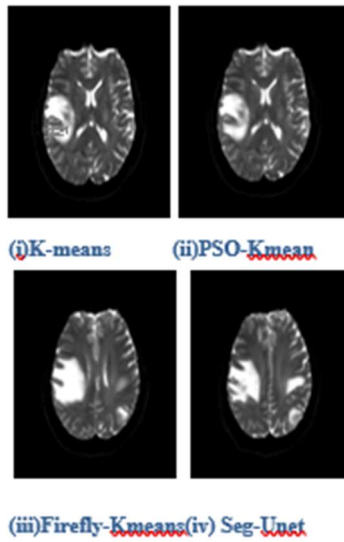
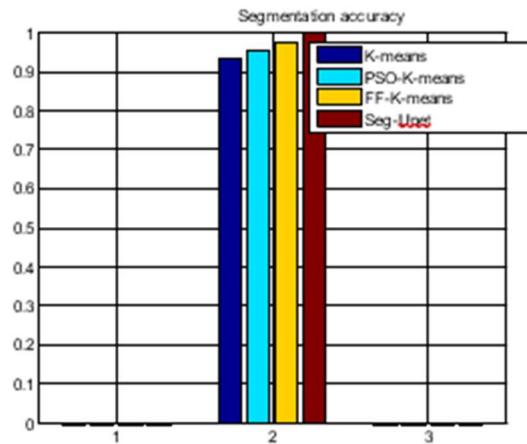


Fig2. Segmentation outputs

Table .1 Performance comparison of various segmentation methods

Segmentation Approach	Sensitivity (%)	Specificity (%)	Overall Accuracy
K-means	75	57	71.4
PSO-K means	87	66	95.5
Firefly-K means	90	87	96.9
Seg-Unet	96	94	99.2



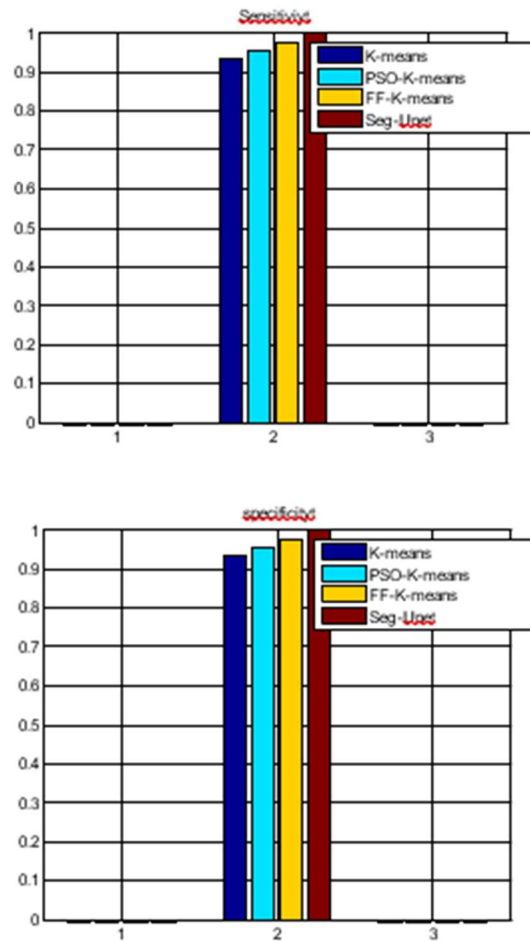


Fig 3. Accuracy, sensitivity, specificity

The results show that the hybrid seg-Unet segmentation algorithm performed better than the PSO-Kmeans and firefly K-means and K-means clustering algorithm according to the sensitivity, specificity, and Segmentation Accuracy while hybrid seg-Unet segmentation algorithm.

VII. CONCLUSION

In this article, the performance comparison of various segmentation methods for detecting tumor from MR images has been discussed. The experiments were conducted on T2 weighted MRI datasets, the comparisons of four segmentation schemes are tabulated in Table 1. It is observed from the table 1, for T2 weighted MR brain images hybrid Seg-Unet architecture technique gives better result as compared to other segmentation schemes. From the enhanced results, qualitatively and quantitatively the hybrid method produces good accuracy outputs.

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