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An Efficient Brain Tumour Extraction in MR Images using Ford-Fulkerson Algorithm

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ABSTRACT

Brain tumor division intends to discrete the diverse tumor tissues, for example, dynamic cells, necrotic core,and edema from typical cerebrum tissues of White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). MRI-basedbrain tumor division studies are drawing in more consideration lately because of non-invasiveimaging and great delicate tissue difference of Magnetic Resonance Imaging (MRI) pictures. With the improvement of very nearly two decades, the inventive methodologies applying PC supported strategies for the sectioning brain tumor are turning out to be more develop and coming closer to routine clinical applications. The reason for this exploration work is to give a far-reaching review to MRI-based brain tumor division techniques. To consider and characterize the tumor pictures, a couple of well-known Edge Detection Techniques have been proposed as of late. This examination work has distinguished KWT (K-Means, Watershed, and Texture) Segmentation Technique and executed and contemplated. From our test comes about, this examination work uncovered that this model neglects to make productive groups order force causes poor tumor characterization precision. This is one of the real issues to anticipate the tumor design and to address this issue, the Ford-Fulkerson Segmentation Technique is proposed and concentrated altogether as far as Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Classification Accuracy. Results set up that the proposed Ford-Fulkerson Segmentation Technique beats KWT in terms of Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Classification Accuracy.

Keywords: K-Means, Watershed, Texture, Edge Detection, Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Classification Accuracy.

1 Introduction

Image Processing [1, 2, 3] is being utilized as a part of numerous continuous applications and medicinal applications also. Some imperative ranges are Computer Vision for errands like the route of Robots, medicinal field, for example, Disease Diagnosis from CT output and MRI Images, Remote Sensing, Video Processing and ID of number plates of moving vehicles and so forth. The reason for Digital Image Processing is robotizing diverse errands and image division is an unavoidable stride in it. Image Segmentation alludes to apportioning a picture into a few sections, taking into account Textures, Colour, Edges or Regions in the picture. It goes for isolating the picture into outwardly homogeneous and particular areas. Shading is viewed as an applicable component when managing the impression of static

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and moving pictures. Visual contrast [3,4] is useful to filter information present in each colour component and to distinguish among alike gray-scale intensities. The mixture of colour and texture has been proved to achieve better results and could be exploited more successful.

Image Segmentation is a critical part of Digital Image Processing. The Image Segmentation can give an outcome that streamlines the presentation of an Image and makes the picture investigation simpler. In the division, a name is doled out to each pixel that is having comparable qualities, similar to shading, surface or force, which will help to partitioned the locales and distinguish the items and their limits. In any case, the issue while handling is the possibility of over-segmentation or under-segmentation.

2 Related Work

Many image segmentation calculations are generally utilized as a part of a few regions. Such segmentation systems may be comprehensively grouped into intermittence based division and comparability based segmentation [1, 2, 3, 4, 5]. To start with class incorporates picture division calculations like edge identification by identifying the edges or pixels between distinctive districts that have quick move in power are removed and recent incorporates division calculations, for example, locale developing and area part and combining or thresholding system. Image Segmentation has an imperative part in therapeutic imaging for the most part in diagnosing variations from the norm in pictures of human body parts. The method for dividing image fluctuates from picture to image furthermore relies on upon the reason for segmentation.

K-Means Clustering Methods [1, 2, 3] has been utilized for therapeutic image segmentation particularly in MR Images of the human mind. For CT sweep pictures, some dynamic shape models [4, 5] can be utilized and various model methodologies [4] are there for sectioning ultrasound pictures of the heart.

Therapeutic field utilizes distinctive division techniques, [4, 5] shows the utilization of segmentation of punctuating examples in fluorescence microscopic images. It's factual displaying helps the different covers meet from an arbitrary starting setup to an applicable one. Another work in [3,5] presents a system to fragment countless from 3-D pictures portrayed by non-homogeneous power and angle sign and skilled to finish surface discontinuities with no bargain in the middle of accuracy and capacity to coordinate the deficient shapes. The division system is a summed up variant of the Subjective Surfaces procedure. But most challenging segmentations in medicinal imaging consist of the processing of edgeless images such as histology images which consists of bright field microscopy images of haematoxylin and eosin (H&E)-stained slices of tissues. Some segmentation works on histology dataset [3, 4, 5], which deals with slices of tera-toma tumour [4, 5], where the intensity neighbourhoods are used to segment bone, cartilage, and obese. Another method for identifying the histological grade of breast cancer based on model classification and image analysis algorithm is described clearly in [3].

From the literature survey[1,2,3,4,5], it was seen that a couple of famous Edge Detection Techniques in particular Threshold-based routines, Region-based systems, Classification and Clustering strategies like K-Means, Fuzzy C-Means (FCM), Markov Random Fields (MRF), Bayes, Artificial Neural Networks (ANN), Support Vector Machines (SVM) and a couple of other Segmentation Techniques, for example, Watershed, Ford-Fulkerson, have been proposed.

This research work has recognized two well-known Edge Detection Techniques, in particular, i. KWT i.e. joining K-Means, Watershed and Texture Segmentation Technique and ii. Portage Fulkerson

Segmentation Technique. The exhibitions of these two procedures have been concentrated completely by actualizing them and the execution of Ford-Fulkerson Technique is enhanced by proposing MRF and CRF based Ford-Fulkerson Technique. The current KWT Technique and proposed model are talked about at the accompanying areas.

3 KWT Edge Strength Merging Technique

Recognizing and Eliminating False Edges amid Image Segmentation is one of the testing issues in Image Segmentation Process. The creators Gullanar and et. al. dissected the execution of consolidating K-Means, Watershed and Texture (KWT) Segmentation Technique[3,4]. The ideas and models of KWT are described beneath.

3.1 K-Means Clustering Technique

Among the hard clustering, K-Means clustering [1,3,5] is forever analyst's first decision in view of its straightforwardness and elite capacity. Here, K is the quantities of groups to be indicated. The formal steps included in this calculation are:

1) Randomly choose 'c' cluster centres.

2) Calculate the distance between every data point and cluster centres.

3) Allocate the data point to the cluster centre whose distance from the cluster centre is minimum of all the cluster centres.

4) Recalculate the new cluster centre using:

$$v_i = \frac{1}{c_i}\sum_{j=1}^{c_i} x_j$$

where, 'c_i' denotes the number of data points in i^{th} cluster.

5) Recalculate the distance between every data point and new attained cluster centres.

6) If no data point was reselected then stop, otherwise repeat from step 3).

The goal of the K-Means algorithm is to diminish the squared error function [3]:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\| x_i^{(j)} - C_j \right\|^2 \quad (1)$$

Here, $\left\| x_i^{(j)} - C_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centrec_j isan indicator of the distance of the n data points from their respective cluster centres.

3.2 Watershed Segmentation

A Watershed [2] definition for the unremitting case can be based on reserve functions. Dependingon the reserve function used one may arrive at diverse definitions. The image f is an element of the space C(D) of real doubleendlessly differentiable functions on a connected domain D with only isolated critical points. Then the geographical distance between point's p and q in D is defined [1] by

$$T_f(p,q) = \inf_{\gamma} \int \gamma \left\| \nabla f(\gamma(s)) \right\| ds \quad (2)$$

Where the infimum is over all paths (smooth curves) γ inside D with γ(0) = p, γ(1) = the topographical distance between a point p € D and a set A ⊆ D is de_ned as $T_f(p, A) = MIN_a \in AT_f(p, a)$.$T_f$is theshortest path between p and q with steepest slope.

3.2.1 Watershed Tree Construction

In the multi-scale representation, the tree's leaves speak to the starting allotment of the image area. Inside Nodes speak to locales acquired by combining the areas relating to their kids. The Root Node speaks to the whole picture support. Amongthese lines, the tree speaks to an arrangement of locales at diverse scales, and it can be viewed as a progressive, area based representation of the data picture. Unmistakably, the tree does not encode all conceivable outcomes for blending areas fitting in with the introductory segment, yet just the most valuable combining steps. In this manner, both the combining request and the area model whereupon the tree development procedure depends on must be deliberately picked.

Compute Gradient-Magnitude Image E of F;

Apply the Watershed Transform on E to get initial partition P;

Compute region model of all regions of P;

Assign regions of P to leaves of T

Compute Region Adjacency Graph (RAG) G of P;

While vertices(G) > 1 do

{

Compute edge costs;

Construct Minimum Spanning Tree(MST) Tm on G

Apply Watershed transform on Tm to build new partition P;

Compute region model of all regions of P;

Establish child-parent relations between regions in T at the previous level and regions in P

Compute RAG G of the new partition.

}

End while

3.3 Texture Segmentation and Statistical Analysis

The statistical approach i.e., an image texture considered as quantitative measure at the regions need to analysis. The mathematical model is discussed at the following section.

3.3.1 Edge Detection

The edge detection is used to determine pixels at a specified region are facilitating to determine the texture complexity.

Give us a chance to consider an image as made out of homogeneously textured areas which appeared in the Fig. 1. It was considered and accepted that the ghostly histograms inside homogeneous areas are steady. The Local ghostly histograms illustrative of every district can be registered from windows inside every area. Give us a chance to consider just the force channel until further notice, which gives the power estimation of every pixel as the channel reaction. At that point, the neighborhood unearthly histogram is identical to the histogram of a nearby window. Under the suspicion of ghostly histogram steadiness inside of the district, the nearby histogram of pixel A can be all around approximated by the weighted whole of agent histograms of two neighbouring locales, where the weights relate to region scope inside of the window and in this way demonstrate which area pixel A has a place with.

Given an image with N pixels and M feature dimensionality o, entirely the feature vectors can be compiled into aM $\times$ N matrix, Y. Assuming that there are L illustrative features, the image typical can be expressed as:

$$Y = Z\beta + \varepsilon \tag{3}$$

Where Z is a M$\times$L matrix whose columns are illustrative features, β is an L$\times$ N matrix's columns are weight vectors, and ε is the model error. The representative feature matrix Z can be calculated from manually nominatedwindows

Within each identical region, and β is then estimated by least squares estimation:

$$\hat{\beta} = (ZTZ)\text{-}1ZTY \tag{4}$$

Segmentation is obtained by examining $\hat{\beta}$ where each pixel is assigned to the segment where the corresponding representative feature has the largest weight.

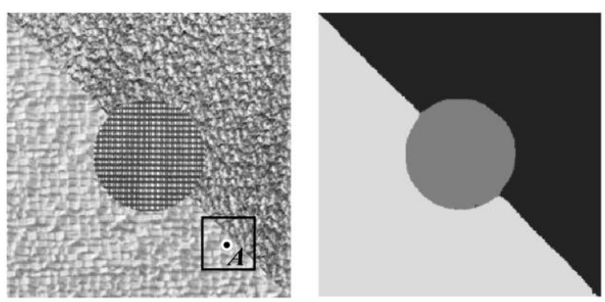

Figure 1: Textured Image with Segmentation

3.4 KWT based Image Segmentation

The KWT [3, 4, 5] is a region-based image segmentation process. This method consists of the following steps. They are

Step 1: Load Image

Step 2: Compute a segmentation function where images' dark regions need to segment

Step 3: Convert a Loaded Image into L* a* b* and compute foreground markers

Step 4: Apply K-Means algorithm and Compute distance and cluster

Step 5: Apply Watershed Segmentation Technique and Texture Segmentation

Step 6: Compute the watershed transform

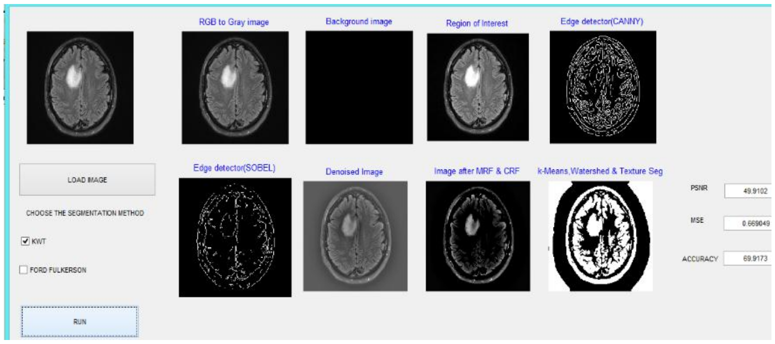

Figure 2: Performance Analysis of KWT

3.4.1 Mean Squared Error(MSE) and Peak Signal to Noise Ratio(PSNR)

The Mean Squared Error (MSE) is the cumulative squared error linking the compressed and the original image and the Peak Signal to Noise Ratio (PSNR) is the measure of Peak Errors. The Statistical model is given below to calculate both the MSE and PSNR.

Mean Squared Error (MSE)

The mathematical model to measure MSE is as given below

$$MSE = \frac{1}{MN}\sum_{Y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I^{'}(x,y]^{2} \qquad (5)$$

Where, I(x,y) is the original image, I'(x,y) is its noisy estimated version (which is really the decompressed image) and M and N are the dimensions of the images value for MSE implies lesser error.

Peak Signal to Noise Ratio (PSNR)

The mathematical model to measure PSNR is as given below

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (6)$$

Where, MAXI is the greatest possible pixel value of the image. A higher value of PSNR has always chosen as itsuggests the ratio of Signal to Noise will be developed. The 'signal' here is the original image, and the 'noise' is the errorin reconstruction.

3.5 Identified Problem

From our experimental results, it was noticed that the KWT Image Segmentation Technique i.e., the combining K-Means, Watershed and Texture-based Image Segmentation technique achieved the segmentation result.

However, from our experimental results, this research work revealed that this model fails to make efficient clusters to classify intensity causes poor tumourclassification accuracy. This is one of the major issues to predict the pattern and to address this issue, the Ford-Fulkerson image segmentation Technique is proposed and framework is described at the following Section.

4 FFT: Ford-Fulkerson Technique

As we discussed at the previous section, it was noticed that we need an efficient image segmentation Technique to effectively segment the tumour images to increaseforecast and classification accuracy of Tumour images. The Ford Fulkerson Technique is proposed to address this issue and it is discussed in this Section.

4.1 Clustering Method based on Ford Fulkerson Segmentation Technique

From the literature survey, in fact, it was noticed that most of brain tumour segmentation algorithms are based on classification or clustering methods such as Fuzzy C-Means (FCM), K-Means, Markov Random Fields (MRF), Bayes, Artificial Neural Networks (ANN), and Support Vector Machines (SVM).

In our work, we considered Ford Fulkerson Technique to improve classification and prediction accuracy. This is based on MRF approach.

MRF had been proposed as it can give an approach to incorporate spatial data into the bunching or order process. In grouping strategies, it diminishes both the conceivable issue of covering and the impact of commotion on the outcome. In the specific instance of cerebrum tumour segmentation, if a district is unequivocally named as mind tumour or non-mind tumour, MRF will figure out whether the neighbour of the marked locale is the same. Contingent Random Fields (CRF) had been proposed to construct probabilistic models to section and mark grouping information. MRF and CRF calculations can speak to complex conditions among information sets to pick up a high precision for the results of cerebrum tumour segmentation.

4.1.1 Ford Fulkerson Procedure

The procedure is developed as follows.

Inputs: Graph G with flow capacity C,

s-Source node and *t*-sink node

Output: A flow f from *s* to *t* which is a maximum

Steps:

Step 1: f (u,v) ←0 for all edges (u,v)

Step 2: While there is a path p from *s* to *t* in G_f, such that c_f (u, v) > 0 for all edges (u,v) ϵ p :

{

1. Find c_f(p) = min{c_f (u, v) : (u, v) ϵ p}

2. For each edge (u,v) ϵ p

{

1. f (u, v) ← f (u, v) + c_f (p) (Send flow along the path)

2. f (v,u) ← f(v,u) – c_f (p) (The flow might be "returned" later)

}

}

Step 3: Stop

4.1.2 Flowchart

The flow chart of our proposed Ford-Fulkerson Technique is presented in this section as follows.

Step 1: Load Image

Step 2: Compute a segmentation function where images' dark regions are need to segment

Step 3: Convert a Loaded Image into L* a* b* and compute foreground markers

Step 4: Apply morphological operation and Compute distance and cluster

Step 5: Apply Ford-Fulkerson Image Segmentation Procedure

Step 6: Compute the transform and create final segmented image

5 Results and Discussions

This proposed method is implemented with MATLAB Tool. Here, the number of Clusters K are initialized and values are given as dynamic to make automatic clusters depends upon the available database. The results of the existing and proposed model are given below.

The developed tool calculated both the MSE and PSNR values for the original and final segmented images which are shown in the Figures.

From the segmented image, we need to extract the required information and features. The features are used to predict or classify the Tumours from normal Image.

The experimental results are demonstrated in the Figures Figure. 2, Figure. 3, Figure. 4, Figure. 5, and Figure. 6.

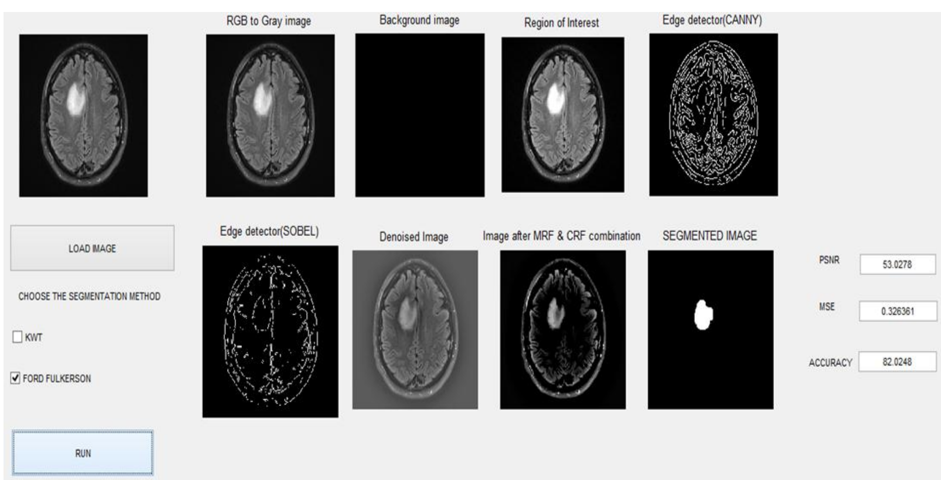

Figure 3: Performance Analysis of Ford Fulkerson

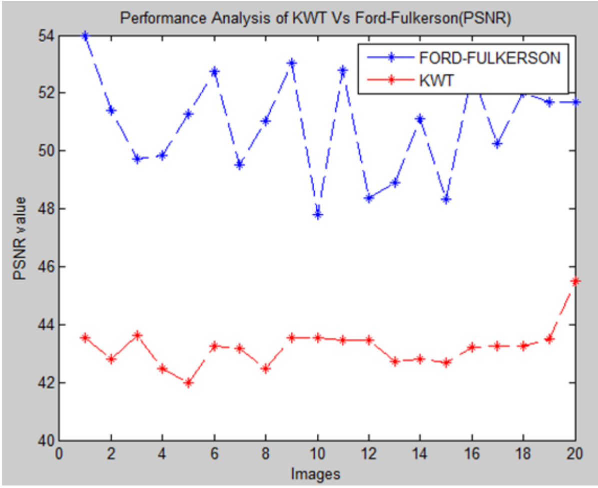

Figure 4: PSNR (KWT vs Ford Fulkerson)

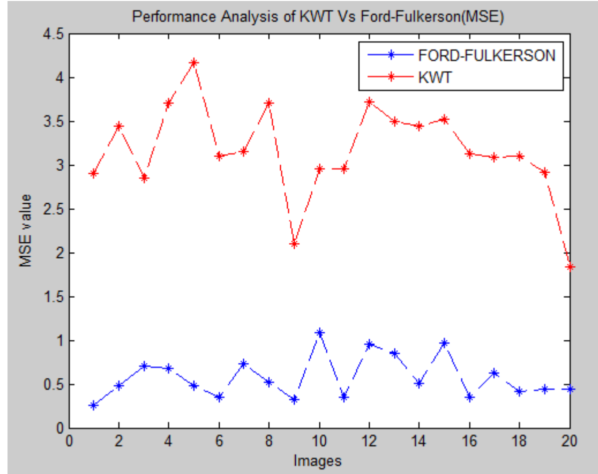

Figure 5. MSE (KWT vs Ford Fulkerson)

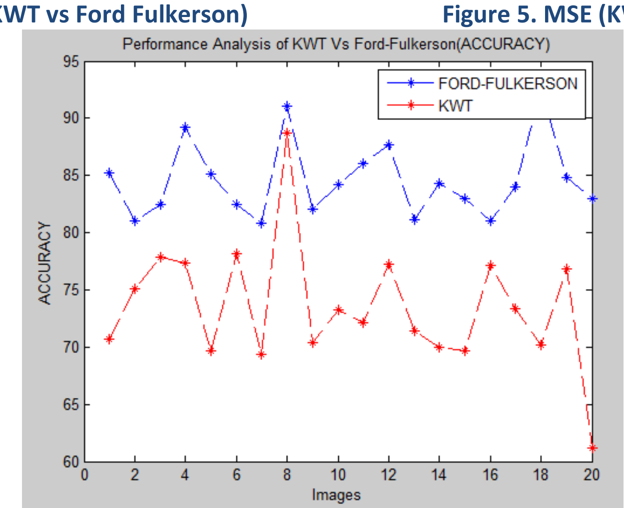

Figure 6: Classification and Prediction Accuracy (KWT vs Ford Fulkerson)

As shown in the Figure. 2 and Figure . 3, the proposed model Ford-Fulkerson was implemented and its performance in terms of PSNR, MSE and Prediction Accuracy for various Tumour Images was identified. From the results, it was noticed that our proposed model is performing well in terms of PSNR, MSE and Prediction Accuracy when compared with existing KWT Segmentation Technique, which are shown in the Figures 4, 5 and 6.

6 Conclusions

This research work has proposed Ford-Fulkerson Segmentation Technique and implemented with MATLABTool. The efficiency of the proposed technique is compared with that of existing KWT (K-Means, Watershed and Texture) Segmentation Technique and established that the proposed model is performing well in terms of Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Classification Accuracy.

REFERENCES

[1] Yong Ning, Xiangjun Zhu, Shanan Zhu, and Yingchun Zhang. 2015. Surface EMG Decomposition Based on K-means Clustering and Convolution Kernel Compensation.

[2] Raffaele Gaetano, Giuseppe Masi, Giovanni Poggi.2015. Marker-Controlled Watershed-Based SegmentationofMultiresolution Remote Sensing Images.

[3] KarteekaPavan, k and SrinivasaRao, ch.2015.A Sequential K-Means Clustering for Mammogram Segmentation.

[4] DibyaJyotiBora, and Anil Kumar Gupta. 2014.A Novel Approach Towards Clustering Based Image Segmentation.

[5] Gullanar, M. Hadi and Nassir H. Salman. 2015. A Study and Analysis of different Edge Detection Techniques.