A Blind Noise Estimation and Removal in Histopathological Images

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Keywords: Histopathology images, Noise Estimation, Image Processing

Abstract: With the advancement in technology for digital pathology, a huge chunk of the visual dataset is prepared for medical experts for disease diagnosis and grading. The introduction of noise in various image modalities in the medical field can distress the result of diagnosis which could lead to inappropriate disease grading and hence delay in treatment. In this, a blind noise estimation and removal technique is proposed for histopathology images. The model uses the wavelet transformed image and block selection approach with a block size of eight for noise estimation. The noise estimated in the model is Gaussian, Poisson, and speckle. The proposed approach is verified on images of Breakhis dataset with all four-magnification scale. The performance of the proposed approach is shown through parameter Signal-to-noise ratio (SNR), mean square error (MSE), root mean square error (RMSE) and peak signal to noise ratio (PSNR)

1 INTRODUCTION

Noise in the digital image is defined as inappropriate and unwanted information residing in an image. This unwanted noise may affect the image quality in different ways. The disturbance is created in pixel values of the image, and hence there is some random variation in pixel value. In medical image analysis, the estimation of noise variance is of utmost importance. To check the stability and working performance of the detection model for disease diagnosis, noise recognition, as well as elimination, is important. With the improvement in digital pathology, a large amount of visual dataset is generated which is available for computer-aided diagnosis (CAD). The availability of dataset encourages the researchers to develop CAD tools for analysing the scanned images developed through digital pathology. Based on the result obtained from CAD tools, the grading of the disease is performed.

For a precise and accurate diagnosis of medical images, it is very essential that the image taken through different technique remains free from blur, noise, and artefacts. The different image acquisition techniques end up in accumulating a large number of numbers of the pixel in per unit area to flourish high-resolution image. They thrive to capture high quality leads to noise accumulation in the resultant image. These noises mask the essential feature which leads to incorrect grading of the disease. Table 1 below reports a brief overview of different image modalities along with noise present in such images. The table below gives the image capturing developing techniques related to different medical image modalities. Due to different faults in different capturing process noise are introduced in the image. There are various noise models for different medical images, and it is shown in Table 1.

There are models developed for other image modalities such as MRI, X-Ray, Ultra-sound, CT etc. using different approaches such as filtering, statistical, block selection, noise variance etc. It can be observed from the literature that no such model is developed for histopathology images. This paper proposes a blind noise estimation model for histopathology images. There is no prior knowledge regarding the noise model hence we are using blind noise estimation approach. In this mode model, the image is transformed into the wavelet domain and perform block division of image in the continuous diagonal, vertical and horizontal component. For each block median absolute deviation is calculated. For denoising, the noisy level and estimated noise level is differentiated. Due to the importance of luminance in the microscopic image the Color space used is YCbCr.

Singh, S. and Kumar, R.
A Blind Noise Estimation and Removal in Histopathological Images.
DOI: 10.5220/0010562700003161
In *Proceedings of the 3rd International Conference on Advanced Computing and Software Engineering (ICACSE 2021)*, pages 67-72
ISBN: 978-989-758-544-9

Table 1: Image modalities with noise and acquiring technique

Image Modality	Technique	Type of Noise
X-Ray	X-ray projection	Gaussian & Poisson Noise
Computed-Tomography (CT)	Cross-sectional body x-ray projection	Gaussian & Quantum Noise
Positron Emission Tomography (PET)	Radioactive tracing	Gaussian Noise
Single-photon emission Computed Tomography (SPECT)	Picturization performed through the nuclear substance. (Gamma camera)	Gaussian Noise
Magnetic -Resonance Imaging (MRI)	Transition in the energy of the photon	Gaussian, Richian, and Rayleigh noise
Ultra-sound	Reflection of the temporal wave with high frequency	Gaussian & multiplicative noise
Microscopic Biopsy	Tissue examined under a microscope. with H&E stains on it	Gaussian, Poisson, and Multiplicative
Mammography	Low dose x-ray system	Gaussian & Poisson Noise

The paper is organized as: already existing model of noise estimation are given in “Related work”. The proposed approach and the dataset used to validate the model is explained in “Material and Method.” This section gives a detailed discussion regarding noise estimation, noise model and Discrete wavelet transform.

The experimental work and result analysis are discussed in “Experimental Result”. The future direction and work proposed is conclude in section “Conclusion”.

2 RELATED WORKS

To best of our knowledge, no such noise estimation model for histopathology images has been sated in the literature. So, we have reviewed paper based on other medical image modality for noise estimation. There are different types of image-modality in the medical image. Every image has a different acquisition technique based on those image capturing approaches; different type of noise is introduced in a different image. The table summarizes the image capturing technique along with the noise present in that image (Goyal, Dogra, Agrawal, & Sohi, 2018)(Dogra, Goyal, Agrawal, & Sohi, 2017). There are several noise models and noise estimation approaches are reported till date such as statistical approaches, patch-based, filter-based and block selection based (Ram & Choudhary, 2014)(Kaur, 2015).

Pieere Gravel et.al. (2004) has developed a method for analysing the statistical property for analysing the statistical property of noise. The model developed establishes the association between the intensity of the image and variance of image. The proposed model was examined on MRI and X-Ray images with Gaussian, Poisson as well as Rician noise(Gravel, Beaudoin, & De Guise, 2004). M.N. Nobi et.al. (2010) has developed noise reduction model for MRI and ultra-sound images having Rician noise and speckle noise. The model integrates the median filter and mean filter(Yousuf & Nobi, 2010). Pierrick Coupe et.al. (2010) has presented an object-based model to estimate Rician noise in MRI using median absolute deviation(Coupé et al., 2010). GnanambalIlango et.al. (2011) has proposed a hybrid approach of noise estimation using different filtering techniques. The estimation technique is used on brain tumour image for Gaussian noise removal (Ilango & Marudhachalam, 2011). Xuvyu Pan et.al. (2012), the authors have presented a blind noise estimation model for CT images. Contrast band filters are used for estimating the noise and for denoising PCA with local pixel grouping is used (Pan, Zhang, & Lyu, 2012). Jose V. Manjon et. al. (2015) has given a two-step approach for Rician noise estimation in MRI. The proposed approach involves the filtering of the noisy image using no-local principal component analysis(PCA) and then using a filtered image as a guide for the non-local mean filter (Manjón, Coupé, & Buades, 2015). F.F. Ting et.al. (2016) has proposed a rapid noise variance estimation method for magnetic resonance image and computed tomography. The author has used Gabor Wavelet Laplacian convolution (GWLC) for noise variance estimation. The type of noise discussed in the work is Rician noise (Ting, Sim, & Wong, 2017). Rajesh Kumar et.al. (2017) has proposed an approach for segmentation of microscopic images for cancer grading. The proposed approach segments the cell and nuclei in the existence of Poisson noise. The authors have used the partial differential equation of order four which relies on the non-linear filter for noise estimation (Kumar et al., 2017). Table.2. gives a brief over of the noise estimation model discussed by various researchers and noise model they have considered.

Table 2: Brief overview noise estimation model stated in the literature

Reference	Image Modality	Type of Noise	Approaches
(Gravel et al., 2004)	MRI X-Ray	Gaussian, Poisson, & Rician	Relationship between noise variance and image intensity
(Yousuf & Nobi, 2010)	MRI Ultra-sound	Rician& Speckle	Integration of median filter and Mean filter.
(Coupé et al., 2010)	MRI	Rician	Two-step approach involves filtering image using non-local PCA and then filtered image used as a guide for non-local Mean filter.
(Ilango & Marudhachalam, 2011)	MRI	Gaussian, Salt-pepper & Speckle	Hybrid filter through Topological approach
(Manjón et al., 2015)	CT, MRI	Additive white gaussian Noise (AWGN)	Contrast band filter
(Ting et al., 2017)	MRI, CT	Rician	Gabor Wavelet Laplacian Convolution
(Kumar, Srivastava, & Srivastava, 2017)	Microscopic Biopsy	Poisson	Fourth-order partial differential equation based on non-linear filter

3 METHOD AND MATERIALS

In the proposed approached we have used block selection method for noise estimation. Fig.2. shows a block diagram of the proposed architecture. Since it is blind noise estimation technique introduction of noises such as Gaussian, Poisson, and speckle, are made in images of Breakhis dataset. For validating our approach, we have used benchmark dataset for experimental work. For noise estimation and denoising we have used images from BreakHis dataset. System configuration with 2 GB GPU, 8 GB Ram i5 processor has been used. The Matlab version 2017b is used for performing an experiment. The images in the dataset are in RGB colour space they are transformed into YCbCr colour space and performed wavelet transform. This section is subdivided into sections- 3.1) Dataset 3.2) Pre-processing 3.3) Noise model 3.4) Wavelet transform 3.5) Noise estimation 3.6) Performance measure.

3.1 Dataset

Breast Cancer Histopathology Database (BreakHis) is publicly available dataset and is prominently used for breast cancer detection. The images are developed by staining the tissue collected through surgical open biopsy and staining them with H&E. A total of 7909 images are them out of which 2440 are benign and 5429 are malignant and they are of magnification factor 40X, 100X, 200X and 400X. For validation of proposed architecture, a single image from each magnification level is taken(Spanhol, Oliveira, Petitjean, & Heutte, 2016)("Breast Cancer Histopathological Database

(BreakHis)," 2014). Fig.1. shows the images used in the proposed approach:

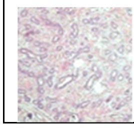
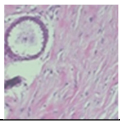
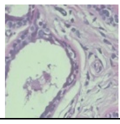
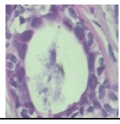
Magnification Factor			
40x	100x	200x	400x
			

Figure 1: Images from BreakHis Dataset

3.2 Pre-processing

The luminance of the coloured images is of utmost importance. And in case of histopathological images, the Color stain signifies the characteristics of an image. So, keeping this in mind we have chosen YCbCr for conversion. The conversion of the RGB image to colour image is:

$$[\mathrm{Y\ Cb\ Cr}] = [\mathrm{R\ G\ B}]\begin{bmatrix} 0.299 & -0.168 & 0.499 \\ 0.587 & -0.331 & -0.418 \\ 0.114 & 0.500 & -0.081 \end{bmatrix} \quad (1)$$

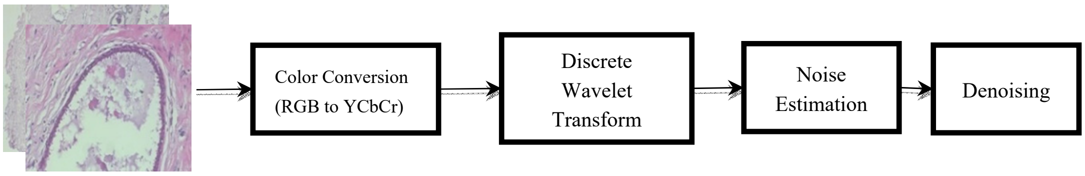


Figure 2: Proposed Architecture for noise estimation and removal

3.3 Noise Model

During digital image acquiring of slides, various sensors are coupled with the microscope. This led to noise introduction in an image due to a decrease in contrast of tissue structure. This occurs due to the lack of proper light and long duration of exposure. Due to this there is a scarcity of photon in sensor and hence the shifting electrons inside the chip get lost and noise intrudes the image. Noise is characterized as a random variable since it is simply a fluctuation in pixel value. The random variables have some probability distribution, which links it with statistical values which is the probability of occurrence (Kaur, 2015). The basic assumption regarding noise $n(x, y)$ noises is an additive random signal that is white Gaussian noise with zero mean value and noise is of high frequency. The noise in an image $J(x, y)$ is represented as

$$J'(x, y) = J(x, y) + n(x, y) \quad (2)$$

Where, J' is the degraded image.

In the proposed approach we have introduced Gaussian, Poisson, and speckle noise in images for noise estimation and denoising purpose.

3.3.1 Gaussian Noise

It is a statistical noise which has the probability density function (PDF) equals to the normal distribution (Gonzalez & Woods, 2002). It can be mathematically given as:

$$I' = I(x, y) \pm G_a \quad (3)$$

Where $I(x, y)$ is the noiseless image and G_a is Gaussian PDF it is given as:

$$G_a = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(a-a')^2}{2\sigma}}, \ -\infty < a < \infty \quad (4)$$

Here a represents the intensity, a' is average(mean) of intensity, and σ standard deviation.

3.3.2 Poisson Noise

The Poisson is introduced in the image due to random fluctuation in photons from source ray emission. This result in temporal and spatial randomness(Gonzalez & Woods, 2002). The PDF for Poisson Noise is given as

$$P(a) = \frac{(np)^2}{a!} \times e^{-np} \quad (5)$$

Here n represents the total number of pixel and p shows the ratio between the noise pixel to the total number of pixels.

3.3.3 Speckle Noise

Another noise which is very common and can be present in microscopic images are speckle noise(Gonzalez & Woods, 2002). Speckle noise is most common multiplicative noise in medical images. It is represented as

$J' = J(x, y) + (J(x, y) \times S_N)$ (6)

Where S_N shows a random noise with zero mean Gaussian PDF.

3.4 Wavelet Transform

The wavelet signifies the analysis and representation of multiresolution images (Jaiswal & Srivastava, 2020) Wavelet transformation are most frequently used in edge detection (Jiang, Shen, Jiang, & Lam, 2009) and image denoising(Coifman&Donoho, 1995). At low frequency, the wavelet transform gives high resolution and with high frequency it gives high resolution time. We can get better noise estimation of an image in the wavelet domain. So, image is transformed in wavelet domain. This transformation is applied over YCbCr image.

Let us consider $\Psi(x)$ as wavelet of 1-D signal, then the scaling parameter p and shifting parameter r is given as:

$$\Psi_{(p,r)}(x) = \frac{1}{\sqrt{p}}\,\Psi\left(\frac{x-r}{s}\right) \qquad (7)$$

Where, f(x) 1-D signal and its wavelet transform is given as:

$$T_{(p,r)}(p, r) = \int_{-\infty}^{\infty} f(x)\Psi_{p,r}(x)dx \qquad (8)$$

3.5 Noise Estimation

Upon excluding the edge, the noise estimation is performed by block division into continuous diagonal, vertical, and horizontal component and then the noise statics are calculated for each block obtained. The noise statistics calculated for blocks are mean absolute deviation. The block size here is taken as eight. The denoising is performed by differentiating noisy image and estimated noise of an image.

3.6 Performance Measure

The quality of the image needs to be quantified. The metrics are put under category object fidelity and subjective fidelity. For testing the performance of enhancement approach, we have calculated error and signal to noise ratio. MSE is error calculated between the input image and the processed image. SNR is the ratio between signal amplitude and noise amplitude(Jain, 1989). The unit of SNR is dB. The formula for calculation of MSE, RMSE SNR, and PSNR is given as

$$E = \frac{1}{lm}\sum_{x=0}^{l-1}\sum_{y=0}^{m-1}[J(x, y) - J'(x, y]^2 \qquad (9)$$

$$RMSE = \sqrt{E} \qquad (10)$$

Here l and m are dimensions of input image J(x,y) and J'(x,y) is the processed image

$$SNR = 20\ \log 10\left(\frac{S_a}{N_a}\right) \qquad (11)$$

$$PSNR = 20 \log 10\, \frac{255^2 lm}{E} \qquad (12)$$

Here S_a is signal amplitude and N_a is noise amplitude.

4 EXPERIMENTAL RESULT

The model explained in this paper is validate on the images taken from BreakHis dataset. The proposed approach is tested on images with different magnification scale and varying noise model. The experiment is performed by selecting five random images from the database and then their value is represented in Table.3 Then the SNR, PSNR, MSE, and MSE is calculated value is computed to quantify the image quality given by the estimation model. Lower the value of MSE, RMSE and higher value of SNR, PSNR shows the betterment of enhancement procedure. Table 3. Gives a brief overview of SNR, PSNR, MSE and RMSE values corresponding to different noise and magnification scale. It is observed for the table that magnification of image does not affect the signal amplitude and noise amplitude ratio.

Table 3: SNR value of the proposed model on the different magnification factor

Image Type	Type of Noise	MSE	RMSE	SNR	PSNR
40X	Speckle	0.3586	0.5968	49.4785	4.5128
	Gaussian	0.4649	0.6805	48.5876	3.3607
	Poisson	0.4663	0.6846	48.1698	3.3197
100X	Speckle	0.3932	0.6250	49.2943	4.1031
	Gaussian	0.4677	0.6826	48.4031	3.3309
	Poisson	0.4904	0.6992	48.2628	3.1208
200X	Speckle	0.3952	0.6273	49.2936	4.0695
	Gaussian	0.4648	0.6804	48.5888	3.3619
	Poisson	0.5182	0.7185	48.1157	2.8869
400X	Speckle	0.4432	0.6632	48.2968	3.5933
	Gaussian	0.5218	0.7441	47.2101	2.5686
	Poisson	0.5734	0.7551	47.1749	2.5686

5 CONCLUSIONS

The noiseless image is every essential medical domain; the detection accuracy totally relies on the eminence of the image. As the work reported in literature there are noise detection and removal model developed for other modalities of the medical image like X-Ray, MRI, Ultra-sound, CT, etc., but there is no such model available for the microscopic image. The model introduced in the paper estimates the noise in microscopic image with assuming some distributed noise such as Gaussian, Poisson, and speckle. The approach is based on the blind noise estimation technique using the block selection method. The block size of the model is 8, DWT is used because it accurately analyses the images with abrupt changes as it is well localized in terms of frequency and time. The denoising is performed using differentiating estimated noise from noisy image. The result is described in signal to noise ratio and error is also calculated and the model performs well for all the magnification level. The lower values of MSE and RMSE and higher values of SNR & PSNR indicates the betterment of proposed enhancement model. In future we would like to develop an estimation model based on the filtering approach and for denoising statistical approach, this could result in better SNR value.

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