Section A-Research paper
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Integrated Segmentation-CNN Framework for Hybrid Multi-level Image Denoising on Different Imaging Systems.

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Abstract

Digital image denoising poses a significant challenge in real-time systems due to the presence of high levels of noise and low-resolution images. The inter- and intra-variance between signals during image acquisition contributes to the noisy artifacts in digital images. Various types of noise, such as Gaussian, speckle, impulsive, and combined noise, can be found in images acquired through Synthetic Aperture Radar (SAR) and medical sensors. Traditional denoising techniques like non-linear median filters, Bayesian filters, and wavelet-based shearlet transforms encounter difficulties in effectively analyzing compressed or noisy images, particularly in preserving edge details.To address the issues related to speckle noise, conventional denoising approaches such as Bayesian denoising, non-local filters, wavelet-based shearlet transformations, and autoencoders are commonly utilized. However, these techniques face challenges when dealing with ultrasound images and medical images that contain multiple additive, multiplicative, and Gaussian noise sources. Furthermore, these models struggle to overcome the problem of sparsity in low Signal-to-Noise Ratio (SNR) images.To overcome these challenges, an innovative approach incorporating a hybrid non-linear filter and segmentation-based CNN framework is implemented to enhance denoising performance across various imaging systems. Experimental simulations are conducted on diverse real-time noisy images to assess the efficiency of this denoising approach in comparison to conventional techniques.

***Keywords* – Image denosing, deep learning, autoencoders, segmentation, thresholding based filering.**

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1.Introduction

Images are an inseparable part of human life and an important element in the processing of daily data. In order to improve image quality using the computer, digital image processing involves modifying digital information. The processing helps to make information extraction and additional analysis clear, sharp and detailed. Image processing is a signal processing subfield for which image input is an input signal and outputs again constitute an image and/or various parameters that define different image features and operations.The noisy image is generally supposed to be the sum of a clean image and some noise. Denoising is a reverse process in which this noise component is removed from the noisy image. In this field extensive work has been done, and we find a wealth of information on the techniques proposed, elaborated and implemented to denoise images. The most preferred way for the transmission of information is the progress in technology, acquisition and transmission of images. Two principal phenomena are the necessity and importance of digital image processing, firstly to improve the pictorial depiction of the image in a common human interpretation and secondly, to treat information for automatic machine perception. In medical image and biography, acoustic imaging, Remote Sensing and military surveillance, digital imaging has a large amount of applications. Image processing is essentially a method for performing certain operations on images so that their information is sufficiently understandable and useful. It is a process in which output is an image or an image or a picture-related feature. Image processing is an integral component of fast-growing technologies such as core research and vision of computers and machines. But due to image sensors and transmission media limitations, images are contaminated by noise. Noise is manifested as signal disturbance which leads to deterred image monitoring, image analysis and image evaluation. Image processing, such as improving and retrieving images, is used to process images that are degraded or blurred. Image denotation is critical in the image processing world. Thus any advancement in image denotation forms an image towards our knowledge of the processing of images and their statistics. However, the information on pixels is also affected during noise removal. The true information from the degraded one needs to be restored while preserving the greatest possible amount of information. The many applications of a digital image make it essential that they are visually informative and adapted to future image treatment applications. Noise removal is an elementary operation in image processing and is a problem in image reconstruction algorithms, ranging from direct, e.g. photographic improvement to technical. The automated processing and image extraction process is hindered by a degraded image. Efficient image is therefore a key task for the processing of images, image recognition and computer vision. Properly demoted image can serve as an effective source for further tasks such as biometrics, medical imaging, monitoring, remote sensing, and defence. The current image acquisition devices are increasingly sensitive to noise, as the number of pixels per unit area continues to rise. As a result, image denoisation techniques are extremely reliable to decrease the effect of noise and artifacts on the resulting image. Noise can be seen in colors or the intensity values of the image as a random fluctuation. Due to noisy channels, errors in acquisition and quantification of data for digital storage, it can occur via transmission medium. In addition Noise modeling is influenced by various agents such as image devices and instruments, image transmission by various media, digitalization processes and environmental factors. It is sometimes very important to find the type of noise that has damaged the image before applying any denoisation technique. A large number of digital image processing studies are dedicated to image denotation. This includes research into developing and extending algorithms and analyzing the functioning of existing algorithms on various parameters. In any signal processing system, Digital image denoising is an important step. During capture, acquisition, transmission and compression, Images are caused by noise of various kinds for a number of reasons. Before it is used for any analysis, the corrupted image must be processed / denoted. Image restoration is the reduction or minimization of degraded images produced image (Castleman & Kenneth, 1979). Degradation is caused by flurry and noise caused by electronic and photometric sources (Reginald & Jan, 1991). Blurries, noises, and relative mobility between the sensing device and the object are introduced into images via noise disturbances, aberrations within the optical system. Noise, errors and omissions during and during the measurement process during the quantification of the Digital Storage data is introduced by a noisy channel in transmission media.

The distribution of Rician is well approximated for higher mean values, similar to that of Poisson, with a Gaussian one. The types of noise that can corrupt images are too numerous to list. Digital images are of particular importance to us, but pictures taken from analog cameras, for example, also suffer from noise. A single scratch may run over a whole image. In Digital Images too, these large structures can occur: Row noise or column noise can affect certain sensors. In those cases, the noise samples may be the same in the line (or column), but between rows (or columns) the noise samples can be different. We will consider only AWG noise, Poisson noise, thermal noise, noise from the salt and popee, JPEG artifacts and stripe-noise from rows and columns. In these theses we are only looking at AWG noise. The two-style models based on the partial difference equations can be nonlinear diffusion in axiomatic approaches to scale, while the second is energy functional minimization[1]. There have been numerous models described here for partially differential equations. The models for the partial differential equation were proposed by [2] and [3], which were based on improved speed controllation by a smoothing model and by Laplacian image of an evolving image rather than the gradients image. [4] have introduced a coupled non-linear diffusion model where diffusion equation smooths the control function. [5] have studied the approach of ultrasound noise removal based on the anisotropic filter study and continue to the anisotropic diffusion matrix. For the control of forward and reverse diffusion, [6] used the local variance. Total Variation (TV) was introduced by [7] by providing a simple and dynamic form to the term "faithfulness." The TV-ROF model, which has been modified, is introduced in [8] on the iteration of the Split Bregman image. Multiplicative regularisation scheme of TV problems deblurring was established in [9]. [10] noted the pixels as edge, noise and internal pixels, and defined speed and fidelity functions that address the impulse noise removal limits on the basis of these definitions. In the case of heavy noise densities and less iterations, existing approaches have treated corrupt and undamaged pixels the same way. The partial differential equation second order utilizes an increasing function as an integral energy function in terms of the absolute value of the gradient operator. This partial differential equation can better protect the edges when the noise is removed, but a serious blocking effect can result in the image. The fourth order model of partial differential equation uses an increasing function as an integral energy function in relation to the Laplacians operator's absolute value. As the laplacian operator does not determine edges, the resulting image smoothness is better than the second order partial differential equation. In [11] the fourth order proves to be effective for solving the staircase effect problem of partial differential equation-based denoising models. The DWT is based on a wide range of image processing algorithms. An important issue is the efficient removal of noise from an image. In many areas of image processing, denoising finds extensive applications. The use of image demoising, like texture analysis, object recognition [12], image segmentation etc. before views and other processing is generally required. Several nonlinear and adaptive filters were recently proposed for this purpose. Image denotation algorithm not Local Means (NLM) which uses PCA for increased precision. In quantitative and qualitative comparison, the Author proposes an image denoising algorithm based on NLM and another PCA image neighbourhood. Calculating neighborhood similitudes to lower dimensional areas after a PCA projection improves the accuracy and the computation costs of the NLM image denoisation algorithm. [13] has developed an additional algorithm for the analysis and derivation of surrogate respirory signals from the single plumb ECG for the analysis of changes in Electro Cardio Graphy (ECG) morphology, based on the principal component analyzes.

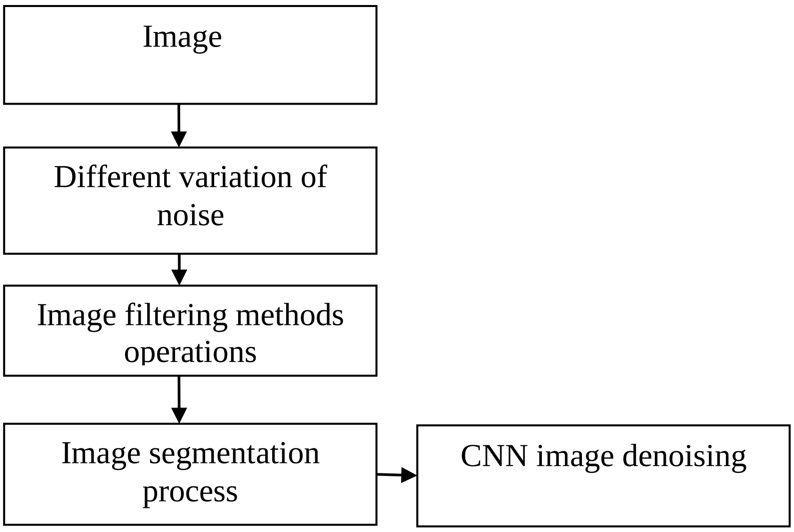

Figure 1: Traditional segmentation based image denoising

In the novel chain graphical model, graph contains both directed and undirected edges. Each edge in the novel chain graphical model represents the joint probability distribution among the random variables[15].

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2.Literature survey

A New approach developed for picture denouncing algorithms in this work to the threshold function in [18]. In connection with threshold functions it uses wavelet transformation to remove noise. Universal, Sure Shrink and Bayes Shrink, normal decline is compared to our threshold functor, it efficiently enhances the SNR. The output of the Bayes Shrink method is far closer to the high-grade image and, unlike other methods, there is no blurring of the image. Unlike BayesShrink, VisuShrink is not able to denoise multiplicative noise. VisuShrink and Universal have demonstrated inefficient denoising of salt and pepper noise. [19]This paper describes a new image noise removal method by fusing a denoising wavelet technique with optimized thresholding functions which significantly improves denoted results. In addition to another wavelet-based denoising algorithm, simulated noise images are used to assess denoising performance. In this paper, it is highly critical to select the threshold in image denotation using waves. An effective approach was proposed for the calculation of the universal threshold based on the wavelet coefficients' spatial context modeling. Modelling of the spatial context involves determining the correlated pixel within the local pixel neighborhood. The threshold estimate therefore depends on the pixels and not on the image size to be denoted. The wavelet coefficients' spatial context information is calculated with the range filter for bilateral filter formation

When compared to the conventional PCA-based method, experiments with a good number of natural images show very good results.[20] states that a number of observations on a same scene of multi channel imaging systems are often noise-corrupted. They are interested in multi-spectral images denoating the wavelet domain in this image. In order to exploit the correlations between different spectral components, they adopt a multivariate statistical approach. In conjunction with the filtering techniques already used with discrete WT, [21] has proposed the use of recently implemented hyper-analytic wavelet transformation (DWT). The result is an image denotational algorithm very easy and fast. Certain results of simulation and comparisons show that the new method's performance is better than the previous thresholding methods. [22] states that the iterative image reconstruction of Compton scatter camera data is required to overcome different difficulties, such as large quantities of data, noise from both low recorded counts and the response of the imagery. The maximum likelihood criterion Image estimate induces noise amplification and a denoise step is therefore necessary. The solution is a denoising method using ML Expectation Maximization wavelet-based thresholds (EM). The thresholds depend on scale of the sub-band coefficients in a high-frequency standard deviation on the appropriate scale. It leads to less reconstruction errors than the MLEM and Gaussian smoothing algorithms, which are also stable. In the [23] proposed a widely used multivariate data denotation method. They investigate why a projection operation inherent in all existing PCA kernel denotation algorithms may sometimes lead to very poor denotation by geometric arguments. On this basis, it proposed an amendment to the projection operation to remedy this issue and incorporate it into any of the KPCA algorithms currently in place. [24] indicates that the most difficult task of the multidimensional probability density (PDF) estimation is involved with the signal processing problems. This paper proposes a solution to this problem by using an iterative gaussanizing rotational family. The general framework consists of the sequence of application of a

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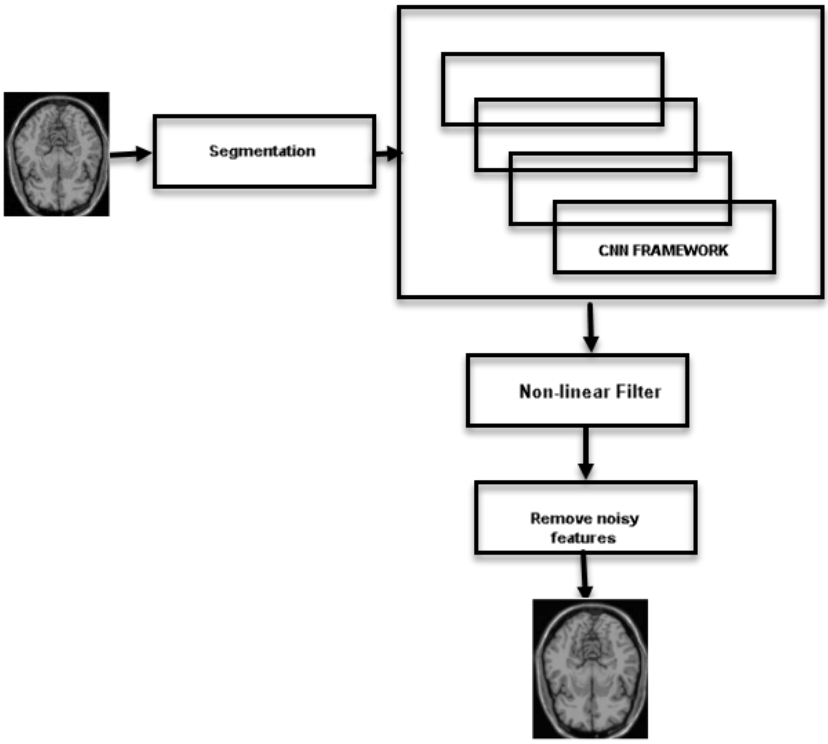
marginal transformation in univariate gaussianization, followed by orthonormal transformations.[25] suggested that thresholding methods for wavelets had a better outcome than conventional methods. However, threshold estimation and threshold selection are still the difficult tasks. A new threshold function for wavelet thresholds is proposed in this paper. This function is continuous and derives higher order. It is therefore ideal for decent methods of gradient learning, such as neural thresholds (TNN). This function is used by the TNN and threshold values are estimated by the lowest mean square (LMS) algorithm for wavelet subband values.

In addition to conventional, hard and soft threshold operators, semi-soft and stein thresholding systems are used in the shrinkage step and thus checked the suitability for denouncing medical images of various wavelets families. These denoising methods were used for the demonstration of the strategy in textured and satellite images. The PSNR for existing test data is evaluated and the accuracy of the classification of these denoising methods is validated. Its experimental results illustrate the efficacy of regular anisotropic distribution for image denotation purposes. [26] proposed a method of image denoise using partial equations. They proposed three different approaches: first of all for blurring, secondly for noise and finally for blurring and noise. These are compared with an average absolute difference, SNR, PSNR, picture fidelity and a medium quadrature error. These approaches are (MSE). The results in various scenarios are achieved. In addition, the result is better than traditional technology compared with different data based on the above five parameters. They examine the way in digital images the two-dimensional empirical mode of decomposition. The three-dimensional cubes are presented, which are in harmony with intuition and physical interpretation and show the performance of BEMD. In order to analyze the behaviors observed and support numerical experiments, a theoretical analysis is provided. The main purpose of their study is to contribute towards a better understanding in digital images of the possibilities and constraints of BEMD. The image is primarily denoted and interpolated, according to [27]. However, the denoisation process can destroy structures on the image edge and bring in artifacts. Edge preservation is a key image in the denotation and interpolation of images. The authors propose a directional denoisation system in order to address these problems, which naturally provides a further directional interpolator. [28] have enhanced the SC technique by providing overall bank frame filter work. The development of new filters that work for various images regardless of their types allows multiple scales of image structures. In a cumulative energy map of pixels to be selected for driving the seam, the authors introduced guide vectors. Experiments were conducted by redefining the filters used for the backward energy seam carving and energy seam carving by passing through new filters each level of the image. In order to eliminate compression fingersprints from image transform coefficients, a typical framework has been developed for the design of antiforensic technologies. This framework is then used to develop anti-forensic techniques, in particular to wip off JPEG-based and wavelet-based compression fingerprints. In addition, the authors have developed a technique for the removal by image compression algorithms of statistical traces of blocking items that split an image into segments in the processing time. The author has shown, with a number of experiments, that anti-forensic technologies can remove forensically detectable image compression traces, without significant impact on the visual quality of the image. In this approach, edge detection and thresholding techniques are implemented on different medical MRI images, geo images to quantify the stability of noisy and error rates.

3. PROPOSED WORK

Conventional methods can be processed in real time in low-end systems, and these methods achieve good efficiency in limited conditions, such as simple context and setting, fixed lighting, and so on. The efficiency of these methods can however, dramatically decrease in complex environments. A single or multi-class anomaly can be identified by profound approaches based on CNN. Conventional approaches to object detection are typically focused on multiple features in order to locate objects in each image. On the basis of low-level visual indications, feature descriptors are used, making it hard to capture representative semantic information in complex circumstances. Finally, each stage of the detection pipeline is separately constructed and configured so that the optimum global solution for the entire system can not be obtained. Here, a novel proposed thresholding based denosing method to reconstruct the original image from the noisy image as shown in figure 3.



Proposed Non-linear CNN framework for image denoise

Proposed CNN based non-linear image denoising model:

A deep machine learning model focused on enhanced artificial neural feed-forward networks is Convolution Neural Networks (CNN). The idea of CNN was inspired by the discovery of a visual system known as the visual cortex in the brain. In a small, overlapping and sub-region of the visual field, the visual cortex of these cells was constructed by several cells called receptive fields and responsible for deciding the light. Local filters represented by these cells, over the input space, are larger receptive fields presented in the more complex cells. In CNN architecture, one or more convolution layers combined with a regular neural network consisting of one or more hidden layers called fully connected (FC) layers can be present. The output layer determining the making of the diction is the new FC layer.

The proposed model used a max pooling feature that intersected the previous layer with a neuron cluster and used the maximum value as the output. These neuron clusters are generated by dividing the input images into non-overlapping two-dimensional spaces and selecting each space considered to be the cluster and the maximum value. Two completely connected layers (dense layers) followed by one output layer (decision making) layer reflect the classification phase of the proposed model. Fully-connected layers are a typical neural network that links all neurons in one layer to all neurons in the next layer. As a weighting sum of the previous layer of features, a particular target output result can be interpreted mathematically. The input of each completely linked layer is a vector of values that can be calculated by multiplying the output of the height and width form of the last max pooling layer with the depth of the neurons (the number of filters used in the last layer of the convolution).

The main processed in the segmentation base noise removal is given as

1.Set μ_{Ci} is the ith segmentation process membership mean.

2. To each k number of segments
3. do
4. The expected mean variance in the segmentaion block is given by

$$E=\sum_{i=1}^{N}\sum_{c=1}^{C}\frac{\Pr ob((px_i,py_c)_i/B_c).e^{-(\frac{D(px_i,py_c)}{\min(px_i,py_c)})}}{\sum_{c=1}^{k}e^{-(\frac{D(px_i,py_c)}{\max(px_i,py_c)})}}\parallel v_0px^3+v_1py^3+v_2px^2py+v_3px^3+v_4py^3+v_5-p_i\parallel^2$$

The multi-level segmentation is performed by using the thresholding method along with the correlation measure as

To each region in the initial segmented regions, compute

$$Seg(G_{\min}(p,q),r)=\min\{\log(r\lambda).\frac{e^{-p/2.\sigma_p^2}}{\sigma_p\sqrt{2.\pi}},\log(r\eta).\frac{e^{-q/2.\sigma_q^2}}{\sigma_q\sqrt{2.\pi}}\}$$

$\text{Multi}-\text{segmented threshold to define the oversegmented regions is defined as}$

$$MST_1(I,\lambda,\eta)=\max\{\lambda,\eta\})*\sum\min\{p*Prob(I/c_1),q*prob((I)/c_2)\}/|N|$$

$$MST_2(I,\lambda,\eta)=\min\{\lambda,\eta\})*\sum\max\{p*Prob(I/c_1),q*prob((I)/c_2)\}/|N|$$

5. Repeat this process till k number of segmented regions for non-linear noise removal procedure.

Non-linear desnoisng filter
The Bayesian probabilistic measure is estimated using the following function:

Computing the best compressive sensing reconstruction measure using the following equation:

$$I_R = (1+\lambda)\frac{\sigma_E^2}{\sqrt{Max(\sigma_O^2 - \sigma_E^2, 0)}}$$

$$B_f = uniCV(D); // \text{Unique column values}$$
$$HB_f = Histobins[] = histogrambin(D)$$
$$GaussianKernel: GK(\phi, \theta) = e^{-\theta^2} / (2 * \log(\phi))$$
$$\psi = gkv = GK(\sum HB_f, 1/2\sum B_f);$$
$$ExponentialGaussian\ Probability = KP(D) = | HB_f / (\sum \log(\psi) * HB_f) |$$
$$PolyDiffusion = PD = KP(D).\frac{1}{2}\int (I_{original}(i, j) - \varphi_{noise}(i, j))^k dxdy + m.\frac{\partial^2 I_{original}(i, j)}{\partial x^2}$$
$$\min\{R(x)\} = PD.\frac{1}{2}\| \sigma_O^2 - \sigma_E^2 \|^2 + I_R.\phi(x)$$

Where, $\phi(x)$ is the non-linear ,non-smooth regularizers. Proposed iterative method is used to solve the R(x), here input noisy image is restored with high PSNR ratio and low error rate.

$$GaussianEntropy: GE(d_i) = -GK(\sum_i d_i .\exp(d_i), \sigma_d)$$

In the above equations, the Gaussian entropy is used to check the feature entropy value based on the Gaussian estimator.
Proposed entropy formula:

$$\varphi = e^{-D^2} / (2 * D_1{}^2) * HB_{D_1} / (\sum \max\{\psi, HB_{D_1}\}) + e^{-D^2} / (2 * D_2{}^2) * | HB_{D_2} / (\sum \exp(\psi) * HB_{D_2}) |$$

4.Experimental Results

To verify the performance of the proposed model to the existing image denoising models, different parameters such as image noise level, image PSNR ratio are taken. For the performance analysis, measurements are choosen through compressive sensing by undersampling k space. Simulated results are performed with 256x256 standard ultrasound medical grayscale images and SAR images under various levels of compression, multiplicative noise with different levels of noise.

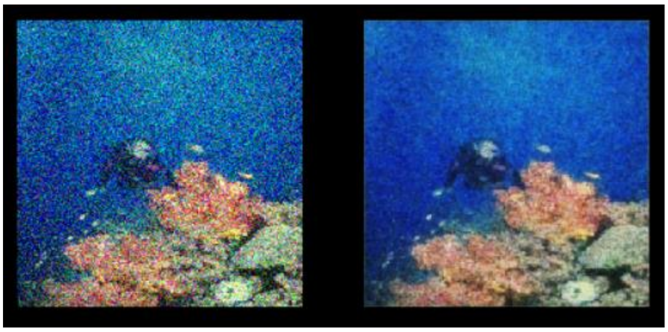


Figure 3: Sample original and denoised image

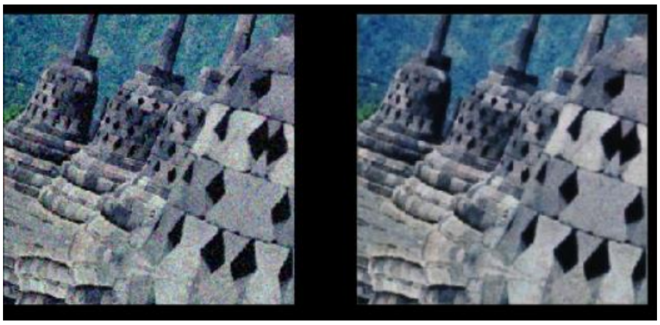


Figure 4: Sample original and denoised image

Figure 3 and 4 illustrate the denoising of each image by using the proposed filter based denoising method. In this figure, proposed denosing method has better error rate than the conventional denoising methods due to segmentation process in the CNN framework.

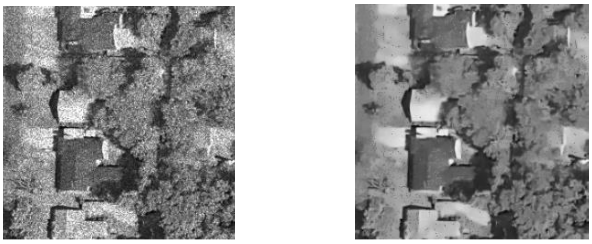


Figure 5: SAR original and denoised Images

Figure 5 illustrate the denoising of SAR image by using the proposed filter based denoising method. In this figure, proposed denosing method has better error rate than the conventional denoising methods due to segmentation process in the CNN framework.

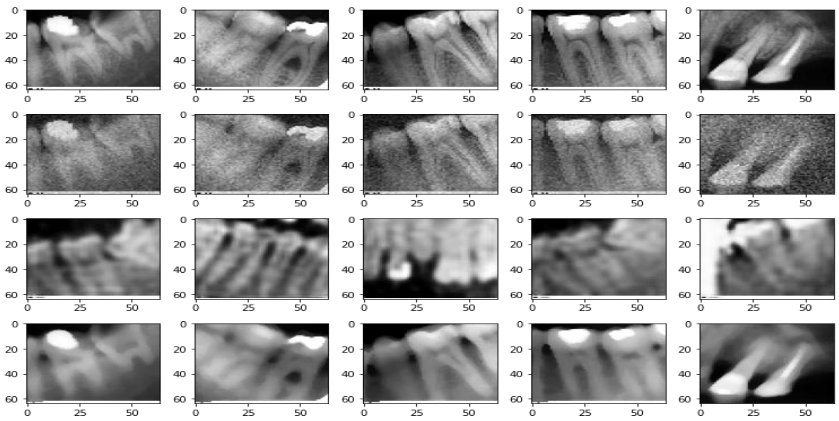


Figure 6: Denosing of medical images

Figure 6, presents the comparision of proposed model to the existing models for image denoising. From the figure, it is clearly observed that the proposed model has high PSNR ratio compared to the noise image using the propsed approach. Also, the quality of the noisy image is optimized using the segmentation based denosing method.

Table 1: Comparative analysis of proposed model to the traditional techniques in terms of average PSNR ratio for all images with different levels of noise levels.

	PSNR(dB) T=0.7		
Models	SAR	Dental	Hyperspectral
LinearFilter	29.34	32.54	29.54
BayesianFilter	28.94	31.75	28.46
WaveletTFilter	29.46	32.4	29.65
Probabilistic based denoising	30.23	33.04	30.24
ProposedApproach	32.5	34.35	31.87

Table 1, describes the proposed model to the traditional techniques in terms of average PSNR ratio for all images with different types of noise levels.

Table 2: Comparative analysis of proposed model to the traditional techniques in terms of average PSNR ratio for all images with different levels of noise levels.

			T=0.75			
Images	LinearFilter	Non-linearFilter	BayesianFilter	WaveletTFilter	Probdenoising	ProposedModel
SAR	4871	4408	4194	4100	3947	3410
DENTAL	4867	4513	4023	4405	4091	3354
Hyperspectral	4861	4098	3964	3967	3991	3319

			T=0.8			
Images	LinearFilter	Non-linearFilter	BayesianFilter	WaveletTFilter	Probdenoising	ProposedModel
SAR	4869	4136	4185	4222	4065	3283
DENTAL	4867	4509	3994	4126	3904	3373
Hyperspectral	4834	4205	4051	4515	3966	3454
			T=0.85			
Images	LinearFilter	Non-linearFilter	BayesianFilter	WaveletTFilter	Probdenoising	ProposedModel
SAR	4837	4100	4142	4104	4166	3484
DENTAL	4863	4561	4173	4048	3893	3465
Hyperspectral	4841	4835	4134	4264	4168	3482

Table 2, describes the proposed model to the traditional techniques in terms of average PSNR ratio for all images with different types of noise levels.

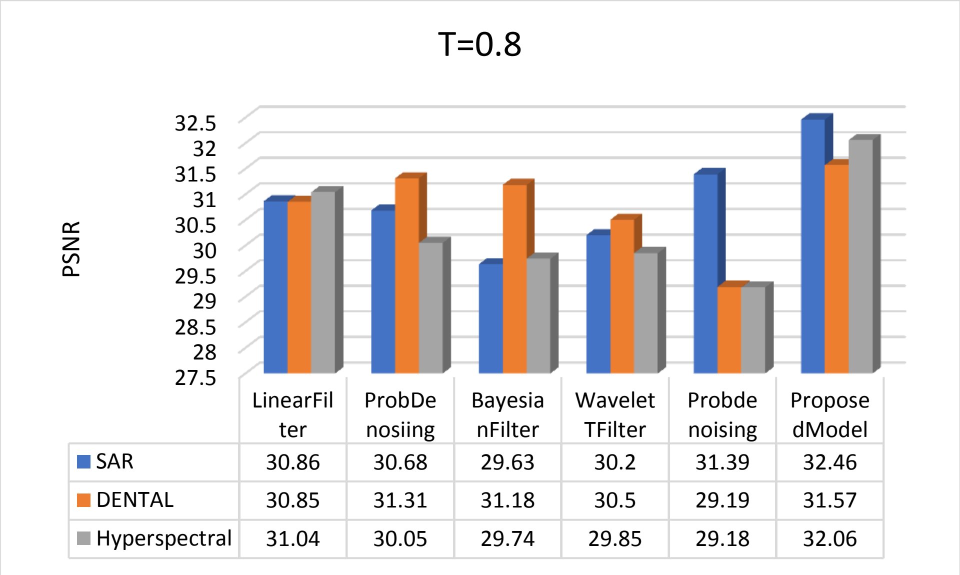


Figure 7: Comparative analysis of proposed model to the traditional techniques in terms of average PSNR ratio for all images with different levels of noise levels.

Figure 7, describes the proposed model to the traditional techniques in terms of average PSNR ratio for all images with different types of noise levels.

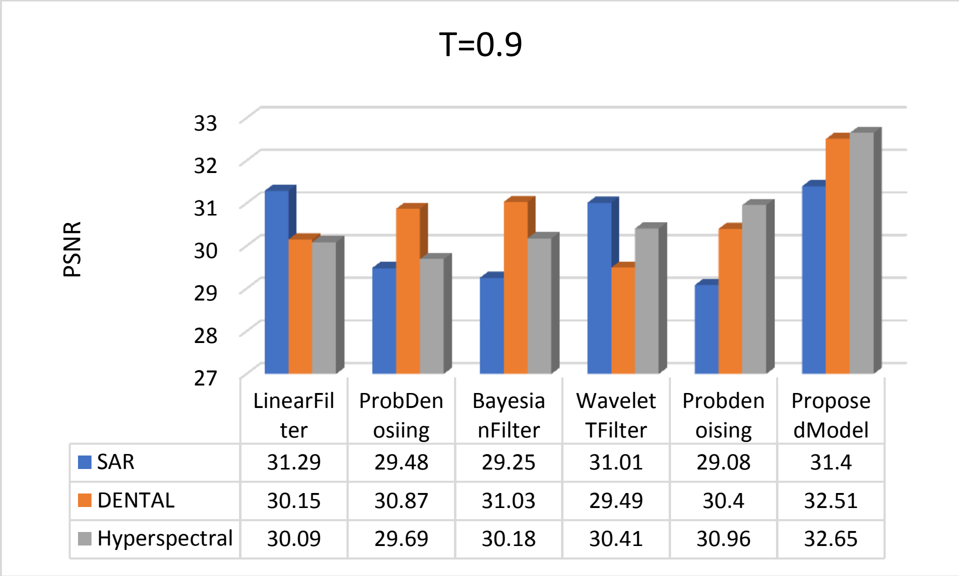


Figure 8: Comparative analysis of proposed model to the traditional techniques in terms of average PSNR ratio for all images with different levels of noise levels.

Figure 8, describes the proposed model to the traditional techniques in terms of average PSNR ratio for all images with different types of noise levels.

5.Conclusion

Probabilistic based image denoising has the potential to make the best image restoration processes in low resolution imaging systems. Most compressed or noisy images are hard to analyse because of the noise on the edges. This makes it hard to use traditional denoising methods like non-linear median filter, Bayesian filter, wavelet-based shearlet transform, etc. Traditional denoising methods like Bayesian denoise, non-local filter, wavelet-based shearlet transformation, autoencoders, etc. are used to get rid of the noise in speckle noise. Because there are many types of noise, like additive noise, multiplicative noise, and Gaussian noise, it is hard to use these techniques to clean up ultrasound images and medical images. These models also can't solve the problem of sparsity in low SNR images. In order to get around these problems, a hybrid non-linear filter and segmentation-based CNN framework is used to improve the level of denosing on different types of imaging systems. Experiment results are simulated on different noisy real-time images to see how well the denosing approach works compared to other methods.

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