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An analysis of noise reduction for sputum smear microscopy images

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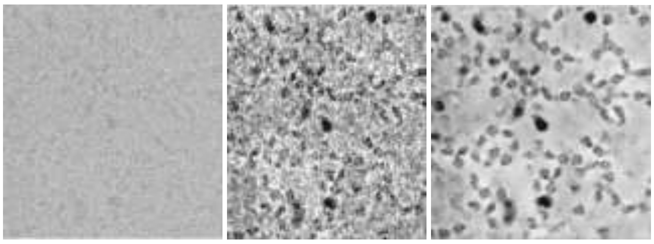
ABSTRACT

Sputum smear microscopy is a primary tool used for the diagnosis of pulmonary TB diseases. Due to its accessibility, minimal bio-safety standard and cost effectiveness, the latter is the most preferred test in low- and middle-income countries [26]. De-noising is a fundamental challenge in microscopy image processing because the images are highly corrupted by salt and pepper noise while transmitting. This paper makes a survey on five methods which can be efficiently applied in de-noising the sputum smear microscopy image processing tasks. The five de-noising methods to publish the survey are namely LCD, GPPCM, IMF, ASWMF and SAF-RGM. The effectiveness of this survey is come along with the metrics such as Peak to Signal noise, Root Mean square Error and the Mean Structure Similarity Index. Many methods for rebuilding spotless images from noisy versions have been proposed. Both the methodology and the outcomes of these methods are dissimilar. This assessment work presents a broad study on image de- noising and suggests a number of promising future research directions.

Keywords: *Pulmonary Tb Diseases; Salt And Pepper Noise; Medical Image Processing; Impulse Noise; Microscopy Image Enhancement.*

1. INTRODUCTION

Image de-noising of medical images has attracted attention of researchers nowadays. Diagnostic imaging is an umbrella term for a wide variety of scans, examinations and images that are used in the field of medicine such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US) and microscopy images. Unfortunately, medical images encounter a various number of noises such as Salt and Pepper, Gaussian, Speckle and Brownian noise [6]. Noise corrupts medical images and hence qualities of the images are degraded. This degradation includes suppression of edges, structural details, blurring boundaries etc. Therefore image de-noising is a very important task and noise should be filtered out, without affecting important features of the image. The speckle noise is found in US images, Rician noise in MRI, random noise in X-Ray and Poisson noise in Scientigraphy data [7]. The noise removal algorithms are meant for removing unwanted information from the digital images, such that the image can be analyzed effectively [8]. Generally there are two kinds of impulse noise. They are fixed valued impulse noise and the other one is the random valued impulse noise. The percentage of pixels corrupted with impulse noise may vary with different environment. Various algorithms with varying de-noising performances have been proposed over the last three decades. Deep learning-based models have recently shown great promise, outperforming all conventional methods. However, these methods are limited by the need for a large training sample size and high computational costs [25]. The two representative measurements to evaluate the performance of a de-noising method are PSNR (Peak Signal to Noise Rate) and SSIM (Structure Similarity Index Measurement). Visual quality comparisons on a set of images are necessary because quantitative measurements can't perfectly reflect visual quality. In addition to noise reduction, edges and textures must be preserved when evaluating a de-noising method [27]. In the case of corrupted images, Fig. 1 depicts the general output of de-noising methods.



(a) (b) (c)

Fig.1. Sample output of image of de-noising., a) Original sputum smear image b) Noisy sputum smear image c) De-noised sputum smear image.

2. SURVEY METHOD

This paper makes a survey with the following five papers in de-noising technique which can be adaptable to sputum smear image noise removal. They are:

- Low complexity method for denoising (LCD) [1]
- Generative patch and Patch clustering method for image denoising (GPPCM) [2].

- Inexact median filters for noise reduction (IMF) [3]
- Weighted Median filter for impulse noise removal. (ASWMF) [4]
- Noise removal using Geman-McClure Estimator (SAF-RGM) [5]

2.1 Low complexity method for denoising (LCD)

Zohreh Hossein Khani et al. [1] advised a low complexity de-noising method to distinguish between noisy and non-noisy pixels. It removes the noise by local analysis of the image blocks. All steps are designed to have low hardware complexity. This method removes impulse noise with an acceptable accuracy. Medical images are almost always contaminated with noise due to some reasons such as errors in data transmission, variation in imaging system characteristics (e.g. lightening.) and so on. This undesired signal could change the anatomical structure. And it degrades the quality of the images and therefore its effect must be minimized before examination. Image histogram and fuzzy [9] method are used to detect noisy pixels. Then, in the restoration stage a median filter is applied around the noisy pixel. For each stage of the proposed method an efficient hardware structure is proposed. This low complexity method consists of the following stages:

- Pixel labeling
- Noise-free pixel detection
- Partitioning
- Local similarity inspection
- Noise removal and pixel restoration
- Image formation.

In the first step of this LCD algorithm, pixels are labeled. Next, to identify the noisy pixels noise-free pixel identification is performed. In the third stage the similarity between neighboring pixels must be examined in order to identify the noisy pixels. The window is partitioned and fed to the similarity inspection module to achieve this goal for each pixel in a 3 x 3 window [10]. Noisy pixels are defined as pixels with intensity values of 0 or 255 that differ from their neighbors [11]. The labeling and similarity inspection procedures are carried out in the same manner that edges are preserved in the local similarity stage. In the noise removal and pixel restoration stage the algorithm is used to replace the noisy pixels with proper values. To generate a noise-free image, noise-free pixels are detected, and restored pixels are reconstructed in the image formation stage.

2.2 Generative patch and patch clustering method for image de-noising (GPPCM)

Bo Fu et al. [2] recommended an image de-noising algorithm based on generative classification to remove the impulsive noise. The salt and pepper noise is driven throughout the image and contains only the maximum or minimum intensity values (i.e., 0 or 255) in the dynamic range. There are two steps to remove the impulsive noise, they are: 1) detection of noisy pixels and 2) repair process. In this work, at first a patch is used as a basic unit to define the patch effectively and to seek a good result for subsequent clustering. A generative model is used to find the salt and pepper noise. Second, by using a generative clustering method the algorithm classifies patches [12]. This gives additional similarity information for noise repairing. At last, the algorithm constructs a non-local switching filter to remove the impulsive noise [13]. This model is used for, classifying the patches by the clustering method to find similar patches. The main steps of this algorithm are:

- Separate noisy image into a set of overlapping patches
- Mark the pixels that have been corrupted by the salt and pepper noise with a local noise identifier [14]
- The size of each patch is L x L and is determined by the noise density. Then, uses the expectation-maximization (EM) method to cluster all of the patches and assign each patch a class label
- In the corresponding class, perform non-local switching filtering for each corrupted pixel
- Combine the de-noised and normal pixels in the final image.

The image patch generation process is explained using a Bayesian model. Patches can be classified using this model, and similar patches can be noticed using the cluster method. The EM clustering method has the potential to suppress noise, so that more similar patches can be found and data regression training can be carried out more effectively [15]. The traditional NLM method degrades the de-noising process during the training process [16]. As a result, a switching filter concept is used to reduce the impact of noise on the block repair model. Researchers can replace suspected noise with the patch's mean because the locations of noise have been marked. Besides this, using a switching non-local filter, all patches in set are used to restore the target patch.

2.3 Inexact median filters for noise reduction (IMF)

M. Monajati et al. [3] suggested an inexact median filter (IMF) for Impulsive noise. Salt and pepper noise is a special kind of impulse noise, where the noisy pixels can take only the maximum and the minimum values in the dynamic range. It seems as aimlessly disband black-and-white dots over gray-level images. Inexact median filter (IMF) achieves largely acceptable image quality under low-cost hardware requirements [17]. An important advantage of IMF is its precise noise cancellation. Also, this work specifically proposes IMFS to remove salts, and IMFP to eliminate peppers, with further hardware complexity reduction. This filter shows the effective results in low cost power consumption, area, and speed. Despite the trade-off between the filtering accuracy and circuit characteristics, the output quality of the filter is largely similar to that of the precise one. The median configurations are possible in both software and hardware. Whereas the median filter is simple to implement in software, it has a high hardware complexity [18]. In this method two bit comparator (TBC) unit tends to result in a comparatively simple filter. When the logic function is simpler, it needs minimal resources to implement, which reduces switching activity and, as a result, lowers power consumption [19]. TBC's logic implementation can be simplified by inserting minor errors in its truth table. Impose the approximation deliberately to ensure that the comparison of 8-bit numbers with salts and peppers is error-free. There are 3 stages in this method:

- Inexact arithmetic for removing peppers
- Inexact arithmetic for removing salts
- Inexact arithmetic for removing salts and peppers.

Using this inexact median filter, it can reduce leakage power by up to 20% when using IMF compared to the previous one. According to our findings, the IMF filter is more energy efficient than the exact one in terms of switching energy.

2.4 Weighted median filter for impulse noise removal (ASWMF)

Jiayi Chen et al. [4] intimated an adaptive sequentially weighted median filter for images corrupted by impulse noise. The three α principles of normal distribution, as well as the local intensity statistics, are fully utilized by adaptive median filter [19]. The three important stages of this method are discussed here.

- *Model of fixed-valued impulse noise:*

In general, the intensity and distribution of fixed valued impulse noise can be used to model it. Impulse noise must have extreme intensity in the image intensity range; for example, in an 8-bit grey image with an intensity range of 0 to 255, impulse noise has intensity values of 0 and 255. When an image is corrupted, impulse noise spreads out random manner and evenly associated with a particular probability.

- *Noise detection by 3 principle and local statistics:*

The local noise-free pixels have a high degree of similarity and are highly correlated with one another, resulting in a local normal distribution that approximates it. Assuming all pixels with extreme intensity are noisy based on the intensity feature of impulse noise may not be valid, as this assumption treats noise-free pixels with extreme intensity as noisy pixels [20]. So employs the 3 principles of normal distribution for further detection based on the just mentioned analyses, with the expectation that the noise detector will be able to distinguish noise-free pixels from noisy pixels with the same intensity value.

- *Noise removal by adaptive sequentially weighted median:*

The adaptive weighted median filter [21] processing is applied to each detected noisy pixel. If noise-free pixels are available on the border, use the weighted operator to perform weighted processing on them. After processing all the detected noisy pixels, replace each unprocessed noisy pixel with the median of its neighborhood pixel, which includes both processed and unprocessed pixels.

The adaptive sequentially weighted median processing, which uses a sequentially weighted operator to accurately distinguish the contributions and impacts of neighbor pixels on the central pixel, can achieve a better recovery result and can restore the edge and structure information very well.

2.5 Noise removal using Geman-McClure estimator (SAF-RGM)

Qianqian Liu et al. [5] put forth a method SAF-RGM using nonlinear spline adaptive filter based on the robust Geman-McClure estimator. The SAF-RGM algorithm is acquired by reducing the cost function relied on the Geman-McClure estimator. It can remove outliers with large amplitude from dataset. This algorithm can give the better performance in the salt and pepper noise. Replications are performed to finalize the SAF-RGM algorithm to reach the excellent performance than the existing spline nonlinear adaptive filtering algorithms. The Geman-McClure estimator is frequently used for designing robust adaptive algorithms and learning systems against impulsive noise [22]. So the SAF-RGM algorithm has a better performance against the impulsive noise. And also it performs the mean and mean square performance analysis of the SAF-RGM algorithm. The advantage of SAF-RGM algorithm is robust against heavy range impulsive noise. The Geman-McClure estimator has been commonly used in computer learning and signal processing [23], and the spline adaptive filtering algorithm is based on it.

The Geman-McClure estimator is based on cost function [24].When the error is a high magnitude signal, the gradient value becomes small. Also, this method runs the SAF-RGM algorithm through a mean and mean square performance analysis. Simulation shows that this algorithm outperforms existing algorithms. As a result, in the presence of impulsive noise, the SAF-RGM achieves a more stable performance than the nonlinear SAF algorithm. The following are the primary contributions of this paper:

(i) For improved performance in the presence of impulsive noises, the Geman-McClure estimator is first applied to the nonlinear spline filter.
(ii) The SAF-RGM algorithm is subjected to mean and mean square performance analyses.

3. ANALYSIS AND DISCUSSION

The PSNR block computes the peak signal-to-noise ratio in decibels, between two images. This ratio is used as a quality measurement between the original and a de-noised image. The higher the PSNR, the better the quality of reconstructed image. PSNR can be computed using Equation (1).

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \qquad (1)$$

Where,

MSE – Mean Square Error

Table 1: PSNR analysis

Methods name	PSNR (db)
LCD	26.41
GPPCM	30.12
IMF	32.44
ASWMF	34.82
SAF-RGM	38.07

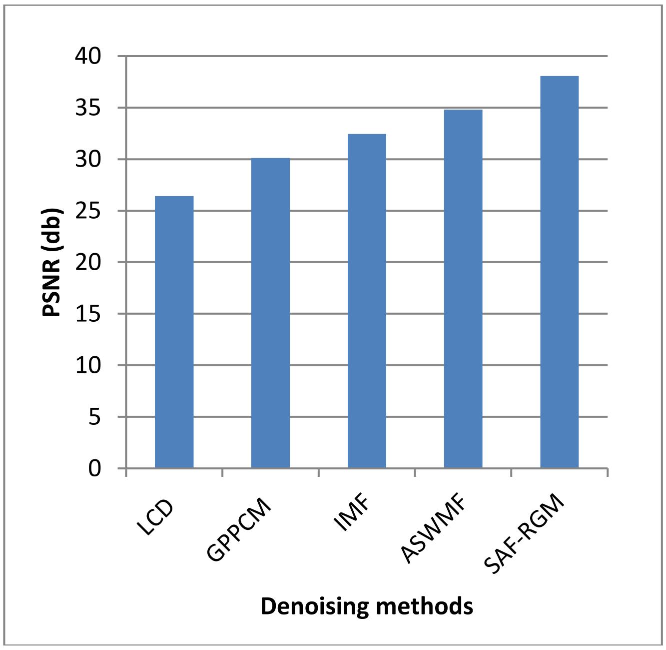


Fig.2. Chart for de-noising PSNR.

Table 1 and Figure 2 illustrate the PSNR analysis for the five different methods namely LCD, GPPCM, LCD, ASWMF and SAF-RGM. The chart shows that the SAF-RGM method gives a better PSNR value when compared to other methods. It gives 38.07 db. The ASWMF method gives 34.82 db, so it's the second best method. The chart describes that the IMF method gives 32.44 db of PSNR. The GPPCM method gives 30.12 db PSNR and the least PSNR giving method is LCD, and its PSNR value is 26.41db.

Table 2: Analysis on techniques used in de-noising methods.

Methods	Publication	Year	Author name	De-noising technique
LCD [1]	Journal of Medical Systems	2018	Zohreh Hossein Khani et al.	Weighted fuzzy filter
GPPCM [2]	Multimedia Tools and Applications	2018	Bo Fu et al.	Generative clustering method
IMF [3]	IEEE	2019	M. Monajati et al.	Histogram based error detection technique
ASWMF [4]	IEEE	2019	Jiayi Chen et al.	Sequentially weighted median filter
SAF-RGM [5]	IEEE	2020	Qianqian Liu et al.	Geman-McClure estimator

The Table 2 contains information on the techniques used in five methods, as well as it gives the publication information.

Table 3: Analysis on merits and demerits

METHODS	MERIT	DEMERIT
LCD	Better accuracy in impulse noise removal	Not efficiently remove the random-valued impulse noise
GPPCM	Obtaining a better de noising effects	Edge structures are damaged heavily
IMF	Execution of this method in low cost	For huge noises the blur occur
ASWMF	Structure and edge information preservation	Not efficiently remove the real time image noise
SAF-RGM	Faster convergence rate and the better tracking	It takes high cast hardware implementation and hardware convention cost

The Table 3 outlines the advantages and drawbacks of the five different methods.

4. CONCLUSION

Noise removal in sputum smear microscopy image is the great challenge for the researchers. The LCD filter, GPPCM filter, IMF filter, ASWMF filter, and SAF-RGM filter are the five recent works on image de-noising methods that reviewed in this paper. This study analyses the noise reduction schemes for medical and other types of images to eliminate impulse noises based on PSNR metrics. The SAF-RGM method is considered as better one because it gives the highest PSNR value 38.07 db. ASWMF method produces the second highest PSNR value 34.82 db. The LCD method provides the least PSNR value 26.41db. SAF-RGM method is suitable for microscopy image de noising because of the high accuracy. For low cast hardware the LCD method is suitable because it contains less complexity. From this survey the future researchers can get information for their research work.

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