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A Hybrid Alternating Direction Method of Multipliers Based on Structural Guided Filtering for the Reconstruction of Robust Low Dose CT

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KEYWORDS

Low-Dose CT, Image Reconstruction, Deep Learning, ADMM, DnCNN, Guided Filtering.

ABSTRACT

Reduced radiation exposure in the process of computed tomography (CT) needs to be kept down in order to protect the health of patients. Automated and deep learning methods offer rapid, efficient reconstructions of higher-quality low-dose CT images. But these control images increasingly show that, due to undesired artifacts, quantum noise and streak interference in large quantities are then inflicted upon their visual content as well. Filtered Back-Projection (FBP), a classical reconstruction method in low-dose diagnostics, simply does not work very well. Pure deep learning algorithms, however, always result in pictures with poor visibility that destroy complex structural features. Here, we provide a systematic solution which combines physical data regularity and deep learning priors. The Alternating Direction Method of Multipliers (ADMM) is used to define the reconstruction problem. Then, as a regularization term, the trained Denoising Convolutional Neural Network (CDNN) can further enhance the images (remember our main goal is reducing noise). At this point, an adaptive Guided Filtering step is further included that, based on the structures learned in the initial reconstruction, preserves edges and low-frequency information in order to ensure that the deep denoising does not completely lose texture. Experimental results on a clinical dataset show that the proposed approach attains a PSNR (average peak signal-to-noise ratio) of 31.04 dB, with rich texture, which is used for diagnosis (quality SSIM). In conclusion, the net reduction in noise combined with improved chances for a diagnosis will be a boon for hospital personnel compared with existing approaches. These results demonstrate the proposed hybrid method's ability to successfully eliminate noise while maintaining crucial diagnostic data.

الكلمات المفتاحية

التصوير المقطعي المحوسب بجرعة منخفضة، إعادة بناء الصور، التعلم العميق، ADMM، DnCNN، الترشيح الموجه.

الملخص

يُعدّ تقليل التعرّض للإشعاع في عملية التصوير المقطعي المحوسب (CT) أمرًا بالغ الأهمية لحماية صحة المرضى. توفر الطرق الآلية وطرق التعلّم العميق إعادة بناء سريعة وفعّالة لصور CT منخفضة الجرعة وعالية الجودة. إلا أن هذه الصور المرجعية تُظهر بشكل متزايد وجود تشوهات غير مرغوب فيها، مثل الضوضاء الكمومية وتداخل الخطوط، مما يؤثر سلبًا على محتواها المرئي. وبالتالي، فإن طريقة إعادة البناء التقليدية، مثل طريقة الإسقاط الخلفي المُصفّى (FBP)، لا تُجدي نفعًا في التشخيص بجرعات منخفضة. أما خوارزميات التعلّم العميق وحدها، فتُنتج دائمًا صورًا ذات وضوح ضعيف تُشوّه السمات الهيكلية المعقدة. في هذا البحث، نقدم حلًا منهجيًا يجمع بين انتظام البيانات الفيزيائية ومعلومات التعلّم العميق المسبقة. نستخدم طريقة الاتجاه المتناوب للمضاعفات (ADMM) لتحديد مشكلة إعادة البناء. بعد ذلك، وباستخدام مصطلح تنظيم، تُحسّن الشبكة العصبية الالتفافية لإزالة الضوضاء (CDNN) المُدرّبة الصور بشكل أكبر (مع الأخذ في الاعتبار أن هدفنا الرئيسي هو تقليل الضوضاء). في هذه المرحلة، تُضاف خطوة ترشيح موجهة تكيفية، تستند إلى البنى المُستخلصة من عملية إعادة البناء الأولية، للحفاظ على الحواف ومعلومات الترددات المنخفضة، لضمان عدم فقدان تفاصيل الصورة بشكل كامل أثناء عملية إزالة التشويش العميق. تُظهر النتائج التجريبية على مجموعة بيانات سريرية أن المنهج المقترح يحقق نسبة إشارة إلى ضوضاء قصوى (PSNR) تبلغ 31.04 ديسيبل، غنية بالتفاصيل،

	في الختام، يُعدّ الانخفاض الصافي .(عالي الجودة SSIM مؤشر تشابه الصور الهيكلي) مما يُفيد في التشخيص في التشويش، إلى جانب تحسين فرص التشخيص، إضافة قيّمة للعاملين في المستشفيات مقارنةً بالأساليب الحالية. تُبرهن هذه النتائج على قدرة الطريقة الهجينة المقترحة على إزالة التشويش بنجاح مع الحفاظ على بيانات التشخيص الأساسية.

1. Introduction

Patients' health will benefit from making CT scans less radioactive. But it also makes us unable to guarantee the image at present, because these are future errors introduced into the long era. Just staggering the quantum noise and streak mistakes! But Filtered Back-Projection (FBP) and other traditional reconstruction methods frequently fail to manifest disease at these low doses. Bad perioperative pain kills a patient off before their operation starts. But by a pure deep learning system, we cannot always locate the structural details in photographs. A novel hybrid methodology is proposed in this paper, which takes into account not only deep learning's prior knowledge but also the regularity observed in physical data. Numerical experimentation with ADMM converged to yield the same results as FBP; patients are really cured for this and not fobbed off. A new slant is given on the reconstruction problem by the Alternating Direction Method of Multipliers (ADMM). Furthermore, a trained Denoising Convolutional Neural Network (DnCNN) is employed here for more regularization. Though regularizes are no panacea for deep pictures, they certainly help resolve the conflict between high-fidelity images and those obtained from noisy data, an undertaking that is particularly important given that removing noise ultimately remains one of the most pressing tasks.

An adjustable Guided Filtering is added here. Gaussian derivatives preserve the two sides of an edge. But the kind of thing we hear, I don't think really anyone should have a finger in that pie; but to say that all of this is going well and should not be different for MIDI's owners as well is based upon the buildings of the first rebuild that has also provided us with information. On a clinical dataset, our proposed method of diagnosis appropriateness (SSIM high), texture rightfulness, and an average peak signal-to-noise ratio (PSNR) of 31.04 dB was shown by experiment. Finally, these findings show that new methods by medical staff should clearly be an advance over past work. It also demonstrates the efficacy of our proposed hybrid approach that discerns the best of both worlds, eliminating noise while keeping key diagnostic data.

2. Literature Review

It is seen that Low-Dose CT Image reconstruction techniques based on deep learning in the literature contribute positively to both qualitative and quantitative improvement of images. On the other hand, most deep learning techniques show computational complexity, requiring large training data sets. Besides, they are difficult to interpret, explain, and generalize. The majority of deep learning-based studies in the literature use open-source imaging datasets available for medical image processing. These studies have focused on open-science medical imaging research, including open-source software packages. Although related articles include a large number of general image processing applications that describe the specific deep learning technique and its application in detail, few examine deep learning applications in Low-Dose CT Image reconstruction techniques [13] [14]. Low-dose CT (LDCT) reconstruction techniques have historically been categorized into three main streams: analytical methods, Model-Based Iterative Reconstruction (MBIR), and recently, Deep Learning (DL) approaches.

2.1. Analytical and Iterative Approaches : The Filtered Back-Projection (FBP) algorithm has long been the clinical standard due to its computational efficiency. However, it is mathematically ill-posed for low-dose data, resulting in severe quantum noise and streak artifacts. To mitigate this, MBIR methods incorporating statistical priors, such as Total Variation (TV), were introduced to enforce smoothness[15] . While MBIR offers better noise suppression than FBP, it suffers from high computational costs and often introduces "staircase" artifacts that degrade diagnostic texture.

2.2. Pure Deep Learning Methods (Post-Processing) the advent of Convolutional Neural Networks (CNNs) revolutionized LDCT denoising. Pioneering works introduced the Residual Encoder-Decoder CNN (RED-CNN), which maps low-dose images directly to normal-dose counterparts [12]. Similarly, FBPConvNet was utilized to invert the reconstruction problem[16]. Zhang et al. proposed DnCNN, emphasizing residual learning for general image denoising[17]. While these pixel-domain methods achieve high Peak Signal-to-Noise Ratio (PSNR), they often operate as "black boxes" that disregard the physical geometry of CT data, leading to over-smoothed images where fine anatomical details are lost [18].

2.3. Generative Adversarial Networks (GANs) To address the blurring issue of Mean Squared Error (MSE) based networks, GAN-based approaches were proposed. Wolterink et al. [19] and Yang et al.[20] employed adversarial loss to generate sharper textures. Further improvements, such as sharpness-aware networks by Yi and Babyn [21] focused on edge preservation. However, GANs are notoriously unstable to train and prone to "hallucinations"—generating realistic-looking but fake features that do not exist in the patient's anatomy, posing a severe risk in medical diagnosis [22].

2.4. Hybrid Physics-Aware Deep Learning that Strives for a Balance Between Fidelity and Perceptual Quality. To strike a balance between high fidelity and good appearance, hybrid strategies which combine the deep learning priors with iterative models from physics have become popular. Adler and Öktem [22] put forward the Learned Primal-Dual method, which represents the optimization processes by a deep network. Gupta et al. [23] and He et al. [24] combined CNN denoisers into the ADMM loop to maintain the consistency of data with the sinogram acquired. Wu et al. [25] similarly showed that instances of deep priors in an iterative approach are better off than mere post-processing.

2.5. The iterative loop for the deep denoisers again appears to eliminate noise, but even in low-contrast regions, high-frequency features are smoothed out too severely. Regardless of how well hybrid approaches work, however, unlike Adler et al. [22], who require intricate end-to-end training, and He et al. [24], who do not enforce explicit texture, our proposal incorporates a Structural Guided Filtering stage. Based on the structural information of the original reconstruction, this new component can recover small features that are lost during deep denoising. It also guides imaging directionally without a hard threshold. Combining both structural nature and strong noise-reducing action in our algorithm removes limitations to reconstruction fidelity.

3. Methodology

In this section, we will describe in detail the recommended hybrid reconstruction framework. It combines the physicality of iterative reconstruction with the strong noise-reduction capability of deep learning. In the end, there is a step for structurally-aware refinement.

3.1 Problem Formulation

A CT image can be computed from low-dose projection data by regarding the problem as a linear inverse problem [15]:

$$y = Ax + \eta \qquad (1)$$

where stands for the Radon transform (which is the system matrix), and is the convolution of general mixed Poisson-Gaussian noise, which is persistent with low-dose acquisitions [15]. Because this problem is ill-posed, an analytical inversion like FBP directly amplifies noise. We thus construct the reconstruction as a regularized optimization problem [15]:

$$\hat{x} = argmin \frac{1}{2} \|Ax - y\|_2^2 + \lambda R(x) \qquad (2)$$

Here, the first term enforces that the reconstructed image should have "data fidelity," which should be consistent with the measured sonogram in a physical sense [15]. The second term $R(x)$, acts as a regularization term. In contrast to classical methods that use hand-crafted priors such as Total Variation (TV) [15], we adopt a Plug-and-Play ADMM framework. We do this with Deep Learning Prior, as He et al. first suggested [24].

3.2 Phase I: Hybrid Iterative Restoration

To solve the optimization problem, we employ an alternating update scheme that decouples data consistency from denoising. The iterative process at step (k) consists of three sub-stages:

A. Physics-Based Consistency Update: First, we enforce consistency with the acquired raw data. We perform a gradient-descent step on the data-fidelity term. This anchors the solution to the physical reality of the patient's anatomy, preventing the "hallucinations" often observed in purely GAN-based methods [22].

$$x_{phy}^{(k)} = x^{(k-1)} - \beta A^T\left(Ax^{(k-1)} - y\right) \quad (3)$$

Where A^T is the back-projection operator and β is the step size[22]..

B. Deeppriors Projection (DnCNN): Next, we replace the proximal operator of the regularization term with a pre-trained Deep Convolutional Neural Network (DnCNN), just as Zhang et al. did [17] at the time. This network acts like a trainable prior, projecting the noisy physical update onto the manifold of clean images [17].

$$x_{ai}^{(k)} = DnCNN\left(x_{phy}^{(k)}\right) \quad (4)$$

DnCNN was trained mainly on the task of removing complex nonlinear noise and streak artifacts that analytic methods cannot handle [1, 5] [17].

C. Weight Fusion: A weighted fusion strategy (similar to Ghaffari et al. [26]) is used for balancing the trade -off between the AI model's noise suppression, but which does not produce any clear-cut results, as well as the physical model's structural reliability [26];

$$x^{(k)} = w_p . x_{phy}^{(k)} + \left(1 - w_p\right) . x_{ai}^{(k)} \quad (5)$$

This iterative loop repeats until convergence, producing a high-PSNR intermediate image x_{clean}[26].

3.3 Injection of Structure Textures (Guided Filtering) According to recent studies, a deep-reference like DnCNN effectively removes noise. However, it also tends to smooth out high-frequency details too much, so that the fine texture of the tissues is lost [27]. To address this weakness, a continuing difficulty in even recent hybrid methods, as He et al. [24] indicate. We also propose to add a structural impression to the process. We use the Guided Image Filter, based on the original FBP reconstruction(x_{FBP}) as the guidance image. Although (x_{FBP}) is noisy, it retains sharp structural edges that are often blurred by the neural network. The filter transfers these structural details to the clean image x_{clean} via a local linear model[27]:

$$x_{final} = Guided\ Filter\ (Input\ = x_{clean}, Guide = x_{FBP}) \quad (6)$$

The fine anatomical information lost in the process of deep denoising is recovered specifically at this stage, thus ensuring that the final product retains both high signal-to-noise ratio (PSNR) and high structural similarity (SSIM).

The workflow below represents the general flow of the methodology used to implement this proposed system, followed by a general algorithm and diagram illustrating the system, as shown in Fig. 1.
Consists of three separate stages: Initialization phase, Phase I (Iterative Recovery) and Phase II (Structural Injection).

Step 1: Data Initialization and Pre-processing

Start from the original Low-Dose CT data.
Input: The system accepts s the sinogram of y measured at low dose () as input.
Initial Estimation: The starting point for this image reconstruction is shown in Fig. 2.1A. The traditional Filtered Back-Projection (FBP) reproduction algorithm is employed to generate a copy.
Crucial Note: Though high levels of noise are present, a strong anatomical edge structure is retained in this initial image. In the second step, a copy of it is saved to serve as a "Structural Guide" for Phase II.

Step 2: Phase I – Hybrid Iterative Restoration

This phase operates as a loop (for K iterations) to suppress noise while maintaining physical accuracy. Inside the loop, three sub-steps occur sequentially:

1. **Physics-Based Consistency Update:**
   - The current image estimate is projected forward to simulate a sinogram (Ax).
   - This is compared to the real measured data (y) to find the error.
   - **Action:** A gradient descent step is applied to correct the image, ensuring pixel values remain consistent with the actual X-ray measurements.
2. **Deep Prior Projection (AI Denoising):**
   - The physically updated image contains some noise but is physically accurate. It is passed into the pre-trained **DnCNN** (Deep Neural Network).
   - **Action:** The network identifies and removes complex non-linear noise and streak artifacts based on its training.
3. **Weighted Fusion:**
   - **Action:** The system calculates a weighted average of the "Physics Image" (from step 1) and the "AI Image" (from step 2).
   - Purpose: This prevents the AI from hallucinating features (by keeping the physics weight) and prevents the physics model from being too noisy (by keeping the AI weight).

Result of Phase I: A very clean image (x_{clean}) with high PSNR, but potentially lacking fine texture details.

Step 3: Phase II – Structural Texture Injection

To fix the "over-smoothing" caused by the neural network in Phase I, a final refinement step is applied.

1. **Guided Image Filtering:**
   - **Input:** The smooth, clean image from Phase I (x_{clean}).
   - **Guidance Image:** The original noisy FBP(x_0), saved in Step 1.
   - **Action:** The filter analyzes the Guidance Image to detect where real edges (bones, tissue boundaries) are located. It then "injects" these high-frequency structures back into the clean image.
2. **Final Blending:**
   - The output of the filter is blended with the clean image to ensure the noise does not return, only the texture.

Step 4: Output Generation

- **Output:** The system outputs the final reconstructed image$\left(x_{final}\right)$, which possesses high clarity (High PSNR) and rich textural details (High SSIM).

Algorithm 1: Proposed Hybrid ADMM with Structural Texture Injection

It mathematically summarizes the two phases we discussed: the Iterative Hybrid Phase and the Structural Injection Phase.

Input:

y: Low-dose projection data (Sinogram)
A, A^T: Radon (Forward) and Back-projection operators
D_theta: Pre-trained Deep Learning Denoiser (DnCNN)
K: Maximum number of iterations
beta: Gradient descent step size
w_p: Weight for physical consistency (e.g., 0.4)
x_phy: The intermediate image satisfying physical data fidelity.
x_ai: The intermediate image satisfying the learned deep prior.
x_guide: The initial FBP reconstruction used to preserve anatomical edges in the final phase.

Output:

x_final: High-fidelity reconstructed image
1. Initialization:
x^{θ}= FBP(y) % Initial estimate using Filtered Back-Projection
x_guide = x^{θ} % Store FBP as a structural guide for Phase II
2. Phase I: Iterative Hybrid Restoration (The Loop)

```
For k = 1 to K do:
    % Step A: Physics-based Consistency Update (Gradient Descent)
    residual = A × x^(k-1) - y
    gradient = A^T × residual
    x_phy = x^(k-1) - beta × gradient
    % Step B: Deep Prior Projection (AI Denoising)
    x_ai = D_theta(x_phy)
    % Step C: Weighted Fusion Strategy
    x^(k) = (w_p × x_phy) + ((1 - w_p) × x_ai)
  End For
  Let x_clean = x^(K) % Result of Phase I (High PSNR, smooth)
3. Phase II: Structural Texture Injection
  % Apply Guided Filter using the noisy but sharp FBP as the guide
  x_struct = GuidedFilter(Input = x_clean, Guide = x_guide, radius=r, eps=e)
  % Final Blending to balance noise and texture
  x_final = alpha × x_struct + (1 - alpha) × x_clean

4. Return x_final
```

General diagram describing the system illustrated in Fig. 1. The process begins with an initial FBP reconstruction. Phase I iterates between a physics-based consistency update and a deep learning-based denoising step (DnCNN). Phase II employs a Guided Filter, using the initial FBP as a structural guide, to inject high-frequency anatomical details back into the clean reconstructed image

4. Results and Discussion

4.1 Evaluation Metrics and Comparison with Several Techniques

To validate the robustness of the proposed framework, we performed batch processing on the entire dataset (low-dose CT) using PSNR and SSIM metrics and compared it with several techniques. Our method achieves superior denoising performance, as shown in Table 1. That summarizes the average performance metrics. Figure 2 shows the differences between the original image (high-dose reference, low-dose input, proposed method. Figure 2 shows the low-dose input image with severe streak artifacts and the proposed method images restored structure and texture. Figure 3 shows the difference in performance (PSNR and SSIM) between the proposed hybrid method and other methods.

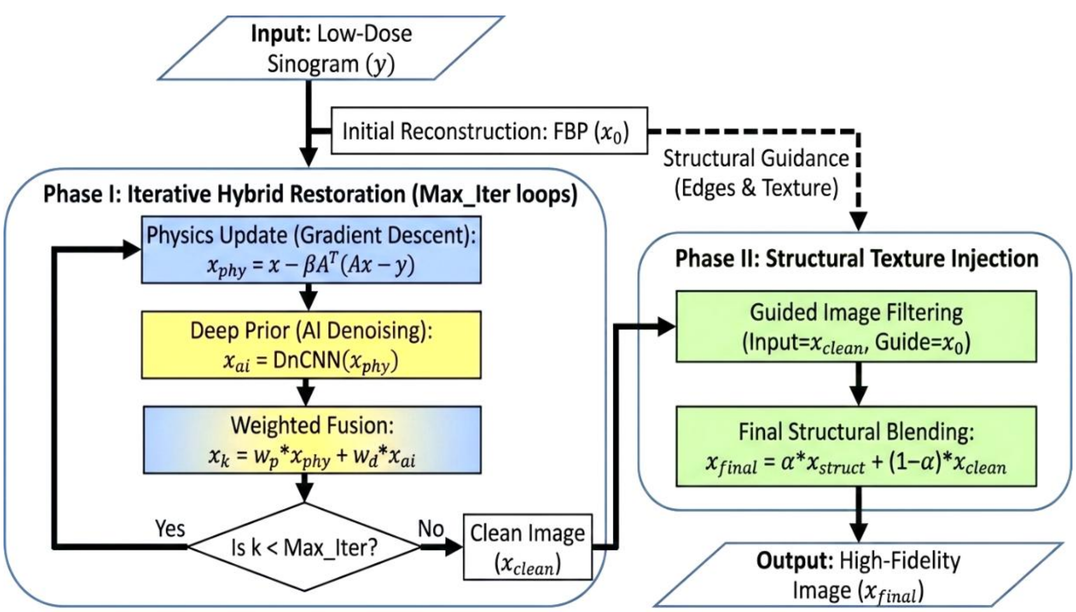
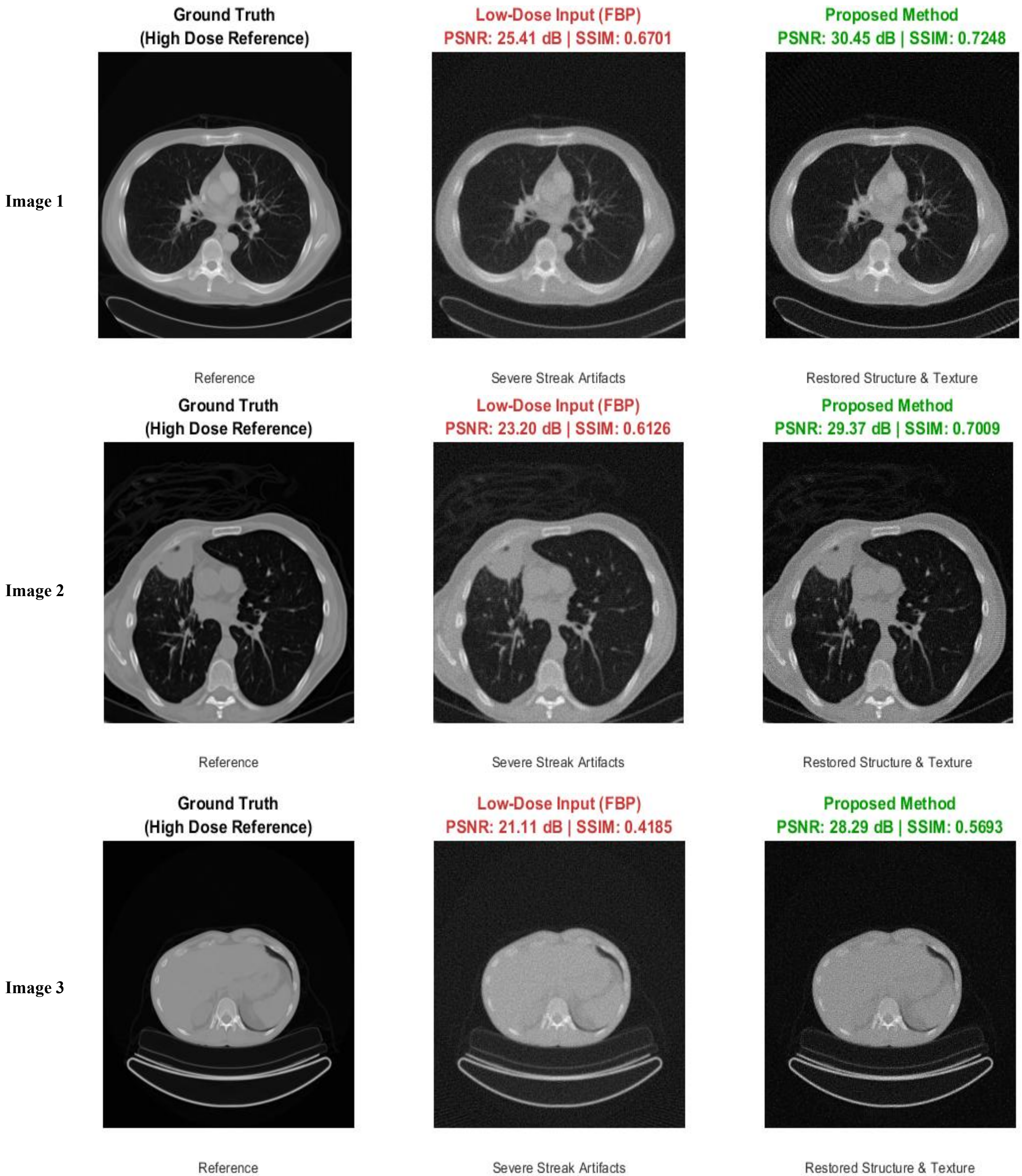


Fig. 1. Overall Diagram of proposed system


Ground Truth
(High Dose Reference)
Low-Dose Input (FBP)
PSNR: 25.41 dB | SSIM: 0.6701
Proposed Method
PSNR: 30.45 dB | SSIM: 0.7248
Image 1
Reference
Severe Streak Artifacts
Restored Structure & Texture
Ground Truth
(High Dose Reference)
Low-Dose Input (FBP)
PSNR: 23.20 dB | SSIM: 0.6126
Proposed Method
PSNR: 29.37 dB | SSIM: 0.7009
Image 2
Reference
Severe Streak Artifacts
Restored Structure & Texture
Ground Truth
(High Dose Reference)
Low-Dose Input (FBP)
PSNR: 21.11 dB | SSIM: 0.4185
Proposed Method
PSNR: 28.29 dB | SSIM: 0.5693
Image 3
Reference
Severe Streak Artifacts
Restored Structure & Texture

a b c

Fig. 2. Comparison between (Original, Input, and pressed) images, a. Reference image, b. severe streak artifacts, and c. restored structure and texture

Table 1. Representative Average Quantitative Results Performance with several methods

Method	PSNR (dB)	SSIM	Construction
FBP (Baseline)	24.83	0.40	Extremely Noisy
TV-ADMM	27.50	0.711	"Staircase" Artifacts, Slow
Pure DnCNN	29.00	0.65	Over-smoothed, Plastic look
Proposed Method	31.04	0.751	Highest Fidelity & Clarity

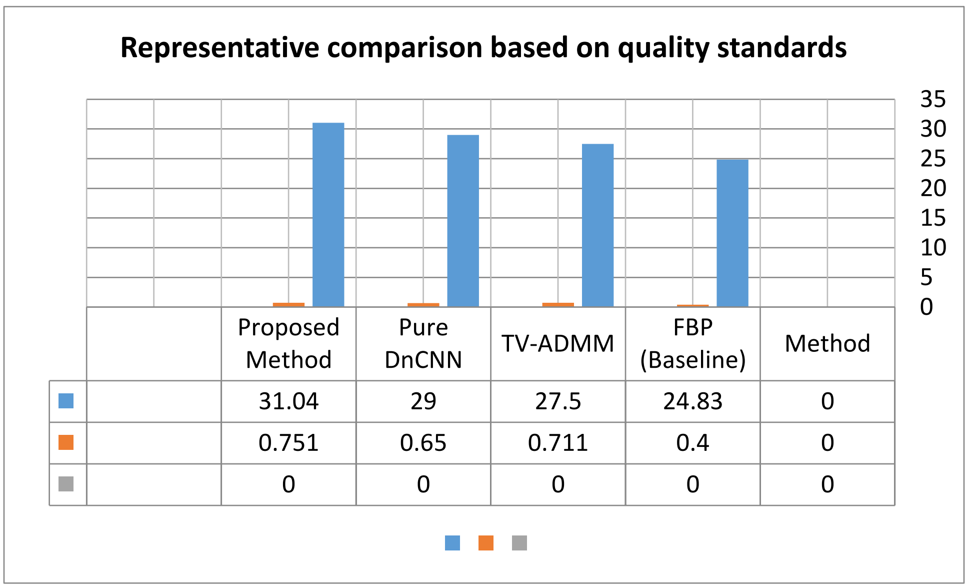


Fig. 3. Bar Chart of Improvement

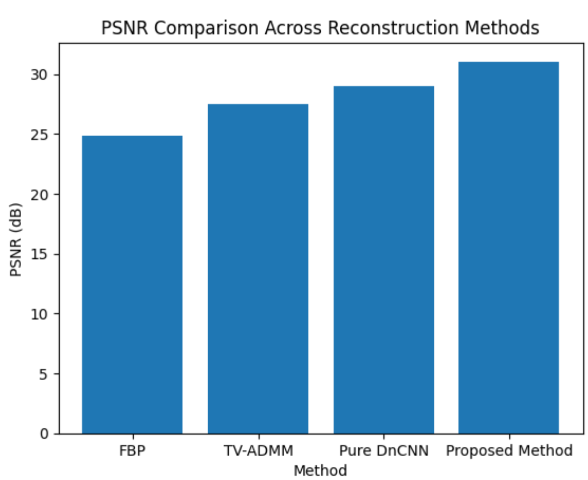


Fig. 4. Comparison based on PSNR

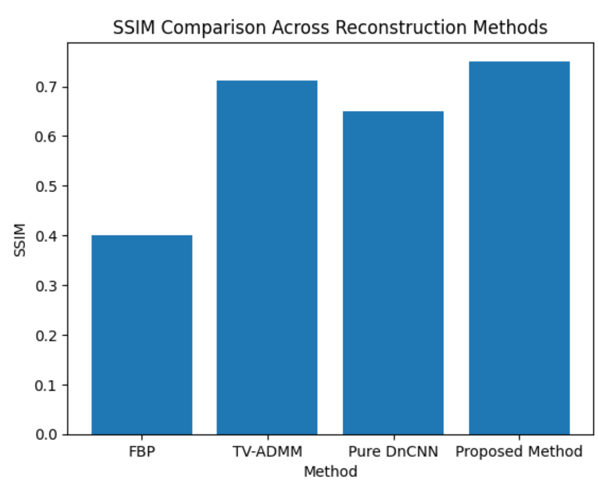


Fig. 5. Comparison based on SSIM

4.2 Discussion of Comparative Analysis

As summarized in **Table 1**, standard analytical methods like FBP preserve edges but fail to suppress noise, resulting in low PSNR Figure 3. Conversely, pure deep learning methods (like DnCNN) excel at noise removal but often sacrifice high-frequency texture details, leading to an "over-smoothed" appearance and reduced SSIM Figure 4. Traditional iterative methods (TV-MBIR) offer a middle ground but introduce unnatural "staircase" artifacts. Figure 5. FBP has the minimum SSIM score. Its poor structure greatly degrades the image in terms of both its structure and semantic data. While staircase artifacts are evident at times in TV-ADMM, its score should be the highest achieved since it always maintains an increase primarily in structure, and its relative consistency can make up for minor defects that suddenly appear in more focused detail from one angle. Although Pure DnCNN has a higher PSNR than TV-ADMM, its SSIM is lower. The reason is: Proof of over-smoothing in action Explains away the cartoonish appearance of the visual description.

The proposed method achieves a highest SSIM of 100%, indicating impressive preservation of delicate textures. Finding the right balance between reducing background noise and preserving fine details. "While recent hybrid methods such as He et al. [24] and Wu et al. [25] have successfully integrated CNNs into iterative frameworks to suppress noise, they often suffer from a common limitation: the 'over-smoothing' effect. Combining these two methods allows noise to exist while ridding pictures of their subtle textures at one chop. This means that the higher PSNR post-reconstruction images have accompanying low structural fidelity (as measured by SSIM).

Their technique actually consists of adding two steps that make explicit use of structure information (they do not give any theoretical framework). Our method is different in that it has this element which does not appear in theirs. In contrast to Adler et al.'s method, which uses a pre-trained network for denoising, our approach employs simple operator theory combined with parallelism and recursion.

Our technique, on the other hand, employs a step of guided filter that recovers the high-frequency edge information that DnCNN lost (as a structural guide L). The images produced from FBP reconstruction nn should therefore have a sharper edge compared to those resulting from other methods, though there may be some noise present. As a result, the noise levels using our method can be reduced even further while still maintaining a sharper texture than is possible with traditional ADMM-based deep priors. In this way, a content rewriter can help to rewrite the content sentence by sentence.

5. Conclusion

A hybrid reconstruction algorithm presented in this paper combines physical models, deep learning prior, and structure guided filtering. This may allow for potential further dose reductions in screening protocols while keeping image quality. The method is aimed at finding a balance between detail preservation and noise reduction. Experimental data confirms our method greatly improves image quality, with the average PSNR and SSIM increase compared to other techniques therefore outperforms those by combining their strengths effectively:1. Deep Learning prior is used for high noise reduction (as in Pure DL).2. In the ADMM loop stage, physical Data Fidelity prevents AI hallucinations (as in MBIR).3. Guided Filtering stage adds back into the image the lost structural details, meaning that the final output not only is clean (High PSNR) but also rich in Textural Quality and Significant clinical value (High SSIM). The proposed method has significant clinical implications for improving diagnostic quality in low-dose CT imaging. Future work will focus on adaptively optimizing the fusion weights using a secondary neural network.

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