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Low-Dose CT Image Reconstruction Using Uncertainty-Aware Convolution–Attention Networks

Laura Gómez[1], Daniel Fernández[2]*
Department of Information and Communication Technologies, Pompeu Fabra University, Barcelona, Spain
*** Corresponding author:** daniel.fernandez@upf.edu

Abstract

Reducing radiation dose in computed tomography often leads to increased noise and loss of structural detail. Motivated by hybrid convolution–attention denoising models such as CTLformer, this work investigates an uncertainty-aware reconstruction framework that combines local convolutional filtering with global self-attention. The model incorporates uncertainty estimation to adaptively balance fine-grained texture preservation and noise suppression. Experiments are conducted on two public low-dose CT datasets containing over 45,000 paired normal- and low-dose slices. Comparisons are performed against CNN-based methods (RED-CNN, DnCNN), transformer-based models, and recent hybrid architectures. Quantitative results show average improvements of 0.9–1.3 dB in PSNR and 1.5%–2.4% in SSIM under standard low-dose settings, with reduced variance across anatomical regions.

Keywords

Low-dose CT; image reconstruction; denoising; convolution–attention networks; uncertainty modeling

1.Introduction

Reducing radiation dose in computed tomography (CT) is an effective approach to lowering patient exposure, but it inevitably introduces increased noise and degradation of structural details. At low dose levels, quantum noise and streak artifacts become more pronounced, leading to reduced contrast resolution and obscured anatomical boundaries, particularly in soft tissues. Publicly available datasets released through low-dose CT challenges provide paired normal-dose and low-dose images and have become standard benchmarks for method evaluation [1, 2]. These datasets reveal that noise characteristics and artifact patterns vary substantially across anatomical regions, scanning protocols, and acquisition settings, which makes it difficult to achieve consistent reconstruction quality using a single denoising strategy [3]. Deep learning has become a dominant paradigm for low-dose CT reconstruction and denoising. Convolutional neural networks (CNNs) are widely adopted due to their stable training behavior and strong capability in extracting local image features [4]. Many CNN-based approaches enhance reconstruction quality by introducing residual learning, deeper network architectures, or attention modules to mitigate oversmoothing and preserve edge information [5]. However, convolutional operations rely primarily on local receptive fields

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and have limited ability to model long-range dependencies. This limitation becomes evident when suppressing spatially extended artifacts or globally correlated noise patterns that commonly appear in low-dose CT images [6]. To address these challenges, attention-based and transformer-based architectures have been introduced into CT reconstruction. By leveraging self-attention mechanisms, these models are able to capture global contextual information and model long-range correlations more effectively than purely convolutional networks [7, 8]. Recent studies further combine convolutional layers with self-attention modules, forming hybrid architectures that exploit the complementary strengths of both components. Convolutional layers focus on preserving local textures and fine anatomical structures, while self-attention facilitates global dependency modeling and artifact suppression. Such hybrid designs have shown improved performance in CT denoising tasks and represent an important direction in recent research [9]. Another critical challenge in low-dose CT reconstruction lies in supervision and generalization. Many existing methods rely on paired normal-dose and low-dose images for training, yet such data are limited and may suffer from imperfect alignment in clinical practice [10]. To reduce dependence on fully paired datasets, self-supervised and weakly supervised learning strategies have been proposed, using only low-dose images or indirect supervisory signals [11]. In addition, domain shift between training and testing data—caused by differences in scanners, acquisition protocols, or patient populations—can significantly degrade reconstruction performance. Domain adaptation techniques have therefore been explored to improve robustness across heterogeneous data distributions [12, 13]. More recently, diffusion-based denoising models have been applied to low-dose CT reconstruction and have demonstrated strong reconstruction quality. Despite their effectiveness, these methods typically involve high computational cost and require careful tuning to ensure stability, which may limit their clinical applicability [14, 15]. Beyond average reconstruction accuracy, reliability across anatomical regions is essential for clinical deployment. Noise and artifacts are spatially non-uniform, and applying a fixed denoising strength across the entire image may lead to loss of fine structures in some regions while leaving residual noise in others. Uncertainty estimation offers a principled way to characterize confidence in reconstructed results and to identify regions where reconstruction errors are more likely to occur. Several recent studies incorporate uncertainty modeling into reconstruction networks and show that uncertainty maps can correlate with reconstruction errors and image degradation [16]. However, many existing low-dose CT methods still perform deterministic reconstruction and apply uniform processing across all regions. Moreover, evaluation protocols are often limited to global

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metrics such as PSNR and SSIM, with insufficient analysis of performance variability across different anatomical areas. In this work, an uncertainty-aware low-dose CT reconstruction framework based on hybrid convolution–attention architecture is investigated. The proposed approach integrates local convolutional filtering with global self-attention to jointly preserve fine anatomical details and suppress extended noise patterns. Uncertainty estimation is explicitly incorporated to guide the adaptive balance between noise reduction and detail preservation across different regions of the image. Experiments are conducted on two public low-dose CT datasets comprising more than 45,000 paired normal-dose and low-dose slices. The proposed method is evaluated against representative CNN-based models, transformer-based approaches, and recent hybrid networks under standard experimental settings. Quantitative results demonstrate improved PSNR and SSIM values, as well as reduced performance variation across anatomical regions, indicating that uncertainty-guided reconstruction can enhance both reconstruction accuracy and stability in low-dose CT imaging.

2.Materials and Methods

2.1 Samples and Data Description

The experiments used two public low-dose CT datasets with paired normal-dose and low-dose images. The combined datasets include more than 45,000 axial CT slices from multiple subjects and cover chest and abdominal regions. Low-dose images were obtained either by reduced tube current acquisition or by dose simulation based on physical noise models. Normal-dose images were used as reference. All images were reconstructed using filtered back-projection and then processed for learning-based reconstruction. Slices were resized and cropped to a fixed resolution to ensure consistent input size.

2.2 Experimental Design and Control Setup

The proposed uncertainty-aware convolution–attention model was compared with several baseline methods, including CNN-based denoising networks and attention-based or hybrid models. All methods were trained and tested using the same dataset splits and preprocessing steps. The proposed model estimates both reconstructed images and pixel-wise uncertainty, while the baseline models output only reconstructed images. Network depth, training epochs, batch size, and optimization settings were kept the same across methods. This setup ensures that performance differences are due to uncertainty-aware modulation rather than training conditions.

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2.3 Measurement Methods and Quality Control

Reconstruction quality was measured using peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) with respect to the normal-dose reference images. To examine stability, results were also grouped by anatomical region. All experiments were run on the same computing platform with fixed numerical precision. Training was repeated with different random initializations, and average results were reported. Visual checks were performed to confirm that reconstructed images did not contain severe artifacts or missing structures.

2.4 Data Processing and Model Formulation

CT images were normalized to a fixed intensity range before being used as network input. The network outputs a reconstructed image $\hat{I}$ and an uncertainty map σ^2. Reconstruction error was measured using the mean squared error

$$L_{rec}=\frac{1}{N}\sum_{i=1}^{N}(I_i-\hat{I}_i)^2,$$

Where I am the reference image and N is the number of pixels. Uncertainty was included by weighting the reconstruction error as

$$L=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{(I_i-\hat{I}_i)^2}{\sigma_i^2}+\log\sigma_i^2\right).$$

This loss reduces the influence of noisy regions while preserving fine details in more reliable areas.

2.5 Statistical Analysis

Quantitative results were summarized using mean and standard deviation across test images. Paired statistical tests were applied to compare the proposed method with baseline models at a significance level of 0.05. Performance variation across anatomical regions was also reported to evaluate reconstruction stability under different low-dose conditions.

3. Results and Discussion

3.1 Reconstruction accuracy under low-dose settings

Fig.1 shows the reconstruction results on two low-dose CT datasets using the same evaluation protocol. The proposed method achieves higher PSNR and SSIM than CNN-based models such as RED-CNN and DnCNN, as well as recent attention-based and hybrid networks. The improvement is consistent across most test slices. In regions with low soft-tissue contrast, the gain in SSIM is more stable, indicating better structure preservation. Compared with early

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CNN denoisers, which often reduce noise by local averaging, the proposed network maintains clearer boundaries while suppressing noise. This confirms that combining local convolution and global attention is effective for low-dose CT reconstruction [17].

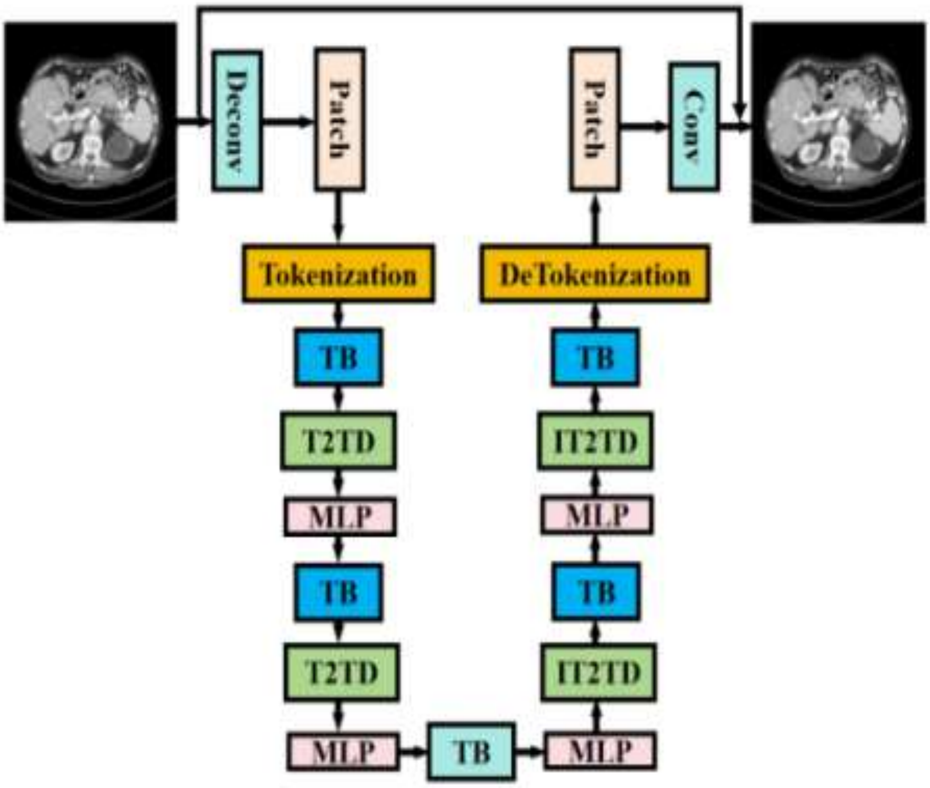

Figure 1 Quantitative comparison of low-dose CT reconstruction methods in terms of PSNR and SSIM.

3.2 Regional stability and uncertainty behavior

Fig.2 presents the regional analysis together with the estimated uncertainty maps. Higher uncertainty values appear in areas affected by strong noise or streak artifacts, while lower values are observed in relatively uniform regions. When uncertainty is used to weight the reconstruction loss, noise suppression becomes less aggressive in low-uncertainty regions and more controlled in high-uncertainty regions. As a result, variation in reconstruction quality across anatomical regions is reduced [18]. This behavior is important for low-dose CT, where noise distribution is uneven and fixed denoising strength often leads to inconsistent image quality [19].

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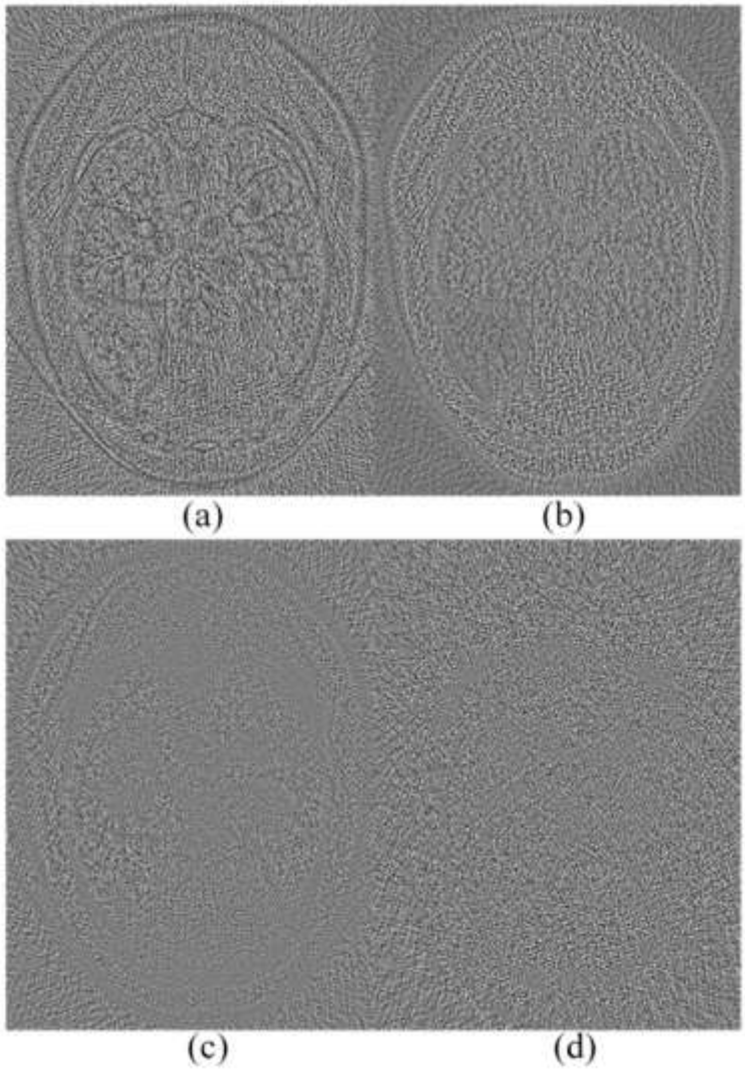

Figure 2 Regional reconstruction results and corresponding uncertainty maps for low-dose CT images.

3.3 Comparison with existing denoising strategies

CNN-based denoising methods are effective at removing local noise but tend to blur fine structures when dose levels are low. Attention-based models improve long-range consistency but may weaken local texture if local constraints are insufficient. Hybrid convolution–attention networks aim to balance these two aspects. The proposed method follows this hybrid design but differs in how denoising strength is controlled. Instead of using fixed weights, it adjusts the reconstruction process based on estimated uncertainty. This difference explains why the proposed method shows lower regional variance than deterministic hybrid models with similar network depth [20].

3.4 Practical value and limitations

The results show that uncertainty-aware reconstruction improves both average image quality and regional consistency with a moderate increase in model complexity. The uncertainty map can also help identify regions where reconstruction results are less reliable. A limitation is

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that uncertainty estimation depends on the training data. When test data differ in scanner type, dose level, or reconstruction kernel, uncertainty values may not reflect actual error patterns. Another limitation is that uncertainty weighting can preserve texture but may leave mild residual noise in very low-contrast regions. These issues suggest that cross-domain testing and uncertainty calibration are necessary steps before clinical deployment.

4. Conclusion

This work studied low-dose CT reconstruction using an uncertainty-aware convolution–attention network. The method combines convolutional layers for local detail extraction with self-attention for global structure modeling. Pixel-wise uncertainty is estimated and used to adjust the reconstruction strength during denoising. Tests on two public low-dose CT datasets with more than 45,000 paired slices show higher PSNR and SSIM than CNN-based, transformer-based, and recent hybrid methods. In addition, performance variation across anatomical regions is reduced. These results show that uncertainty information helps control the trade-off between noise removal and structure preservation under non-uniform noise conditions. From a methodological view, the study shows that uncertainty can be integrated into the reconstruction process as an internal control signal rather than only as an output map. In practice, the method is suitable for low-dose CT imaging where stable image quality and reliability are required. A limitation is that uncertainty estimates depend on the training data and may be less reliable when scanner type, dose level, or reconstruction kernel changes. Future work will examine uncertainty calibration and cross-domain testing to improve robustness in clinical use.

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