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Low-Dose CT Image Denoising Using Cycle Consistent Adversarial Networks

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Abstract
Computed tomography (CT) has been widely used in modern medical diagnosis and treatment. However, ionizing radiation of CT for a large population of patients becomes a concern. Low-dose CT is actively pursued to reduce harmful radiation, but faces challenges of elevated noise in images. To address this problem and improve low-dose CT image quality, we develop an image-domain denoising method based on cycleconsistent adversarial networks (CycleGAN). Different from previous deep learning based denoising methods, CycleGAN can learn data distribution of organ structures from unpaired full-dose and low-dose images, i.e. there is no one-to-one correspondence between full-dose and low-dose images. This is an important development of learning-based methods for low-dose CT since it enables the model growth using previously acquired full-dose images and later acquired low-dose images from different patients. As a proof-of-concept study, we used the NIH-AAPM-Mayo Clinic Low Dose CT Grand Challenge data to test our CycleGAN denoising method. The results show that the proposed method not only achieves better peak signal-to-noise ratio (PSNR) for quarter-dose images than non-local mean and dictionary learning denoising methods, but also preserves more details reflected by images and structural similarity index (SSIM). Our investigation also reveals that a larger sample size leads to a better denoising performance for CycleGAN.

1- 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. 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 loosing the clarity of minute details.

Figure 1.1(a): True Image

Figure 1.1(b): Noise

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 an image. The sub image or patches are p88rocessed and manipulated and put back into the image to form a final resulting image.

2-Literature Review

This chapter summarizes prior works which are carried out in the area of denoising using BM3D. The literature survey also contains few highlights of deep learning in image denoising**.**

A. BUADES and et al. have stated the challenges posed by denoising method. And further the paper states the inefficient of the existing methods and most algorithm creates artifacts and removes fine structures from image. The paper was structured with the main focus to 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.

Peyman Milanfar and et al have presented some of the relationships between techniques and also bayesin approaches. Their work proposes to define new insights both theoretically and practically. Algorithms related to Block matching and 3D filtering and also methods for iterative improvement have been discussed. An approach has also been laid out for performance analysis and improvement of existing filtering algorithms.

Mukesh C. Motwani and et al have discussed the challenges involved in denoising for researchers. The literature describes various algorithms with their concepts, merits and demerits pertaining to image denoising. The literature significantly contributes in depicting some contributions relevant to the field of denoising. After discussing the popular methods and overview of algorithms a brief evaluation is provided to the best methods which are currently used and suitable future scope is also listed down.

Kostadin Dabov and et al 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 are 3D 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 blocks which consist of groups that are jointly filtered.

Marc Lebrun and et al discussed the implementation of open-source execution for the existing BM3D method. The focus was given on addressing all parameters and also confirm existing optimality. New notation was depicted and all notation were made transparent from the original BM3D literature.

Kostadin Dabov, and et al 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 neighborhoods, 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 Pointwise SA-DCT filter.Kostadin Dabov and et al proposed method which exploits nonlocal 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 transform 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.

Kostadin Dabov and et al introduced principal component analysis method which exploits non-local image modeling and local shape based adaptive anisotropic estimation. Groups based on similar patches are exploited by non-local modeling and de noising is performed using spectrum shrinkage. Effectiveness of shrinkage is its ability to transform or represent true image data and hence separating it from noise. Firstly, image patches are employed which have adaptive shape, and secondly PCA are employed on these adaptive shape neighbourhoods. The PCA is obtained by Eigen value decomposition.

Qian Chen and Dapeng have stated the benefit of BM3D and showed how BM3D can be utilized to attain better performance can be achieved in the area of denoising. However, the ineffectiveness is observed when image is heavily contaminated with noise. The author has addressed the issue by proposing bounded BM3D scheme. The novelty is split in two sections where firstly the scheme allows partition of image into multiple regions and then identify boundary in-between the region. Block matching is restricted within the region and hence preserves geometric features like edges, being diluted from collaborative filtering in BM3D. When compared against BM3D the proposed method from authors has better visual performance and decibel point increase of 0.23dB-1.33dB in PSNR for heavy noisy images.

Aram Danielyan, and et al have stated how adaptive non local patch wise method estimate is having its benefit in image denoising. The paper analyses how frames are synthesized for BM3D modeling and use them to develop de-blurring algorithm which is based on Lagrangian technique. During simulation, proposed algorithm efficiently has been able to outperform against other methods. Aram Danielyan, and et al described family of block matching algorithm, which has been proposed in the scope of non-local patch wise modeling.

In the paper authors have constructed analysis and synthesized frames which formulates BM3D image and from the frames develops an iterative algorithm which targets de blurring. The paper also discusses about different approach to de-blurring problem where first the author briefs about minimization of single objective function and then Nash equilibrium which balances the two objective functions. Experimentation shows how decoupled algorithm which is derived from Nash equilibrium has best interpretation numerically as well as visually. Hence the algorithm shows how BM3D provides a value addition as an advanced image de noising method.

Kostadin Dabov and et al stated BM3D as powerful technique actively involved in image de noising. Specifically non-local modeling through collaborative filtering is exploited. This allows determining mutually identical image blocks and grouping them into 3D arrays. BM3D can also be utilized to sharpen image and simultaneously denoising image by combining it with transform domain alpha rooting. The thresholds are modified by observing the α-root and their magnitude which is set as α> 1, and thus amplifying the difference in values between grouped blocks. Further performance can be increased with the use of global α in the entire image and hence different degree of sharpening can be carried out at different area of image which mainly works on content dependent information. The paper proposes using α for sharpening of image through an estimation which is weighted estimates of the low as well as high frequency and also considering edge content of the average block. The method is shown to generate an improvement visually and high PSNR over its counterpart.

Kostadin Dabov and et al proposed restoration method so as to exploit restoration technique. This work proposes BM3D for colored noise which can be used in two step de-blurring method for improving regularization after inversion in Fourier domain. Hard thresholding with regular inversion is used as an initial step and the second step involves Wiener inversion using BM3D with collaborative Wiener filtering and results show that proposed technique outperforms the current method which has been validated using PSNR.

3-Noise Types in an Image

Low-Dose CT Image Denoising Using Cycle Consistent Adversarial Networks Chapter 3 Noise Types in an Image This chapter describes different types of noise that could corrupt an image and mathematical models for the noise are discussed. Due to demand for capturing devices and usage of image sensors, camera devices which are vulnerable to noise and hence, de-noising techniques are important as they improve the appearance of image in terms of quality and enhance minute structural details. Noise can be quantified by analysing number of pixels being corrupted in an image. Other than the above explained situation noise in the digital image may be due to other factors such has: a) situation by the imaging sensors. b) Illumination levels of sensor and variation in sensor temperature c) communication channel interference d) thermal energy of heat.

In an image, noise is intensity variation in a random manner. It is noticed as spots or as grains like in the image. Few denoising algorithms can reduce or remove the visibility of noise by smoothing except in the dissimilarity borders. But obviously these methods can sometimes perform well due to low dissimilarity details. In order to perform de noising process prior knowledge on the type of noise present plays an important role. Various noise modelled can either be in a Gaussian, salt & pepper, uniform distribution, or speckle noise. Noise can be in form of additive or multiplicative form

Gaussian Noise :It is an additive type of noise where every each pixel is sum of the true value and random noise. The noise is always independent from intensity at every point.

The probability distribution morphologically represents bell shape as in Figure.

$$p(k) = (\frac{1}{\sqrt{h\sigma\sigma^2}} e^{\frac{-n^2}{\sigma^2}} \qquad (3.3)$$

Where n is gray level and standard deviation for noise given by σ

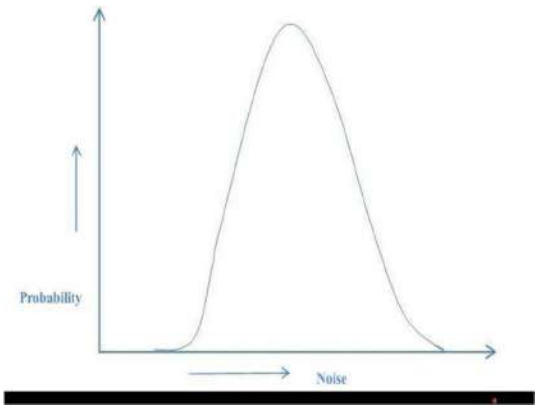

Figure 3.1 Gaussian Noise Distribution

4- Existing System Performance Analysis of BM3D on Still Images

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.

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 arise 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), is currently renowned state-of-the-art 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

5- Modification of BM3D on Spatial Domain CT Images

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 have 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.

6-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.

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