LOW DOSE CT IMAGE DENOISING USING CYCLE CONSISTENT ADVERSARIAL NETWORKS

Mr.PRASAD RAYI[1], Mr. CHANDRA SEKHAR TADI[2]

[1]Associate Professor, International School of Technology and Sciences for Women, Rajanagaram, Andhra Pradesh-533294.

[2]Assistant Professor, International School of Technology and Sciences for Women, Rajanagaram, Andhra Pradesh-533294

ABSTRACT:

Low-dose computed tomography (CT) imaging is a valuable diagnostic tool but often produces noisy images that can impede accurate interpretation. In this study, we propose a novel approach for denoising low-dose CT images using cycle-consistent adversarial networks (CycleGAN), a deep learning technique. By training the CycleGAN on unpaired datasets of low-dose and high-dose CT images, our method learns to effectively reduce noise and enhance image quality without relying on explicitly paired training examples. We evaluate our approach on a diverse dataset of low-dose CT scans, comparing it with traditional denoising methods. The experimental results demonstrate that our CycleGAN-based denoising method achieves significant noise reduction and improves the overall image quality. Furthermore, the denoised images exhibit visual coherence and preserve important structural details. The promising outcomes of our study indicate the potential of CycleGAN for enhancing low-dose CT imaging, leading to improved diagnostic accuracy and patient care. Our work contributes to the advancement of denoising techniques in medical imaging, showcasing the applicability and effectiveness of deep learning approaches in addressing the challenges of noisy low-dose CT images.

INTRODUCTION

Image processing has been an area which has adopted and revolutionized with continuous changes and growth with demand. The demand has been with respect to new problem definition or improvement of the present solution at a very fast pace. As healthcare and visual experience in the form of entertainment has taken limelight visual data transmission and quality of image assessment has gathered even more importance.

*Corresponding Author

So in general terms image processing could be described as evaluation of image where input can be an image or frames from a video and output can either be an image or set of characteristics derived from images. Till the revolution of 3D scanners, image processing was only meant to be a two-dimensional matrix though the algorithms or methodology used for 2D matrix could also satisfy the 3D dimension with minute adjustments. One area of Image processing is image de noising, where attempts are carried out to restore an image with some knowledge about the cause of degradation. Though image denoising has been a very old concept it still remains a very important research topic, as basically it can be associated with a product in terms of entertainment and diagnosis where denoising is the final step or it can be associated as preprocessing step when the task is associated with feature extraction. Literature survey shows that there are plenty of denoising methods which include methods such as Gaussian, Probability, filter such as wiener and wavelets. All these methods still follow the traditional method of averaging. As observed in Figure 1.1(b), noise in the image has averaged areas which does not have the same similarities as that of the actual image and thus averaging process could reduce the noise and could leave the true image with some information also being averaged and thus losing the clarity of minute details

Though concept of averaging comes from the law of variance in probability, if an example is considered where pixels which is the intensity in the image contains 9 pixels of same intensity and all are averaged together then noise is reduced by a factor of 3. It shows that averaging concept is relatively simple but, which pixel to be considered for averaging is a difficult task and would not impact noise and too much averaging may create loss of information. A large number of methods have been developed to overcome the challenges involved in averaging, among them median filtering is the simplest which relies on the fact that adjacent pixels are most likely to be similar. Further, other methods based on literature are developed and attempts are being made to find like pixels and perform a better selective based averaging. Most of the recent works have involved applying filters in transfer domain such as Wavelet or DCT. Patch based block denoising method presently has attracted many researchers due to its effectiveness to tackle small sub images in a image. The sub image or patches are processed and manipulated and put back into the image to form a final resulting image.

LITERATURE SURVEY

BUADES and et al. [5] have stated the challenges posed by denoising method. And further the paper states the inefficient of the existing methods and most algorithm createsartifacts and removes fine structures from image. The paper was structured with the main focusto derive or define mathematical model and create experiment methodology in order to compare and classify denoising algorithms. Secondly the paper addresses Non local algorithm, which is known for preserving structure in digital image, and also how it has shown to be asymptotically optimal, when static image model is considered. The performance evaluation for all methods is characterized into four ways: mathematical, magnitude of the noise, perceptual mathematical, quantitative mathematical by tables of L2 distance. The powerful evaluation is however carried out by visualization of method noise on natural image.

Kostadin Dabov and et al [6] addressed method based on narrative de noising, which improved representation in transform domain. The improvement was carried by stacking 2D fragments into 3D array denoted by means of groups and a method of Collaborative filtering is employed which is described to be a special procedure because it could reveal smallest and finest details and also preserves the essential features. The main steps briefed in the literature are3D transformation, shrinkage in transform spectrum and finally perform inverse 3D transformation. The resulting output of simulation is likely to hold a 3D estimate of image blockswhich consist of groups that are jointly filtered.

Kostadin Dabov, and et al [8] have discussed how both non local method and locally adaptive anisotropic estimation can benefit the efficiency of denoising method. The method used discusses about grouping adaptive-shape neighbourhoods, which has a surrounding square super set similar to a block matching procedure. In this paper 3-D decor relating transform has been implemented and computed as separable composition with adaptive DCT called as SA-DCT and orthonormal transform where SA stands for Shape-Adaptive. Using hard thresholding or the wiener noise is attenuated which is called as spectrum shrinkage. Overall method presented in the paper generalizes and utilizes two existing filters which are the BM3D filter and

Point-wise SA-DCT filter. Kostadin Dabov and et al [9] proposed method which exploits non-local image modeling and anisotropic estimation. The process uses grouping of adaptive shape neighborhoods whose surrounding is estimated to be similar as per block matching. The data is stacked together hence the resulting structure would be 3D in structure having a shape of adaptive cross sections. Due to the similarity and also due to adaptive section of shape the 3D groups are characterized into high correlation along all the three dimensions. 3D de-correlation transforms when computed as a composition of SA –DCT and 1D transform can attenuate noise by shrinking and hard thresholding. Inversion of the transform will produce estimate for all neighbors, and are returned to the original location which are aggregated with estimates derived from other different groups. Hence the algorithm generalizes BM3D and point-wise SA-DCT filter which is capable of exploiting shrinkage on adaptive shape support.

EXISTING SYSTEM

This chapter provides the details and the highlights of the initial research work, performance analysis of BM3D, its mathematical aspects and the results of BM3D algorithm. The motivation for image de-noising approaches comes from the fiction that during the practice a digital image is captured, quantized, recorded and transmitted, it will inevitably be contaminated by a variety of noises, which will result in annoying artifacts and decrease in the visual quality. There is an increasing demand of image de-noising in various applications and abundant number of de-noising methods has been devised from many disciplines. Most of these methods depend on some mere assumptions about the clean signal so as to detach it properly from the random noise [6]. Ellenberger et al stated that "the noise found in an image is not interrelated with exact image contents that occurs in the image, because it arises from the noise sources as explained above instead of its content itself. Noise usually contains pixels that are quite different in appearance than neighbouring pixels, noise can be eliminated by an approach called averaging or taking the combining areas where the true image data are similar. In case of averaged areas, the noise do-not share the same information as that of the actual image, hence the process of elimination of the noise to a great extent with the actual image data largely intact. BM3D (Block Matching and 3D filtering) [6], is currently renowned state-of-the-art

ISSN 2277-2685
IJESR/Sep. 2022/ Vol-12/Issue-3/1-8
Mohammed Abdul Junaid *et. al.,* / International Journal of Engineering & Science Research

real-time algorithm in the area of denoising. The main concept behind it on a self-structured similarity matching by enrichment sparse representation of image blocks in transform-domain rather than in spatial domain. The enrichment of the sparseness can be gained by forming a group of similar 2D image patch and transforming into 3D arrays. Later since each different groups can have same block repeatedly leading to overlapping a collaborative filtering is applied so as to deal with these formed 3D groups [6].

PROPOSED SYSTEM

Today healthcare has advanced due to the reach of medical device which are able to diagnose by itself or display the organ of interest in quick time. Hence computer aided diagnosis system has gained focus which highlights in operation involving restoration, extraction and recognition. These operations are possible or tend to have higher accuracy only if image is not contaminated from any form of noise. Hence denoising becomes the main focus for any algorithm and it becomes a challenging area in the research even if there are many denoising algorithms. Working in the area of denoising, especially medical image is cumbersome task because crucial details in the image has to be taken care of. Keeping these main objectives as primary focus we propose a modified denoising approach which incorporates wavelet transform into the most popular block matching three-dimension algorithm. The results when tested over a set of image set proves that denoising using modified BM3D it is possible to obtain a better PSNR and visual quality when compared with BM3D. Optical computed tomography or popularly known by CT due to its non-invasive and nonradioactive nature has been widely used in medical imaging. Recently its application in dermatology and ophthalmology have increased. As CT is not affecting the skin or entering body it creates a cross section of the tissue, but there are chances that it could be contaminated by granular noise also called as speckle noise, which could disturb the crucial details of retina. Though there are several algorithms, it is still important that more efficient algorithm is necessary which preserves the detailed structure of images. Many methods have been derived to enhance image quality and which is degraded by speckle noise, while the most preferred method for speckle noise removal has been anisotropic diffusion. Bo Chong and Yong-Kai Zhu have proposed a method for novel speckle noise reduction in CT image which is described in and a technique on wavelet based soft thresholding have been described in. By using Modified Lee and Kuan adaptive reduction.

METHODOLOGY

Speckle noise is a signal dependent noise as its property changes along with the signal due to its multiplicative nature. Therefore, signal dependent noise are hard to eliminate without allowing any loss in crucial image information such as edges or texture. Based on the literature survey it was found that patch-based methods produce the best de nosing result when Gaussian noise is considered but same would not hold good if it is a speckle noise. Here CT image is considered by incorporate median filter so as to remove the signal dependency aspect. The steps followed for de nosing is presented below

1. An input noisy CT image is considered.
2. Median filter is used to convert the signal dependency.
3. Block matching is used so as to determine the spatial coordinates of the blocks in z , that are similar to currently processed one.
4. A 3D array (group) is formed by stacking the blocks located at the obtained locations.
5. UDWT is applied at each point to perform transformation of the image and restore the detailed coefficients and then use the approximation coefficients. Dimensionality reduction does not reduce by using UDWT on original image to extract detailed coefficients using wavelet and the decomposition usually are conducted up to level 4.
6. After performing UDWT on the image, thresholding of detailed coefficients at every level is processed for hard threshold.
7. The image is reconstructed with inverse transform i.e the low frequency components required are processed by inverse un-decimated wavelet transform.
8. The image obtained from the previous last step is once again forwarded to un-decimated wavelet transform so that possible coefficients are calculated again.
9. Lastly Wiener filter is applied and then inverse discrete wavelet transform is applied on the image.

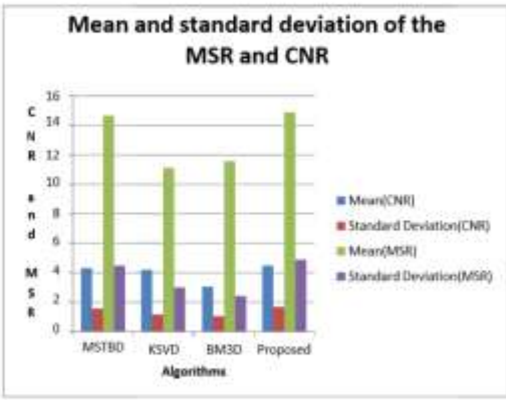
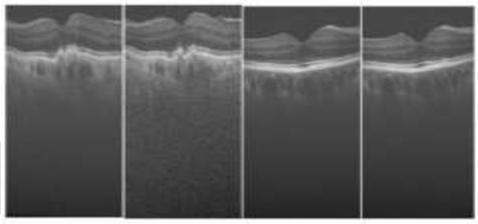


Fig.1. Mean and standard deviation of the MSR and CNR results for 10 SDCT retinal images using the, BM3D, K-SVD, MSBTD method.

Provides a graphical representation of the Mean and standard deviation of the MSR and CNR results for 10 SDCT retinal images using the, BM3D, K-SVD, MSBTD methods.



(a) MSTBD (b) KSVD (c)BM3D (d) Proposed

CONCLUSION

In this paper, we develop a novel image-to-image translation method based on CycleGAN for low-dose CT image denoising without aligned image pairs. The preliminary results are promising with better image appearance and quantitative measures than BM3D and KSVD. Our study also shows that increasing the training sample size can improve the CycleGAN based denoising method. For future work, we plan to optimize network architectures for better denoising performance and to compare it with other deep-learning based denoising methods.

REFERANCES

[1] M. Aharon, M. Elad, A. Bruckstein. "K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation". IEEE Transactions on Signal Processing, 2006, 54(11):4311-4322.

[2] K. Dabov, A. Foi, V. Katkovnik, E. Karen. “Image Denoising by Sparse 3-D TransformDomain Collaborative Filtering”. IEEE Transactions on Image Processing, 16(8):2080-2095, 2007.

[3] E.Y. Sidky and X. Pan. "Image reconstruction in circular cone-beam computed tomography by constrained, total-variation minimization." Physics in Medicine & Biology 53, no. 17: 4777, 2008.

[4] H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou, and G. Wang. "Low-dose CT with a residual encoder-decoder convolutional neural network." IEEE transactions on Medical Imaging 36, no. 12: 2524-2535, 2017.

[5] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville and Y. Bengio, "Generative adversarial nets," in Advances in neural information processing systems, 2014.

[6] J. M. Wolterink, T. Leiner, M. A. Viergever and I. Išgum, "Generative adversarial networks for noise reduction in low-dose CT," IEEE transactions on Medical Imaging, vol. 36(12), no. 12, pp. 2536-2545, 2017.

[7] Q. Yang, P. Yan, Y. Zhang, H. Yu, Y. Shi, Y. Z. Zhang and L. Sun, "Low-dose CT image denoising using a generative adversarial network with Wasserstein distance and perceptual loss," IEEE transactions on Medical i\Imaging, vol. 37(6), pp. 1348-1357, 2018.