Image Processing to Diagnose Prostate Cancer in Early Stage

S.Nirmala Nambikai Mary[#1], **P.Jeya Durga**[*2], **S.Miruna Joe Amali**[#3]

[#] *K.L.N. College of Engineering, Madurai*

[1]nirmalajustin@gmail.com

[2]jeyaocteves@gmail.com

[3]joe.miruna@gmail.com

***Abstract*—** Image datasets contain huge wealth of information and time constraints in images which causes the image analysis algorithm to fail. Also speckle and patched images will result in more no of false positive test results which make a drastic impact on the lifestyle of people. In order to avoid this, in the proposed work, the image restoration and image imputation is performed. Image restoration is done by adding uniformly distributed speckle noise to the image and then removes the distortions from the image caused during image creation process. Image imputation is done by taking low resolution images and then creates high resolution image. Restoration and imputation are done by using Gaussian Mixture Model (GMM) and Maximum Posteriori (MAP) segmentation methods which will make the resultant image more exact and plausible. Gaussian model uses multivariate Gaussian distribution with mean and covariance. Gaussian mixture model captures the low resolution nature of patch variability in the image and restore the missing data. In the proposed work, highly imputed resultant images are achieved which reduce no of false positive test results and shows progress in accuracy and precision. In the proposed work, the maximum posteriori algorithm is linear iteration method which is suitable for simple images.

***Keywords*—** **Image processing,Prostate cancer,Image de-noising,Image segmentation,Gaussian Mixture Model, Expectation Maximization;**

I. Introduction

Prostate cancer is the most common cancer detected in elderly men. There are several screening techniques available in the medical field to identify cancer. Treatment is available but it is most successful when the cancer is in early stage. Clinical images contain huge wealth of information but have time constraints. This makes the analysis algorithm fail which results in more no of false positive test results. There are several image processing techniques available which can be applied to divide the image into multiple different regions and identifying the edges of it. Image noise removal is one of the most important tasks in image processing which removes the distortions present in the image. Distortions degrade the image quality. Image restoration is the process of the removing the disturbances in the image and retaining its quality. Image segmentation splits the image into multiple segments and restores the image by reconstructing it. In this paper, Filters are used to remove the noise from the image and Gaussian Mixture Model and Expectation Maximization algorithms are applied to reconstruct the image to retain the quality of the image. This paper is organized as follows. In the first section, several related works on image processing are discussed. In the second section, it reviews the linear and non linear filters applied on the image. In the third section, it reviews Gaussian Mixture model and its characteristics. In the fourth section, it reviews Expectation Maximization algorithm and restoring of data. In the fifth section, performance of linear and non linear filters is compared.

II . RELATED WORKS

A. Image restoration by iterative de-noising and backward projections by Tom tirer and Raja giryes, the paper presents IDBP (Iterative De-noising and Backward Projections) solution for inverse problems. This paper uses Plug and Play framework with off the shelf de-noisers to remove the inverse problems such as image deblurring and inpainting. Off the shelf de-noisers leverage the capabilities of already existing de-noisers and requires less parameter estimation and tuning. The approach is competitive and achieve promising results compared to the existing de-noisers. This approach requires fewer neural networks.

B. Gaussian Mixture Markov Random Field for image de-noising and reconstruction by Ruoqiao Zhang and Charles A. Bouman, a novel GM-MRF (Gaussian Mixture Markov Random Field) is presented. This approach is very expressive model for inverse problems like de-noising and reconstruction. This approach forms a global image model which merges Gaussian Mixture and Markov Random Field models. This also provides an analytical framework for Maximum Posteriori estimation with the capabilities of Markov Random Field.

C. On convergence properties of the EM (Expectation Maximization) algorithm for Gaussian Mixtures by Lei Xu and Michael Jordan, This paper forms a mathematical connections between Expectation Maximization algorithm and gradient based approaches for maximum likelihood of finite mixtures. EM step in parameter space is obtained using gradient and convergence of EM with its properties are presented. The advantages and disadvantages of EM with gradient approaches are discussed.

D. Image restoration using Gaussian Mixture Model with spatially constrained patch clustering by Milad Niknejad, and Hossein Rabbani, this paper addresses the issues of restoring the degraded images using Gaussian Mixture model. This paper assumes that the accumulation of similar patches in the neighborhood are derived based on Gaussian distribution with mean and covariance. This paper considers spatial distance between patches in the clustering. This also introduces aggregation of weights for reconstruction of images from recovered patches.

E. Non-local Sparse Models for Image Restoration by Julien Mairal1 and Francis Bach, the paper presents two different approaches to image restoration. One approach to learn the basics set adapted to sparse signal descriptions and another approach to exploit explicitly the similarities of natural images. These approaches are effective and successful in image classification and image restoration using local means approach. This paper combines non local means and sparse coding into unified image model where similar patches are decomposed using same sparse patterns.

III. IMAGE DE-NOISING

Image de-noising is one of the major task in image processing. Image de-noising includes image noise removal and image restoration. Image de-noising removes the noise which is the variation in the image. Noise is represented as function of signal and noise from the acquired image. The image noise is represented as follows.

$$f(i,j) = s(i,j) + n(i.j) \quad (1)$$

Process n is acquired image f with initial signal s. And the de-noise of the degraded image x is given by,

$$x = s + n \quad (2)$$

where s is the original image and n is the noise with unknown variance.

For de-noising, linear and non-linear filters are used. Linear filters remove noise by convolving the original image by masking for smoothing operation. Linear filters are generally fast. The output of linear filter is linear function of its inputs. Non-linear filter output is not a linear function. These filters are good at preserving the edges of the given image.

A. Mean Filter

Mean filters are linear filters. Mean filters remove noise from the image by considering the image as pixel matrix and calculating the average mean value. Then the filter replaces the center value of the image pixel matrix with the mean value. The process is repeated until all the pixel values are replaced with the mean value in the neighbourhood. This filter is known as average filter. This filter is really fast. But they fail to preserve the edges of the image. All title and author details must be in single-column format and must be centered.

6	4	2
7	1	3
5	9	8

Fig. 1 Pixel matrix for Mean Filter

In the sample mean filter matrix, the average mean is 5.The mean filter first replaces the center value of the image with mean value 5 and then replaces the all the neighborhood values similarly.

B. Median Filter

Median filters are simple and powerful for smoothing images. This filter removes noise by ranking the pixels in an increasing order in the image pixel matrix. This filter goes through each entry in the matrix and sort the entries in an increasing order and identifies the median value. Then replaces the pixel values with the median value. The process is repeated until all the pixel values in the matrix are replaced in the neighborhood. Median filters preserve the edges of the images.

24	125	127	128	154
12 6	125	127	128	126
121	116	154	126	128
120	116	120	124	124

Fig. 2 Pixel matrix for Median Filter

The median pixel matrix of the imae values and their sorted order is

{116,120,121,124,125,126,127,128,154}.The median value is 125.The pixel matrix is replaced with the median value. The process repeats until all the pixel values are replaced with the median value in the neighbourhood.

IV. IMAGE SEGMENTATION

Image segmentation divides the image into multiple segments of different regions. Image segmentation identifies the patch variability of the low resolution images and calculates the prior density of the patch based upon the various segmentation models available.

A. *Gaussian Mixture Model*

Image is pixel matrix where each element is a pixel. The value of pixel refers the intensity of the image or the color which is a number.

$$f(x) = \sum_{i=1}^{k} \mathrm{pi}(\mathrm{N}(\mathrm{X}|\mu\mathrm{i}, \sigma\mathrm{i}^2)) \tag{3}$$

Where k is the number of regions and pi>0 in such way that pi=1.

$$\mathrm{N}(\mu, \sigma^2) = \frac{1}{\sigma i \sqrt{2pi}} \exp -(\mathrm{xi} - \mu) / 2\sigma\mathrm{i}^2 \tag{4}$$

μ, σ^2 are the mean and standard deviations of i where i is region class for a given image. The pixel matrix values are the lattice data which uses Gaussian Mixture Model for parameter estimation. The parameter is denoted as θ.

B. *Expectation Maximization –Maximum Posteriori*

There is EM algorithm available for parameter estimation. EM algorithm is linear iteration which is suitable for simple images. EM algorithm involves several steps for estimating parameter. The steps are as follows.

Step1: Read the input image. Observed image class is i={1,2,3,4……k} and represented as vector xj

$$\mathrm{xj}, \mathrm{j} = 1 \ldots \mathrm{n} \text{ and } \mathrm{i} = 1 \ldots \mathrm{k}.$$

Step 2: Initialize the parameter θ, where $\theta = \{\mathrm{p1} \ldots\ldots \mathrm{pk}, \mu 1 \ldots\ldots \mu\mathrm{k}, \sigma 1^2 \ldots\ldots \sigma 2^2\}$

Step 3: Expectation and Maximization steps are calculated. And the steps are repeated until specific error. From this, conditional mean imputation is performed. Reconstruction of labeled image of each true pixels.

Step 4: $(pij)^{(r+1)} = p^{(r+1)}(i|xj)$ (5)

Step 5: $p^{(r+1)}(i|xj) = (pi)^r(N(\mathrm{xi}|\mu\mathrm{i}, \sigma\mathrm{i}^2)/f(xj)$ (6)

Step 6: $p^{(r+1)} = 1\backslash n \sum_{j=1}^{n} (\text{pij})^{r}$ (7)

Step 7: $(\mu\text{i})^{r+1} = \frac{\sum_{j=1}^{k} (\text{pij})^{r+1} x_j^{r+1}}{\text{n}(\text{pi})^{r+1}}$ (8)

Step 8: $(\sigma\text{i}^2)^{r+1} = \sum_{j=1}^{k} pij^{r+1} \left(\frac{xj-(\mu\text{i})^{r+1}}{\text{n}(\text{pi})^{r+1}}\right)$ (9)

Step 9: Iterate step 4 to step 8 until there is a specific error where $\sum_{i}^{n} \text{ei}^2 < \varepsilon$

Step 10: Compute the maximum of iteration pij.

$$\text{pij} = Arg\ Max\,\text{pij}^{(final)} \quad (10)$$

Step 11: Finally reconstruct the image with true pixel values. EM-MAP algorithm is label base modeling. Each labeled image shows that each image is corresponding to different type of labels. Prior and posterior probabilities are made until to get a convergence. Final posterior values of MAP are used labeling. There are several parameters play an important role in choosing the initial values for EM-MAP such as different classes, weights, means and co variances.

V. PERFORMANCE ANALYSIS

In this analysis, the execution times between mean and median filters are provided and the quality of the images are compared. The most important performance criteria is minimum MSE and PSNR values. The Median filters have minimum MSE and PSNR than Mean filters comparatively.

S.No	Mean Filter Technique(ms)	Median Filter Technique(ms)
1	21	20
2	11	7
3	18	1
4	7	1
5	7	1

Fig 3. Performance analysis –execution time

The minimum PSNR values for multiple series for mean and median filters are provided as a graph.

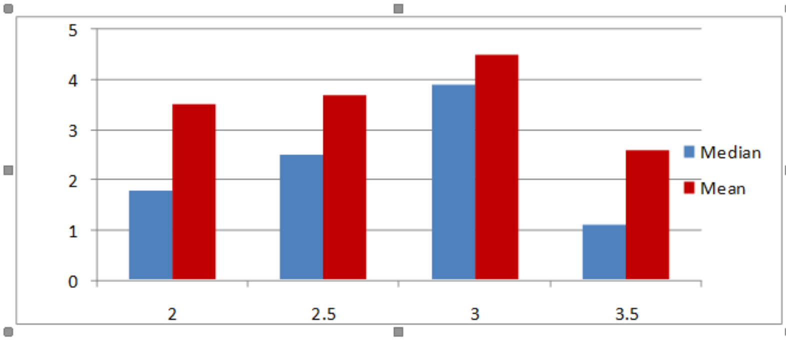

Fig 4. Performance analysis –PSNR levels

Minimum MSE and PSNR values, execution time analysis and the quality of image shows that the median filters have better image preservation ,better quality, better performance. Median filters are preferred for de-noising.

VI. CONCLUSIONS

In this paper, in the first section, image processing techniques are discussed in general. In the second section, various survey papers are discussed. In the third section image de-noising with various filtering techniques such as mean and median filters are discussed for noise removal. The execution time for median filter is comparatively less than mean filter. The PSNR and MSE for median filter is relatively less than mean filter which results in better image preservation. In the fifth section, segmentation methods using Gaussian mixture model and Expectation Maximization algorithms are discussed for high resolution. In the proposed work, the maximum posteriori algorithm is linear iteration method which is suitable for simple images. In the next section, performance analysis between mean and median filters are discussed which are used to compare the effectiveness of filtering techniques. In the proposed work, highly imputed resultant images are achieved. This helps in clear assessment and reduces no of false positive test results in prostate cancer diagnosis. This paper results shows progress in accuracy and precision. The obtained results have shown a significant improvement of the proposed work performance especially regarding about the sensitivity, robustness face and hardiness in relation to noise and the accuracy of the edges between regions and also the results have proven that the proposed work has better segmentation result and low computational burden.

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