

Image Restoration & Registration for Brain Tumor Detection

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Abstract— Magnetic Resonance Imaging (MRI) is very important tool used in neuroanatomy. Brain tumor Detection is performed along with image registration, restoration. Removal of noises and obtaining good accuracy in image is main concern of Image Restoration. Filters are used for noise removal. Registration is done using nonlinear spatial transformations. Particularly, problems related to matching magnetic resonance imaging (MRI) brain image data obtained from various subjects and with various imaging conditions are solved in registration. Research is extended towards tumor detection. Analysis of tumor is performed to find parameters like area, perimeter and eccentricity of a tumor. This integrated approach of all three operations gives excellent results with highest accuracy.

Index Terms— Magnetic Resonance Imaging, Registration, Restoration, Brain Tumor detection, spatial transformation.

I. INTRODUCTION

Medical science has done great development in biomedical imaging field in the last two decades. Field of artificial intelligence and computer vision technologies have developed to a great extent and now this advanced technology have been effectively put into practice for medical applications such as diagnosis of various diseases like cancer, biomedical imaging for 3D tissue harmonics and 3D vessel lumen segmentation techniques. Computational neuro-anatomy is a new growing field of applications in neuroscience. It promises an automated methodology to characterize neuroanatomical configuration of structural magnetic resonance imaging (MRI) brain scans [1].

A tumor can be defined as a mass of tissues which grows. High death rate because of brain tumor have greatly increased the importance of Brain Tumor Detection. Real time diagnosis of tumors is done using k-means algorithm after doing registration and restoration techniques [7].

Restoration is based on method of de-blurring MRI images in the spatial domain. Removal of noises and obtaining good accuracy in image is main concern of Image Restoration[2]. For the same purpose filters like median filter, Gabor filter are used[8]. In addition with this un sharp masking and Contrast Limited Adaptive Histogram Equalization can also performed[3]. Output is finalized by comparing PSNR & MSE of used filters[2],[4].

Image registration is an important technique used in this methodology. It is used to find spatial transformation, in which each point of an image is mapped onto its corresponding point of another image. Results are compared in standard anatomical coordinate system [6].

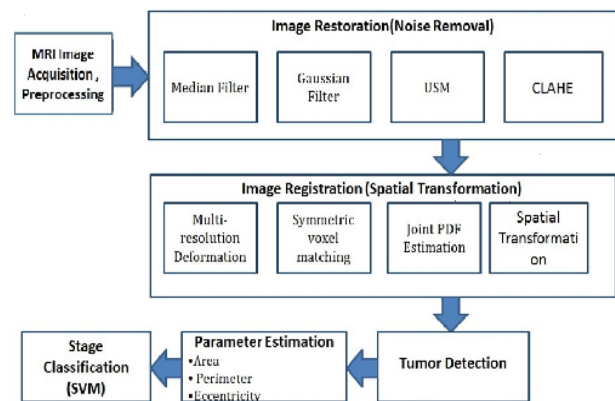


Fig1. Block Diagram of Proposed Approach

Tumor is detected using K-means algorithm. The existing method is based on the thresholding and region growing. But thresholding method ignores spatial characteristics hence k-means algorithm is much better than conventional methods. Analysis of tumor is performed to find parameters like area, perimeter and eccentricity of a tumor[7].

I. IMAGE RESTORATION

Removal of noises and obtaining good accuracy in image is main concern of Image Restoration. For the same purpose we are using filters like median filter, Gabor filter. With this we are also doing un sharp masking and Contrast Limited Adaptive Histogram Equalization.

A. Median Filter

It is nonlinear spatial filter use for removing outlier noise and preserves edges in an image. It is also called as rank order filter or order statistics filter. It replaces value of pixel by median of all gray levels in the neighborhood of that pixel. Generally, to calculate the median of a set of gray values, arrange the values in the set in ascending order. Then the middle most value in the string is the median. This is in case of odd number of values. Use of odd number filter avoids additional averaging of middle two pixel of order set as required for even number of elements.

Hence to calculate median of image arrange pixels in the ascending order i.e. $X(0) < X(1) < X(2) \dots < X(N-1)$
Where, $X(0)$ is the minimum value of gray level.

$X(N-1)$ is the maximum value of gray level.

Then median value is obtained using,

$$F_{med} = [X(N/2) + X(N/2 - 1)] / 2 \quad \text{--if N is even} \quad (1)$$

$$= X[(N-1)/2] \quad \text{----- if N is odd} \quad (2)$$

And then selecting middle pixel value which is assigned to the center pixel.

Hence, Median filter removes speckle noise and impulse noise which appears as black and white dots i.e. salt and pepper noise.

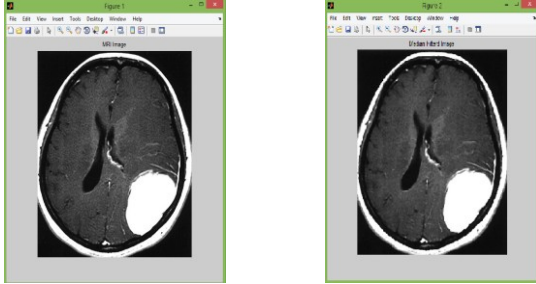


Fig2. Image restoration using Median Filter
(a)Original Image (b) Median Filtered image
Mean Square Error (MSE) = 10.17,
Peak Signal to Noise ratio = 38.01

B. Un-sharp Masking (USM):

Un-sharp masking (USM) is method which is used to obtain a sharp image. Firstly, image is blurred by passing it through the LPF and then this filtered image is subtracted from the original image. It produces the unsharped mask. un-sharped mask is combined with the negative image, which gives less blurry image. The resulting image can be less accurate. An un-sharp mask is generally a linear or nonlinear filter that amplifies the high-frequency components of a signal.

The un-sharp filter is used for image enhancement which enhances high frequency components in an image. It is a simple sharpening operator. It creates a sharp image by subtracting blurred version of image from original image. Un-sharp masking gives us high boost filtered output. Following steps are performed in Un-sharp Masking approach to sharpen image:

1. Pass the original image through Low Pass filter to blur the image.
2. Subtract the Low Pass filtered image from the original. It will produce the mask.

$$F(x,y) = I(x,y) - I'(x,y) \quad \text{-----} \quad (3)$$

Where, $I(x,y)$ is the original image

$I'(x,y)$ is the blurred image

$F(x,y)$ is the mask

3. Add the mask to the original:

$$G(x,y) = I(x,y) + k * F(x,y) \quad \text{-----} \quad (4)$$

Here k is a weight.

When $k = 1$ it is unsharp masking;

$k > 1$ it is highboost filtering;

when $k < 1$ it de-emphasize the contribution of a mask.

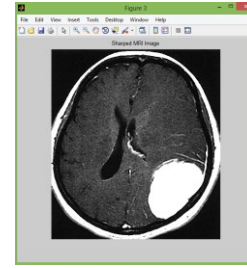


Fig3. Image restoration using Unsharp Masking

C. Contrast Limited Adaptive Histogram Equalization:

CLAHE is used in medical imaging for enhancing the low-contrast image for example portal films. Contrast Limited Adaptive Histogram Equalization is an advanced version of Adaptive Histogram Equalization. Hence it is used in medical imaging. Image is divided into small tiles, CLAHE operates on each tile separately. Contrast of each tile is enhanced. Bilinear interpolation is used to eliminate artificially created boundaries. The contrast is limited to avoid noise amplification that might be present in the image.

Disadvantage of simple histogram method is intensity saturation, in which information loss occurs. More accurate results are obtained by extending CLAHE method. Which leads to fast and accurate post-diagnostic procedures in ailments.

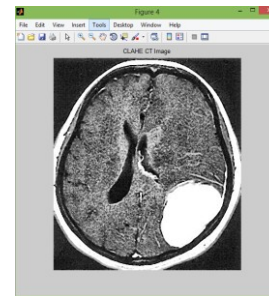


Fig4. Image restoration using CLAHE

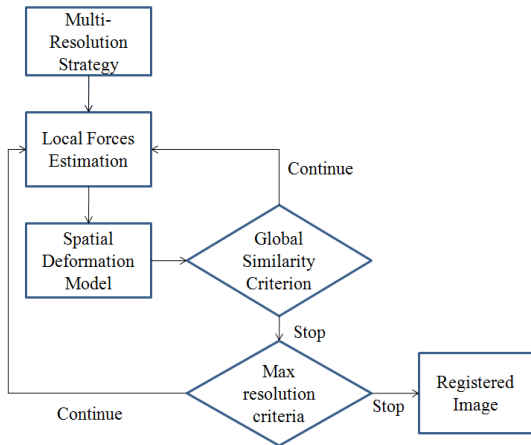
II. IMAGE REGISTRATION

Image registration method includes various types of geometric transformations ranging from simple translations with rotations to high-dimensional nonlinear nonparametric transformations are used neuro anatomy. This paper deals with registration process which is done with the use of nonlinear local adaptive transformation. In this technique same or functionally dependent intensities of an image are considered.

This algorithm uses Tissue Probability Maps (TPM) for the calculation of point similarity measures which improves registration accuracy. Here a criteria of convergence is used. Extraction of local forces by calculation of similarity and spatial deformation model producing the displacement field are the two main steps repeated in iterative process in which floating image is deformed to match with a

reference image. These two parts are totally independent. Convergence algorithm is made faster using multi resolution strategy propagating from coarser to final levels. Technique used in registration are: Symmetric Voxel Matching, Multi Resolution Deformation and Joint PDF Estimation.

A. Flowchart



B. Symmetric Voxel Matching

Symmetric Voxel Matching is done to find point similarity. Mutual information is calculated in terms of entropy as shown below,

$$I(M,N) = H(M) + H(N) - H(M,N)$$

$$= \sum_{m,n} P_{MN}(m,n)$$

Here, $I(M,N)$ = Mutual information of random variables of images M & N

$H(M)$ = Entropy of M

$H(N)$ = Entropy of N

$H(M,N)$ = Joint Entropy of M & N

$P_M(m)$ & $P_N(n)$ are marginal PDF

$P_{MN}(m,n)$ = Joint PDF of random variables M & N resp.

$I(M,N)$ can be rewritten as below which is average of K point similarities S_{MI} is defined for each voxel x.

$$I(M,N) = \sum_{m,n} \frac{K_{m,n}}{K} \log_2 \frac{P_{MN}(m,n)}{P_M(m)P_N(n)}$$

$$= \frac{1}{K} \sum_x \log_2 \frac{P_{MN}(m,n)}{P_M(m)P_N(n)} I(M,N)$$

$$= \frac{1}{K} \sum_x S_{MI}(x)$$

The point similarity measure S_{MI} is given by

$$S_{MI} = \log_2 \frac{P_{MN}(m(x),n(x))}{P_M(m(x))P_N(n(x))}$$

In symmetric registration each voxel is considered separately and local forces are calculated as differences

between forward and reverse forces. Forces are determined by the gradient of a point similarity measure. Interpolation from neighboring grid points has to be involved because point similarity measure is evaluated in non grid positions due to displacement field applied on image grid. Interpolation used here is generalized partial volume interpolation (GPV). The forces are normalized to avoid effect of their scaling before performing spatial deformation on force field.

Normalized Mutual Information (NMI) gives global similarity measure. Registration convergence can be observed using NMI. It is calculated as follows,

$$\tilde{I}(M,N) = \frac{H(M) + H(N)}{H(M,N)}$$

Where $I(M,N)$ is Normalized Mutual Information.

Relative change of NMI from previous iteration i-1 to current iteration i shows convergence of registration.

$$C^i = \frac{\tilde{I}^i(M,N) + \tilde{I}^{i-1}(M,N)}{\tilde{I}^{i-1}(M,N)}$$

C. Multi-Resolution Deformation:

The local forces calculated by symmetric voxel matching do not consider spatial relation among neighbor pixels. Here, combined elastic incremental spatial deformation model is used which is based on continuum mechanics. In this, partial differential equation associated with linear elasticity is solved by convolution filtering. Displacement is calculated as a reaction of local forces applied on floating image.

$$u_f = c^i * f \text{-----(1)}$$

$$u^{(i)} = (u^{(i-1)} + u_f^{(i)} * G_I) * G_E \text{-----(2)}$$

Equation (1) uses Hook's Law to calculate irregular displacements and equation (2) defines spatial deformation properties by regularizing the displacement with the help of convolution filters. In this paper Elastic kernel is used for Joint PDF estimation. Results obtained using Gaussian kernel is more reliable than elastic kernel but Gaussian Kernel does not provide control over compressibility, due to dependence of spatial dimensions. So it is disadvantageous to use Gaussian Kernel in particular registration task.

In this algorithm it is assumed that smoothing provided by spatial deformation model suppresses false forces arised due to normalization. Hence the convergence of registration is achieved in number of iterations is depends upon degree of initial misregistration of images, Number of iterations are more if images are highly misaligned but will be very less if images are closely aligned.

Error can be introduced due to two reasons during registration process 1st is because of incorrect estimation of point similarity function and 2nd is because of brain images complexity with gradient based computation of forces which leads to suboptimal registration solutions.

Input to the registration is roughest or coarsest image, registration is carried on different resolution levels to get finer resolution image output. Re-sampling of displacement field obtained at previous level is considered at next level.

Discontinuities caused by various intensity distribution of images are used in various resolution levels. In this way, correctness of registration is improved with respect to higher value of mutual information. Multi resolution technique accelerates the registration process because number of iterations decreases when resolution becomes finest.

D. Joint PDF Estimation

Joint PDF describes the point similarity of an images. Joint PDF is estimated using global joint histogram. Joint histogram describes the intensity relationship in correctly registered images.

In this algorithm, joint histogram and point similarity $S(m,n)$ is recalculated after each step of change of displacement field. Interpolation used in finding joint histogram is done using GPV algorithm. The error induced due to use of joint histogram is done using tissue probability maps (TPMs). TPM values gives the probability of occurrence of given tissue in that location. Joint PDF can also be calculated using Parzen Windowing Technique. In Parzen Windowing Technique random samples drawn from an unknown joint intensity distribution,

$$P_{MN}(i) = \frac{1}{K_{\Omega}} \sum_{s_j \in \Omega} f(i - s_j)$$

Here, $i[m,n]$ is a intensity pair for which joint PDF is calculated,

$P_{MN}(i)$ is calculated by summing the values of kernel or window function f , which is calculated using each sample intensity pair s_i . Weighted kernel function by the probabilities is obtained from TPMs.

$$h_{MN}(i) = \sum_{c=1}^T \sum_{j=1}^S P_c(X_{c,j}) f(i - S(X_{c,j}))$$

$$O = \sum_i h_{MN}(i)$$

$$P_{MN}^{Prior}(i) = \frac{h_{MN}(i)}{O}$$

Here, T = No. of TPMs

S = No. of intensity pairs sampled in each TPM at $X_{c,j}$

The kernel function f used in this process is Gaussian function. 3-D Gaussian filter is used to find Tissue Probability Map. Same number of samples are taken for each of the type of tissues, that is for white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF).

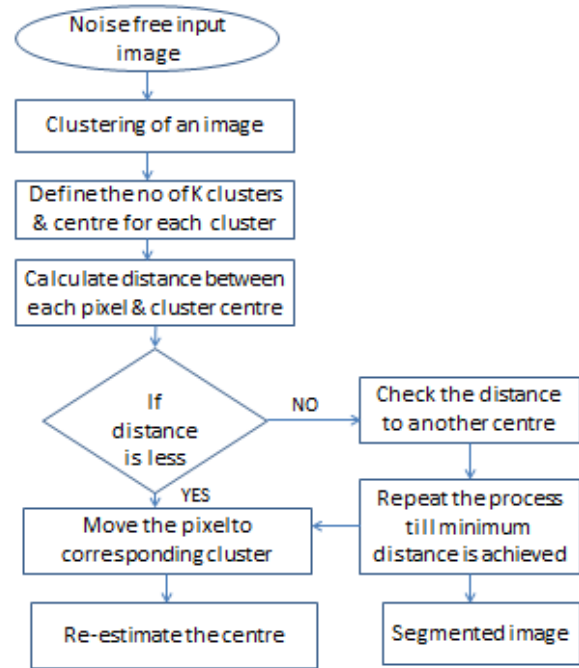
III. TUMOR DETECTION

A. K-Means Clustering :

K-Means algorithm is used for segmentation of image in brain tumor detection. Clustering is the main approach in this algorithm. Clustering means making groups of the pixels of an image according to special characteristics of that pixel. K is the number of clusters of an image. Initially define the value of K. Then determine the center of each cluster randomly. After that find the distance between each pixel and

center of cluster. Out of all these distances which distance is minimum, move the pixel to that cluster. Then center is re-estimated and distance is calculated. This process continuous until center is converges.

B. Flowchart for K-Means clustering:



C. Mathematical Expression:

Calculate the cluster mean M by the following formula:

$$M = \frac{\sum_{t,c(i)=k} X_i}{N_k}, \quad k = 1, \dots, k$$

Calculate the distance between each pixel and cluster center $D(i) = \arg \min |x_i - M_k|^2$

Repeat the process until the center converges.

D. Algorithm:

1. Perform the clustering of an image by grouping the pixels.
2. Define the no. of clusters by determining the value of K.
3. Estimate center of the cluster.
4. Calculate the distance between each pixel and each cluster center
5. If the pixel is close to the center than any cluster centers then move pixel to that cluster.
6. Otherwise check the distance for next cluster.
7. Re-estimate the center.
8. Repeat the process until the center converges.

IV. FEATURE EXTRACTION

By using K-Means algorithm Clustered image is obtained at the output. This clustered image is applied to Thresholding process. Thresholding means binarisation of an image. Because of thresholding dark pixel becomes more darker and white pixel becomes more brighter. Hence by thresholding gray level image is converted into binary image. For this process some threshold is defined and each transform coefficient is compared with the threshold value. If it is less than threshold value then it is considered as zero and if greater then considered as one.

Consider a gray scale image $f(n)$ having N gray level and threshold is defined say T . In thresholding each pixel is compared with the threshold T such that,

$$H(n) = 1 \text{ if } f(n) \geq T \\ = 0 \text{ if } f(n) < T$$

V. APPROXIMATE REASONING

To determine the area of the tumor thresholding method is used. Hence our image contains only two values either one or zero i.e. white or black respectively. Here 256×256 Jpeg image having maximum size. Hence gray scale varies from 0 to 255 along width and height of an image. Binary image can be represented as the summation of black and white pixels. It is given by following equation,

$$I = \sum_{W=0}^{255} \sum_{H=0}^{255} [f(0) + f(1)]$$

No of pixels = $W \times H = 256 \times 256$

$f(0)$ = White pixel

$f(1)$ = Black pixel

$$P = \sum_{W=0}^{255} \sum_{H=0}^{255} [f(0)]$$

P = No of White pixels

1 pixel = 0.264 mm

Size of tumor S can be calculated by following equation,

$$S = ((\sqrt{P}) * 0.264) \text{ mm}^2$$

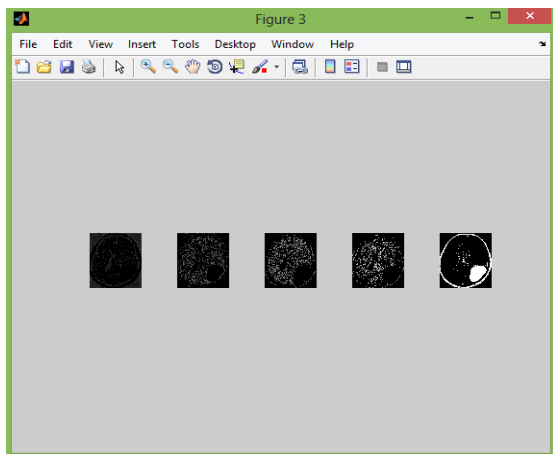


Fig5. Output of K-Means clustering

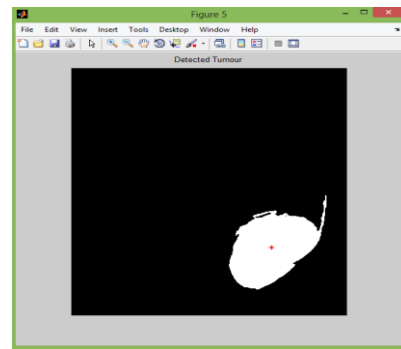


Fig6. Tumor Detected in MRI

VI. CONCLUSION & RESULT

This paper basically deals with the tumor detection technique. For better result restoration and registration algorithms are used to correct the MR image. Registration and restoration are followed by tumor detection. Different noises which are there in MR image are removed by restoration algorithm using various filters. This restored image is given as input to registration algorithm. Multi-resolution strategy and non-linear local adaptive transformation are used in registration to form finer resolution image from coarser image. This finer resolution image is highly aligned resolved image. After registration algorithm, process proceeds towards tumor detection, In which tumor is extracted using k-means technique. Area of extracted tumor is calculated and stage of that tumor is determined. This whole method can be used to get more accurate and reliable results.

VII. REFERENCES

- [1] R. E. Woods, S. L. Eddins, R. E. Woods, R. C. Gonzalez and S. L. Eddins "Digital Image Processing," 2nd Edition, Pearson Education, New Jersey, 2002.
- [2] Ameya Atre, Kathleen Vunckx, Kristof Baete, Anthonin Reilhac, Christophe M. Deroose, Kristof Baete, Koen Van Laere, and Johan Nuyts, Member, IEEE. "Evaluation of three MRI based anatomical priors for quantitative PET brain imaging." IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 31, NO. 3, MARCH 2012
- [3] B. Mitta, B. Mittal, R. Garg, and S. Garg, "Histogram Equalization Techniques for Image Enhancement," *International Journal of Electronics and Communication Technology*, Vol. 2, No. 1, 2011, pp. 107-111.
- [4] Jeba Akewak, "Digital image processing and image restoration", May 2011
- [5] J. A Stark, "Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization," *IEEE Transactions on Image Processing*, Vol. 9, No. 5, 2000, pp. 889-894. <http://dx.doi.org/10.1109/83.841534>
- [6] Tomas Kasparek, Ivo Provaznik, Daniel Schwarz, Ivo Provaznik and Jiri Jarkovsky "a deformable registration method for automated morphometry of

MRI brain images in neuropsychiatric research “IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 26, NO. 4, APRIL 2009.

- [7] T. Arivoli, A. Lakshmi, J.selvakumar, “Brain Tumor Segmentation and Its Area Calculation in Brain MR Images using K-Mean Clustering and Fuzzy C-Mean Algorithm” IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012) March 2012.
- [8] T. Veerakumar, C.H.Prem Chand, , Adabala N.Subramanyam and S.Esakkirajan —Removal of high density salt and pepper noise through Modified Decision Based Un-symmetric Trimmed Median Filter,|| IEEE trans.vol 18. issue 5. pp 287-290. Mar 2011

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