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Prevalent Degradations and Processing Challenges of Computed Tomography Medical Images: A Compendious Analysis

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Abstract

Computed Tomography (CT) has remained an important component of medical imaging since its inception. In general, it is preferred to keep the radiation dose as low as possible during the CT examinations to prevent patients as well as operators from the dangerous side effects of these radiations, which in an extreme case may lead to cancer. However, reducing the radiation dose leads to undesirable degradations which not only reduce the visual quality of CT images, but also make such images difficult to interpret in clinical routines. The most common degradations in low-dose CT images include blur, noise and low-contrast. Over the recent years, considerable research has been made to process these degradations. However, they still remain open for research due to the wide variety of challenges they offer. In this article, the causing factors of such degradations are addressed adequately. Furthermore, the challenges that face the processing of these degradations are mentioned in detail. Finally, this article is intended for researchers who are approaching this topic to understand the aforesaid issues extensively.

Keywords*: computed tomography, blur, noise, low-contrast, image degradation, processing challenge.*

1. Introduction

The last few decades have witnessed tremendous advancements in technology in different scientific domains. One of the very rapidly developing technologies is medical imaging which is still on expansion in terms of innovation and discovery. Thanks to the evolution of computers and imaging technologies, medical imaging has significantly enhanced the diagnostic procedures, where an inspection of the images captured via a variety of imaging technologies aided the experts in identifying various health problems. Medical imaging is defined as the procedures and techniques used to produce images for clinical purposes like medical procedures, disease diagnosis and medical sciences [1]. Medical imaging also refers to a collection of methods used to generate images of the human body and is considered as an important tool to diagnose and detect various diseases. Furthermore, it is one of the fastest growing fields in the medical research. The tremendous development in different modalities of medical imaging have led to a significant improvement in the patient care, offering early diagnosis and detailed indications on patients conditions, which allows effective and pertinent treatments. The discovery of new diseases and the early diagnosis of existing diseases eventually served to enhance the overall efficiency of healthcare services [2].

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As a function of image acquisition technology, medical imaging consists of various imaging techniques including X-Ray, Mammography, Angiography, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, Magnetic Resonance Angiography (MRA), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and functional MRI. Different imaging modalities can be used to acquire diverse information about the human body. Computed Tomography (CT) is generally applied in a number of industrial applications, but it is also widely used as an effective medical imaging technology [3]. In modern medicine, CT imaging plays a critical role in diagnosing, staging, planning treatment and therapeutic assessment of different diseases [4, 5]. In most cases, CT imaging is used to discover lung and breast cancers, trauma and osteoporosis screening [6]. CT is generally preferred for examination of areas vulnerable to motion such as lungs or detection of lung nodules [7, 8]. Thanks to the advancements in technology, CT imaging has expanded to cover other applications including angiography, colonography and urology [9]. Similarly, CT is used for the diagnosis of small bowel pathology [10], pleomorphic adenoma in salivary glands [11] and myocardial infarction [12]. Furthermore, it is also utilized for brain imaging and is known to produce better details on denser tissues with less degradation. The use of CT is also known to be effective in prostate brachytherapy to determine the placement of the radioactive and also to confirm the seed location post-procedure [13]. Usually, CT imaging is preferred over MRI due to a number of factors such as cheaper cost, less imaging time, wide availability, ease of access, acceptable recognition of calcification and excellent quality of bone features [14]. Figure 1 shows an outside view of a modern CT system.

Figure 1. A Modern CT Scan Machine

Images obtained using CT scans can be conceptualized as being the sum of edges, uniform intensities, a repeated structure of fine-scale textures and a noise component [15]. CT images carry significant importance in a number of health services and it is desirable to improve the quality of these images for a better analysis and understanding [16]. Hence, the problems which affect CT images and reduce their quality must be studied carefully and efficient solutions to these problems must be provided. These problems are generally termed as degradations and have many types such as blur, noise and low-contrast [17]. Accordingly, these degradations are handled by using image enhancement and restoration methods. In the field of image processing, low-level and high-level methods are used to process degraded images. The low-level methods normally utilize a scant knowledge about the content of the image. Examples of low-level methods include image sharpening, edge extraction and image compression.

In contrast, high-level methods are founded on plans, aims and knowledge. It attempts to imitate the human way of thinking to obtain the ability to determine decisions consistent with the information present in an image [18]. Image enhancement and restoration have been attractive research and development areas in image processing for many years [19]. Image enhancement methods are aimed at improving the visual quality of images by modifying the appearance of images via improvements in brightness, contrast and/or colors. In addition, these enhancement methods can be employed to highlight certain image features and improve the quality of an image by enhancing its intensity [20]. On the contrary, the aim of image restoration is to recover a latent image from its degraded observation with as much details as possible [21]. Image restoration methods are aimed at reducing degradations such as noise and blur to produce better quality images. The use of image enhancement and restoration methods can serve to provide improved quality results. Such methods can function in a spatial or frequency domain. Spatial domain operations are applied directly on image pixels, while frequency domain operations are applied by first transforming the image to the frequency domain using the Fourier transform. Summarizing, the enhancement and restoration methods provide an improved image quality by exposing more obscured details and revealing more vital information to the observer. There exist a vast variety of image enhancement and restoration techniques and employing the appropriate combination for a given problem results in significant improvements in the visual quality of images.

2. Image Degradations

Considering the significance of imaging in the medical science, image processing techniques carry vital importance to obtain precise and meaningful information from medical images. Since the inception of CT scans, it has received considerable attention in the medical field [22]. Such scans are helpful in identifying diseases by obtaining images using X-rays. Briefly, the radiations passing through human body are received by a detector and are collected by a computer device to get a cross-sectional image. Figure 2, shows an illustrative diagram of a CT system.

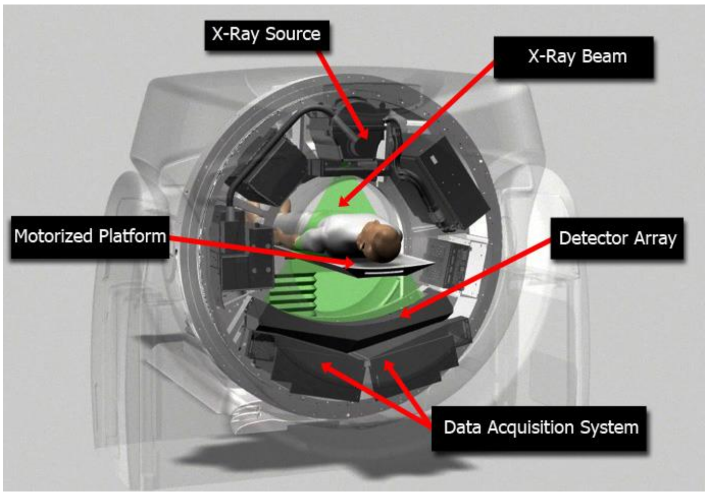


Figure 2. An Ilustrative Diagram of a CT System

Going into details, X-ray beams are projected through the body at different angles and a row of detectors positioned on the opposite side of the source to record the intensity loss during propagation. The collected data correspond to the line integral of the attenuation field associated with the internal organs can be used to produce a cross-sectional image. The collected data is then combined by a computer to form a tomographic image [23].

The idiom tomography denotes as image (-graph) of a slice (tomo-). This system produces images of a single slice of tissue from the body. The benefit of a tomographic image over a projection image is its capability to show the anatomy in a slice of tissue with the absence of overlying or underlying structures. A basic computed tomography system consists of X-ray generation, detection, digitization, processing and a computer for image processing and reconstruction. X-rays passing through human body are attenuated at different rates by different tissues. The attenuated X-rays are collected by detectors and transformed into digital numbers or data using analog to digital converters. Then, the digital data is sent to a computer for image formation. CT imaging technology has evolved enormously in the recent years. However, CT images are known to be degraded by various acquisition artifacts and may contain degradations like noise [24], blur [25] and low-contrast [26]. Figure 3, shows the degradations of noise, low-contrast and blur.

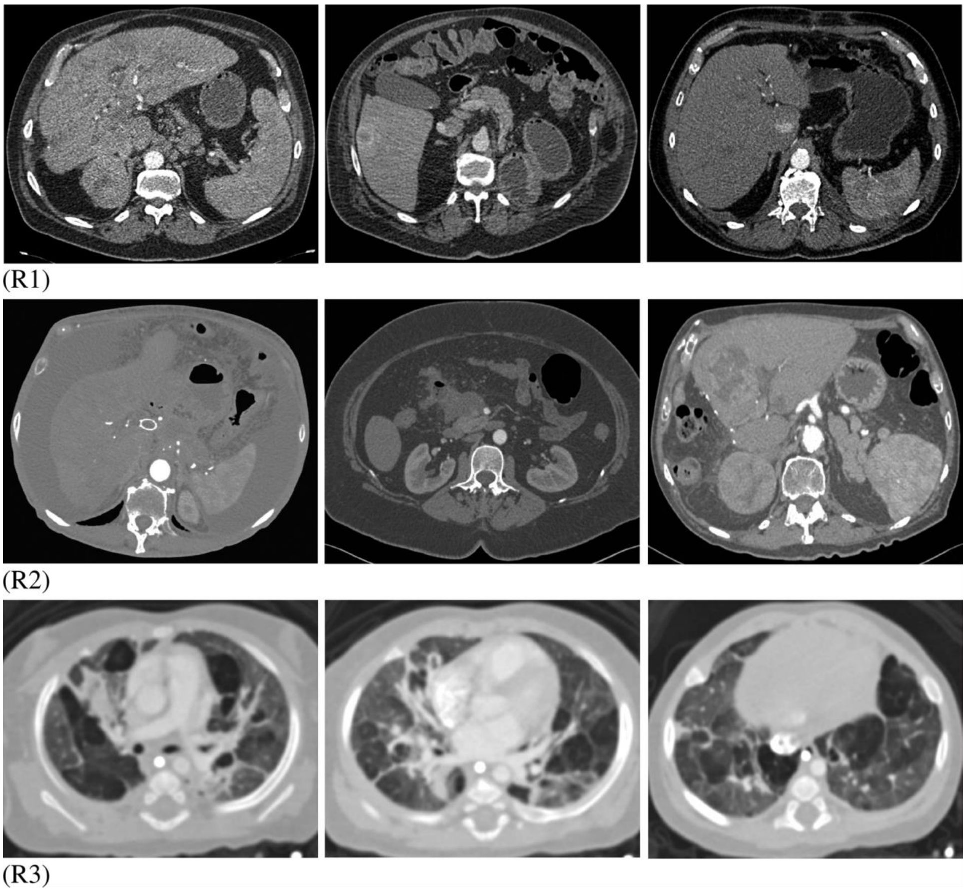


Figure 3. The Prevalent Degradations of CT Images. Rows from R1 to R3: (R1) Noisy Images; (R2) Low-Contrast Images; (R3) Blurry Images

The first degradation is noise which can be of many types, the most common with CT images is the additive white Gaussian [7- 27]. Noise is considered as an unwanted image component that makes it hard to identify the important elements as it decreases the visibility of low-contrast details [14]. The main factor causing the occurrence of noise in CT images is the usage of low radiation dose during the scanning procedure. Previously, the amount of radiation transmitted to the patients during the examination was considered too high compared to other radiological examinations [28]. Therefore, health concerns were increased because of the dangerous biological effects of radiation. The exposure to high radiations could eventually cause cancer, skin erythema, skin tissue injury and birth defects [23]. Consequently, low radiation dose was preferred to reduce the risks to the health of patients as well as operators. Previously, many scientific studies have confirmed the high incidence of cancer due to high radiation exposure, in which the amount of radiation obtained at pediatric helical CT is equal in dosage to those who experienced atomic bomb exposure. Moreover, the amount of radiation used in a CT examination is nearly 10 to 100 times higher than a usual X-ray examination. In addition, CT tests use 47% of entire medical radiation, even though it represents just 7% of whole radiology examinations [14]. Additional research showed that the number of CT scans achieved in the United States raised from three million in 1980 to 70 million in 2007.

As stated by the same research, these 70 million tests caused 29,000 cancers eventually. Thus, every year, CT scans cause approximately 14,500 deaths. Therefore, one of the main considerations in recent medical CT radiology is reducing the radiation exposure to individuals. Unfortunately, there is an essential balance between radiation doses and imaging quality, in which a higher imaging quality is generated from higher radiation dose and vice versa [29]. Reducing the radiation dose in CT scans to avoid health risks results in images with noise and other types of degradations [28]. It is therefore desirable to reduce the radiation of CT scans to an extent where the effect on the image quality is as low as possible [30]. Consequently, CT scan manufacturers and scholars are researching new methods to maintain an acceptable image quality when the radiation dose is reduced. Thus, image denoising algorithms are usually used, because these algorithms are the simplest and cheapest way to attenuate the noise while maintaining a good image quality in both sinogram space (projections) as well as image space [31]. In addition to low radiation dose, other factors which lead to the occurrence of noise include photon-counting errors [32] and finite exposure time [21].

Likewise, real-world limitations such as imaging hardware, detector space and resolution [33], loss of image data during the acquisition process, sensor and detector errors also lead to image noise. Moreover, noise also appears in CT images due to issues in the absorption of X-ray photons, where the less number absorbed, the noisier the image [34]. Likewise, using inadequate image reconstruction methods can also produce noisy images [35-36]. Similarly, different acquisition techniques [37], different sources of interferences in an imaging system and the limited capability of a display system may result in noisy CT images [38]. In addition, using low tube voltage scans reduce the radiation dose but increases the image noise [39]. The second common degradation in CT images is low-contrast artifact [10-26] and [40-41]. The low-contrast artifact occurs due to different acquisition, transmission, storage, display devices and diverse sorts of reconstruction and enhancement algorithms [42].

Similarly, partial volume effects as well as low radiation dose can reduce the contrast of CT images [43]. Moreover, the unwanted image noise can cause the low-contrast artifact [44]. In addition, smoothing filters applied to reduce such noise also degrade the contrast [14]. The third degradation is blur, which reduces the visibility of important image components [14-45]. The type of blur that affects CT images is mostly Gaussian [25-95]. Generally, the finite size of the X-ray source focal spot and the detector element in the CT array leads to image blur. Furthermore, noise also can lead to blurry CT images [45]. Blurring can also be the result of imperfect resolution of the imaging system [46]. Likewise, in some cases, loss of image data during the acquisition process results in blurry images [21]. At times, application of low-pass filters to reduce noise from CT images also blurs these images. In addition, a low radiation dose causes the upsurge in noise and results in a blurred image. During the CT scan process, the quantity of blurring is defined by the focal spot size and the detector size while during the image formation process, blurring occurs due to the voxel size and the nature of the utilized filter [14].

Additionally, various image denoising methods and their respective implementations have a similar simple concept of noise attenuation through image blurring. Blurring can occur locally by a Gaussian smoothing approach or anisotropic filtering [47]. The degradations discussed above affect the quality of CT images significantly, obscuring the correct anatomical and physiological feature representation. Noise usually provides an undesirable appearance to the image with a spotted, grainy or snowy form. Besides, noise can hide and reduce the clarity of specific features in an image such as low-contrast items [48]. The existence of noise reduces the image quality and hides its important details which hamper the segmentation, feature extraction, recognition of small details, quantitative analysis and diagnosis of diseases [37]. The presence of noise reduces the accuracy and reliability of medical images. Hence, a suitable denoising process is often required before extracting the information from the examined image [42].

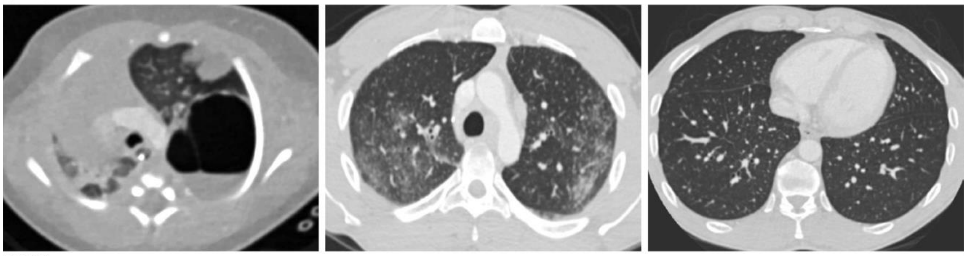
Also, improving the contrast of CT images may lead to enhanced tumor recognition, because liver and tumor tissues have equivalent gray levels in liver tumor segmentation [49]. Furthermore, the blur hides important information that indeed exists in an image. Moreover, low image contrast, noise and other artifacts may lead to a faulty segmentation process [50]. Improving the image contrast is important to assess the severity of a disease near the soft tissue regions [46]. Researchers in different areas of image processing aim to process the aforementioned degradations in CT images to obtain adequate quality results. The need to reduce undesirable degradations and enhance the spatial resolution of images has increased in the recent years [51]. Improvements in imaging machinery and image processing methods have significantly increased the clarity of CT images and contributed to achieve a better diagnosis of different diseases [20]. These image enhancement and restoration methods can improve the overall image resolution as attenuating the noise and blur while improving the contrast lead to better quality results.

3. Processing Challenges

CT is an important mean which is extensively used in the medical field to detect and diagnose different diseases accurately. For an accurate diagnosis, the visual quality of the images should be high with as low degradations as possible [37]. In most cases, however, CT images suffer from different degradations. Sometimes, these degradations affect an image independently. For example, CT images may suffer from noise [52], low-contrast [26] or blur [53]. But in some cases, a combination of these degradations may occur and affect an image. CT images may have low-contrast and noise [50- 56], or blur and noise [57-60]. Figure 4 shows different low-contrast-noisy and blurry-noisy CT images. The presence of noise in CT images may hinder the process of accurate disease diagnosis, hide important image details, reduce the lucidity of low-contrast details, obstruct the segmentation procedure and hamper the feature recognition and extraction processes [14, 61]. Likewise, the blur hides vital information that indeed exists in an image [62] and the low-contrast makes the recognition of tumors difficult [49], produces a faulty segmentation process [50], makes it hard to detect the problems near soft tissue regions [46] and reduces the visibility of small medical details [63].

Many denoising methods, such as, anisotropic filtering [64], total variation [65], Gaussian smoothing [66], wavelet thresholding [67], SUSAN filter [68] and non-local means [69] have been used to reduce image noise. However, they inevitably blur the fine image details, remove some of the important image details and/or produce an unrealistic contrast [14-19]. Likewise, many deblurring methods, such as, inverse filter [70], regularized filter [71], Van-Cittert algorithm [72], Richardson-Lucy algorithm [73], Poisson MAP algorithm [74], Landweber algorithm [75], Wiener filter [76] and constrained linear least-squares deconvolution [77] have been used to reduce the image blur. However, such methods may cause a number of other issues including noise amplification and ringing artifacts [78], boundary artifacts [79], low deblurring ability [80] and high calculations times [77]. Similarly, many image enhancement methods, such as, histogram equalization [81], Sigmoid function [82], low-pass, high-pass, homomorphic filters [83], normalization [84], log and power law transformations [85, 86], contrast stretching [87] and Retinex model [88] have been used to improve the low image contrast. However, using these methods may result in washed out artifact and abnormal brightness [89], contouring artifact [90], unnatural appearance [91] and noise amplification [92].

(R1)



(R2)

Figure 4. The Multi-Degradations of CT Images. Rows from R1 to R2: (R1) Low-Contrast-Noisy Images; (R2) Blurry-Noisy Images

Restoring blurry-noisy images is a challenging task because blur is a low pass signal and noise is a high pass signal. To deblur an image, a high pass filter is applied, but this leads to amplify the latent image noise. On the other hand, applying a low pass filter to attenuate noise leads to blurring in the processed image [93]. Consequently, when attempting to recover a blurry-noisy image using a single algorithm, the results are mostly unsatisfactory. In certain cases, attenuating the noise of CT images can increase the blur and decrease the contrast [94]. Moreover, recovering low-contrast-noisy images is also challenging as the low-contrast artifact reduces the lucidity of the noise information leading to a defective denoising process. It can be concluded that recovering an acceptable quality image from its degraded observation has become a significant step for a better diagnostic process in computed tomography. Thus, developing efficient, reliable and robust methods to corroborate this purpose is considered an essential requirement.

4. Conclusion

In conclusion, efficient, new and trustworthy image enhancement and restoration methods are highly required to provide a better visual quality for CT images. The aforementioned subjects are highly important, not only in the imaging area, but also in the medical field, as testified by the increasing number of published articles, books and conferences over the last few years. Moreover, they have a high profile in the medical field due to their direct impact on the effectiveness of disease diagnosis and ultimately on the human life. The need for new methods which can efficiently process CT images while preserving their important details is fundamental to deliver visually improved images, which will eventually help specialists to provide accurate diagnosis of different diseases. Finally, it is more cost effective to improve the perceived quality of CT images using software rather than hardware.

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References

[1] D. Ganguly, S. Chakraborty and T. Kim, "A Cognitive Study on Medical Imaging", International Journal of Bio-Science & Bio-Technology, vol. 2, no. 3, **(2010)**, pp. 1-18.

[2] J. Marks and L. Højgaard, "Medical Imaging for Improved Patient Care", European Science Foundation Policy Briefing, vol. 28, **(2007)**, pp. 1-8.

[3] J. Kim, J. Fessler and Z. Zhang, "Forward-Projection Architecture for Fast Iterative Image Reconstruction in X-Ray CT", IEEE Transactions on Signal Processing, vol. 60, no. 10, **(2012)**, pp. 5508-5518.

[4] M. Bazalova, Y. Kuang, G. Pratx and L. Xing, "Investigation of X-ray Fluorescence Computed Tomography (XFCT) and K-Edge Imaging", IEEE Transactions on Medical Imaging, vol. 31, no. 8, **(2012)**, pp. 1620-1627.

[5] J. Chen, J. Cong, L. Vese, J. Villasenor, M. Yan and Y. Zou, "A Hybrid Architecture for Compressive Sensing 3-D CT Reconstruction", IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 2, no. 3, **(2012)**, pp. 616-625.

[6] T. Messay, R. Hardie and T. Tuinstra, "Segmentation of pulmonary nodules in computed tomography using a regression neural network approach and its application to the Lung Image Database Consortium and Image Database Resource Initiative dataset", Medical Image Analysis, vol. 22, no. 1, **(2015)**, pp. 48-62.

[7] G. Andria, F. Attivissimo and A. Lanzolla, "A statistical approach for MR and CT images comparison", Measurement, vol. 46, no. 1, **(2013)**, pp. 57-65.

[8] Q. Li, "Recent progress in computer-aided diagnosis of lung nodules on thin-section CT", Computerized Medical Imaging and Graphics, vol. 31, no. 4, **(2007)**, pp. 248-257.

[9] E. Dougeni, K. Faulkner and G. Panayiotakis, "A review of patient dose and optimisation methods in adult and paediatric CT scanning", European Journal of Radiology, vol. 81, no. 4, **(2012)**, pp. e665-e683.

[10] W. Zhang, J. Liu, J. Yao, A. Louie, T. Nguyen, S. Wank, W. Nowinski and R. Summers, "Mesenteric Vasculature-Guided Small Bowel Segmentation on 3-D CT", IEEE Transactions on Medical Imaging, vol. 32, no. 11, **(2013)**, pp. 2006-2021.

[11] N. Kakimoto, S. Gamoh, J. Tamaki, M. Kishino, S. Murakami and S. Furukawa, "CT and MR images of pleomorphic adenoma in major and minor salivary glands", European Journal of Radiology, vol. 69, no. 3, **(2009)**, pp. 464-472.

[12] R. Blankstein, I. Rogers and R. Cury, "Practical tips and tricks in cardiovascular computed tomography: Diagnosis of myocardial infarction", Journal of Cardiovascular Computed Tomography, vol. 3, no. 2, **(2009)**, pp. 104-111.

[13] S. Ghose, A. Oliver, R. Martí, X. Lladó, J. Vilanova, J. Freixenet, J. Mitra, D. Sidibé and F. Meriaudeau, "A survey of prostate segmentation methodologies in ultrasound, magnetic resonance and computed tomography images", Computer Methods and Programs in Biomedicine, vol. 108, no. 1, **(2012)**, pp. 262-287.

[14] F. Attivissimo, G. Cavone, A. Lanzolla and M. Spadavecchia, "A Technique to Improve the Image Quality in Computer Tomography", IEEE Transactions on Instrumentation and Measurement, vol. 59, no. 5, **(2010)**, pp. 1251-1257.

[15] B. Vandeghinste, B. Goossens, R. Van Holen, C. Vanhove, A. Pižurica, S. Vandenberghe and S. Staelens, "Iterative CT Reconstruction Using Shearlet-Based Regularization", IEEE Transactions on Nuclear Science, vol. 60, no. 5, **(2013)**, pp. 3305-3317.

[16] K. Mala, V. Sadasivam and S. Alagappan, "Neural network based texture analysis of CT images for fatty and cirrhosis liver classification", Applied Soft Computing, vol. 32, **(2015)**, pp. 80-86.

[17] R. Lagendijk and J. Biemond, "Basic Methods for Image Restoration and Identification", In: Bovik, A. C. (Ed.), the Essential Guide to Image Processing, USA: Academic Press, **(2009)**, pp. 323-347.

[18] R. Paruchuri, "Segmentation of Human Lung CT Scans Using Hybrid Method", Master's Thesis, University of Lübeck, Germany, **(2006)**.

[19] X. Yan, M. Zhou, L. Xu, W. Liu and G. Yang, "Noise Removal of MRI Data with Edge Enhancing", IEEE 5th International Conference on Bioinformatics and Biomedical Engineering, Wuhan, China, **(2011)** May 10-12, pp. 1-4.

[20] T. Acharya and A. Ray, "Image Processing", Hoboken, N.J: John Wiley, **(2005)**.

[21] T. Pham, "Supervised restoration of degraded medical images using multiple-point geostatistics", Computer Methods and Programs in Biomedicine, vol. 106, no. 3, **(2012)**, pp. 201-209.

[22] H. Zhang, J. Ma, J. Wang, Y. Liu, H. Han, H. Lu, W. Moore and Z. Liang, "Statistical image reconstruction for low-dose CT using nonlocal means-based regularization. Part II: An adaptive approach", Computerized Medical Imaging and Graphics, vol. 43, **(2015)**, pp. 26-35.

[23] M. Haque, M. Ahmad, M. Swamy, M. Hasan and S. Lee, "Adaptive Projection Selection for Computed Tomography", IEEE Transactions on Image Processing, vol. 22, no. 12, **(2013)**, pp. 5085-5095.

[24] S. Hashemi, S. Beheshti, R. Cobbold and N. Paul, "Adaptive updating of regularization parameters", Signal Processing, vol. 113, **(2015)**, pp. 228-233.

[25] Y. Sun, L. Zhang, J. Zhang and L. Shi, "Neural Network Blind Equalization Algorithm Applied in Medical CT Image Restoration", Mathematical Problems in Engineering, vol. 2013, **(2013)**, pp. 1-10.

[26] T. Tan, K. Sim, C. Tso and A. Chong, "Contrast enhancement of computed tomography images by adaptive histogram equalization-application for improved ischemic stroke detection", International Journal of Imaging Systems and Technology, vol. 22, no. 3, **(2012)**, pp. 153-160.
[27] P. Gravel, G. Beaudoin and J. DeGuise, "A Method for Modeling Noise in Medical Images", IEEE Transactions on Medical Imaging, vol. 23, no. 10, **(2004)**, pp. 1221-1232.
[28] Y. Chen, W. Chen, X. Yin, X. Ye, X. Bao, L. Luo, Q. Feng, Y. li and X. Yu, "Improving low-dose abdominal CT images by Weighted Intensity Averaging over Large-scale Neighborhoods", European Journal of Radiology, vol. 80, no. 2, **(2011)**, pp. e42-e49.
[29] W. Yu, Y. Chen and L. Lua, "De-Noising of Low-Dose CT Images Using Space-Time Nonlocal Means Over Large-Scale Neighborhoods", Proceeding of the International Conference on Complex Medical Engineering, Harbin, China, **(2011)** May 22-25, pp. 455-459.
[30] X. Wang, G. Hu, B. Yan, Y. Han, L. Li and S. Bao, "Fast Low-Dose Reconstruction From Truncated Data in Dental CT", IEEE Transactions on Nuclear Science, vol. 60, no. 1, **(2013)**, pp. 174-181.
[31] S. Do, W. Karl and H. Pien, "A Novel Hybrid Algorithm for Accelerating CT Reconstructions and Improving Low-Dose Image Quality", IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Chicago, USA, **(2011)** March 30-April 2, pp. 1516-1519.
[32] R. Clackdoyle and M. Defrise, "Tomographic Reconstruction in the 21st Century", IEEE Signal Processing Magazine, vol. 27, no. 4, **(2010)**, pp. 60-80.
[33] W. Li-yan and W. Zhi-hui, "Fast Gradient-Based Algorithm for Total Variation Regularized Tomography Reconstruction", IEEE 4th International Congress on Image and Signal Processing, Shanghai, China, **(2011)** October 15-17, pp. 1572-1576.
[34] M. Aslan, A. Ali, A. Farag, B. Arnold, D. Chen and P. Xiang, "3D Vertebrae Segmentation in CT Images with Random Noises", IEEE 20th International Conference on Pattern Recognition, Istanbul, Turkey, **(2010)** August 23-26, pp. 2290-2293.
[35] S. Goshima, M. Kanematsu, H. Nishibori, D. Miyazawa, H. Kondo, N. Moriyama and K. Bae, "Image quality and radiation exposure in CT of the pancreas: 320-MDCT with and without adaptive iterative dose reduction versus 64-MDCT", Clinical Radiology, vol. 68, no. 11, **(2013)**, pp. e593-e600.
[36] S. Ramani and J. Fessler, "A Splitting-Based Iterative Algorithm for Accelerated Statistical X-Ray CT Reconstruction", IEEE Transactions on Medical Imaging, vol. 31, no. 3, **(2012)**, pp. 677-688.
[37] A. Choubey, G. Sinha and S. Choubey, "A Hybrid Filtering Technique in Medical Image Denoising: Blending of Neural Network and Fuzzy Inference", IEEE 3rd International Conference on Electronics Computer Technology, Kanyakumari, India, **(2011)** April 8-10, pp. 170-177.
[38] S. Youssef, E. Korany and R. Salem, "Contourlet-Based Feature Extraction for Computer Aided Diagnosis of Medical Patterns", IEEE 11th International Conference on Computer and Information Technology, Pafos, Cyprus, **(2011)** August 31-September 2, pp. 481-486.
[39] M. Kidoh, T. Nakaura, S. Nakamura, S. Oda, D. Utsunomiya, Y. Sakai, K. Harada and Y. Yamashita, "Low-dose abdominal CT: Comparison of low tube voltage with moderate-level iterative reconstruction and standard tube voltage, low tube current with high-level iterative reconstruction", Clinical Radiology, vol. 68, no. 10, **(2013)**, pp. 1008-1015.
[40] G. Iwasokun and O. Akinyokun, "Image Enhancement Methods: A Review", British Journal of Mathematics & Computer Science, vol. 4, no. 16, **(2014)**, pp. 2251-2277.
[41] Q. Song, J. Bai, D. Han, S. Bhatia, W. Sun, W. Rockey, J. Bayouth, J. Buatti and X. Wu, "Optimal Co-Segmentation of Tumor in PET-CT Images With Context Information", IEEE Transactions on Medical Imaging, vol. 32, no. 9, **(2013)**, pp. 1685-1697.
[42] H. Bhadauria and M. Dewal, "Efficient Denoising Technique for CT images to Enhance Brain Hemorrhage Segmentation", Journal of Digital Imaging, vol. 25, no. 6, **(2012)**, pp. 782-791.
[43] T. Economopoulos, P. Asvestas and G. Matsopoulos, "Contrast enhancement of images using Partitioned Iterated Function Systems", Image and Vision Computing, vol. 28, no. 1, **(2010)**, pp. 45-54.
[44] S. Goliaei and S. Ghorshi, "Tomographical Medical Image Reconstruction Using Kalman Filter Technique", Ninth IEEE International Symposium on Parallel and Distributed Processing with Applications Workshops, Busan, South Korea, **(2011)** May 26-28, pp. 61-65.
[45] E. Rollano-Hijarrubia, R. Manniesing and W. Niessen, "Selective Deblurring for Improved Calcification Visualization and Quantification in Carotid CT Angiography: Validation Using Micro-CT", IEEE Transactions on Medical Imaging, vol. 28, no. 3, **(2009)**, pp. 446-453.
[46] M. Hussien and M. Saripan, "Computed Tomography Soft Tissue Restoration Using Wiener Filter", IEEE Student Conference on Research and Development, Putrajaya, Malaysia, **(2010)** December 13-14, pp. 415-420.
[47] D. Sharma and G. Jindal, "Computer Aided Diagnosis System for Detection of Lung Cancer in CT Scan Images", International Journal of Computer and Electrical Engineering, vol. 3, no. 5, **(2011)**, pp. 714-718.
[48] H. Bhadauria and M. Dewal, "Medical image denoising using adaptive fusion of curvelet transform and total variation", Computers & Electrical Engineering, vol. 39, no. 5, **(2013)**, pp. 1451-1460.
[49] N. Abdel-massieh, M. Hadhoud and K. Amin, "Automatic Liver Tumor Segmentation from CT Scans with Knowledge-based Constraints", IEEE 5th Cairo International Biomedical Engineering Conference, Cairo, Egypt, **(2010)** December 16-18, pp. 215-218.

[50] S. Steger, N. Bozoglu, A. Kuijper and S. Wesarg, "Application of Radial Ray Based Segmentation to Cervical Lymph Nodes in CT Images", IEEE Transactions on Medical Imaging, vol. 32, no. 5, **(2013)**, pp. 888-900.
[51] D. Kim, D. Pal, J. Thibault and J. Fessler, "Accelerating Ordered Subsets Image Reconstruction for X-ray CT Using Spatially Nonuniform Optimization Transfer", IEEE Transactions on Medical Imaging, vol. 32, no. 11, **(2013)**, pp. 1965-1978.
[52] D. Trinh, M. Luong, J. Rocchisani, C. Pham, H. Pham and F. Dibos, "An Optimal Weight Method for CT Image Denoising", Journal of Electronic Science and Technology, vol. 10, no. 2, **(2012)**, pp. 124-129.
[53] S. Anand and R. Shantha Selva Kumari, "Sharpening enhancement of Computed Tomography (CT) images using Hyperbolic Secant Square filter", Optik - International Journal for Light and Electron Optics, vol. 124, no. 15, **(2013)**, pp. 2121-2124.
[54] K. Kanal, J. Chung, J. Wang, P. Bhargava, M. Gunn, W. Shuman and B. Stewart, "Impact of Incremental Increase in CT Image Noise on Detection of Low-contrast Hypodense Liver Lesions", Academic Radiology, vol. 21, no. 10, **(2014)**, pp. 1233-1239.
[55] F. Zhu, T. Carpenter, D. Gonzalez, M. Atkinson and J. Wardlaw, "Computed tomography perfusion imaging denoising using Gaussian process regression", Physics in Medicine and Biology, vol. 57, no. 12, **(2012)**, pp. N183-N198.
[56] P. Truc, T. Kim, S. Lee and Y. Lee, "Homogeneity- and density distance-driven active contours for medical image segmentation", Computers in Biology and Medicine, vol. 41, no. 5, **(2011)**, pp. 292-301.
[57] Y. Sun, L. Zhang and J. Duan, "Research of Medical Image Variable Step-Size Blind Restoration Algorithm", In: Hu, W. (Ed.), Advances in Electric and Electronics, Berlin: Springer-Heidelberg, **(2012)**, pp. 583-590.
[58] A. Zifan and P. Liatsis, "Medical Image Deblurring via Lagrangian Pursuit in Frame Dictionaries", In Developments in E-systems Engineering, Dubai, UAE, **(2011)** December 6-8, pp. 86-91.
[59] Y. Lou, X. Zhang, S. Osher and A. Bertozzi, "Image Recovery via Nonlocal Operators", Journal of Scientific Computing, vol. 42, no. 2, **(2010)**, pp. 185-197.
[60] A. Khare, U. Tiwary And M. Jeon, "Daubechies Complex Wavelet Transform Based Multilevel Shrinkage for Deblurring of Medical Images in Presence of Noise", International Journal of Wavelets, Multiresolution and Information Processing, vol. 7, no. 5, **(2009)**, pp. 587-604.
[61] A. Schilham, B. Van Ginneken, H. Gietema and M. Prokop, "Local noise weighted filtering for emphysema scoring of low-dose CT images", IEEE Transactions on Medical Imaging, vol. 25, no. 4, **(2006)**, pp. 451-463.
[62] G. Cui, H. Feng, Z. Xu, Q. Li and Y. Chen, "A modified Richardson–Lucy algorithm for single image with adaptive reference maps", Optics & Laser Technology, vol. 58, **(2014)**, pp. 100-109.
[63] E. Seeram, "Computed tomography", St. Louis, Mo: Saunders/Elsevier, **(2009)**.
[64] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 7, **(1990)**, pp. 629-639.
[65] L. Rudin, S. Osher and E. Fatemi, "Nonlinear total variation based noise removal algorithms", Physica D: Nonlinear Phenomena, vol. 60, no. 1, **(1992)**, pp. 259-268.
[66] M. Lindenbaum, M. Fischer and A. Bruckstein, "On Gabor's contribution to image enhancement", Pattern Recognition, vol. 27, no. 1, **(1994)**, pp. 1-8.
[67] D. Donoho, "Ideal Spatial Adaptation via Wavelet Shrinkage", Biometrica, vol. 81, **(1994)**, pp. 424-455.
[68] S. Smith and J. Brady, "SUSAN—A New Approach to Low Level Image Processing", International Journal of Computer Vision, vol. 23, no. 1, **(1997)**, pp. 45-78.
[69] A. Buades, B. Coll and J. Morel, "A Review of Image Denoising Algorithms, with a New One", Multiscale Modeling & Simulation, vol. 4, no. 2, **(2005)**, pp. 490-530.
[70] D. Ghiglia, "Space-invariant deblurring given N independently blurred images of a common object", Journal of the Optical Society of America A, Optics and image science, vol. 1, no. 4, **(1984)**, pp. 398-402.
[71] A. Jain, "Fundamentals of digital image processing", Englewood Cliffs, NJ: Prentice Hall, **(1989)**.
[72] A. Bennia and S. Riad, "Filtering capabilities and convergence of the Van-Cittert deconvolution technique", IEEE Transactions on Instrumentation and Measurement, vol. 41, no. 2, **(1992)**, pp. 246-250.
[73] D. Biggs and M. Andrews, "Acceleration of iterative image restoration algorithms", Applied Optics, vol. 36, no. 8, **(1997)**, pp. 1766-1775.
[74] A. Carasso, "Linear and Nonlinear Image Deblurring: A Documented Study", SIAM Journal on Numerical Analysis, vol. 36, no. 6, **(1999)**, pp. 1659-1689.
[75] L. Liang and Y. Xu, "Adaptive Landweber method to deblur images", IEEE Signal Processing Letters, vol. 10, no. 5, **(2003)**, pp. 129-132.
[76] S. Suhaila and T. Shimamura, "Image Restoration Based on Edgemap and Wiener Filter for Preserving Fine Details and Edges", International Journal of Circuits, Systems and Signal Processing, vol. 5, no. 6, **(2011)**, pp. 618-626.
[77] Z. Ye and H. Mohamadian, "Comparative and Quantitative Study of Fundamental Approaches on Digital Aerial Image Deblurring", International Journal of Modeling and Optimization, vol. 2, no. 4, **(2012)**, pp. 378-383.

[78] J. Lee and Y. Ho, "High-quality non-blind image deconvolution with adaptive regularization", Journal of Visual Communication and Image Representation, vol. 22, no. 7, **(2011)**, pp. 653-663.
[79] Z. Bai, D. Cassani, M. Donatelli and S. Serra-Capizzano, "A fast alternating minimization algorithm for total variation deblurring without boundary artifacts", Journal of Mathematical Analysis and Applications, vol. 415, no. 1, **(2014)**, pp. 373-393.
[80] W. Zhiming, B. Hong and Z. Li, "Image Deblurring by Fast Non-local Means and Bregmanrized Operator Splitting", Proceeding of the Second International Conference on Electric Information and Control Engineering, Washington, USA, vol. 1, **(2012)**, pp. 776-779.
[81] T. Celik, "Two-dimensional histogram equalization and contrast enhancement", Pattern Recognition, vol. 45, no. 10, **(2012)**, pp. 3810-3824.
[82] N. Hassan and N. Akamatsu, "A New Approach for Contrast Enhancement Using Sigmoid Function", The International Arab Journal of Information Technology, vol. 1, no. 2, **(2004)**, pp. 221-225.
[83] R. Chouhan, R. Jha and P. Biswas, "Enhancement of dark and low-contrast images using dynamic stochastic resonance", IET Image Processing, vol. 7, no. 2, **(2013)**, pp. 174-184.
[84] A. Łoza, D. Bull, P. Hill and A. Achim, "Automatic contrast enhancement of low-light images based on local statistics of wavelet coefficients", Digital Signal Processing, vol. 23, no. 6, **(2013)**, pp. 1856-1866.
[85] R. Arun, M. Nair, R. Vrinthavani and R. Tatavarti, "An Alpha Rooting Based Hybrid Technique for Image Enhancement", Engineering Letters, vol. 19, no. 3, **(2011)**, pp. 1-10.
[86] C. Tsai, 'Adaptive Local Power-Law Transformation for Color Image Enhancement', Applied Mathematics & Information Sciences, vol. 7, no. 5, **(2013)**, pp. 2019-2026.
[87] C. Yang, "Image enhancement by modified contrast-stretching manipulation", Optics & Laser Technology, vol. 38, no. 3, **(2006)**, pp. 196-201.
[88] W. Chao, C. Cho, Y. Shih, Y. Chen and C. Chang, "Correction of Inhomogeneous MR Images Using Multiscale Retinex", International Journal of Image Processing, vol. 1, no. 1, **(2007)**, pp. 1-16.
[89] C. Ravichandran and V. Magudeeswaran, "An Efficient Method for Contrast Enhancement in Still Images using Histogram Modification Framework", Journal of Computer Science, vol. 8, no. 5, **(2012)**, pp. 775-779.
[90] S. Lal and M. Chandra, "Efficient Algorithm for Contrast Enhancement of Natural Images", International Arab Journal of Information Technology, vol. 11, no. 1, **(2014)**, pp. 95-102.
[91] H. Woo, J. Park, C. Wang, S. Ahn and J. Chong, "Contrast Enhancement with Slope Modification", IEEE 18th International Symposium on Consumer Electronics, JeJu Island, South Korea, **(2014)** June 22-25, pp. 1-2.
[92] C. Zuo, Q. Chen and X. Sui, "Range Limited Bi-Histogram Equalization for image contrast enhancement", Optik - International Journal for Light and Electron Optics, vol. 124, no. 5, **(2013)**, pp. 425-431.
[93] A. Duijster, P. Scheunders and S. De Backer, "Wavelet-Based EM Algorithm for Multispectral-Image Restoration", IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 11, **(2009)**, pp. 3892-3898.
[94] B. Jakoby, Y. Bercier, C. Watson, B. Bendriem and D. Townsend, "Performance Characteristics of a New LSO PET/CT Scanner With Extended Axial Field-of-View and PSF Reconstruction", IEEE Transactions on Nuclear Science, vol. 56, no. 3, **(2009)**, pp. 633-639.
[95] M. Jiang, G. Wang, M. Skinner, J. Rubinstein and M. Vannier, "Blind deblurring of spiral CT images", IEEE Transactions on Medical Imaging, vol. 22, no. 7, **(2003)**, pp. 837-845.

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