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De-Noising X-Ray Images BY Fast Non-Local Mean FOR Pulmonary Tuberculosis Detection – An Application

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There are numerous facets of our existence, including the medical field, that need the use of digital photographs. However, medical pictures may get distorted due to noise, particularly Poisson noise, which can dramatically lower the quality of X-ray images. This can be especially problematic in emergency situations. Denoising an image is a basic image processing method with the goal of reducing the amount of noise present in a picture. The Peak Signal-to-Noise Ratio, abbreviated as PSNR, is a statistic that is often used to evaluate the quality of denoised photographs. This research indicates that the Non-Local Means (NLM) approach is successful in decreasing Poisson noise in X-ray lung images taken from the publicly accessible Shenzhen (SH) and Montgomery (MC) datasets. The datasets were obtained from Shenzhen and Montgomery, respectively. Images of the lungs are often blurry, thus in order to denoise them, the NLM method, more especially the Fast Local Means approach, is used. The following three important metrics—peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and root mean square error (RMSE)—are used in the process of performance analysis of the method. The results of the experiments make it abundantly evident that the suggested method is capable of effectively preserving picture edges while simultaneously lowering noise. As a consequence, the X-ray images are upgraded to have a higher PSNR, an increased SSIM, and a lowered RMSE.

Keywords: Poisson noise, denoising, NLM, PSNR, SSIM, RMSE.I.

INTRODUCTION

Noise may come from a number of causes, such as faults with the equipment, problems with the data gathering, or interference, and it is possible for this noise to distort digital pictures, which are significant in many different ways. The term "noise" refers to any disruption in a picture that is not desired. Noise cannot be eliminated entirely, however it may be mitigated by the use of several image processing methods [1].Eliminating noise from photos is a challenging undertaking, particularly in the field of medical imaging, where high-quality images are essential for providing correct diagnoses. When creating denoising algorithms for medical pictures, it is essential to ensure that the edges and fine features of the images are maintained while simultaneously improving the images' overall quality. [2].

The formation of an X-ray picture begins with the subjecting of a particular area of the patient's body to X-ray radiation and the subsequent recording of the radiation's attenuation or absorption by the area. Poisson noise is a sort of background noise that is generated by these imaging systems. This type of noise is also known as shot noise, photon noise, Schott noise, or quantum noise. Poisson noise is a basic uncertainty in the measurement of light intensity. This uncertainty is caused by the discrete character of light and the separate detection of photons, and it is referred to as the Poisson distribution. Poisson noise is a sort of background noise that is not influenced by factors such as temperature or frequency; rather, it is determined by the characteristics of the photon detector. The shift from analogue to digital technology has been absolutely necessary in the field of medical imaging in order to achieve higher picture quality. Poisson noise, on the other hand, presents a hurdle since it is signal-dependent. This implies that the noise becomes more noticeable as the brightness of the picture increases. In order to do this, specialized algorithms must be used. When sensors can only pick up a small number of photons, a sort of noise known as Poisson noise is produced. This indicates that there is insufficient data to construct an accurate picture of the situation. [4,5]. Imaging techniques such as X-ray and nuclear imaging are notorious for having high levels of Poisson noise. [6].

This paper aims to reduce Poisson noise in X-ray images to improve image quality and facilitate more accurate disease detection. The study uses the Non-Local Means (NLM) denoising technique, which builds on the strengths of conventional algorithms while addressing their limitations.

II. RELATED WORKS

Umadevi [7] proposed a novel hybrid model to effectively reduce Poisson noise in X-ray images. Their approach combined Independent Component Analysis (ICA) and Multi Wavelet Denoising (MWD) techniques. They evaluated the hybrid model's performance by assessing its PSNR and denoising speed. To compare its capabilities, they compared it to a previous system.

Khursheed et al. (8) proposed a unique methodology to mitigate Poisson noise in X-ray images. Their method calculates the cumulative total of logarithmic gradients in 3x3 windows for each pixel, addressing bias using logarithmic values from the central pixel. They tested this approach on various levels of Poisson noise, including Lena images, X-rays, PET scans, and SPECT images. Performance assessment was based on (MSSIM) and (MSE), revealing superior results compared to Median and Wiener filters. This method produced visually improved outputs, particularly evident in SPECT images.

Kirti et al. (2019) introduced a spatial domain method to address Poisson noise reduction by modifying the bilateral filter framework. Their Poisson reducing bilateral filter (PRBF) demonstrated superior efficacy compared to iterative strategies.

Thierry et al. (2010) presented PURE-LET, a denoising approach focused on reducing Poisson unbiased risk in the image domain. This method utilized undecimated discrete wavelet transform with potential further modifications involving wavelet analysis.

Donho et al. (11) emphasized the well-recognized effectiveness of wavelet thresholding for denoising. Wavelet thresholding involves dividing a signal into approximation and detail sub-bands, with coefficients in the detail sub-band undergoing thresholding (hard or soft). Wavelet thresholding can autonomously process different frequency components of an image, but it tends to attenuate edge sharpness. Roy et al. [1] proposed a hybrid denoising model that outperformed other methods in terms of PSNR, IQI, uniformity, and consistency across various image types. They found that applying bilateral filters before and after decomposition improved performance.

Wang et al. [12] used a wavelet thresholding approach for denoising COVID-19 CT images, incorporating an upgraded particle swarm optimization algorithm to obtain threshold functions.

Bansal et al. (2013) enhanced the NLM image denoising method by integrating PCA, improving precision and reducing computational load by calculating denoising weights based on subspace distances rather than the full space. This modification resulted in improved accuracy and computational efficiency.

III. MATERIALS AND METHODS

A. Dataset

The initial step in algorithm training entails the collection and construction of a dataset. Having a dataset is essential for training our algorithms for specific tasks. In our research, the use of chest X-ray (CXR) images is crucial for training our algorithms, as we are primarily focused on the denoising process, which holds significant importance for subsequent stages. Acquiring medical data can be a challenging process due to the sensitive nature of the information involved and the need for extensive documentation. Fortunately, many scholars and researchers have made medical data available to facilitate the extraction of valuable insights and knowledge. We sourced our data from two publicly accessible datasets, specifically the Montgomery County (MC) X-ray collection and the Shenzhen China (SH) dataset [25].

B. Non- Local Mean (NLM)

The NLM technique, a recent innovation in noise reduction, employs a unique approach distinct from the methods mentioned earlier. Unlike traditional local smoothing filters, NLM takes a different approach by calculating a non-local average of all pixels within the image. This process entails computing the average value of pixels with similar intensities based on their spatial distance, effectively reconstructing a single pixel. Each pixel's estimation involves a weighted average calculation, determined by the similarity between pixels in the image. The weights assigned to each pixel depend on this similarity measure and are determined by the disparity in intensity grey level vectors between the pixel in question and the target pixel [16]. The correlation between image pixels and the independent, identically distributed nature of noise enables noise cancellation through pixel averaging, resulting in a pixel value that closely approximates its original value. The Non-Local Means (NLM) algorithm has proven highly effective in noise reduction. However, its significant computational requirements have limited its widespread adoption. Additionally, NLM has limitations in situations requiring substantial noise reduction, as it operates on noisy image patches [13].

Within the scope of this research, a number of NL X-ray denoising approaches have been investigated [17]. The noise reduction technique known as nonlocal means was first presented in the publication by [18]. This technique involves replacing a noisy pixel in an image with a weighted average of other pixels exhibiting similarity, even if these other pixels are located in different parts of the same image. These nonlocally selected pixels are what are referred to as "nonlocal selected pixels."

Let's denote u = {u(i), i = 1, 2, 3, ..., I} as the genuine image and v = {v(i), i = 1, 2, 3, ..., I} as the image affected by noise, with I representing the total number of pixels. Consequently, we can formulate the image model that accounts for the noise as follows:

v = u + n,

where n ={ n(i) , i= 1,2,3…,I} is a noise.

Comparison of the similarity between the image patch that is centred on each pixel that has to be processed and all of the image blocks that are spread out over the complete picture is the standard method for finding the weight in the NLM approach to image denoising. This technique is part of the standard technique for determining the weight in the NLM approach to image denoising. This is done in order to determine the weight. This strategy makes use of a search zone that is big enough to include the whole picture. It is common knowledge that, in real-world situations, using a broad search window with a size of K by K may successfully cut down on the amount of computing complexity that is required. In a similar vein, using a more compact similarity block with dimensions k by k may also help to streamline the computing process [16].

1) Algorithm:

In the initial step, a substantial search window (K×K) is established, centered around pixel i. Simultaneously, a block of dimensions k×k is created, also centered at pixel i.

Moving to the second step, the user is directed to specify a square block of size k*k, centered at location j, within the previously defined search window. Following this, the square block at center point j is allowed to traverse within the designated search window. Subsequently, weight coefficients w(i, j) are computed for two comparable blocks, with i and j representing their respective centers, utilizing Gaussian-weighted Euclidean distance.

The third step involves calculating the weight coefficient w(i, j), followed by iterating through all j locations inside the search window.

In the fourth and final phase of the process, the weight coefficient undergoes normalization. Then, the pixel value for the denoised point i is determined by applying the weighted sum formula, as outlined in reference [19].

$$\tilde{v}(i) = \sum_{j \in K \times K} w(i, j) \times v(j)$$

The variable w(i, j) serves as a measure of similarity between the blocks centered on pixel i and pixel j.

Image denoising is accomplished by performing a final step in which the process entails scanning over all of the image's pixels to get the desired result.

IV.EXPERIMENTAL ANALYSIS AND RESULTS

To assess the efficiency of our system, we carry out testing on a varied range of noisy images. Subsequently, we employ the Non-Local Mean algorithm to process these noisy images, and we subsequently make a comparison between the outcomes achieved through our existing method and the novel approach. When evaluating the performance of image processing techniques, it is customary to utilize metrics such as (PSNR), (SSIM), (RMSE).

A. PSNR

The PSNR is a quantitative metric that assesses the connection between the highest attainable power of an image and the intensity of the noise it experiences, typically measured in decibels. This ratio serves as an indicator for gauging image quality concerning its compressed version. A higher image quality can be deduced from a lower mean squared error (MSE) and a higher PSNR value.

$$PSNR = 10. \log\_10\left(\frac{UL_i^2}{MSE}\right) = 20. \log\_10\left(\frac{UL_i}{\sqrt{MSE}}\right)$$

Where UL is the Upper Limit of an image D, MSE is a Mean Square Error, expressed as

$$MSE=\frac{1}{mn}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\|(Oi,j)-D(i,j)\|^2$$

Where D is denoised image and O is original image

B. (SSIM)

The SSIM is a metric utilized to quantify the degree of resemblance between two provided pictures. The SSIM of two pictures, denoted as D and O, may be mathematically described as follows:

$$SSIM=\frac{(2\gamma_D\gamma_O+x_1)(\sigma_{D0}+x_2)}{(\gamma_D^2+\gamma_O^2+x_1)(\sigma_1^2+\sigma_2^2+x_2)}$$

In the given equations, γ_D and γ_O represent the means of two variables, D and O, respectively. The symbols σ_1^2 and σ_2^2 stand for the variances of D and O, respectively, while σ_D0 represents the covariance between these two variables. Furthermore, the variables x_1 and x_2 are defined as the squares of constants, namely (k_1 L) and (k_2 L), respectively, which are introduced to ensure stability.

k_1 = 0.01 and k_2 = 0.03 are the default values that are often used to characterise the dynamic range of pixel values inside the picture, which is typically indicated as L. The range of the SSIM is constructed as a closed interval spanning from 0 to 1, with a greater SSIM value indicating improved picture quality. This range may vary from 0 to 1.

C. RMSE

The RMSE is a statistic that is used to assess the average difference between the original picture and the denoised version of the image. The RMSE is a statistic that has a range that goes from 0 to positive infinity, with lower RMSE values indicating better model performance.

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\|(Oi,j)-D(i,j)\|^2}$$

I. NLM DENOISING for MONTGOMERY DATASET

IMAGE	PSNR	SSIM	RMSE
MCUCXR_0004_0	26.964553112094332	0.9359420832590122	11.437010631858625
MCUCXR_0017_0	27.079783021930062	0.8876273473427299	11.286285429043552

MCUCXR_0021_0	26.084222091897885	0.9490010143072339	12.656950331379244
MCUCXR_0258_1	26.961095188725754	0.8950867015176169	11.441564705335832
MCUCXR_0019_0	25.702747931831013	0.9188120567931121	13.225216304224212

II. NLM DENOISING for SHENZHEN DATASET

IMAGE	PSNR	SSIM	RMSE
CHNCXR_0001_0	24.407711991725787	0.8815043879625438	15.351633047694826
CHNCXR_0006_0	24.347105674897996	0.868330148805613	15.459124567820476
CHNCXR_0010_0	24.229540325885665	0.8518259563402223	15.669789562188145
CHNCXR_0135_0	24.229979335204014	0.8770953766797621	15.668997586918207
CHNCXR_0076_0	24.346535916242026	0.8159053754576803	15.46013865610537

V.CONCLUSION AND FUTURE DIRECTIONS

Within the realm of medical research, the presence of noise in biomedical imaging is a considerable difficulty. In recent years, there has been an increasing emphasis on the study of medical image denoising, an area that has gained major interest from scholars. One of the main reasons for this attention is the importance of reducing noise in medical images. Denoising methods continue to be in great demand, notably in the field of medical image processing, and more specifically for X-ray pictures, which are subject to restrictions as a result of the photon sensitivity of the imaging device.

In this study, the NLM algorithm is employed as it effectively addresses the constraints that conventional algorithms often encounter. The performance evaluation of the NLM algorithm reveals noteworthy findings. On the Montgomery (MC) dataset, the model yields average values of 26.5 for PSNR, 0.92 for (SSIM), and 12.0 for (RMSE). Conversely, on the Shenzhen (SH) dataset, the corresponding values are 24.31 for PSNR, 0.85 for SSIM, and 15.0 for RMSE.

These results clearly demonstrate the method's superiority in terms of higher PSNR, increased (SSIM), and lower RMSE when compared to traditional algorithms. As a result, this technique proves highly suitable for addressing Poisson noise in X-ray medical imaging modalities. Looking ahead, the future direction involves the development of novel techniques and subsequent performance assessments in comparison to the established NLM algorithm.

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