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Effective Preprocessing of Medical Images using Denoising Techniques

S. Asha, M. Parvathy

Abstract: Since the last few decades, image denoising is one of the most widely concentrated areas of research in the domain of image processing. A wide variety of denoising algorithms have been explored to date, but the problem of noise prevention in Magnetic Resonance Images is still a great barrier to the diagnosis and treatment of certain diseases. This paper mainly focuses on the study and analysis of different Denoising algorithms, the type of noise handled, and their efficiency. Preprocessing of medical images is considered one of the important steps that can enhance the accuracy in the prediction of various diseases. The presence of noise and other artifacts are believed to degrade the prediction accuracy which is the important metric that directs physicians to prolong further in providing clinical guidance to the patients. Most of the algorithms perform denoising in the complex domain. Deep learning-based Denoising algorithms are found to produce more promising results than traditional ones. However, the number of training samples and the training time are some limitations worth mentioning. Magnetic Resonance Images are sources of input for medical diagnosis of a variety of diseases. On removal of noise, these images can go a long way in the early diagnosis of numerous fatal diseases and can save lives. The predominant objective of this summary is to direct the researchers to choose prompt denoising techniques appropriate for their applications despite the available limitations in the same. This review is comprehended with the main aim of suggesting effective image denoising approaches that can go a long way in enhancing the quality of biomedical images.

Keywords: Deep Learning, Denoising, Image Processing, Magnetic Resonance Imaging, preprocessing.

I. INTRODUCTION

An image, when being processed, generates an enhanced version of it or extracts some useful information from it. Processing can be either analog or digital using the corresponding fundamentals of interpretation. Digital Image Processing focuses on the manipulation of images using digital computers and is exponentially on the rise in the last few decades. Owing to multidisciplinary applications, this field has set forth tremendous technological advancements that gain attention worldwide. An image is a function f (x, y) of two continuous variables x and y. After proper sampling and converting to a matrix of numbers, it can be digitally processed.

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* Correspondence Author

S. Asha*, Research Scholar, Department of Computer Science and Engineering, Sethu Institute of Technology, Pulloor, Kariapatti (Tamil Nadu), India.

Dr. M. Parvathy, Professor and Head, Department of Computer Science and Engineering, Sethu Institute of Technology, Pulloor, Kariapatti (Tamil Nadu), India.

Digital images fall into any one of the following three categories like Binary, Gray Scale, and Colour Images. Image processing finds its applications in a wide variety of domains. Industrial automation and Robotics are gradually found to be relying promptly on Image Processing [1]. Preservation of Architectural Heritage makes use of Image processing combined with Deep Learning [2]. Machine Learning and Image Processing go hand in hand with boosting harvesting in agricultural industries [3]. Image Processing finds its application in almost all of the recent technologies in Disease Prediction and mortality rate reductions [4]. Applications of image processing are not limited to the above-mentioned categories. Only some essential applications are discussed. This paper will mainly focus on the summary of challenges produced by noise in processing the images related to healthcare and some probable solutions for the same. Image acquisition technologies have witnessed the evolution of advanced modalities like X-Rays, Magnetic resonance imaging(MRI), Ultrasound Transducers(US), digital Photon Emission Tomography(PET), and Computed Tomography Scanners(CT)[5]. Some of the major challenges in medical images are noise, the need for adaptability to available technologies, the need for more and more tools and technologies for efficient ground truth generation, proper algorithms for heterogeneous image sources, appropriate models for the trustworthy generation of patient-specific data and many more [6-8]. Inevitable noise is the most deteriorating component in the image that degrades its quality and affects the quality of generated ground truth[9]. A magnetic resonant image should have not only good characteristics like good spatial resolution and high acquisition speed, but also should be noise-free to the expected level. The rest of the paper is organized as follows: The relevant and related review of literature is elaborated in section II and Section III discusses the various types of noise that could probably degrade the quality of MR images. Section IV outlines a few of the existing denoising approaches that could enhance biomedical image characteristics. Section V tabulates some of the denoising approaches concerning their evaluation metrics and also focuses on the results and discussion of the same. Finally, section VI concludes the review and provides suggestions for enhancements.

II. LITERATURE REVIEW

A wide variety of studies have been carried out in the healthcare domain that makes use of image denoising techniques in the preprocessing stage for enhancing the prediction accuracy.

This work [10], introduced a novel work for noise elimination in MRI using the Discrete Wavelet Transform and the Independent Component Analysis. This approach reduced the available speckle, Gaussian, and salt and pepper noise considerably. Another research[11], that uses the Sparse representations along with the singular value decomposition produced considerable improvement in denoising MR images non-locally. In addition to reducing residual noise, this approach prevents artifacts and blurring too. These three staged methods provided outperformed results when compared to various real-time and simulated state –of –the art methods. The research work [12], uses the Bayes Shrinkage-based fused wavelet transform along with the block-based autoencoder. This approach[13] removes noise from the Magnetic resonant images and also prevents the loss of edge information that is significant in the prediction of diseases. Convolution Neural Networks (CNN) play a vital role in denoising medical images. This study involves a CNN with an encoder-decoder structure using global and local residual learning for network training in image denoising and had generated promising results in doing the same. Deep learning techniques have the capability of learning a nonlinear transformation using acquired information without the use of an explicit hypothesis[14]. This capability is beneficial and is used in Arterial Spin Labeling Perfusion MRI denoising which is a non-invasive approach that can measure cerebral blood flow quantitatively. The method has produced a reasonable increase in the accuracy of prediction using the denoised images. Most healthcare-related images get affected during image acquisition, transmission, and even storage. This research[15], presents an approach for denoising brain MRI with the use of curvelet transform thresholding in combination with the Wiener filter and evaluates the work using Peak Signal to Noise Ratio, Mean Square Error, and Similarity Search Index Measure. Better results were found to be generated by curvelet denoising than the wavelet approach. But, the combination of both the methods emerged with extraordinary performance in reducing noise concerning the same set of metrics respectively.

III. TYPES OF NOISE IN MRI

A random variation in the color information or brightness of an image constitutes noise. The reasons for the presence of noise are many and are found to be present in an image almost during image acquisition, transmission and even processing too if not handled properly. The noise will be prone to produce adverse effects if not treated with proper domain knowledge. Among the multiple modalities in medical imaging, MRI is gaining remarkable appreciation and importance because of its spatial resolution, acquisition speed, Signal to Noise Ratio, and visual quality. Amidst all these upgrading characteristics, during image acquisition, the presence of noise still prevails and degrades the image quality. This results in the loss of critical information that may misguide the diagnosis and treatment of certain fatal diseases. Noise also results in the creation of artifacts in the medical images, resulting in false diagnoses. When analyzing medical images, limited exposure types and poor lighting paves way for the degradation of the specimens, thereby raising the influence of noise. Noise in an MRI may be due to stochastic variation, physiological processes, eddy currents, body motion, and many other reasons too[10].

A. Gaussian Noise

Gaussian noise is a statistical noise that has the probability density function equal to the normal distribution. It changes each pixel in the image from its original value [11,12]. Random Gaussian function gets added to the image function. An image with Gaussian noise has the pixels with their original values and a random Gaussian noise equivalent.

B. Rician Noise

Rician noise is image dependent and it can be computed from real and imaginary images. Removing Rician noise from medical images is a challenging area of interest for researchers[13]. It generally reduces the image contrast and produces fluctuations in the data.

C. Speckle Noise

Speckle noise is a type of multiplicative noise. In medical images during diagnosis, speckle noise introduces a backscattered wave-like appearance. This is caused by reflections dispersed by the microscope that flows through the internal organs [14]. The critical information in the image needed for diagnosis gets distorted.

D. Poisson Noise

Poisson noise is generated as a result of the nonlinear responses from the image detectors and image recorders. The random fluctuations of the photons contribute to this type of noise. Generally, the recording and detecting techniques involve arbitrary electron emission similar to Poisson distribution and often inculcates a mean response value, thereby using the Poisson expression [15].

IV. DENOISING MRI IMAGES

Denoising is considered to be one of the most important tasks in image processing. It finds its applications in most single-dimensional or multi-dimensional signals. Noise, edge, and texture are all high-frequency components and need special attention to be distinguished during denoising so that prevention of inevitable information loss can be promised. Being an inverse problem in its mathematical perspective, denoising continues to be a challenging task for years. Amidst all its tough challenges, denoising still prevails in producing new techniques day by day over the decades [16]. The following sections will review some of the advancements in this field. The denoising methods can be roughly classified as i) Spatial domain-based methods and ii) Transform domain methods, Spatial domain method is a classical denoising method that excels in denoising by using the calculated grey value of each pixel based on correlation with original image pixels. It is sub-categorized as Spatial domain filtering and Variational denoising methods [17].

A. Spatial Domain Filtering

Filtering modifies or enhances an image. It is a neighborhood operation that operates on required pixels based on applying some values to the neighboring pixels [18]. The filters used may be linear or non-linear.

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The choice of the filter depends on the type of data to be processed and the nature of the processing that is to be performed. Besides being used, the filters must produce promising performance in preserving the original image with critical information needed for medical diagnosis and decision making. Spatial domain filters may be Nonlinear or Linear.

B. Non-Linear Filters

Non-liner filters are believed to remove noise without any explicit effort for identifying the presence of noise first. To a reasonable extent, these filters are capable of removing noise but often result in the blurring of images and making the edges invisible. This resultant blurring of edges can be reduced by using a Median filter which is a non-linear smoothening technique [19]. The current pixel's intensity in the image will be replaced by the median of the neighborhood pixel's intensities. This median value will not be affected by the individual spikes of the noise. By applying this filtering iteratively, the image can be denoised efficiently. Slow processing, high expense, and computational complexity are the limitations of these types of filters.

C. Linear Filters

Linear filters change the output linearly with changes in the input. The optimal linear filter that is being widely used is the Mean filter which is ideal for the Gaussian noise in terms of mean square error. Each pixel intensity in the image will probably be replaced by the mean of the intensities of the neighborhood pixels. The pixel values that are unreliable of the surrounding thereby get eliminated. The Wiener filter is another reliable filter that does linear time-invariant filtering of a noisy image. It generates an estimate of the target random process by assuming known stationary signal, additive noise, and noise spectra. It minimizes the Mean Square Error to a reasonable extent.

D. Transform Domain Techniques

Transform domain usually focuses on wavelet-based filtering techniques. Depending on the basis functions, transform domain filtering can be categorized into data-adaptive and non-adaptive filters.

E. Data Adaptive Transforms

Independent Compound Analysis is the used Data Adaptive transformation method that comprises key components, projection detection, and factor analysis. Being frequently used for the Blind source partition problem, this method has its importance because it can support the denoising of both Non -Gaussian and Gaussian distribution. The computational cost is the only limitation of this type of filtering technique.

F. Non-Data Adaptive Transforms

Non-data Adaptive forms are further categorized as Spatial Frequency Domain Filters and Wavelet Domain filters[20] A spatial Frequency Domain filter uses Fast Fourier Transforms (FFT) with Low Pass Filters (LPF). A cut-off frequency is predefined and all frequencies lower than the cut-off passes the filter and the others attenuate the filter. Processing in the frequency domain is computationally faster than in the spatial domain. Wavelet, on the other hand, is a mathematical function that divides the target into different scale components. Wavelet Domain-based filtering is in turn classified as Linear and Non-linear techniques. Weiner filter is the optimal Wavelet Domain-based filter. The Wiener channel is used where information degradation is viewed as Gaussian based and the criteria for exactness is the Mean Square Error. The wavelet transform here maps the signal domain-based noise to noise in the transform domain. The threshold capacities utilized are Hard Thresholding and Soft Thresholding. A function is said to be Hard thresholding if its input is greater than the threshold. The input arguments being reduced to zero is called soft thresholding.

G. Performance Evaluation Metrics

The important quantitative measures for evaluating the denoising algorithms are Peak Signal to Noise Ratio (PSNR), Mean-Squared Error (MSE), and Structural Similarity Index Measure (SSIM). MSE and PSNR find their application in comparing the quality of image compression whereas SSIM lends application in similarity measurement between the images.

Mean Squared Error is a measure of the squared error between pixels of the images that are compared. For minimizing error, the value of MSE needs to be low. It can be defined as,

$$MSE=\sum_{M,N} [I_1(m, n) - I_2(m, n)]^2 / (M * N), \quad (1)$$

M denotes the number of rows and N denotes the number of columns in the image.

PSNR represents the signal-to-noise ratio between the two images compared. Being used as a quality measurement metric, a higher PSNR value indicates better quality. It can be defined as

$$PSNR = 10\log_{10}(MAX^2 / MSE), \quad (2)$$

MAX is the maximum value that can be achieved in the input image datatype.

SSIM is a measure of the similarity between two images. Considering one of the images as the ground truth, SSIM measures the quality of the other image based on similarity.

$$SSIM (x, y) = [l (x, y)]^{\alpha} \cdot [c (x, y)]^{\beta} \cdot [s (x, y)]^{\gamma} \quad (3)$$

where,

$$l (x, y) = (2\mu_x\mu_y + C_1)/ (\mu^2_x + \mu^2_y + C_1), \quad (4)$$

$$c (x, y) = 2(\sigma_x\sigma_y + C_2)/ (\sigma^2_x + \sigma^2_y + C_2), \quad (5)$$

$$s (x, y) = (\sigma_{xy} + C_3) / (\sigma_x\sigma_y + C_3) \quad (6)$$

and μ_x, μ_y, σ_x, σ_y and σ_{xy} are the local means, standard deviations and cross-covariance for images x, y

V. RESULTS AND DISCUSSION

The significance of denoising is to achieve improvement in the quality of images by generating enhanced image versions without any loss of crucial information. The presence of Rician noise makes the job of the physicians tedious when it comes to disease diagnosis and treatment. This is because most clinical decisions completely rely on image-based modalities for their analysis. The removal of noise is the most challenging research-oriented area of interest. Table I lists some of the effective approaches used to handle various noise present in medical images. A wide variety of algorithms and approaches are being used for this purpose, each with its advantages and limitations. Machine Learning algorithms go a long way in showing better performance. Deep learning techniques outperform most Machine Learning approaches, but the increased training time is a limitation to be considered.

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Table I: Denoising Techniques for Magnetic Resonance Images

Reference No	Noise Handled	Methodology used	Mean Square Error (MSE)	Peak Signal to Noise Ratio (PSNR)	Structural Similarity Index Measure (SSIM)
[21]	Gaussian	Stein's Unbiased Risk Estimator ($\sigma = 8.2 \times 10^{-6}$)	3.6943×10^{-11}	30.866	0.7795
		Using Blindspot Network ($\sigma = 8.2 \times 10^{-6}$)	3.9075×10^{-11}	30.626	0.7708
		Non-Local Means ($\sigma = 8.2 \times 10^{-6}$)	3.9826×10^{-11}	30.555	0.7661
[22]	a. Gaussian, b. Rician, c.Combined Gaussian and Rician noise	Bayes shrinkage-based fused Wavelet transform	a. 77.590 b. 81.443 c. 81.333	a. 29.232 b. 29.022 c. 29.028	a. 0.613 b. 0.748 c. 0.747
		Block-based Autoencoder network.	a. 96.482 b. 90.180 c. 89.354	a. 28.286 b. 28.299 c. 29.028	a. 0.573 b. 0.548 c. 0.581
[23]	Rician	Variational mode decomposition in two stages (T1-w axial brain MRI with severe lesion corrupted by 13% Rician noise)	-	25.24	0.59
[24]	Rician	Non-Local Means filters with bias correction (images with noise above 9%.)	0.0243	79.6433	1.0000
[25]	Rician and Poisson	Patch-based dictionary learning using K Singular value decomposition algorithm and residual learning for 2D Images (5 % Rician Noise)	18.031	37.532	0.805
		For 3D Images ((5 % Rician Noise)	16.930	39.869	0.875
[26]	Rician	Cascaded multi-supervision convolutional neural network. (Specific model)	-	36.31	0.9016
		Blind model (Noise = 15)		35.65	0.8844
[27]	Rician	CNN with dilated convolution and wide activation blocks to consider inter-voxel correlations.	6.281	26.25	0.822
[28]	Rician	a posteriori (MAP) model with the weighted nuclear norm. Noise $\sigma = 10$	-	37.00	0.979
[29]	Rician	Block difference-based filtering technique (9%)	1.504	39.06	0.9672
[30]	Gaussian, Speckle, Salt, and Pepper Noise (Noise Level = 0.9)	Discrete Wavelet Transform and Independent Compound Analysis. (Gaussian)	-	19.58	0.4050
		Speckle		25.58	0.8026
		Salt and Pepper		18.93	0.5215
[31]	Rician	low-rank matrix approximation (LRMA) with weighted Schatten p-norm minimization regularization (WSNMD-3D) noise=5%	-	36.70	0.967
[32]	Rician	Deep and wide CNN (5% noise)	-	37.5686	0.9817
[33]	Rician and Gaussian	Non-Local Means Algorithm based on Kolmogorov Smirnov distance. (Rician)	0.0036	-	0.9309
		Gaussian	0.0034		0.9309
[34]	Rician	Maximum a Posteriori (MAP)estimator based on alternating minimization method. (9% noise) PD weighted MRI	-	24.5553	0.8797
		T1 weighted MRI		25.4795	0.8571
		T2 weighted MRI	-	23.2241	0.8919
[35]	Gaussian	Chi-Square Unbiased Risk Estimation with Bilateral filtering.	-	27.46	92.18%

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From the table I, it is evident that the PSNR value is high for the approaches that effectively take the knowledge domain from Deep learning techniques. The mean square error rate of the Deep learning techniques is also predominantly low, thereby highlighting their significance. The SSIM values for Deep Learning-based denoising techniques prove to be very effective and conclude that Deep learning-based denoising techniques outperform most of the other techniques.

VI. CONCLUSION

The significance of Denoising techniques is elaborated using precise and consistent summaries that enables researchers to analyze the existing approaches and deploy them efficiently. The various approaches to Denoising of medical images are studied and the methodologies adopted in each approach are discussed. This paper has surveyed some of the existing techniques for denoising of Magnetic Resonance Images, mainly for the removal of Rician noise. The paper concludes that most of the approaches have shown competing performance from each other but have their limitations too. The proper algorithm based on the application has to be selected for optimal denoising performance. Also, Deep Learning approaches outperform most of the existing techniques and are expected to witness still better performances shortly.

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AUTHORS PROFILE

S.Asha, is a research scholar in the Department of Computer Science and Engineering at Sethu Institute of Technology, Pulloor, Kariapatti. She received her Bachelor's degree in Computer Science and Engineering at St.Xavier's college of Engineering, Manonmaniam Sundaranar University in 2003. She received her master's degree in Computer Science and Engineering from Noorul Islam College of Engineering, in 2005. Her area of interest includes Machine Learning and Image Processing and has published related papers at national and international conferences.

Dr. M. Parvathy is a Professor and Head of the Computer Science and Engineering Department at Sethu Institute of Technology, Pulloor, Kariapatti. She received her Bachelor's degree in Computer Science and Engineering at Madurai Kamaraj University in 2000. She received her master's degree in Computer Science and Engineering from Anna University, Tirunelveli in 2009. She completed her doctorate in Information and Communication Engineering from Anna University, Chennai in 2015. Her main research focus is on Data Mining, Big Data, and IoT, and has published many research papers in National/International journals and conferences. Email: parvathy@sethu.ac.in