Low-dose CT denoising via a hybrid network of transformer and residual dense network

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Low-dose computed tomography (CT) imaging is a crucial diagnostic tool that reduces radiation exposure for patients but often suffers from increased noise and reduced image quality. To address these challenges, we developed a hybrid network that combines the strengths of stochastic block (StoBlock) and residual dense networks (RDN) to enhance the denoising of low-dose CT images. The hybrid network employs a StoBlock with distribution stochastic window to capture both local and global features of images, effectively reducing noise while preserving important details. The transformer processes features across the entire image, enhancing the extraction of relevant features and suppressing unwanted noise. Complementarily, the RDN component refines image details through densely connected convolutional layers. These layers learn and integrate residual features across the network, improving the overall image quality by enhancing texture and edge preservation. We trained this network using a mean absolute error (MAE) loss function, chosen for its stability in training and sensitivity to outliers, crucial for high-quality denoising. The performance of our hybrid model was compared against several advanced denoising methods using metrics like peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and root mean squared error (RMSE). Our results demonstrated superior performance of the hybrid network, with higher PSNR and SSIM scores indicating not only reduced noise but also improved visual quality. These outcomes suggest that our hybrid network can significantly enhance diagnostic accuracy while maintaining low radiation exposure, promising better patient outcomes and safer diagnostic practices.

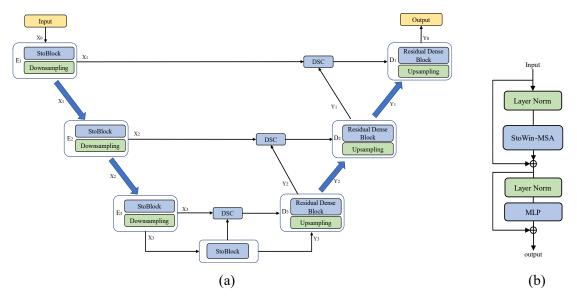


Figure. 1. (a) The architecture of a hybrid network with an encoding part consisting of stochastic blocks (StoBlock) [1] and a decoding part comprising residual dense blocks, featuring depthwise separable convolution (DSC); (b) The Stochastic Window Transformer structure with multi-head self-attention with stochastic window partition (Sto-WinMSA).

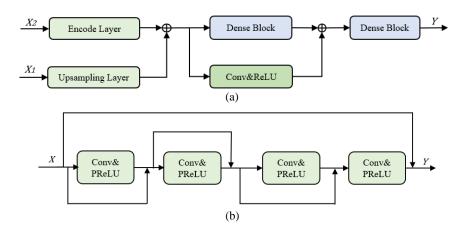


Figure. 2. (a) A residual dense block combining features of residual and dense networks [2-3]; (b) A dense block with serially connected convolutional blocks enhanced by jump connections.

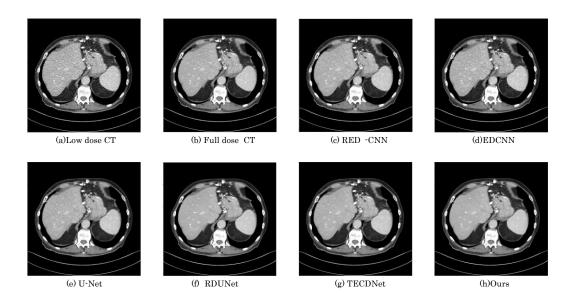


Figure. 3. Transverse slice comparisons between different methods where (a) represents low-dose images, (b) represents full-dose images, (c) to (g) show noise reduction results from comparison methods, and (h) is the result of our method.

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|---|--------|-------|--------|--|--|--|--|--|
| Metheds | PSNR | SSIM | RMSE | | | | | |
| LDCT | 29.249 | 0.876 | 14.245 | | | | | |
| RED-CNN | 32.848 | 0.908 | 9.291 | | | | | |
| EDCNN | 32.738 | 0.906 | 9.424 | | | | | |
| U-Net | 32.731 | 0.907 | 9.415 | | | | | |
| RDUNet | 33.709 | 0.919 | 8.445 | | | | | |
| TECDNet | 33.338 | 0.915 | 8.801 | | | | | |
| Ours | 33.776 | 0.919 | 8.382 | | | | | |

| Table 1. | The results | were compar | ed with | those of | btained | using o | other methods. |
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