A Spatio-Frequency Domain Anisotropic Filtering for Contrast Enhancement of Histopathological Images

Dr. J. Samuel Manoharan^{1*}, Dr. V. Parthasaradi², K. Suganya³

¹Professor/Dept. of ECE, Sir Isaac Newton College of Engineering and Technology, Velankanni Road, Papakoil, Nagapattinam – 611102, South India

^{2,3}Asst. Professor/Dept. of ECE, Sir Isaac Newton College of Engineering and Technology, Velankanni Road, Papakoil, Nagapattinam – 611102, South India

*drjsm1530@ieee.org

ABSTRACT

Medical images play a critical role in diagnosing of several symptomatic and asymptomatic disorders and medical conditions for early treatment to prevent and reduce fatalities. Medical image processing has played an indomitable role in processing of these medical images from age old times. Preprocessing and contrast enhancement is a critical and foremost stage in any medical image processing technology. This research article proposes a novel edge preserving spatio-frequency domain anisotropic filtering in a hybrid filtering approach to overcome the limitations of existing methods like lack of edge preserving features, significant loss of data during filtering process etc. In the proposed work, the process of filtering has been done in the frequency domain which least reflects any modifications in the time domain representation which forms the motivation behind the proposed utility. Histopathological images like red blood cells (RBC), white blood cells (WBC) and platelets whose analysis is of great significance in medical domain for detection of several abnormalities, is taken as the prime dataset for investigation in this research work. Three noise types involving Speckle, Impulse and Gaussian which normally tend to corrupt medical images has been taken for the filtering and enhancement process. Performances in terms of peak signal to noise ratio (PSNR), structural similarity index (SSIM) to analyze the edge structure deformity indicate superior performance of proposed hybrid filtering approach.

Keywords: Histopathological images, Medical Image Processing, Preprocessing, Anisotropic diffusion filtering, discrete wavelet transform, contrast enhancement.

I. INTRODUCTION

The field of clinical and diagnostic medicine has undergone a great revolution with huge contributions and innovations in the field of image acquisition modalities as well as appropriate and highly efficient image processing technologies and standards. Early detection from various modalities of the images such as X-rays, CT and MR images etc. have brought fruitful results in drastically reducing the mortality rate, especially in the past decade. Each imaging modality serves its own purpose based on the application and target objective or image under study. Histopathological are a special class of images that find great utility in detection and complex processing for information extraction for various disorders with major emphasis towards cancer detection. They are alternately termed as biopsy reports which is a sort of less invasive method of detection procedure. Similar set of images termed as whole slide imaging is an emerging area of research in recent times due to the ample set of information gathered from processing of these

slide images. They capture high resolution digital images of the which could be projected onto a viewing screen for analysis. This research paper has taken whole blood slide images as the substrate image or the basic platform for the proposed research investigation. Whole blood slide images related to blood cells namely Red Blood Cells (RBC), White Blood Cells (WBC) and Platelets are an integral part of the pathology department and are critical in the detection of abnormal counts of RBCs or WBCs which are probable indicators of onset of cancer. Since these images are obtained through a scanning process which is a type of image acquisition model, noise tends to be an integral part during the scanning process which imprint themselves on the smear or the whole slide image. Since the whole slide images are given as inputs to complex microscopic systems for further analysis, the morphological features of the images should be free of noise. Speckle noise, shot noise, Gaussian noise are common noise factors which are incident on these type of imaging modalities. These noise components tend to degrade the overall contrast of the image as well do not provide clear distinction of boundaries and edges making their consequent processes like segmentation to be well below expected standards. This may subsequently result in erroneous outputs. Sample whole blood slide images of RBC, WBC and platelets are depicted in figure 1 shown below.



Figure 1 Whole blood slide image of a. RBC b. WBC c. Platelets

As observed in figure 1, the above whole blood slide is reflective of a single sample of the blood sample. Under normal circumstances a huge volume of the RBCs and WBCs are observed. Hence, a systematic and organized manner of processing using sophisticated image processing methods offer to be ideal candidates for deducing information from these types of whole blood slide images. Essential findings from these whole blood slide samples include the size and dimensions of these cells, the count per sample (a single blood drop contains millions of these cells). Based on threshold values, the analysis of possible abnormal cells and their count is effectively used to predict the onset or current stage of any earlier occurred disorders. Apart from detection of certain types of cancers based on the feature of these cells, some common disorders like Sickle cell anemia, Jaundice, Malaria, onset of kidney failure and Thrombocytopenia could be identified from these blood slide cells. A typical differentiation between normal and sickle cell anemia condition is projected in figure 2 shown below.



Figure 2 Differentiation between normal and sickle cell anemia

[Courtesy: Understand Hematology Report, 2016]

In figure 2, a clear differentiation between normal and sickle cell anemia could be identified. The blood cells tend to deform into a sickle shape as depicted by arrowhead and hence the nomenclature. In a similar manner many such disorders could be understood both from count values of blood cells as well as their features. Noise component removal from these samples is quite challenging and not as easy as it may sound. This is primarily because noise component removal using conventional filters like sharpening or smoothening may tend to degrade some of the vital information it may contain thus leading to faulty dimension computations. Thickening or thinning of the edges due to the filtering process may result in incorrect dimension and area calculation which have a cascading and fatal effect on the biopsy report. Various types of noise models exist. However, those inflicting considerable impact or degradation to the whole blood slide image include speckle noise, impulse noise and the Gaussian distribution noise. These three types of noise are associated with the image acquisition methods with noise being generated from sources like switching, amplifier switches and glitches, internal thermal disturbances etc. Hence, a systematic method of noise removal must be thought of to preserve the vital information as well as the boundaries of these cells to aid in morphological-based feature computation. The rest of the paper is organized into a systematic survey of literature related to some preliminary preprocessing methods in section 2 followed by the proposed hybrid filtering model presented in section 3. Section 4 presents the experimental findings with section 5 drawing the concluding remarks based on the research findings.

II. RELATED WORK

Image preprocessing is an integral part of any image processing technology as almost all images obtained through different modalities are prone to various types of noise distributions. In a way, they perform enhancement of the image under study by removing the noise components, sharpening or smoothening the edges and boundaries. Many such preprocessing methods are observed in the literature. A few recent and most related methods have been discussed in this

section to gain a better understanding in formulating the proposed contrast enhancement approach.

A comprehensive review of various enhancement methods applicable for various imaging modalities like MRI, CT, PET, X-Ray images have been discussed in the literature [1]. A significant finding of this survey is that in spite of many effective methods available such as histogram equalization, logarithmic point morphological processing etc. each have their own limitations for a specific modality. It has been stated that histogram equalization does not quite suit applications involving edge enhancements which is essential in case of MRI and CT images. Other findings include suggestion of utility of methods like gradient descent methods and adaptive histogram equalization methods for denoising applications.

A significant number of preprocessing methods for breast imaging applications involving mammogram images have been observed in the literature. Conventional filtering methods like Mean, Median, Wiener and adaptive median filters have been utilized in the literature [2] for mammogram images. Optimal performances have been achieved by creating a mask-and-filter approach over the images under study. An elaborate formulation into each of these filter types along with their implementations have been formulated in the literature [3] as well. Special emphasis on contrast limited adaptive histogram equalization (CLAHE) has been elaborated by the authors. A note on various morphological operations such as erosion and dilation have been elucidated as well. Filtering along with CLAHE methods have been successfully utilized on mammographic images [4] for image enhancement. Median filters have also been combined with CLAHE [5] for providing required image enhancement. However, CLAHE methods suffer from limitations such as limited region of operation on the subject image and its quite computationally expensive nature.

Image enhancement methods using machine learning have also been observed in significant numbers in the literature. These include combination of CLAHE with fuzzy methods to constitute the fuzzy filtering [6]. However, this method is computationally complex as it involves a transformation of input features to fuzzy sets and outputs followed by training with a neural network architecture. Global histogram equalization methods together with wiener filtering have also been utilized in literature [7] for image enhancement.

Utilization of frequency domain processing for preprocessing have been on the rising trend as they tend to preserve the intensity values when viewed from the spatial domain. Median filters have been employed in the frequency domain using well-known transform like discrete wavelet transform (DWT) [8]. Frequency domain transforms help best in approximating the high frequency components which are more characterized by presence of noise components. Threshold concepts are invoked to identify pixels below and above the threshold point as nonnoise and noise pixels, respectively. Despite them being quite effective, choice of appropriate wavelet function and decomposition level dictates the denoising efficiency. Furthermore, utilization of apt filters for the decomposed sub-bands helps in defining the efficiency. An elaborate study on the effect of decomposition levels on image quality and processing could be observed in the literature [9]. Hybrid combinations of wavelet decomposition together with K-

SVD model have been able to overcome the challenges associated with selection of optimal threshold values for denoising using wavelet transforms [10]. Soft computing methods have also been effectively applied over MRI images [11] and mammogram images [12].

III. PROPOSED WORK

A spatio-frequency domain preprocessing model based on discrete wavelet transform is proposed in this research work for whole blood smear images. Gaussian, Impulse and Speckle noise are considered as prominent noise sources as observed from the survey of literature especially for medical images. A typical image could be modeled as

$$I(x, y) = M(x, y) + \gamma \tag{1}$$

In equation (1), the M(x, y) term reflects the message content of the image composed of both high and low frequency content together with the noise term termed as gamma. The gamma distribution could be Gaussian, Impulse or Speckle. In the above case, the Gaussian noise model could be projected as

$$\gamma_{Gaussian} = \frac{1}{\sqrt{2\pi\sigma}} e^{-(M-\mu)^2/\sigma^2}$$
(2)

In equation (2), M denotes the pixel values of input image which are usually gray level pixel values, μ , the mean, σ , the variance and σ^2 which is the standard deviation. Speckle noise is a multiplicative noise pattern while impulse gives a salt and pepper appearance. The flow process of proposed filtering model is depicted in figure 3 shown below.



Figure 3 Scheme of proposed hybrid Anisotropic diffusion filtering model

The internal structure of a typical DWT is a tree-based filter structure which is depicted in figure 4.



Figure 4 Illustration of a single stage DWT tree structure

A single stage of DWT decomposes the given image content into high frequency and low frequency bands to produce four sub bands known as approximation band composed of low frequency components which reflect the visual content of the image, the diagonal, horizontal and vertical bands which reflect the high frequency band.

Following the K- level decomposition into low frequency and three high frequency bands, an anisotropic diffusion filter is employed to achieve the desired contrast enhancement. Apart from filtering of noise contents, this filter also tends to preserve the visual content of the image thus aiding in the enhancement of the given image. The diffusion process is mathematically modelled as

$$dif f_{I(x,y)} = \nabla d. \nabla M + d(x,y) \Delta M \tag{3}$$

In equation (3), ∇ denotes the gradient operator, Δ denotes the Laplacian operator, M denotes the gray scale image content and *d* denotes the diffusion constant. The objective behind utilization of the proposed anisotropic filtering is to help preserve the image content which tend to get degraded when conventional filter masks are being utilized. In the overall process, the first stage DWT helps to better identify the noise components due to their characteristic sub-band decomposition nature followed by the filtering process. Vast experimentation over the histopathological images has been conducted in MATLAB environment and the findings presented in the following section.

IV. RESULTS AND DISCUSSION

For experimentation, RBC cells, WBC and Platelets have been taken as input images. Noise in the form of Speckle, Impulse and Gaussian have been added in varying magnitudes reflected in terms of mean and variances. Variances of speckle noise has been varied in terms of 0.0001, 0.001, 0.01 and 0.1 for the given sample. It is depicted in figure 5 shown below.



Figure 5 RBC cells affected with varying intensities of speckle noise

In a similar manner, RBC cells have been taken and contaminated with Impulse noise with varying variances of 0.08, 0.06, 0.04 and 0.02. The distribution and visualization after addition of noise is depicted in figure 6 shown below.



Figure 6 RBC cells affected with varying intensities of Impulse noise

Following Speckle and Impulse noise distribution, Gaussian noise with constant mean and varying variances of 0.08, 0.06, 0.04 and 0.02 is added which have been projected in figure 7 shown below.



Figure 7 RBC cells affected with varying intensities of Gaussian noise

The above samples from figures 5-7 are given as input to the proposed hybrid filtering module composed of a K=1 level DWT and anisotropic diffusion filter to provide the preprocessed and contrast enhanced image. Application of DWT for a scale K=1 provides four sub bands as mentioned in previous sections namely the approximation, vertical, horizontal and diagonal bands. The approximation represents the message content while the other three depict the high frequency bands. The band generation is depicted for a speckle noise contaminated image in figure 8 shown below.



Figure 8K=1 DWT decomposition of given

Speckle noise contaminated image

In a similar manner, impulse noise contaminated image subjected to K=1 DWT is projected in figure 9 shown below.



Figure 9K=1 DWT decomposition of given

Impulse noise contaminated image

Similarly, Gaussian noise corrupted image subjected to K=1 DWT is projected in figure 10 shown below



Figure 10K=1 DWT decomposition of given

Gaussian noise contaminated image

The above images corrupted with Speckle, Impulse and Gaussian noises respectively are now given as input to the anisotropic diffusion filter to get the contrast enhanced and preprocessed image. The denoised images obtained from the three different types of noise are depicted in figure 11 shown below.

Enhanced Image from Speckle Noise Enhanced Image from Impulse Noise Enhanced Image from Gaussian Noise



Figure 11 Enhanced & Preprocessed images

from a. Speckle Noise b. Impulse Noise c. Gaussian Noise

Apart from the projection of denoised and enhanced images as shown in figure 11, performance metrics like peak signal to noise ratio (PSNR), structural similarity index measure (SSIM) reflect the efficiency of the proposed filtering process. The PSNR is expressed in decibels (dB) while the SSIM is a ratio measure and lies in the interval of [0->1]. A zero indicates poor resemblance to reference image while 1 indicates perfect match with reference image. The PSNR analysis is compared with existing methods like Mean, Median, Wiener, CLAHE and Adaptive histogram equalization methods in a tabular manner presented in table 1.

	Noise Variance			
Technique/Filtering Methods	0.0001	0.001	0.01	0.1
	PSNR (dB)			
Proposed hybrid filter	19.41	18.61	17.41	15.82
CLAHE	18.11	16.41	15.65	14.01
AHE	17.89	16.02	15.55	13.28
Wiener	17.45	16.01	15.59	13.11
Median	17.10	15.69	15.01	12.90
Mean	17.01	15.59	15.08	12.08

Table 1 Comparative analysis of filtering methods towards Speckle Noise - PSNR

The PSNR analysis towards Impulse noise is tabulated in table 2 shown below.

	Noise Variance			
Technique/Filtering Methods	0.8	0.6	0.4	0.2
	PSNR (dB)			
Proposed hybrid filter	23.41	24.98	26.45	27.11
CLAHE	22.11	23.01	25.40	26.77
AHE	21.98	22.65	24.96	25.89
Wiener	21.01	21.56	22.98	24.01
Median	20.98	21.01	21.74	23.12
Mean	20.56	20.64	21.01	22.65

Table 2 Comparative analysis of filtering methods towards Impulse Noise - PSNR

In a similar manner, the PSNR measure towards Gaussian Noise is projected in table 3 shown below

Table 3 Comparative analysis of filtering methods towards Gaussian Noise - PSNR

	Noise Variance			
Technique/Filtering Methods	0.8	0.6	0.4	0.2
	PSNR (dB)			
Proposed hybrid filter	16.99	17.45	18.01	18.99
CLAHE	15.04	15.65	16.45	17.35
AHE	14.87	15.05	15.99	16.04
Wiener	14.66	15.01	15.45	15.98
Median	14.28	14.45	15.01	15.33
Mean	14.01	14.65	15.24	15.30

Above tables validate the superiority of proposed hybrid filtering approach. The analysis of SSIM is projected in figure 11 shown below. Figures 12 - 13 project the SSIM performance towards Impulse and Gaussian Noise, respectively.



Figure 11 SSIM performance towards Speckle Noise



Figure 12 SSIM performance towards Impulse Noise



Figure 13 SSIM performance towards Gaussian Noise

In all the cases observed in figures 12 - 13, optimal performance of proposed spatiofrequency based hybrid filtering is observed justified by high SSIMs which are reflective of how close the outcome is to the reference image. Similar experimentations have been performed over WBC and platelet images and superior observations have been made in each case.

V. CONCLUSION

Preprocessing and contrast enhancement are essential and integral processing stages in any image processing technology and application. They play a critical role especially in medical images as such medical images have a zero tolerance towards any loss of data which may result in wrong diagnosis. Hence, a careful and systematic method of preprocessing is desired and a prerequisite. A novel spatio-frequency domain anisotropic filtering combined with the powerful sub-band decomposition feature of DWT has been utilized in this research paper. The experimentations have been done on histopathological images which are quite critical to diagnosis of several diseases and disorders. Performances have been simulated and projected visually along with numerical performance metrics like PSNR and SSIM. Superior performance has been observed in each case at reduced complexity and structural cost.

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