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Comparative Study of Denoising Methods for Medical Images

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Abstract: Digital modalities are extremely important in the medical field. The introduction of noise during the gathering of medical images, on the other hand, is unavoidable and is a natural event. The presence of noise reduces image quality and accuracy. Image denoising improves the accuracy of medical image processing and has a wide range of applications in both research and clinical practise. A lot of work has gone into developing an efficient and reliable method for medical image denoising. Despite some hopeful discoveries, developing a completely noise-free approach for medical images remains a difficult task. This work conducts a comprehensive assessment and analysis of all available Image Denoising techniques, covering their numerous concerns and challenges, as well as their benefits. To summarise, different medical modalities produce different types of noise, and in order to address that noise, a sophisticated, dedicated, non-iterative, quick, and easy denoising technique is required.

Keywords: Medical Images, DenoisingTechniques, Filters, Chromosomes

1. Introduction

Medical imaging is a strong technique for creating visual images of the inside of a body, and it's very valuable for clinical analysis and medical intrusion. Medical imaging, often known as digital modalities, lifts the veil from the human body's internal systems, which are obscured by the skin and bones. It aids clinicians in the diagnosis and treatment of ailments. It's also useful for spotting anomalies in normal anatomy. EEG(Electroencephalography),ECG(Electrocardiography), and MEG (Magneto Encephalography) are primarily intended for recording and mapping data relating to the human body throughout time, and are not intended to make images from the data acquired. Medical imaging, on the other hand, includes radiology, which includes a variety of imaging techniques such as X-ray imaging, MRI (Magnetic Resonance Imaging), Ultrasound imaging or Ultrasonography, Endoscopy, Tactile imaging, thermography, PET (Positron Emission Tomography), and SPECT (Single-photon emission computed tomography). These techniques are primarily designed to produce images from captured data. Noise is a key issue in the above medical picture modalities that emerges during image capture. Because each picture modality imaging system is different, this noise or degradation in an image is distinct. Noise in a photograph degrades image quality dramatically. It has an impact on both human abilities and computer-assisted methods in terms of interpretation and accuracy. Feature extraction from medical images, image analysis, image identification, and measurements are only a few examples which get affected due to this noise. The presence of noise reduces image quality and accuracy. As a result, the relevance of identifying and removing noise from medical images is well understood. It improves the accuracy of medical image analysis and has a wide range of applications in both research and clinical practise. Over the last 60 years, a lot of work has gone into developing an efficient and reliable method for medical picture denoising. Despite the promising results, developing a completely noise-free approach for medical images remains a difficult task. As a result, image denoising must be completed prior to running the image processing application. In general, low-pass strainers and noise content can cause a picture to be distorted. This low-pass strainer employs convinced operation to blur/smooth the image. Image restoration has proven to be useful in a variety of applications, including planetary imaging, medical imaging, isolated sensing, microscopic imaging, and gunshot deblurring [2]. This paper's main goal is to eliminate noise from medical photographs. As previously stated, a variety of medical imaging techniques are available, each with its own picture collection process, hence noise is not specific to these medical imaging systems.Primary picture denoising in the spatial domain is accomplished by averaging the image. This, however, causes blurring at the corners. In the spatial domain, the anisotropic diffusion principle is a prominent denoising approach. It uses a gradient of brightness function to distinguish edges and boundaries from smooth regions. However, when the brightness gradient created by noise is higher than the edge, this strategy fails. Due to its simplicity and non-iterative nature, bilateral filtering is another common strategy in the spatial domain. However, one of the most difficult issues is parameter selection. Because the method considers global image statistics rather than local statistics, it is an amazing technique for noise reduction; nonetheless, this technique requires greater time complexity than other algorithms. The BM3D algorithm (block matching and collaborative filtering) adds a new dimension to the denoising approach. This technique is considered to be state-of-the-art; yet, it is sophisticated in nature and requires additional processing time. Nonlocal means (for Poisson and Speckle noise) and BM3D for Poisson and Speckle reduction are the current state-of-the-art algorithms. There are numerous factors to consider while creating a new denoising algorithm for medical photos. The preservation of fine details in medical images is critical in order to preserve significant patient information. For rectifying medical picture evaluation by doctors or practitioners, a precise distinction between genuine image content and noise is expected. The new method is expected to improve the detectability of radiographic images. Existing state-of-the-art spatial approaches are iterative and have a higher time complexity. With its global processing method and non-iterative nature, the suggested denoising algorithm should have less computational complexity. Because medical images are huge in size, processing large images takes longer. The time it takes to process a large medical image increases as the size of the image increases. As a result, to reduce time complexity, a selective region-based picture denoising method is required.

2. Filter Models

In general, there are two types of filters used for denoising technique.

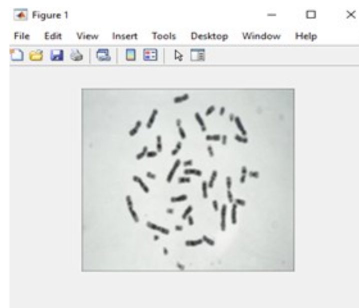
2.1. Linear Filters

Linear filters are mean filters or average filters. The filtering method involves taking an average of the pixel values. The three types of Mean Filters are as follows.

Arithmetic Filter by Mean: It calculates the average value of the corrupted image g(x, y) in the mxn-squared region defined by the kernel. The entire image is divided by the mask size mn at the end of the filtering process. At position (x,y), the output of picture f is given by,

$$f(x,y)=\frac{1}{mn}\sum_{(s,t)\in Sxy} g(s,t)$$

As a result of blurring, the filter smooths out local fluctuations in an image, and noise is decreased.

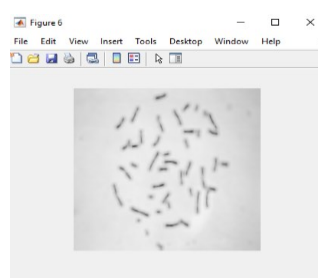


Geometric Mean Filter: It calculates the (mxn)th root of the value by multiplying the product of the pixels in the sub image window. This value takes the place of the sub image's centre pixel. The disadvantage of this filter is that during the smoothing process, it loses less image detail.

$$f(x,y)=\left[\prod_{(s,t)\in S_{xy}} g(s,t)\right]^{\frac{1}{mn}}$$

The Harmonic Mean Filter works well with salt and Gaussian noise, but not with pepper noise. The equation tells us what it is.

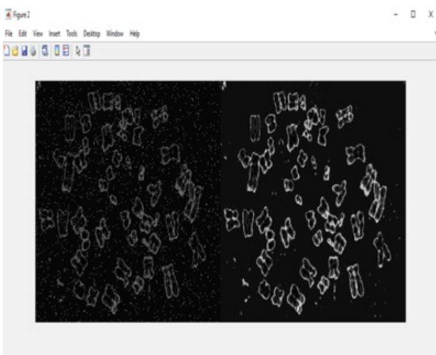
$$f(x,y)=\frac{mn}{\sum_{(s,t)\in S_{xy}} \frac{1}{g(s,t)}}$$



2.2. Nonlinear Filters

Non-linear filters are statistical filters. They determine the restored pixel in the sub picture area by ranking all of the pixel values in that area in a particular order. The median of the intensity levels of all the pixels in that window replaces the value of the pixel at the centre of the window (x,y). It works well with noise, salt, and pepper (unipolar and bipolar impulse noise). When compared to linear smoothing filters of the same size, it creates less blurring.

$$f(x,y) = \underset{(s,t)\in S_{xy}}{median} \{g(s,t)\}$$



Max and Min Filters: In the Max filter, the sub image window's centre pixel is replaced by the maximum pixel value in the near vicinity. It finds the brightest points in an image and reduces pepper noise.

$$f(x,y) = \max_{(s,t)\in S_{xy}} \{g(s,t)\}$$

In the Min filter, the value is replaced by the window's minimum pixel intensity. It discovers the darkest points in an image and decreases salt noise due to its high value.

$$f(x,y) = \min_{(s,t)\in S_{xy}} \{g(s,t)\}$$

Midpoint Filter:

The midpoint between the maximum and minimum values in the sub picture or window is calculated with the Midpoint Filter. It is most effective when dealing with Gaussian and uniform noise.

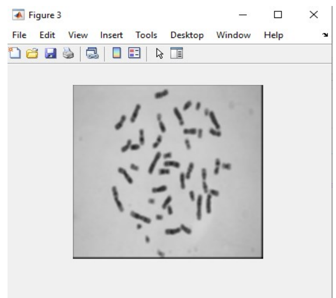
The midpoint between the maximum and minimum values in the sub picture or window is calculated with the Midpoint Filter. It is most effective when dealing with Gaussian and uniform noise.

$$f(x,y) = \frac{1}{2}\left[\max_{(s,t)\in S_{xy}} \{g(s,t)\} + \min_{(s,t)\in S_{xy}} \{g(s,t)\}\right]$$

Alpha Trimmed Mean Filter:

It removes the d/2 lowest and maximum intensity values of g(s,t) in the sub image neighbourhood Sxy with the Alpha Trimmed Mean Filter. The leftover pixels are then averaged. It is used to remove numerous types of noise, such as a Gaussian and Salt & Pepper combination.

$$f(x,y) = \frac{1}{mn-d} \sum_{(s,t)\in S_{xy}} g_r(s,t)$$



Gaussian Filter

A Gaussian function of two variables has the basic form:

$$h(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where x and y are considered to be integers, and is the standard deviation. We sample the function around its centre to build a filter mask. It's a bell-shaped function that adjusts the bell's width and tightness. The weighted mean filter is also known as the Gaussian mask, because the weights in the centre are higher than those in the periphery.

Wiener Filter:

Wiener filtering achieves the best balance of inverse filtering and noise smoothing. It simultaneously removes additive noise and inverts blurring. In terms of mean square error, Wiener filtering is the best option. In the inverse filtering and noise smoothing process, it reduces the overall mean square error. The original image is estimated linearly. The strategy is based on a stochastic framework.

3. Literature Review

Two sections make up the literature review. To begin, a review of the literature on spatial domain picture denoising approaches will be presented. Second, there are reviews of the literature on transform domain denoising methods.

Literature Review on Spatial Domain Denoising Techniques

September 2010, [3]: Charles-Alban Deledalle, Florence Tupin, and Loic Denis The authors of this study presented the non-local mean (NLM) algorithm for removing Gaussian noise from images. However, in this research, the NLM method has been tweaked to deal with Poisson noise-corrupted images. For estimating nonlocal means, PURE (Poisson Unbiased Risk Estimator) is employed, and Newton's Method is used to provide optimum parameter estimation in a few rounds. The algorithm's core premise is to compare noisy patches and patches of a pre-estimated image using probabilistic similarities. This algorithm's two major drawbacks are its iterative strategy and computing complexity.

October 2009 [4]: Pierrick Coupe, Pierre Hellier, Charles Kervrann, and Christian Barillot The non-local means approach is used to reduce speckle noise in ultrasound pictures in this paper. For modelling speckle noise, the authors suggested a Bayesian framework. The suggested algorithm's main advantages are the preservation of correct edges and structural features. They also employed a block-wise technique rather than a pixel-wise approach to speed up the algorithm. Similarly, Pearson distance is used to determine similarity. OBNLM stands for 'Optimised Bayesian NL-means with block selection,' as the author put it. The algorithm's restriction is the issue of selecting settings for experimentation.

August 2010, [5]: Balocco S., Gatta C., Pujol O., Mauri J., Radeva P. The research proposes a fully automatic speckle reduction denoising algorithm as well as a change to the basic bilateral filter. This filter is referred to as a 'Speckle Reducing Bilateral Filter' by the author (SRBF). For processing multiplicative noise that follows the Rayleigh distribution, its technique considers local statistics. Maximum likelihood estimation is used to estimate the parameters of the Rayleigh pdf (probability distribution function). The size of the speckles is calculated directly from the image and utilised for image denoising. The authors tested their method on a variety of simulated and real ultrasound pictures with varying levels of noise. They demonstrated that the proposed method is equivalent and effective in terms of time complexity. Calculating the size of speckles is a restriction.

March 2012, [6]: Markku Makitalo and Alessandro Foi The authors present an unbiased Anscombe transform for Poisson-Gaussian mixed noise in this study. The Anscombe transform is mostly used to stabilise the variance of images that have been distorted by Poisson noise. The Anscombe transform was first proposed by the same researchers, however they only considered Poisson noise and a biassed inverse transform. With testing, the authors established that the Anscombe transform should have exactly unbiased inverse as opposed to algebraic or asymptotic inverse for perfect 24 denoising outcomes. They also demonstrated that using a combination of the generalised Anscombe transform and the BM3D method to remove Poisson noise is a state-of-the-art technique.

Literature Review on Transform Domain Denoising Techniques

August 2013, [7]: Gregorio Andria, Filippo Attivissimo, Anna M. L. Lanzolla, and Mario Savino An exponential threshold for despeckling ultrasound pictures was presented in this research. The wavelet coefficients of the ultrasound image are used to evaluate this adaptive data-driven exponential threshold. In the wavelet domain, the suggested method presented empirical observations concerning clean and noisy ultrasound pictures. According to the authors, detailed subbands of clean ultrasound images have a heavy-tailed distribution, whereas noisy images have a smooth distribution. As a result, noisy coefficients are remapped using an exponential threshold based on these empirical observations. Speckle noise can be suppressed while signal details are preserved using this technique.

March 2013, [8]: Jun Liu, Xue-cheng Tai, Haiyang Huang, Zhongdan Huan To reduce mixed noise, the authors suggest a generic weighted norm based on the energy minimization model in this study. In their studies, the authors included Gaussian-gaussian mixture, impulse noise, and Gaussian-impulse noise from the images. Normally, the authors' technique is based on the maximum likelihood estimation framework and sparse representations over a learned dictionary, but in this paper, the authors' approach is based on the

maximum likelihood estimation framework and sparse representations over a taught dictionary. The general model of the algorithm is its strength, since it can function effectively in both Gaussian and non-Gaussian noise circumstances. Due to the time-consuming two-stage processing (sparse coding and dictionary learning), the computational complexity is higher than the K-SVD approach.April 2014, [9]: V. Vijay Kumar Raju, M. Prema Kumar The two authors proposed employing Dual tree complex wavelet transforms and Curvelet transforms to denoise MRI and X-ray images. The authors stated in this research that Curvelet transform-based picture denoising outperforms Dual tree wavelet transform in terms of PSNR. When compared to the Dual tree complex wavelet transform, the key advantage of this approach is that it keeps certain standard features and edge information. The authors utilised soft and hard thresholding, which is a limitation of this technique. If the thresholding method is tweaked, the results may improve even more.

S. Rajavelu V.P. Palanisamy, Varun P. Gopi, Pavithran M. Nishanth T. Balaji, Varun P. Gopi, Pavithran M. Nishanth T. Balaji, S. Rajavelu V.P. Palanisamy, February 2014, [10]: These researchers utilised an undecimated double density dual-tree wavelet transform with a sub-band adaptive cutoff for picture denoising in this article. The statistical properties of each sub-band are analysed to find an adaptive threshold, which is then applied using modified soft thresholding. The disadvantages of the discrete wavelet transform (DWT) are that it is shiftvariant and has less directionality. The DDDTDWT (double density dual tree discrete wavelet transform) is a shift-invariant transform that captures directional information. The UDDDT-DWT (undecimated double density dual tree discrete wavelet transform) improves on the DDDT-DWT by making it shift-invariant. This algorithm's shortcoming is its high computational complexity.

June 2015, [11]: C.J. Li, H.X. Yang, Y.Y. Cai, B. Song The authors presented an approach based on Nonsubsampled Contourlet Transform (NSCT) and bilateral filtering to reduce image noise more effectively. The noisy image is first divided into multi-scale and multidirectional sub-bands using NSCT, and each high-pass component's directional sub-bands are processed by the new threshold function, which is derived by the Bayes threshold, which is based on stratified noise estimation. The low-pass sub-band generated image is further denoised in the spatial domain by bilateral filtering during reconstruction. Using advanced transform, the outcomes of an algorithm can be enhanced.

[12] Wang-Q Lim, May 2010: The authors of this research claimed that assessing the image's intrinsic geometrical properties is critical for image processing applications. Many algorithms/techniques have been proposed by researchers to do this. The authors created the Discrete Shearlet Transform (DST), which enables efficient multiscale directional representation, and demonstrated that the transform's implementation is built in a discrete framework using a multiresolution analysis (MRA). The computing cost of the Discrete Shearlet Transform is similar to that of the DWT, but it is not less than the transform's limitation. Another drawback of this transform is its high memory consumption.

4. Conclusion

For smooth regions in the spatial domain, averaging is utilised. This, however, causes blurring at the corners. In the spatial domain, the anisotropic diffusion principle is a prominent denoising approach. Using the brightness function's gradient, it was able to distinguish edges and boundaries from smooth regions. When the brightness gradient caused by noise is higher than the edge brightness gradient, this approach fails. Due to its simplicity and non-iterative nature, bilateral filtering is another common strategy in the spatial domain. The challenge of parameter selection, on the other hand, is critical. Due to the global consideration of image statistics rather than local statistics at the time of processing, the nonlocal means algorithm is an impressive technique for noise reduction. This strategy, however, necessitates a higher level of time complexity than previous algorithms. The BM3D algorithm (block matching and collaborative filtering) adds a new dimension to the denoising approach. This technique is considered to be the current state of the art; nonetheless, it is sophisticated and requires more processing effort. Given the circumstances, it is evident that medical picture denoising techniques are in high demand around the world. The process of creating a denoising algorithm for medical images has numerous facets. One of the most crucial requirements is to preserve the fine details of the medical image so that any essential patient information is not lost during the noise removal process. Denoising technology is supposed to provide a clear distinction between genuine image content and noise for accurate medical image interpretation by doctors or practitioners. The new method is expected to improve the detectability of radiographic images. Existing state-of-the-art procedures are iterative and have a higher level of time complexity. As a result of the global processing method and non-iterative nature of the proposed denoising technology, it should have less computing complexity. The size of medical images is huge, so processing large images takes longer. To reduce temporal complexity, a selective region-based picture denoising technique is required.

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