Brain Tumour Segmentation Based on SFCM using Back Propagation Neural Network

Swetha P, Mohanram S

***Abstract:** Magnetic Resonance image (MRI) is predominant in clinical application. MRI used in diagnostic and therapeutic applications and it is pain free treatment. Blur boundaries in high resolution medical resonance image, the tumour segmentation and classification is very hard. In identification method brain tumour is used to upgrade the accuracy and reduce the analysis time. The tumour tissues classified into four they are normal, begin, premalignant and malignant. In MR images, the amount of data is high to explain and analysis. In current years, segmentation of tumour in magnetic resonance image has essential in research field of clinical imaging. Exact shape, size and location of tumour can diagnose. The diagnostic method contain four stages, pre-processing, feature extraction, classification and segmentation.*

***Keywords:** Digital image processing, Magnetic resonance image, Spatial fuzzy c-means clustering, Back propagation neural network, Raspberry pi.*

I. INTRODUCTION

1.1 Digital Image Processing

The recognition of entity in an image applied in image processing techniques. Noise can be removed, feature extraction is to locate lines & regions in possibly areas with certain textures. The clever bit is to explain the group of these shapes into single objects. First problem is AI, In that an object can appear very contrast, when we observed from dissimilar angles or under dissimilar lights. Another Problem is to decide the features belong to which object, background or shadow etc. The image is in two-dimensional array format. An image can be processed optically or digitally with a computer**.**

By digital processing the image to a string of numbers that can be employed by the computer is been reduced. By combining more pixel which makes image, by increase the pixel value the clarity of an image improved. Normally a image have 262,144 or roughly 250,000 pixels. Pixel values in the output image depend on the input value of single pixel.

II. PROPOSED SYSTEM

2.1 Description

- This Project Proposes to spot the tumour from MRI scanned medical images using multi clustering model and morphological process.
- In segmentation process MRI image is divided into multiple layer.
- Medical resonance image is get hold of its noise are removed using medium filter and then Spatial Fuzzy C means Clustering algorithm is applied for segmentation of MRI images.
- The morphological process is used to smooth the tumour region from the noisy background.
- The segmentation primary and secondary regions are compressed with hybrid techniques for telemedicine application.

2.2 Block Diagram

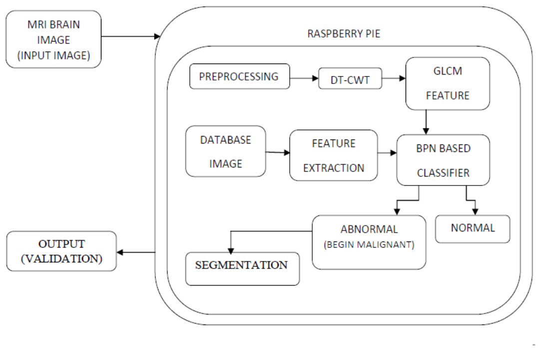


Fig 2.3: Block diagram

2.3 Preprocessing

Image restoration is an operation of taking noise in an image, Estimate the clean real image. In many format corruption comes such as noise, motion blur and camera misfocus. Image restoration can be in different form in image enhancement. Design is to emphasize the characteristic of the image that makes the image more clear to observer point of view. Image enhancement technique provide image packages not used in previous model in the process, but creates the image (like contrast extend or focus by a nearest neighbour procedure). With Image improvement noise are often effectually take out by sacrificing some resolution, however this can be not acceptable in several application. Resolution is bad in fluorescence microscope. So that the image processing technique is applied to revive the object in advanced format. It is capable of increased resolution, especially in axial direction which removes the increased noise contrast.

2.4 Dual-Tree Complex Wavelet Transform (Dt-Cwt)

DT-CWT is the advanced version of discrete wavelet transform hold additional properties. It is invariant and directional selective in additional dimensions can be achieved by dismissal factor of 2 dimensional signals, which is underneath than the undecimated discrete wavelet transform. The multidimensional dual-tree CWT is not independent but it is established on a computational efficient and filter bank (FB). The dual-tree complex wavelet transform shows a complex wavelet

Revised Manuscript Received on August 05, 2019.

Swetha P[1], PG Scholar, Department of Electrical and Electronics Engineering Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai

Mohanram S, Assistant Professor, Department of Electrical and Electronics Engineering Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai

with good properties, and shows a range of signal in image processing.

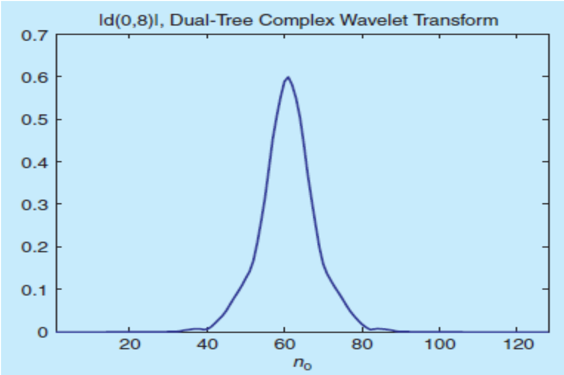


Fig 2.4(a): Dual- Tree complex Wavelet Transform.

The real DWT create both small and large wavelet coefficient. In contrast, Coefficient is produced by analytic CWT, magnitude is directly proportional to their edge. Here, the trial signal is a step edge at *n = no x(n) = u(n - no).* The figure 2.4(a) shows the *d(0, 8)* at stage 3 in Real-Valued Discrete Wavelet Transform and in Filter Banks, as a function of number. In the x-axis, the real coeffient *d(0, 8)* is computed using the conventional real DWT. In the y-axis, the complex coefficient uses the dual-tree CWT.

Note: To find extract shape we use wavelet transform. By using this we get three information Horizontal information, Vertical information, Diagonal information.By using these information we can extract features.

2.5 Gray Scale Co-Occurrence Matrix

The texture character explores the gray level spatial vulnerability of texture. Co-occurrence matrix of mathematical definition is as follows:

- Position operator P(i, j),
- A = n x n matrix
- A[i,j] is the number that points out gray level (intensity) g[i], in the position framed by *P*, correlative to points with gray level g[j].
- Let c = n x n matrix that is processed by spliting A with the total number of point pairs that desire P. C[i,j] is a measure of joint probability that a pair of points which desire the P which have the values of g[i,j].
- Co-occurrence matrix defined by P.
- Examples for the operator P are: "i above j", or "i one position to the right and two below j", etc.

Let *t* be the vector, co-occurrence matrix C_t is defines the gray-level *(a, b)* :

$$C_t(a,b) = card\{(s, s+t) \in R^2 | A[s] = a, A[s+t] = b\}$$

Here, $C_t(a, b)$ is the number of site-pair, denoted the *(s, s + t)* that are discreted by a vector *t*, with a gray-level of *s*, and *b* being the gray-level of *s + t.*

Haralick proposed the following texture features:

1. Energy
2. Contrast
3. Correlation
4. Homogeneity

Hence, Haralick feature, we obtain a co-occurrence matrix. These co-occurrence matrix constitude the spatial distribution and depends on the gray level in a local area. Each **(i,j)** represent the probability of one pixel under a established distance and angle. Set of analysed data are figured, and called as feature vectors.

Energy: Energy and entropy is same both are related to randomness of an image. Energy is a gray-scale texture which measure the homogeneity changes. P(x,y) is GLCM

$$E = \sum_x \sum_y p(x,y)^2$$

Contrast: Contrast finds the dissimilarity between the maximum and minimum pixel intensity in the image and maintain colour, clarity and texture.

$$\boldsymbol{I = \sum \sum (x-y)^2 p(x,y)}$$

Correlation Coefficient: Measure the joint probability and identified pixel pairs.

Correlation:$\boldsymbol{sum(sum((x-\mu x)(y-\mu y)p(x,y)/\sigma_x\sigma_y))}$

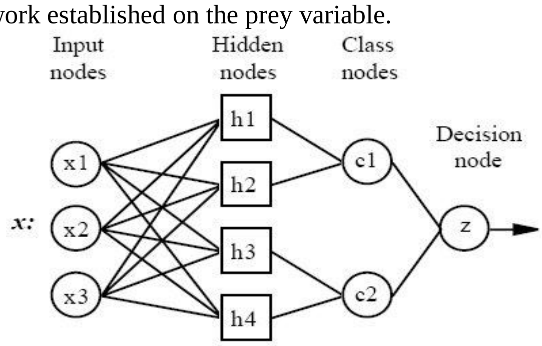
Homogeneity: Homogeneity is the measurement that calculate the closeness sharing of components in the gray scale co-occerrence matrix to diagonal.

$$\textbf{Homogenity} = \boldsymbol{sum\left(sum\left(\frac{p(x,y)}{1+[x-y]}\right)\right)}$$

Note: By using this matrix we extract five features Energy, Entropy, Correlation, Contrast, Homogenity. In DT-CWT we handled images but now we have to handle image features. These values are carried to a Neural Network.

2.6 Back Propagation Neural Network

Back Propagation neural network (BPN) and General Regression Neural Networks (GRNN) have similar architecture, but basic is different. Probabilistic network perform the classification, the prey variable is definite, where as general regression of neural network perform the regression the prey variable is continuous. If BPN network is selected, DTREG spontaneously select the correct network established on the prey variable.



Architecture Of Bpn:

All BPN networks have four layers:

- Input layer
- Hidden layer
- Pattern layer
- Decision layer

Each node in the output and hidden layer is attached to all and previous node. Hidden and output layer has two levels,it is more powerful compared to other network which has single learning level so it can handle more intricate nonlinear problem

Note: Basic work of neural network is to find normal or abnormal. Neural network stores extracted feature in a array or matrix format . This work is done in both data set image and input image. Then it compare both features and classify whether it is normal or abnormal.

2.7 Spatial Fuzzy Clustering Model

Spatial Fuzzy Clustering model method incorporate spatial information, the weight of each clusters are adjusted after the cluster division in the neighbour is consider. FCM calculates the function in the domain in first pass. In second pass, the detail of each one pixel is depict to the domain. Maximum similarity between cluster and functions at two sequential iterations which is lesser than the least threshold value will be stopped.

The idea of FCM is using the weight that minimize the total weighted mean-square error:

$$J(w_{qk}, \mathbf{z}^{(k)}) = \Sigma_{(k=1,K)} \Sigma_{(k=1,K)} (w_{qk}) \| \mathbf{x}^{(q)} - \mathbf{z}^{(k)} \|^2$$

$$\Sigma_{(k=1,K)} (w_{qk}) = 1$$

$$w_{qk} = (1/(D_{qk})^2)^{1/(p-1)} / \ \Sigma_{(k=1,K)} (1/(D_{qk})^2)^{1/(p-1)}, \ p > 1$$

The FCM allow each feature vector for every single cluster with a napped truth value (between 0 and 1). According to the max weight of the feature vector all-inclusive clusters transfer to feature vector.

Eliminating EMPTY CLUSTERS:

The fuzzy remove the vacant clusters. Outside the fuzzy clustering bend calculation of XB validity is modified. Without removing, the mini distance of prototype pair used in the equation may be the distance of vacant cluster pair. We call the method of removing small clusters by passing 0, so that it will remove the vacant clusters.

After the fuzzy c-means clustering iteration, for the purpose of resemblance and to pick the optimal result, calculate the cluster centres and then modify the clustering validity κ:

$$\nu = \{(1/K)\Sigma_{(k=1,K)}\sigma_k^2\}/D_{min}^2$$

$$\sigma_k^2 = \Sigma_{(q=1,Q)} \ w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2$$

D_{min} is the minimum distance between the cluster centres.

The Modified Xie-Beni validity κ is defined as

$$\kappa = D_{min}^2 / \{\Sigma_{(k=1,K)}\sigma_k^2\}$$

The variance of each cluster is calculated by adding over only the members of each group over all Q for each group, which difference with the original Xie-Beni validity measure.

$$\sigma_k^2 = \Sigma_{\{q:\ q \text{ is in cluster } k\}} \ w_{qk} \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2$$

The spatial function is included into membership function as given in Equation,

$$u_{ij} = \frac{u_{ij}^p \square_{ij}^q}{\sum_{k=1}^c u_{kj}^p \square_{kj}^q}$$

Note: Clustering is nothing but grouping. Separate the affected pixel into one group and not affected pixel in other group which is called as spacial fuzzy c-means clustering. Then segmentation will be done affected area will be in white colour and non affect area will be in black colour. And show the extract location of the tumour.

III. SIMULATION OUTPUT

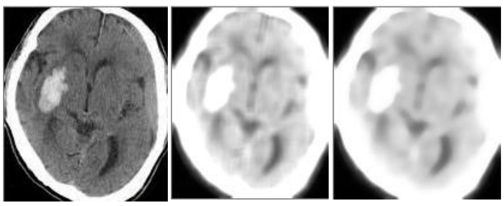


Fig 7.1(a): Input image , Gaussian image and Gray image

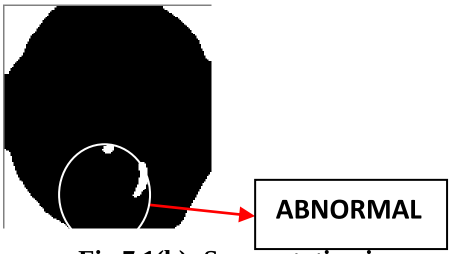


Fig 7.1(b): Segmentation image

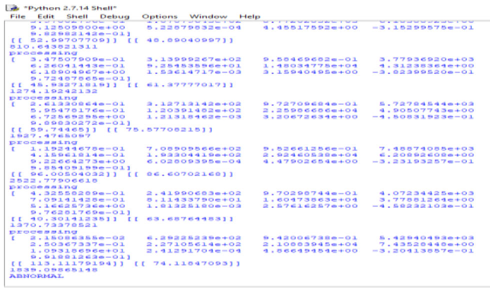


Fig 7.1(c): Abnormal Result

CONCLUTION

The defects in the MRI (Magnetic resonance image) images is identified with the help of image processing, in that the machine learning concept called Back propagation neural network is used to identify and classification of the tumour in the image. In test image the features are extracted to classify the image.

The same features will be extracted in the data set image, by these set of features we can classify the input image is normal or abnormal. Based on the training the back propagation neural network, the detection is achieved. And by the segmentation method exact location of tumour is detected.

REFERENCE

1. S.P.Awate and Whitaker, R. T., "Multiatlas segmentation as nonparametric regression," IEEE transactions on medical imaging, vol.33, pp. 1803-1817, 2014.
2. Brain Tumour segmentation using K-Means and fuzzy C-means clustering algorithm International journal of computer science and information technology research excellence,vol.3 No.2
3. Haibo Wang, Angel CruzRoa, Ajay Basavanhally, Hannah Gilmore, “Cascaded ensemble of convolutional neural network (Vol. 9041). [90410B], Feb 16 2014
4. M. G. Hart, Price, S. J., and Suckling, J., “Analysis for pre-operative brain mapping in neurosurgery,"British journal of neurosurgery, vol. 30, pp. 506-517, 2016.
5. Bjoern H. Menze, Koen Van Leemput, Danial Lashkari., “Segmenting glioma in multi-model image using a generative model for brain lesion segmentation”.,14th International Conference, in Toronto, Canada (pp.18-22)., sep.2011
6. R. C. Gonzalez and Woods, R. E., "Digital image processing prentice hall," UpperSaddleRiver,NJ,2002.
7. Z. Tang and Fan, Y., "Groupwise image registration guided by a dynamic digraph of images," Neuroinformatics, vol. 14, pp. 131-145, 2016.
8. S.Bauer et al., “A survey of MRI-based medical image analysis for brain tumor studies,” Physics in medicine and biology, no. 13, pp. 97–129, 2013.
9. Karen Simonyan & Andrew Zisserman., “Very deep convolutional networks for large-scale image recognition” Cornel university, 10 Apr2015