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BRAIN TUMOR DETECTION USING MEAN SHIFT CLUSTERING AND GLCM FEATURES WITH EDGE ADAPTIVE TOTAL VARIATION DENOISING TECHNIQUE

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ABSTRACT

The paper presents an automatic brain tumor detection technique in noise corrupted images. The Denoising of the image is implemented using Edge Adaptive Total Variation Denoising Technique (EATVD). The technique is used to preserve the edges in the process of Denoising image. Once the noise is removed from the image, the image is segmented using mean shift clustering. The segmented parts are sent to gray level co-occurrence matrix for feature extraction. The features are used by multi class SVM to detect the tumor in the images. The step followed extracts the tumor with increased precision in noisy images.

Keywords: tumor, denoising, multi class SVM, GLCM, EATVD, noisy images.

1. INTRODUCTION

Magnetic resonance imaging (MRI) can be modelled in the following way. First consider a conducting loop of wire. The magnetic dipole moment of the wire is defined as the product of current going in through the wire, the cross section area of the wire and the unit vector that is perpendicular to the surface area.A proton spins on its axis at the subatomic level, and because of its spinning it contains a charge of 1.602 x 10^{-19} coulomb. This creates a group of current loops stacked on the top of one another and these current loops all add up giving a magnetic dipole moment. Whenever the dipole moment is subjected to an external magnetic field, this magnetic dipole moment will have a tendency to line up with the unit vector along the magnetic field but it won't line up all the way. The angular momentum of the spinning proton will prevent from lining up completely but then it will have precision axis (consider a top rotating on its axis as well as pressing about a precision axis) the precision axis is in the direction of external magnetic field. Now let's take some radiation and emit that radiation laterally towards the precision axis. If the angular frequency of the radiation is equal to the angular frequency of the proton then they are said to be in resonance.

Here, the frequency of the incident radiation is matching with that of the proton, then whenever the proton comes in sync with the lateral position of the incident radiation (because of the pressing about the precision axis), it experiences a force or torque in that direction, as shown in the figure. Then as it rotates same phenomena occurs in the exact opposite (180 shift) position, the proton experiences a torque in the direction of the radiation. Constantly, because of this the precision in flattening out and when the radiation is turned off if flips back to where it was initially that is pressing an axis that is parallel to external magnetic field. This is the fundamental mover in the magnetic resonance imaging machine and the entire description known as magnetic resonance.

The body has la lot of water in it, thus having a lot of hydrogen. Initially all these hydrogen atoms have dipole moments that are oriented in all the different directions and are totally random. When we apply an external magnetic field all the protons line up in a particular direction. As they are rotating and also pressing on an axis that is parallel to the magnetic field. When the emitted radiation that is lateral to that precision axis, the radiation comes in and flattens them out as discussed previously and when the radiation is turned down all the hydrogen atoms flip back and return the previous state. And in doing so radiation is emitted. And that radiation can be detected and accounted for to form and image.

In 1973 there was a break through by a man by the name of P.c. Loterberg. When a person is placed in a tube and takes a very strong magnetic field around 5 tesla and there is a magnetic field along the axis of the tube the all the protons in the body will line up. Then produce a secondary magnetic field that will produce a filed gradient so that the magnetic field is increasing along the axis of the tube. This results in different lomor frequencies along the tube. In such a case when we emit radiation in the cavity then only those protons that are processing at that frequency will emit radiation. Only parts of body that have water in it will emit radiation and we get a white picture and Bones will not.

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Segmentation plays an important role in analysis of medical images for computer-aided diagnosis and therapy. Segmentation is the challenging and complex task in medical imaging due to imprecise nature of images.

For neurological pathology clinical study and research fully automatic brain tissue classification from magnetic resonance images (MRI) is very important. The important task is to segment the MR images in to different classes especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) accurately. The useful diagnostic information can be known from regional volume calculation. In neurodegenerative disorders such as Alzheimer disease, in movement disorders such as Parkinson or Parkinson related syndrome, in white matter metabolic or inflammatory disease, in congenital brain malformations or perinatal brain damage, or in post traumatic syndrome, quantization of gray and white matter volumes are considered for calculations.

K. Umamaheswari and P. Rajesh implemented a technique where the noise is first extracted form the tumour image using wiener filter [1]. Then the tumour detected is extracted with increased precision. K. B. Vaishnavee and K. Amshakala [2] used SOM clustering for segmentation of the image and proximal SVM is used for the classification of the segmented tumour parts. Cellular automaton based on Gray-level co-occurrence matrix (GLCM) was implemented by Chaiyanan Sompong and Sartra Wongthanavasu for determining the local transition function [3]. Ahmed Faisal and Sharmin Parveen denoised the images using partial derivative equations and segmented the image using seed based region growing technique [4].

Section II introduces wiener filter and the effected of the filter in denoissing the tumour images. Section III depicts the implementation of edge adaptive total variation denoising. Mean shift clustering is presented in section IV and GLCM in section V.

2. WIENER FILTER

Noise removal is an image preprocesing technique intended to enhance the features of the image corrupted by noise. A specific case here is adaptive filtering where the denoising is actually done based on the noise content present in an image locally. Let us assume the the corrupted image is determined by $\hat{I}(x,y)$, the noise variance across the entire image is depicted by σ_y^2, the local mean is given by $\widehat{\mu_L}$ around a pixel window and the local variance in a window is given by $\hat{\sigma}_y^2$. Then, a possible way of denoising an image is shown as below:

$$\hat{\hat{I}} = \hat{I}(x,y) - \frac{\sigma_y^2}{\hat{\sigma}_y^2}\,(\hat{I}(x,y) - \widehat{\mu_L})$$

Now if the noise variance accross the image is equal to zero,

$$\sigma_y^2 = 0 \;=>\hat{\hat{I}} = \hat{I}(x,y)$$

If the global noise variance is small, and the local variance is larger than the global variance then the ration is almost is equal to one, i.e.
If

$$\hat{\sigma}_y^2 >> \sigma_y^2, \text{ then } \hat{\hat{I}} = \hat{I}(x,y)$$

As a high local variance depicts the presence of an edge in the image window considered.

A case when the local and global variances are equal then, the equation becomes

$$\hat{\hat{I}} = \widehat{\mu_L} \text{ as } \hat{\sigma}_y^2 \approx \sigma_y^2$$

This is the average intensities in a normal region. The above to anologies simply mean that the output is simply the mean value of the window around a pixel if no abnormalities are present or if there is an edge the edge is passed to the output. This is the inherent functionality of a wiener filter. The filter takes the window size as input and calculates the rest based in the input image.

The following results present the study of noise removal in brain tumour images using wiener filter.

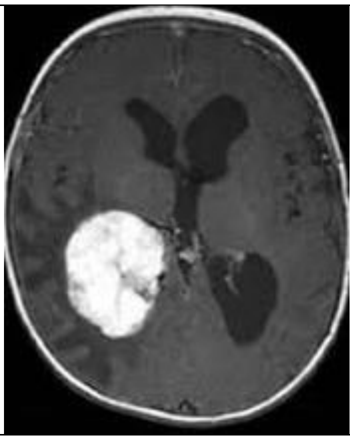

Figure-1. Input MRI image with tumour.

Figure-2. Image with 4% speckle noise.

The aim is to study the effect of wiener noise removal on the edges

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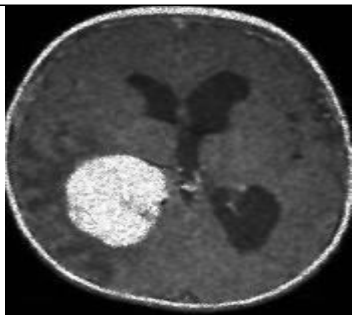
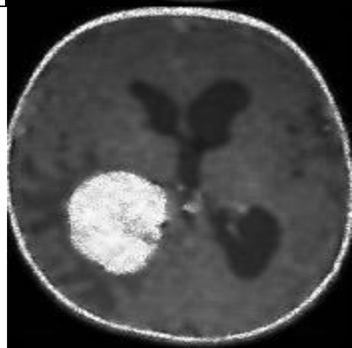
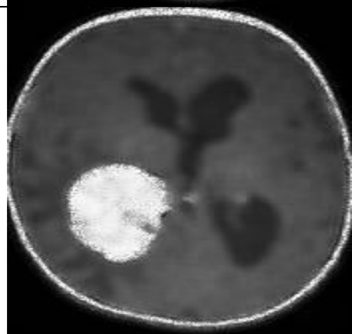
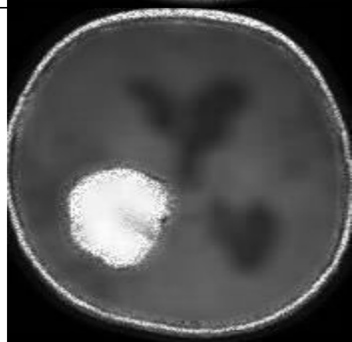
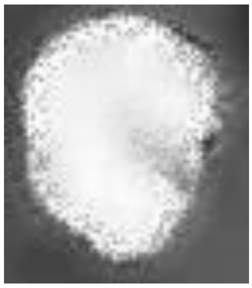
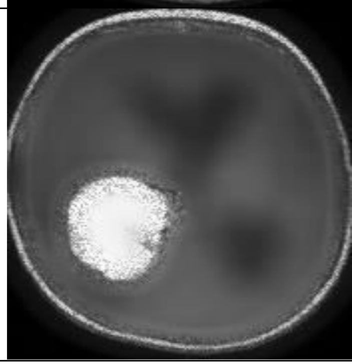
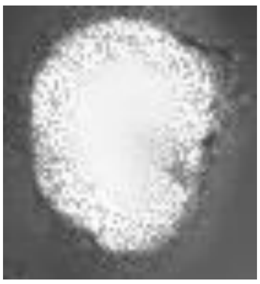
Wiener window size	PSNR	RMSE	SSIM	Output image	Zoomed tumour part
3x3	74.4135	0.0485	0.9999		
5x5	74.4635	0.0482	0.9999		
7x7	74.0471	0.0506	0.9999		
13x13	72.5506	0.0601	.9998		
23x23	70.1010	0.0797	.9996		

Figure-3. Results of denoising by wiener filter.

With the help of above results, the point to be illustrated is the fact that even though the PSNR of the resultant image is high, the noise content present in the image not properly removed. This is clearly depicted in the last column of the table above. Increasing the size of the filter further increases the blurriness in the image, rather than removing the noise. Such noisy tumour part cannot be segmented exactly. This problem can be solved by the use of total variation denoising.

3. EDGE ADAPTIVE TOTAL VARIATION DENOISING

During the process of de-noising a signal, or in other terms smoothing down the undesired fluctuations present in a signal, the algorithms conventionally used also smoothen the actual variations present in the signal. This causes the blurring of the signal as the edges are suppressed in the image. The total variation Denoising is an edge preserving Denoising technique that retains the sharp edges to a large extent. We use a variant of total variation Denoising technique which focuses even more on preserving the edges while Denoising, which EADTV is proposed by Hua Zhang and Yuanquan Wang [5].

Algorithm

Initialization

Initialize weight of the TV term in the cost function.

Initialize length of the major axis of the ellipse (minor axis is unit-length).

Initialize number of iterations.

Processing

Get the edge directions over the entire image using the equation:

$$(\cos(\theta(x,y)), sin(\theta(x,y))) = (n_1((x,y)), n_2((x,y)))$$

Where the edge direction is estimated after applying a gaussian smoothing filter on the noisy image.

$$\left(n_1((x,y)), n_2((x,y))\right) = \frac{-g_y, g_x}{\sqrt{g_x^2 + g_y^2}}$$

(g_x, g_y) are the gradient vectors.

4. MEAN SHIFT CLUSTERING

The clustering algorithm used is meanshift clustering. The traditional clustering techniques need the cluster count as input, like k means and fuzzy c means which vary from image to image. The algorithm is listed below.

Algorithm

Initialization

biggest size in each dimension
smallest size in each dimension
bounding box size
indicator of size of data space
when mean has converged
center of clust
track if a points been seen already
number of points to possibly use as initialization points
used to resolve conflicts on cluster membership

Process

a. pick a random seed point
b. use this point as start of mean
c. intilize mean to this points location
d. points that will get added to this cluster
e. used to resolve conflicts on cluster membership
f. loop until convergence
g. dist squared from mean to all points still active
h. points within BandWidth
i. add a vote for all the in points belonging to this cluster
j. save the old mean
k. compute the new mean
l. add any point within bandWidth to the cluster
m. mark that these points have been visited
n. if mean doesn't move much stop this cluster
o. check for merge possibilities
p. distance from possible new clust max to old clust max
q. if its within bandwidth/2 merge new and old
r. record the max as the mean of the two merged (I know biased towards new ones)
s. record which points inside
t. add these votes to the merged cluster
u. increment clusters
v. record the mean
w. store my members

V GLCM FEATURE EXTRACTION

GLCM_Features1 helps to calculate the features from the different GLCMs that are input to the function. The GLCMs are stored in a i x j x n matrix, where n is the number of GLCMs calculated usually due to the different orientation and displacements used in the algorithm [6 - 7].

1. Contrast = sum_i(sum_j((i-j)^2 * p(i,j)))
2. Correlation = sum_i(sum_j((i - u_i)(j - u_j)p(i,j)/(s_i.s_j)))
3. Correlation = sum_i(sum_j(((ij)p(i,j) - u_x.u_y) / (s_x.s_y)))
4. Energy = sum_i(sum_j(p(i,j)^2))
5. Homogeneity = sum_i(sum_j(p(i,j) / (1 + |i-j|)))
6. Homogeneity = sum_i(sum_j(p(i,j) / (1 + (i-j)^2)))

Where:
u_i = u_x = sum_i(sum_j(i.p(i,j)))
u_j = u_y = sum_i(sum_j(j.p(i,j)))
s_i = s_x = sum_i(sum_j((i - u_x)^2.p(i,j)))
s_j = s_y = sum_i(sum_j((j - u_y)^2.p(i,j)))

Multi class SVM [8] is used to classify the segmented regions and identify the tumour part.

The following figure represents the result of the proposed denoising algorithm edge adaptive total variation denoising. The first column represents the PSNR of the obtained output with respect to the original image. Root mean square error is depicted in the second column. The structural similarity index is displayed in the third. This is followed by the output image of the proposed technique and then the tumour part is zoomed out to display the performance of the algorithm in noise removal.

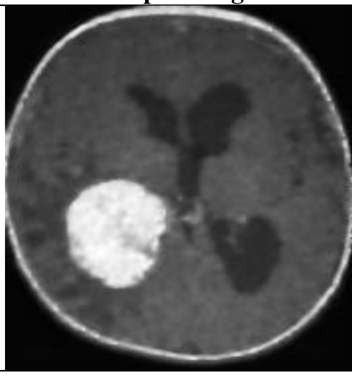
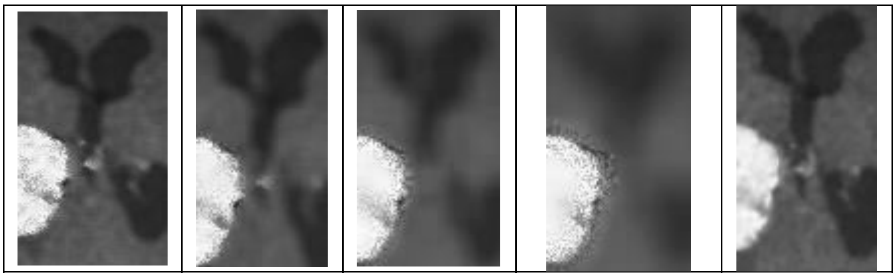
PSNR	RMSE	SSIM	Output image	Zoomed tumour part
74.04	0.0506	.9999		

Figure-4. Result of image noising using edge adaptive total variance denoise technique.



5x5 weiner	7x7	13x13	23x23	EATVD

Figure-5. The effect of denoising on edges.

Figure-5 shows the outputs of wiener filter of varying sizes and the EATVD technique. The effect of blurring of the edges is clearly visible in case of wiener filter when the filter size increases. EATVD retains the edges present.

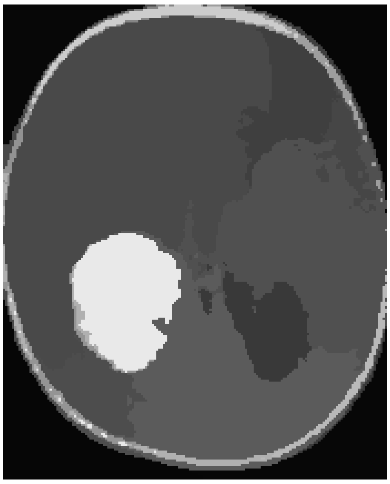


Figure-6. Result of meanshift clustering.

The result of the denoised image is sent to the mean shift clustering. The technique segments the image into parts effectively. The cluster centres are updated according to the pixel value and unlike the traditional clustering techniques like k means or fuzzy c means, the cluster count is generated dynamically based on the image.

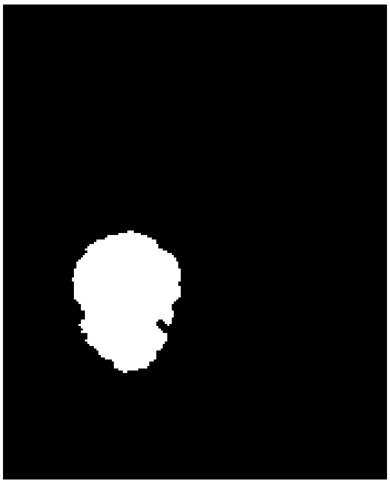


Figure-7. Identified tumour.

Finally the GLCM features are sent to multi class SVM which recognizes the tumour part from rest of the segments.

CONCLUSIONS

The edge adaptive total variation denoising technique is used to preserve the edges in the process of denoising the image. The PSNR values obtained are high in comparison to the traditional techniques. The noised image is segmented using mean shift clustering which is a complete automatic image segmentation technique. The features Contrast, Correlation, Energy, Homogeneity, Homogeneity describes the texture of the segments. The features are used by multi class SVM to detect the tumor in the images efficiently.

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