A multi-level method noise based image denoising using convolution neural network

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Abstract

Gaussian noise has been the bane of any and every denoising process under the sun. Being a very corrosive noise with huge disruptive potential, this has received much attention form the image restoration community. Building on the premise, a novel framework is proposed to leverage multi-level image denoising that iteratively removes gaussian noise while recovering details lost during processing. This framework uses existing deep learning based CNN systems whilst enhancing the same by the addition of method denoising to the process. This framework is habile in competing with state-of-the-art technologies and outperforming them in some cases.

Keywords: DnCNN, Denoising, Method noise, Gaussian, PSNR

1. Introduction

The generation or capturing of images in the real world, often get contaminated with discrepancies in the form of random variations in colour forms, incongruous brightness variations, and so on. These unwanted discrepancies that are capable of corrupting the quality of the image are also termed as “image noise”. The additive white Gaussian noise, speckle noise, Poisson – Gaussian Noise are some of the commonly found noise in various images. Since, occurrence of noise while capturing, transmitting, and recording image is quite frequent, the denoising of images has been a very crucial step in the procedure of image processing, and rapid developments have been made in image denoising with the passage of time. Various researches have been conducted in the field of image denoising, and some of the state-of-the-art techniques of the same are discussed below:
One of most familiar categories of image denoising methods is the Spatial Domain Filtering [1], which analyses the correlation among the image patches on the original image to calculate the gray-scale of each pixel and utilizes this to remove noise from the image. It comprises of various approaches, one of which commonly applied is the Sparse Representation technique, in which a dictionary is formed for the image representation and this dictionary is learned using K-SVD algorithm for denoising the noisy image. Similarly, in non-local means approach (NLM) [2], each pixel is evaluated as an average of other pixels centred at locations similar to the location of the estimated pixel. The Low-Rank Minimization technique is known to create matrix based on similar patches present in the noisy image and through the exploitation of the matrix formed, it is very efficient in reducing the image noise. Moving further, the Transform Domain Filtering, compared to Spatial Domain Techniques known for transferring the noisy image to another domain and then applying a denoising technique to remove the noise from the image. It consists of the techniques, such as Data Adaptive Transform, which applies Independent Component Analysis algorithms for image denoising. The Non-Adaptive Transform comprises of Spatial-frequency Domain method, which designs a frequency domain filter using low-pass filtering in such a way that the image information passed spreads in the domain of low frequency while the noise spreads in the domain of high frequency. Another sister approach in this transform technique is Wavelet-domain Transform technique, which divides the input data into a scale-space representation for noise removal from the image. All these techniques have certain merits and demerits in performance and efficiency when used for pragmatic applications.

This study proposes a novel framework in the field of image denoising in which the digital images are denoised using Multi-level Method Denoising via the implementation of Convolutional Neural Network (CNN). The paper is thus divided into following sections: (i) Literature survey of various image denoising techniques will be provided in Section 2, (ii) Methodology and algorithm used will be explained in Section 3, (iii) Experimental results will be presented in Section 4, and (iv) Conclusion will be provided in Section 5.

2. Literature Review

This decade has witnessed seminal developments in the field of image processing with predilection towards Image denoising by the implementation of deep learning framework like Convolutional Neural Network (CNN). Some of these carefully selected works are reviewed in this section of study. [3] Some researchers have amalgamated CNN with auto decoders to denoise small size images, these boot size images are generated by combination of heterogeneous imageries. [4] Propose new methods that amalgamates both NSS and CNN for image denoising thus works robustly in all kinds of images in the work titled “Block-Matching Convolutional Neural Network for Image Denoising”. Some researchers have presented work that aims to understand the efficacy of various deep learning algorithm and finding their respective loop holes [5] via using Dn-CNN with Blind denoising, residual learning strategy. [6] Aims to comprehend if CNN can be effective, high performance, can do fast-flexible non-blind denoising and other areas like image restoration via literature survey. The application of deep learning is not limited to image denoising and has also expanded towards image restoration as elucidated in [7], where encoders uses CNN and decoders implement multilayer Long Short-Term memory network for image restoration. Various available literature also describes approaches for robust denoising, like [8] maps every noise entity end to end so as to handle Gaussian impulse mixed noise. The task of image denoising becomes abstruse when certain kinds of medical images enter the scenario, but studies have shown seminal results with tricky imageries of PET scan, like [9] uses training loss function to preserve image details, use actual data to train last few layers. [10] Certain researchers have extended image denoising to real
world noisy images that contain various types of noises. Various existing image denoising algorithms also work upon denoising imageries while subsampled noisy images are transformed to low-frequency subband, 2D band stacking is done get 3D blocks, then keeping NSST coefficients same denoising is done by CNN. Lately, researchers have also done work towards improving primitive CNN namely [12] aims to deliberate local attributes that primitive CNN misses out by implementing graph-based algorithms. Image denoising is critical to various image metrics, [13] has proposed cardinal work; namely, Biooptimization based filtering system is used for getting a better PSNR ratio via implementing Swarm based optimization & bilateral filter and algorithms called Dragonfly (DF) and Modified Firefly (MFF). [14] Aims to make CNN network easily trained and more effective in less time and samples, via batch normalization and residual learning. Various studies have drawn inspiration from abstruse deep learning networks like U-net, namely [13] aims to denoise both single level & multi-level noise with consecutive down scaling and up scaling via CNN and u-net based framework. [15] Addresses the problems of CNN networks that take long time to train, and suffer from performance saturation as it amalgamates two frameworks namely batch renormalization & BRDNet. Many applications of image processing are utilizing the concept of transform domain based approaches for denoising [17-25] and fusion [26-29].

The concept of attention augmentation is also used for image denoising namely, [16] addresses the issue of weakening of deep CNN frameworks are depth increases via using Attention based network i.e. sparse block (SB), a feature enhancement block (FEB), an attention block (AB) and a reconstruction block (RB) [30, 31].

| Paper title | Advantages | Disadvantages |
|-------------|------------|---------------|
| Medical image denoising using convolutional denoising autoencoders | It succeeds in addressing the issues of high computation cost, and scarcity of large training set | Lags back as resizing of images reduces their resolution quality. And, the study presented is data specific with no proper architecture to apply the approach again |
| Block-matching convolutional neural network for image denoising | Its proves to be efficient for both images of irregular nature & those having repetitive patterns, also considers both local and global attributes of image | Since the approach requires multiple iterations it becomes complex to execute. |
| Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising | The approach proves its efficacy in pointing out various loop holes like GPU capacity, time & space complexity to specify problems with areas for scope of improvement | It hardly provides any kind of work or recommended suggestions towards solution of the specified problem. |
| Convolutional Neural Networks for Image Denoising and Restoration | The paper is advantageous as it describes why and how additive white noise can give bad results in cnn image denoising | Unable to deliver any novel technique. |
| Methodology                                                                 | Description                                                                                           | Limitations/Remarks                                                                 |
|----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Image denoising and restoration with CNN-LSTM Encoder Decoder with Direct Attention | This approach provides better performance as compared to auto decoders,                                 | Limited to deliberated data set.                                                    |
| Mixed Gaussian impulse noise reduction from images using convolutional neural network | This methodology is fruitful due to its lightweight structure, faster computing and easy implementation  | Lags behind in high end & abstruse computing problems due to its light weight structure |
| PET image denoising using a deep neural network through fine tuning.        | Preserves the image features as mentioned in the research                                              | Its application may or may not extend beyond PET scans like X-rays, sonography etc  |
| FFDNet: Toward a fast and flexible solution for CNN-based image denoising. | The presented work uses tuneable noise map as input and proves its efficacy by being faster, and handling wide range of noises and spatial noise as well. | The literature does not provide its further applications. |
| Image denoising with graph-convolutional neural networks                   | It proves advantageous as local attributes are identified and deliberated upon.                        | Due to availability of multiple graphing algorithms choosing best fit is time consuming. |
| Optimal bilateral filter and convolutional neural network based denoising method of medical image measurements | It proves to be very robust in medical images.                                                         | Its applications may or may not apply to other domain of imagery data.              |
| Edge-preserving image denoising using a deep convolutional neural network. | It succeeds in preserving the edges as mentioned in the study.                                        | Is not pragmatic for real use as Computation complexity and time will increases and identifying NSST constants is a lengthy procedure. |
| Enhanced CNN for image denoising.                                          | More effective in less time and limited training data                                                  | The literature does not provide its further applications.                          |
| Deep iterative down-up CNN for image denoising                            | Provides novel approach & effective results for the deliberated set of medical images                  | The approach may or may not apply to real world noisy images                         |
| Image denoising using deep CNN with batch renormalization                 | It shows good performance on grounds of solving the problem of internal covariate shift & small minibatch problems. | As it follows a multistep procedure it may consumes more time & space complexity than other approaches. |
Attention-guided CNN for image denoising

This approach is very effective in real noise, synthetic & blind noise.

The process is complex, and is not very robust with other types of noise.

3. Proposed Methodology

The flowchart elucidates the detailed workflow of the proposed framework from the insertion of the image to the generation of the denoised image. The process begins with the selection of the desired image followed by conversion to greyscale if the image is not black and white. Post this, the image is fed as input to the proposed framework for processing. Leveraging an advanced convoluted neural network amalgamated with deep learning, the system extracts the pixels it presumes to be contaminant followed by resolution to a contingent approximate of the original. Subsequently, the principal of method denoising is implemented in which the denoised image is subtracted from original noisy image resulting in exclusion of artifacts colloquial to the original image falsely purged as noise. This artifact map is then regurgitated into the machine and re-processed to salvage the imagery details veiled in the artifacts output is once again subtracted from the original artifice to find even miniscule details lost in this process. Finally, the two layers of denoised artifact are superimposed onto the primordial denoised image to formulate the final image. The efficacy or performance of proposed framework is illustrated with the help of three powerful reference-based image metrics namely PSNR, SSIM, UIQI. All the findings of this endeavour have been explained in great detail in the next section.
4. Results and discussion

In this section qualitative analysis is done on the basis of Fig 2-8. It is amply evident that the introduction of a minute amount of Gaussian noise has rendered a huge blow to the quality of the image. The two noise of 0.5.

Fig 2 shows the Lena image, which is a standard image used in the image manipulation domain, along with its denoised counterparts. The original and denoised images are shown side by side for better comparison. Almost all the noise has been removed in (b) and it looks very close to the original image. Some blur is noticed in the reflection in the mirror and near the tip of the subject’s nose. Otherwise the face is clear and features such as eyes are crisp and clear. In (c) residual non-homogeneity is observable at higher magnification due to absence of sufficient for the system to reconstruct the image. Edges out of focus are the biggest victims with noticeable blur and jaggedness at the rim of the hat. All highlights (light falling on the subject and background) are discernible from both images albeit at a lower sharpness.

Fig 3 shown the four images related to peppers image. The framework performed reasonably well in recovering the creases of the black background fabric although in 3(d) they look a bit unnatural. All the reflections on the surface of the vegetables look natural and closely resemble the original in terms of brightness and clarity. Due to well defined contrast
Fig. 2. Lena Image results from the proposed framework (a) Original Image (b) Noisy image (c) denoised Image at 0.5% noise (d) Denoised Image at 2% noise.

(between the vegetables and between the vegetables and the background, the edges are in pristine condition. Even the high value denoised image 3(d) shows some crisp edges like in the onion at the right corner.

Fig. 3. Peppers Image results from the proposed framework (a) Original Image (b) Noisy image (c) denoised Image at 0.5% noise (d) Denoised Image at 2% noise.

In this figure the background sky maintains the uniformity of the original in the low noise image whereas the high noise image shows patches of non-uniformity. Further the outline of the buildings in the background are not as pronounced in the higher noise value. Most features of the face and body are recovered with some patches of discoloration in the second image. All noise has been removed from the black areas with umpteen accuracy. The outline of the coat is prominent against the background without and blurring of the edges. No other distortion is noticed along the straight lines although the very small buildings to the left of the subject have suffered slight loss of sharpness.

Fig. 4. Cameraman Image results from the proposed framework (a) Original Image (b) Noisy image (c) denoised Image at 0.5% noise (d) Denoised Image at 2% noise.
### TABLE II: IMAGE METRICS FOR NOISY AND DENOISED IMAGES

| Noise Variance | PSNR Noisy | PSNR Denoised | SSIM Noisy | SSIM Denoised | UIQI Noisy | UIQI Denoised |
|----------------|------------|---------------|------------|---------------|------------|---------------|
| Image1         | 0.005      | 23.02706      | 33.78286   | 0.377198      | 0.929777   | 0.339965      | 0.805375     |
|                | 0.02       | 17.19018      | 31.11317   | 0.177094      | 0.890025   | 0.18553       | 0.726435     |
| Image2         | 0.005      | 23.29258      | 30.46515   | 0.438789      | 0.906505   | 0.372999      | 0.679517     |
|                | 0.02       | 17.52173      | 27.72841   | 0.254782      | 0.844357   | 0.25543       | 0.579066     |
| Image3         | 0.005      | 23.06901      | 36.27728   | 0.307105      | 0.951495   | 0.251041      | 0.782212     |
|                | 0.02       | 17.44344      | 32.67774   | 0.132131      | 0.901935   | 0.127892      | 0.654459     |

Table 1 shows the values of SSIM, PSNR and UIQI for all the images in an easily understandable structured format. The higher the values of these scores, the closer is the image to the original. At 5% noise or 0.005 variance, Image 2 had slightly better PSNR for noisy Image while Image 3 had the best increase in score after denoising. It also had the best improvement in high noise SSIM score of 0.87 or 72%. Compared to the low noise, the high noise images had an average a decrease of score of about 6 points of PSNR and 0.2 of the others. According to both PSNR and UIQI the denoised image 2 at high noise was the least improved with UIQI below 0.7 which represents a sub standard image. The tables 3-6 erudite the puissant of the proposed framework by comparing said framework with other contemporaries as referred.

### TABLE III. CAMERAMAN IMAGE COMPARED AT 0.5% NOISE VARIENCE

| Denoising Technique | PSNR | UIQI | SSRI |
|---------------------|------|------|------|
| [18]                | 29.2249 | 0.4068 | 0.6549 |
| [19]                | 30.6382 | 0.4465 | 0.7131 |
| [20]                | 29.2385 | 0.4001 | 0.6564 |
| [21]                | 29.6735 | 0.4090 | 0.6810 |
| [22]                | 29.1311 | 0.4210 | 0.7247 |
| [23]                | 28.6364 | 0.4343 | 0.7124 |
| Proposed Framework  | 33.7829 | 0.8054 | 0.9298 |

### TABLE IV. CAMERAMAN IMAGE COMPARED AT 2% NOISE VARIANCE

| Denoising Technique | PSNR | UIQI | SSRI |
|---------------------|------|------|------|
| [18]                | 25.7373 | 0.3069 | 0.4255 |
| [19]                | 25.2749 | 0.2598 | 0.5294 |
| [20]                | 23.4905 | 0.2703 | 0.3641 |
| [21]                | 25.4029 | 0.3130 | 0.4962 |
| [22]                | 23.5102 | 0.2517 | 0.3745 |
| [23]                | 22.0521 | 0.2305 | 0.5482 |
| Proposed Framework  | 31.1132 | 0.7264 | 0.8900 |
TABLE V. LENA IMAGE COMPARED AT 0.5% NOISE VARIANCE

| Denoising Technique | PSNR   | UIQI   | SSRI   |
|---------------------|--------|--------|--------|
| [18]                | 31.5319| 0.4833 | 0.6688 |
| [19]                | 32.0857| 0.5034 | 0.7653 |
| [20]                | 28.7405| 0.4004 | 0.5624 |
| [21]                | 30.3695| 0.5262 | 0.7450 |
| [22]                | 30.6843| 0.4546 | 0.6493 |
| [23]                | 28.0774| 0.5184 | 0.7794 |
| Proposed Framework  | 25.6185| 0.8062 | 0.8271 |

TABLE VI. LENA IMAGE COMPARED AT 2% NOISE VARIANCE

| Denoising Technique | PSNR   | UIQI   | SSRI   |
|---------------------|--------|--------|--------|
| [18]                | 27.6824| 0.3815 | 0.5281 |
| [19]                | 29.1802| 0.3821 | 0.6075 |
| [20]                | 24.8623| 0.2684 | 0.3325 |
| [21]                | 27.6824| 0.3815 | 0.5281 |
| [22]                | 26.7013| 0.3195 | 0.4326 |
| [23]                | 26.6036| 0.4244 | 0.7052 |
| Proposed Framework  | 23.1854| 0.7155 | 0.7418 |

Fig. 5. Lena histogram images (a) 0.5% and (b) 2%; Peppers histogram images (c) 0.5% and (d) 2%.
Fig. 7. Cameraman histogram (a) 0.5% and (b) 2%

Fig. 4-6 shows the histogram plots corresponding to the original image and denoised image for all the three images respectively. The deviation between the lines show the difference between the images, with no deviation meaning that the images are identical. The nearly arrant overlapping of the red and blue(denoised & original) lines is testimony of the admirable performance of the system. The mean divergence between the two lines is greater for images at high noise levels which is in conformity with the qualitative analysis. Among the six histograms, the one corresponding to denoised peppers image at 0.5% noise gives the best results. It shows almost flawless overlapping between the original and denoised images. On the other hand, the histogram of cameraman image at 2% noise shows the most lateral shift from the original. While this is the largest deviation amongst all of images, it still generates very good result, better than any manual technique can achieve.

5. Conclusion

This paper discusses a novel gaussian image denoising framework that works implementing deep learning CNN and enhancing its performance with method denoising. The performance of the proposed framework is evaluated by qualitative visual means, using image metrics such as PSNR, SSIM and UIQI and graphical functions namely plotting histograms. The framework is tested on three standard images with artificially introduced gaussian noise of two different intensities. Their in-depth analysis enacted, exhibited that the proposed framework provided scores superior to other state-of-the-art techniques, thus validating its enhanced performance and reliability. No reduction in black levels are observed and the edges are preserved with a high degree of finesse. This framework proves to be an effective tool for image denoising in real world applications.

References

[1] Fan, L., Zhang, F., Fan, H., & Zhang, C. (2019). Brief review of image denoising techniques. Visual Computing for Industry, Biomedicine, and Art, 2(1), 7.
[2] Buades A, Coll B, Morel JM (2005) A non-local algorithm for image denoising. In: Abstracts of 2005 IEEE computer society conference on computer vision and pattern recognition. IEEE, San Diego, pp 60–65. https://doi.org/10.1109/CVPR.2005.38
[3] Gondara, Lovedeep. “Medical image denoising using convolutional denoising autoencoders.” 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW). IEEE, 2016.
[4] Ahn, Byeongyong, and Nam Ik Cho. "Block-matching convolutional neural network for image denoising." arXiv preprint arXiv:1704.00524 (2017).
[5] Zhang, Kai, et al. “Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising.” IEEE Transactions on Image Processing 26.7 (2017): 3142-3155.
[6] Zuo, Wangmeng, Kai Zhang, and Lei Zhang. "Convolutional Neural Networks for Image Denoising and Restoration.” Denoising of Photographic Images and Video. Springer, Cham, 2018. 93-123.
[7] Haque, KazizNazmul,Mohammad Abu Yousuf, and Rajib Rana. “Image denoising and restoration with CNN-LSTM Encoder Decoder with Direct Attention.” arXiv preprint arXiv:1801.05141 (2018).
[8] Islam, Mohammad Tariqul, et al. ”Mixed Gaussian-impulse noise reduction from images using convolutional neural network.” Signal Processing: Image Communication 68 (2018): 26-41.
[9] Gong, Kuang, et al. "PET image denoising using a deep neural network through fine tuning." IEEE Transactions on Radiation and Plasma Medical Sciences 3.2 (2018): 153-161.

[10] Zhang, Kai, WangmengZuo, and Lei Zhang. "FFDNet: Toward a fast and flexible solution for CNN-based image denoising." IEEE Transactions on Image Processing 27.9 (2018): 4608-4622.

[11] Shahdoosti, Hamid Reza, and Zahra Rahemi. "Edge-preserving image denoising using a deep convolutional neural network." Signal Processing 159 (2019): 20-32

[12] Valsesia, Diego, Giulia Fracastoro, and Enrico Magli. "Image denoising with graph-convolutional neural networks." 2019 IEEE International Conference on Image Processing (ICIP). IEEE, 2019.

[13] Elhoseny, Mohamed, and K. Shankar. "Optimal bilateral filter and convolutional neural network based denoising method of medical image measurements." Measurement 143 (2019): 125-135.

[14] Tian, Chunwei, et al. "Enhanced CNN for image denoising." CAAI Transactions on Intelligence Technology 4.1 (2019): 17-23.

[15] Yu, Songhyun, Bumjun Park, and JechangJeong. "Deep iterative downup CNN for image denoising." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2019

[16] Tian, Chunwei, Yong Xu, and WangmengZuo. "Image denoising using deep CNN with batch renormalization." Neural Networks 121 (2020): 461-473.

[17] Tian, Chunwei, et al. "Attention-guided CNN for image denoising." Neural Networks 124 (2020): 117-129.

[18] Rajan, Jeny, and M. R. Kaimal. "Speckle Reduction in Images with WEAD and WECD." Computer Vision, Graphics and Image Processing. Springer, Berlin, Heidelberg, 2006. 184-193.

[19] Gorgel, Pelin, Ahmet Sertbas, and Osman N. Ucan. "A wavelet-based mammographic image denoising and enhancement with homomorphic filtering." Journal of medical systems 34.6 (2010): 993-1002.

[20] Bartyzel, Krzysztof. "Adaptivekuwahara filter." Signal, Image and Video Processing 10.4 (2016): 663-670.

[21] Wang, Xin. "Lee filter for multiscale image denoising." 2006 8th international Conference on Signal Processing, Vol. 1. IEEE, 2006.

[22] Mustafa, Zeinab A., et al. "Reduction of Speckle Noise and Image Enhancement in Ultrasound Image Using Filtering Technique and Edge Detection." Journal of Clinical Engineering 45.1 (2020): 51-65.

[23] Dutt, Vinayak, and James F. Greenleaf. "Adaptive speckle reduction filter for log-compressed B-scan images." IEEE Transactions on Medical Imaging 15.6 (1996): 802-813.

[24] Jindal, M., Bajal, E., Chakraborty, A., Singh, P., Diwakar, M., & Kumar, N. (2020). A novel multi-focus image fusion paradigm: A hybrid approach. Materials Today: Proceedings.

[25] Dhaundiyal, R., Tripathi, A., Joshi, K., Diwakar, M., & Singh, P. (2020, April). Clustering based Multi-modality Medical Image Fusion. In Journal of Physics: Conference Series (Vol. 1478, No. 1, p. 012024). IOP Publishing.

[26] Singh, P., & Shree, R. (2017). A New Computationally Improved Homomorphic Despeckling Technique of SAR Images. International Journal of Advanced Research in Computer Science, 8(3).

[27] Kumar, P., & Diwakar, M. A novel approach for multimodality medical image fusion over secure environment. Transactions on Emerging Telecommunications Technologies, e3985.
[28] Tyagi, T., Gupta, P., & Singh, P. (2020, January). A Hybrid Multi-focus Image Fusion Technique using SWT and PCA. In 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 491-497). IEEE.

[29] Kumar, M., & Diwakar, M. (2019). A new exponentially directional weighted function based CT image denoising using total variation. Journal of King Saud University-Computer and Information Sciences, 31(1), 113-124.

[30] Singh, P., & Shankar, A. (2021). A novel optical image denoising technique using convolutional neural network and anisotropic diffusion for real-time surveillance applications. Journal of Real-Time Image Processing, 1-18.

[31] Singh, P., Diwakar, M., Shankar, A., Shree, R., & Kumar, M. (2021). A Review on SAR Image and its Despeckling. Archives of Computational Methods in Engineering, 1-21.