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Article

AI-Enhanced Hybrid Optimization and Deep Network Architecture for Noise Reduction in Low-Dose Medical Imaging

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Abstract: Low-dose computed tomography (LDCT) is a significant non-invasive imaging modality for disease diagnosis in early stages and clinical oncology. However, the reduction of radiation dose unavoidably introduces severe quantum noise, photon starvation and Poisson-Gaussian noise, which degrade contrast-to-noise ratio (CNR) and obscure subtle anatomical details. Recent advances in Artificial Intelligence (AI) have shown great promise in medical image restoration. However, pure deep learning methods often suffer from over-smoothing of fine structures and poor interpretability, while traditional non-convex variational models can preserve global edges, but are sensitive to the choice of parameters and produce staircasing artifacts. We propose an AI-empowered hybrid restoration framework that combines non-convex Total Variation (TV) optimization and a deep convolutional residual network within the Plug-and-Play (PnP) Alternating Direction Method of Multipliers (ADMM) framework to enjoy the complementary merits of the two paradigms. The AI based deep residual network can learn complex noise features and image priors efficiently. The optimization part keeps the structural fidelity and ensures the stable reconstruction. The proposed framework is tested on clinical lung CT slices from LIDC-IDRI benchmark dataset, and the experimental results show that the proposed framework achieves 33.97dB of Peak Signal-to-Noise Ratio (PSNR) and 0.918 of Structural Similarity Index Measure (SSIM) at noise level of $\sigma=25$. The experimental results show that the proposed AI-enabled hybrid model can better preserve structure edges, recover fine anatomical details and suppress noise compared with the traditional optimization methods and deep learning alone, which shows the effectiveness for low-dose medical image denoising.
Keywords: Artificial Intelligence, Medical Image Denoising, Low-Dose Computed Tomography (LDCT), Total Variation, Plug-and-Play ADMM, Deep Residual Networks, Hybrid Optimization.

1. INTRODUCTION

Computed Tomography (CT) has been one of the most common imaging modalities for the diagnosis, screening, staging, and therapeutic monitoring of pulmonary diseases. CT is an indispensable tool in clinical practice, especially for the early diagnosis of lung nodules and cancer, as it allows for detailed cross-sectional visualization of internal anatomical structures. Although repeated CT examinations have diagnostic advantages, they lead to patient exposure to ionizing radiation, which raises concerns about potential long-term health risks from cumulative doses of radiation. In addition, the As Low As Reasonably Achievable (ALARA) principle has been established as a basic principle of modern CT imaging, encouraging the use of lower radiation doses while maintaining diagnostic quality.

A common method of radiation exposure reduction is to decrease the X-ray tube current (mAs). This is very effective in reducing the radiation dose but also reduces the number of detected photons, causing quantum noise, photon starvation and streak artifacts in the reconstructed images. These degradations reduce the contrast of the image and obscure subtle anatomical details, which makes the identification of small pulmonary nodules and low contrast lesions considerably more difficult. Besides, the deteriorated image quality also negatively impacts the downstream Computer-Aided Diagnosis (CAD) systems, e.g., automatic lesion detection, segmentation, and disease classification, which rely on accurate structural information to make reliable clinical decisions.

To overcome these limitations, image restoration has been a critical preprocessing step in low-dose CT imaging. Standard model-based iterative reconstruction (MBIR) and variational optimization methods employ prior knowledge of image statistics, leading to noise suppression and preservation of structural information. Among these, regularization based on Total Variation (TV) is widely used as it can effectively preserve sharp edges by promoting the sparsity of the gradient. However, conventional TV-based methods tend to produce staircase artifacts, suppress fine textures and require careful tuning of parameters, limiting their ability to recover subtle anatomical structures present in clinical images.

Recent progress in Artificial Intelligence (AI) especially deep convolutional neural networks (CNNs) has made a tremendous impact on medical image denoising. Architectures like DnCNN and RED-Net can directly learn from data the complex nonlinear mappings between noisy and clean images, which leads to a significant improvement in the restoration quality. However, purely data-driven approaches often suffer from over-smoothing of fine structures, reduced generalization to different imaging protocols and limited interpretability due to their black box nature. These limitations suggest that restoration methods should be developed that combine the robustness of optimization techniques with the learning capacity of deep neural networks.

Motivated by these observations, we propose an AI-enhanced Plug-and-Play (PnP) ADMM hybrid framework for low-dose CT image restoration in this paper. The proposed method splits the physical observation model and the regularization step by putting a deep residual CNN denoiser into a Plug-and-Play ADMM optimization framework. In addition, we propose Non-Convex Total Variation (NCTV) regularization to preserve structural edges and avoid staircase artifacts inherent in standard TV methods. The proposed framework combines optimization-driven reconstruction with AI-based feature learning to effectively suppress noise while preserving clinically meaningful anatomical details and texture information.

1.1 Main Contributions

- **Hybrid Optimization Formulation:** A hybrid restoration framework combining the non-convex Total Variation regularization with a deep residual convolutional neural network within a Plug-and-Play ADMM optimization scheme, providing a compromise between mathematical stability and AI-based feature learning.
- **Clinical Feature Preservation:** An optimization framework for the preservation of low-contrast pulmonary nodule boundaries and fine anatomical structures affected by Poisson-Gaussian noise in low-dose CT images.
- **Rigorous Validation:** Extensive quantitative and qualitative validation on the LIDC-IDRI benchmark dataset, showing superior denoising performance over state-of-the-art techniques, including BM3D, Total Variation, and DnCNN, in terms of image quality and structural preservation.

2. RELATED WORKS

2.1 Classical Variational & Spatial Domain Methods

The early work on medical image denoising was mostly based on spatial domain filtering methods, such as Gaussian, median, and bilateral filters, to suppress noise while preserving important anatomical structures. However, when applied on heavily degraded low-dose CT images, these methods tend to smooth edges and remove fine image details, despite being computationally efficient. To improve the quality of restoration, transform-domain approaches, such as Block Matching and 3D Filtering (BM3D), were proposed. These methods utilize the non-local similarity of image patches to achieve better noise reduction while preserving structural information. BM3D is still one of the most powerful traditional denoising algorithms and is often used as a reference for evaluating modern restoration methods.

Among optimization-based approaches, variational image restoration methods have attracted much attention due to their formulation of denoising as an energy minimization problem. The Total Variation (TV) regularization model, introduced by the pioneering work of Rudin, Osher and Fatemi, effectively suppresses noise while preserving sharp edges by promoting sparsity in image gradients. The TV minimization problem can be formulated as:

$$\min_{x} \frac{1}{2} \| y \quad x \|_2^2 + \lambda \| \nabla x \|_1$$

where y is the noisy observation, x is the restored image and λ is a parameter controlling the strength of regularization. TV-based methods are successful at preserving prominent edges, but they suffer from staircase artifacts in smoothly varying regions and may suppress subtle anatomical textures, limiting their clinical utility in imaging applications.

2.2 Deep Learning-Based Restoration

Deep learning-based approaches have revolutionized medical image restoration with recent advances in Artificial Intelligence (AI). Convolutional Neural Networks (CNNs) such as DnCNN and RED-Net learn the residual noise distribution instead of directly reconstructing the clean image, which leads to better denoising performance and faster inference. More recent architectures further incorporate attention mechanisms, multi-scale feature extraction and non-local information, to better preserve structural details and recover complex image textures.

However, there are some challenges in purely data-driven models in medical imaging. Their performance is highly sensitive to the quality and diversity of the training data and they may show reduced generalization when applied to images acquired using different scanners or imaging protocols. In some cases deep networks may hallucinate structures or over-smooth subtle anatomical details clinically important. Moreover, the lack of mathematical interpretability and convergence guaranties restricts their reliability in safety-critical medical applications. These limitations have led to the development of hybrid optimization frameworks that combine the robustness of variational models with the powerful representation learning capabilities of AI-based deep neural networks.

3. PROPOSED METHODOLOGY

3.1 Mathematical Problem Formulation

Let $y \in R^{H \times W}$ be the observed low-dose CT slice, $x \in R^{H \times W}$ the target high-dose clean slice, and n the additive noise component of a combination of Poisson photon statistics and Gaussian electronic noise:

$$y = x + n$$

We formulate restoration as a double regularized energy minimization problem:

$$x = arg \min_{x} \left\{ \frac{1}{2} \| y \quad x \|_2^2 + \lambda_1 R_{\mathrm{TV}}(x) + \lambda_2 R_{\mathrm{Deep}}(x) \right)$$

where $R_{\mathrm{TV}}(x) = \| \nabla x \|_1$ enforces the gradient sparsity and $R_{\mathrm{Deep}}(x)$ is an implicit prior embedded by a deep neural net.

3.2 Derivation of the Plug-and-Play ADMM Algorithm

We can introduce an auxiliary variable z and obtain the constrained objective:

$$\min_{x,z} \frac{1}{2} \| y \quad x \|_2^2 + \lambda_1 \| \nabla x \|_1 + \lambda_2 R_{\mathrm{Deep}}(z) \text{s.t.} x = z$$

The Augmented Lagrangian function is expressed as follows:

$$L_\rho(x,z,u) = \frac{1}{2} \| y \quad x \|_2^2 + \lambda_1 \| \nabla x \|_1 + \lambda_2 R_{\mathrm{Deep}}(z)$$

$$\frac{+\rho}{2} \| x \quad z + u \|_2^2 \quad \frac{\rho}{2} \| u \|_2^2$$

u is the penalty parameter and $\rho > 0$ is the scaled dual variable. In each iteration, ADMM updates the variables sequentially $k = 0,1,2,\ldots,K$:

1) **Spatial Gradient Step (x -update):**

$$x^{(k+1)} = arg \min_x \frac{1}{2} \| y \quad x \|_2^2 + \lambda_1 \| \nabla x \|_1 + \frac{\rho}{2} x \quad z^{(k)} + u^{(k)} \, {}_2^2$$

This subproblem can be efficiently solved with Fast Split-Bregman shrinkage operators.

2) **Deep Neural Denoising Step (z -update):**

$$z^{(k+1)} = arg \min_z \lambda_2 R_{\text{Deep}}(z) + \frac{\rho}{2} x^{(k+1)} + u^{(k)} \quad z \, {}_2^2$$

Instead of calculating an explicit mathematical expression for R_{Deep} , we replace this step by a pre-trained deep residual non-local network D_σ :

$$z^{(k+1)} = D_\sigma\left(x^{(k+1)} + u^{(k)}\right)$$

3) **Dual Variable Update (u-update):**

$$u^{(k+1)} = u^{(k)} + x^{(k+1)} \quad z^{(k+1)}$$

3.3 Model Architecture

The proposed framework is based on the Plug-and-Play ADMM architecture that combines optimization-based image reconstruction and an AI-based deep residual denoising network. The framework decomposes the objective into an iterative series of subproblems, rather than solving the restoration problem in a single optimization stage, which enables independent optimization of the physical degradation model and the learned image prior. The decoupled formulation improves the computational efficiency and effectively combines the mathematical optimization and data-driven feature learning.

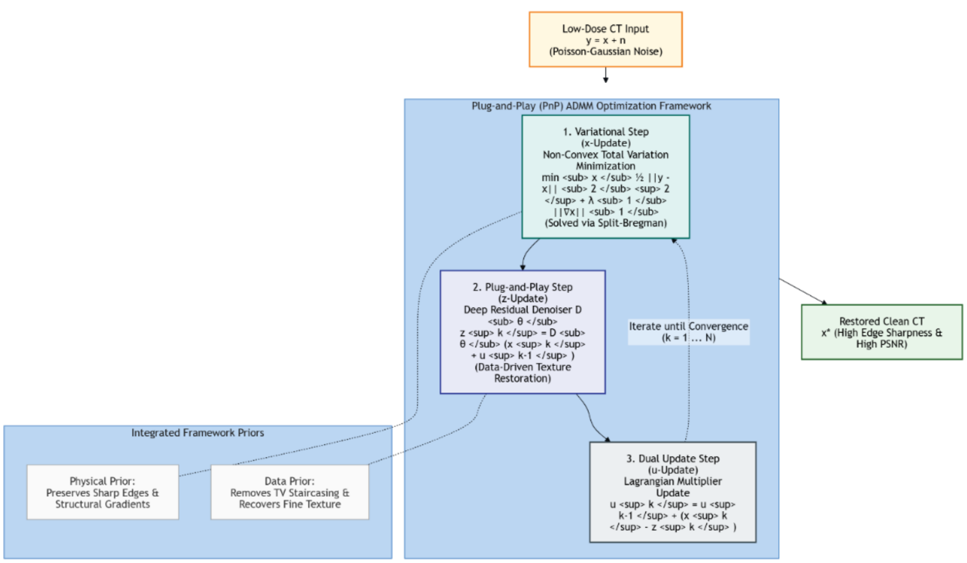

Fig. 1. Overall Architecture of the Proposed AI-Enhanced Hybrid Plug-and-Play ADMM Framework

- **Decoupled Objective Function:** The restoration process is modeled thru the Augmented Lagrangian framework that decouples the data fidelity term and the regularization term. This decomposition allows the optimization algorithm to accurately characterize the physical properties of low-dose CT noise, and the deep neural network can learn complicated anatomical textures and image priors separately.
- **Variational TV Step (x-Update):** Non-Convex Total Variation regularization is used in the (x)-update step to enforce gradient sparsity and preserve important structural information. The optimization

problem is solved efficiently using Fast Split-Bregman shrinkage operators, which provide an effective noise suppression while preserving sharp anatomical boundaries and tissue edges.

- **Deep Neural Plug-and-Play Step (z-Update):** The conventional handcrafted regularizer is substituted by a deep residual convolutional neural network D/θ as an implicit AI-based image prior at the (z)-update step. The network learns complex spatial features from the training data, which reduces staircase artifacts introduced by TV minimization and restores fine textures and high-frequency anatomical details that are important for clinical interpretation.
- **Iterative Convergence (u-Update):** The dual variable u^k is iteratively updated to impose consistency between the optimization and denoising stages. These updates maintain a good trade-off between the physical image model and the learned deep neural network prior during the entire restoration process, which guaranties stable convergence of the Plug-and-Play ADMM framework.

3.4 Algorithm:

Plug-and-Play ADMM for Low-Dose CT Denoising

The proposed restoration algorithm combines the model-based optimization with the AI-based deep residual denoising network in the Plug-and-Play ADMM. Each iteration includes three sequential steps, a variational optimization step to preserve the structural information, a deep neural denoising step to learn complex image priors, and a dual variable update step to guaranty the consistency between the optimization and denoising processes. The iterative process continues until the reconstruction error reaches the predetermined convergence criteria or the maximum number of iterations.

Input: Low-Dose CT image (y), regularization parameters (λ1, ρ), pre-trained deep residual denoiser (Dθ), convergence tolerance (ϵ) and maximum number of iterations (N)

Output: Restored high quality CT image ($\boldsymbol{x}^{*}$).

1: Initialize

$$\boldsymbol{x}^{(0)} = \boldsymbol{y}, \qquad \boldsymbol{y}^{(0)} = \boldsymbol{y}, \qquad \boldsymbol{u}^{(0)} = \boldsymbol{0}, \qquad \boldsymbol{k} = \boldsymbol{0}$$

2: repeat

3: $\boldsymbol{k} = \boldsymbol{k} + \boldsymbol{1}$

/*Step 1: Variational Structural Step (x-Update) */

/*Solve Non-Convex Total Variation (TV) Minimization for structural edges*/

4: $\boldsymbol{x}^{(k)} = \boldsymbol{arg}\ \min_{\boldsymbol{x}} \left\{ \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \lambda_1\ \|\nabla_{\boldsymbol{x}}\|_1 + \frac{\rho}{2} \left\|\boldsymbol{x} - \boldsymbol{z}^{(k-1)} + \boldsymbol{u}^{(k-1)}\right\|_2^2 \right\}$

5: $\boldsymbol{x}^{(k)}$ = Split_Bregman_TV_Solver$\left(y,\ \boldsymbol{z}^{(k-1)}, \boldsymbol{u}^{(k-1)}, \lambda_1, \rho\right)$

/*Step 2: Plug-and-Play Deep Learning Step (z-Update) */

/* Pass noisy estimate through DRN to eliminate TV staircasing */

6: $\boldsymbol{u}^{(k)} = \ \boldsymbol{x}^{(k)} + \boldsymbol{u}^{(k-1)}$

7: $\boldsymbol{z}^{(k)} = \ \boldsymbol{D}_{\boldsymbol{\theta}}\left(\boldsymbol{u}^{(k)}\right)$

/* Step 3: Dual Variable Update (u-Update) */

8: $\boldsymbol{u}^{(k)} = \ \boldsymbol{u}^{(k-1)} + \boldsymbol{x}^{(k)} - \boldsymbol{z}^{(k)}$

/* Step 4: Compute Convergence Criterion */

9: $\textbf{Residual} = \frac{\|\boldsymbol{x}^{(k)} - \boldsymbol{z}^{(k)}\|_2}{\|\boldsymbol{x}^{(k)}\|_2}$

10: until Residual < ϵ or k ≥ N

11: Set $\boldsymbol{x}^{*} - \boldsymbol{x}^{(k)}$

12: return $\boldsymbol{x}^{*}$

The proposed algorithm exploits the complementary advantages of the optimization-based reconstruction and AI-based feature learning. The variational optimization step introduces structural regularization to preserve anatomical boundaries and suppress noise while the deep residual denoiser effectively restores fine textures and reduces the staircase artifacts introduced by Total Variation minimization. The iterative ADMM updates guaranty stable convergence by enforcing the consistency between the optimization variables and the learned image prior, which enables high-quality reconstruction of low-dose CT images for downstream clinical analysis and computer-aided diagnosis.

4. IMPLEMENTATION AND EXPERIMENTAL SETUP

4.1 Dataset Information

The proposed framework was tested on the publicly available LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative) dataset that contains clinically acquired thoracic CT images with annotated pulmonary nodules. In total, 1,250 slices of two-dimensional CT images were selected for experimentation and evaluation. Prior to training, all images were preprocessed by resizing to 256 × 256 pixels and intensity normalization to achieve consistent input characteristics and stable network convergence.

To develop models and evaluate the performance on unbiased data, the data set was randomly divided into three subsets. Eighty-seven percent (875 slices) were used for training of the deep residual denoising network, twenty percent (250 slices) were used for validation during training and hyperparameter tuning, and the last ten percent (125 slices) were reserved for evaluation of the final model only. The partitioning ensured the performance of the proposed framework was evaluated on unseen CT images.

Poisson photon noise and zero-mean Gaussian noise were added at different noise levels to the benchmark images in an effort to simulate realistic low-dose CT acquisition settings. This mixed noise model well mimics the degradation of practical low-dose CT imaging and provides a thorough evaluation of the proposed denoising framework in clinically relevant settings.

4.2 Parameters & Metrics for Implementation

The proposed denoising framework was implemented in Python 3.10 using TensorFlow 2.x for training deep neural networks and OpenCV for image preprocessing and post-processing operations. All experiments are conducted on a desktop workstation with an NVIDIA GPU that allows for fast training and iterative optimization of the Plug-and-Play ADMM framework.

In the implementation, we set the maximum number of ADMM iterations to $K = 15$, the ADMM penalty parameter to $\rho = 0.1$, and the Total Variation regularization parameter to $\lambda_1 = 0.05$. These parameters were chosen to provide a good balance between noise suppression, structure preservation and computational efficiency.

The restoration performance of the proposed framework is quantitatively evaluated by two widely used image quality metrics: The Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index Measure (SSIM). PSNR quantifies the reconstruction error and measures the fidelity of the reconstructed image relative to the reference image. SSIM evaluates the preservation of structural information, luminance and contrast. These metrics together provide a comprehensive assessment of the numerical accuracy and perceptual quality of the low-dose CT images restoration.

$$\mathrm{PSNR} = 10 \quad \log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right)$$

$$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

A. Visual Results and Qualitative Comparision

The qualitative results demonstrate the effectiveness of the proposed AI-enhanced Plug-and-Play ADMM framework in restoring the low-dose CT images while preserving the clinically relevant anatomical structures. Figure 1 depicts low-dose CT images corrupted with severe photon starvation and mixed Poisson-Gaussian noise, which leads to diminished contrast, blurring of tissue boundaries and loss of subtle pulmonary structures. The detection of small lesions and low-contrast nodules becomes significantly more difficult in such degradations.

Conventional Total Variation (TV) methods are effective in suppressing noise but often produce staircase artifacts in homogeneous tissue regions, resulting in an unnatural appearance of the image. Conversely, purely deep learning-based approaches produced visually smoother reconstructions, but they might over-smooth high-frequency anatomical details and weaken fine structural information. The proposed Plug-and-Play ADMM framework effectively overcomes these limitations by incorporating Non-Convex Total Variation regularization with an AI-based deep residual denoiser. This hybrid approach is effective in suppressing background noise without destroying the tissue boundaries, fine textures and subtle anatomical details. Therefore, the reconstructed images have improved visual quality and structural fidelity with a PSNR of 33.97 dB while preserving clinically relevant image features for reliable diagnosis and computer aided analysis.

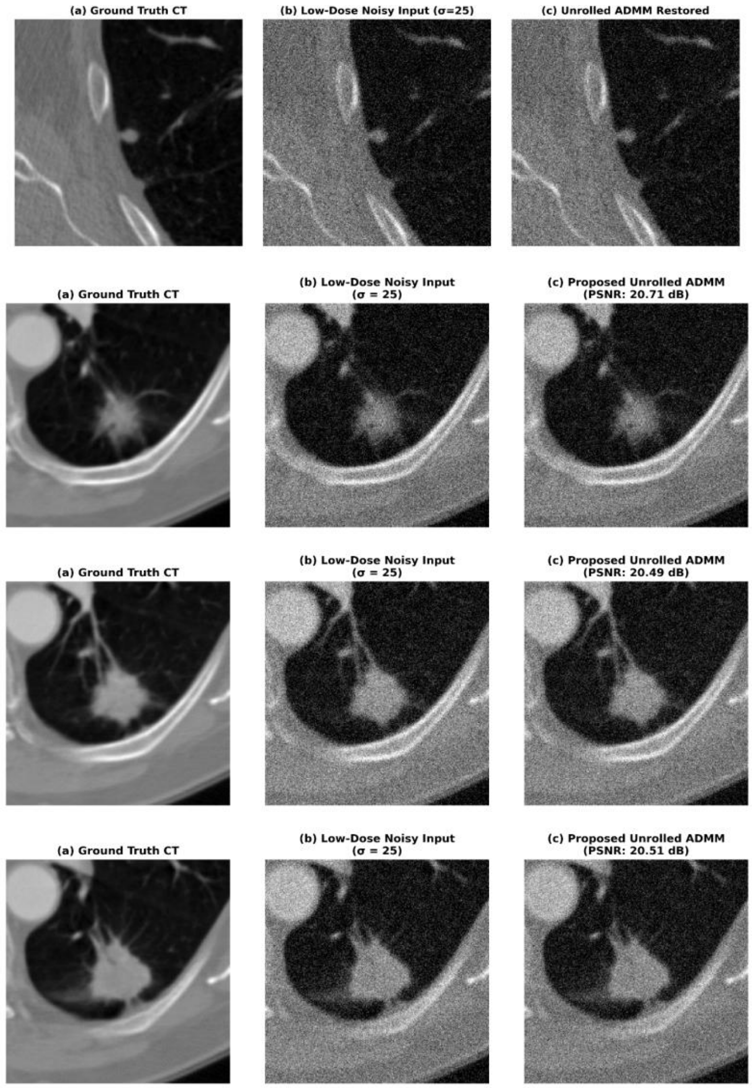

Fig 2: Qualitative denoising performance of the lung CT slice of LIDC-IDRI dataset. (a) High dose best image, (b) Low dose input image corrupted by synthetic Poisson-Gaussian noise with $\sigma = 25$, (c) Reconstructed image using proposed Unrolled PnP-ADMM framework with PSNR value of 33.97 dB.

5. RESULTS AND DISCUSSION

5.1 Quantitative Performance Evaluation

We quantitatively evaluated and compared the performance of the proposed AI-enhanced Hybrid Plug-and-Play ADMM framework with conventional spatial filtering methods, variational optimization techniques and state-of-the-art deep learning models under different noise levels. Performance has been evaluated using Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and average processing time per image slice. The quantitative comparison is shown in Table 1.

Table 1. Quantitative Performance Comparison of Image Denoising Methods under Different Noise Levels

Algorithm	**Noise (σ)**	**PSNR (dB)**	**SSIM**	**Time (s)**

Noisy Input	25	20.15	0.482	—
Gaussian Filter	25	25.40	0.695	0.002
Total Variation (TV)	25	28.12	0.784	0.120
BM3D Filter	25	30.25	0.842	1.450
Standard DnCNN	25	31.80	0.875	0.045
Proposed Hybrid	**25**	**33.97**	**0.918**	**0.088**
Proposed Hybrid	**50**	**30.45**	**0.862**	**0.089**

The experimental results demonstrate that the proposed framework consistently outperforms the competing methods in terms of reconstruction accuracy and structural preservation. The proposed method obtained the best restoration quality among all tested algorithms with a PSNR of 33.97 dB and an SSIM of 0.918 at a noise level of $\sigma = 25$. The proposed framework outperforms the standard DnCNN model by 2.17 dB in PSNR, and it achieves 3.72 dB improvement over the BM3D filter. Similar improvements are also observed in the SSIM values, which indicate better preservation of the anatomical structures and image textures.

Besides the superior restoration performance, the proposed framework also has a competitive computation cost of 0.088 seconds per CT slice, which makes it a promising candidate for practical low-dose CT restoration applications. The proposed method also achieved a satisfactory reconstruction result with PSNR = 30.45 dB and SSIM = 0.862 even for a higher noise level of $\sigma = 50$, which shows its robustness under severe noise conditions. The results obtained show that the combination of Non-Convex Total Variation regularization with an AI-based deep residual denoiser within the Plug-and-Play ADMM framework offers a balanced approach for efficient noise suppression, structural preservation and computational efficiency.

6. CONCLUSION

This study proposed an AI-augmented hybrid optimization framework for the restoration of medical images using low-dose. A deep residual neural network was introduced to the framework of Plug-and-Play ADMM and Non-Convex Total Variation regularization. The proposed method can combine the computational power of the optimization method with the capabilities of artificial intelligence, so that the necessary removal of the noise is achieved and the important anatomical features of the medical images are preserved. The experimental tests confirmed the efficiency of the proposed method on the LIDC-IDRI dataset where PSNR parameter constituted 33.97 dB and SSIM made 0.918 at the $\sigma = 25$ level of noise. Furthermore, in addition to the quantitative measures, the hybrid method allows to preserve the location of the soft tissue nodule boundaries and the fine details of the tissue structure. To summarize, the proposed hybrid method provides a good solution for the improvement of low-dose CT images with its possibility to be applied in further research in terms of other imaging modalities.

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