Image reconstruction techniques using deep learning networks with high quality segmentation

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Abstract. Translational CT (TCT), in developing nations, a low-end computed tomography (CT) technology are relatively common. The limited-angle TCT scanning mode is often used with large-angle scanning to scan items within a narrow angular range, reduce X-ray radiation, scan long objects, and prevent detector discrepancies. However, this scanning mode greatly reduces the picture quality and diagnostic accuracy due to the added noise and limited-angle distortions. A U-net convolutional neural network-based approach for limited-angle TCT image reconstruction has been created to reconstruct a high-quality image for the limited-angle TCT scanning mode (CNN). The limited-angle TCT projection data are first examined using the SART method, and the resulting picture is then fed into a trained CNN that can reduce artifacts and maintain structures to provide a better reconstructed image. Simulated studies are used to demonstrate the effectiveness of the algorithm designed for the limited-angle TCT scanning mode. In contrast to certain modern techniques, the developed algorithm considerably lowers noise and limited-angle artifacts while maintaining image structures.

Keywords. Deep Learning. Network segmentation, Image reorganisation, CNN.

1 Introduction

Medical imaging methods including computed tomography (CT), magnetic resonance imaging (MRI), X-ray, and ultrasound have been used to see body limbs, organs, and other tissues. However, images obtained using these imaging modalities might have poor signal-to-noise (SNR) and contrast-to-noise ratios as well as visual artefacts [1]. To address these

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problems and improve picture quality for improved visual perception, understanding, and analysis, image reconstruction methods have been created. Three fields—radionics, computer-aided detection and diagnosis, and medical image analysis—have successfully used deep learning (DL) techniques. [2–3]. Deep learning, often referred to as representation learning, has lately gained a lot of interest for the interpretation of medical pictures [4] [5]. By being able to recognise attributes from the raw input data during training, deep learning surpasses typical machine learning techniques. It can learn abstractions depending on inputs thanks to its several hidden layers [6]. Deep learning is rapidly being applied in a variety of fields, including medical image reconstruction, as a result of recent advancements in effective computing infrastructures like cloud computing and graphics processing units (GPUs) computing platforms. [3].

Reconstructing an image involves utilising measurements to build a picture. When reconstructing an image, the encoding function is inverted, creating a representation of the object in the sensor domain, or sensor encoding. Because analytical knowledge of the proper inverse transform may not exist a priori in the face of sensor non-idealities and noise, image reconstruction is a difficult undertaking. [7]. The issue with conventional approaches to image reconstruction is that it is not always possible to determine the precise inverse transform. Additionally, when dealing with actual noisy data, they employ approximations made using potentially error-prone chains of highly calibrated signal-processing units. [7]. A revolution in picture reconstruction will be brought about by deep learning algorithms. [8]. Moreover, methods based on deep learning enhance the dependability, speed, and accuracy of medical picture reconstruction.

2 Methodology

Using the flowchart and procedure for the recommended reporting elements for systematic reviews and meta-analyses (PRISMA), relevant research publications [6] were identified. The four primary phases are the following: The four stages of the study are as follows: (1) identification, which entails gathering articles from a variety of sources; (2) screening, which involves removing duplicates and inadequate articles; (3) eligibility, which involves analyzing the articles to determine their suitability for further review and excluding those that are unsuitable; and (4) the last stage, also known as the included phase, which involves the articles that are actually included in the study.

2.1 Reconstruction Techniques

Long scan times, artefacts, and restrictions on the signal-to-noise ratio (SNR) may make it difficult to use conventional MR reconstruction approaches. Only by increasing radiation doses can mathematical assumptions that appear as image noise in filtered back projection, the typical method for rapid CT reconstruction, be eliminated. Iterative reconstruction (IR) techniques, which have been widely used in CT for decades but have only just been available in MR, may alter the image's texture and undermine its quantitative integrity while lowering noise and enabling for the optimization of CT dose or MR scan durations.

Applications for "deep learning reconstruction" (DLR) are based on an application of neural network-based machine learning. DLR offers an even higher improvement in SNR than IR, while maintaining the quantitative integrity of measurements like MR anisotropy values and the image texture (noise power spectrum).

Strategies To Take Advantage of DLR
Deep learning is used to reconstruct acquisitions more quickly or at lower dosages in order to maintain or improve picture quality. A CT imaging factor, such as tube current or potential, is accordingly decreased after the reconstruction's capacity to minimise noise has been calibrated. Depending on the tactics used to exchange signal (which DLR can recover) for scan duration, there are a variety of complex opportunities for MR acceleration.

2.2 Empirical Results

The suggested denoising network's qualitative and quantitative empirical data are presented in this section. The effect of noise level and reconstruction stride size on the effectiveness of denoising is also discussed.

Visual Impression:

The proposed denoising network exceeds the benchmark strategy in terms of the accuracy of the denoising it can execute by achieving higher PSNRs. The chin and cheeks of the woman in the first batch of photos seem to have a larger degree of smoothness after being processed by the denoising network in comparison to the photos that have been processed using VST+BM3D. Similar outcomes can be observed in the background, where my denoising network has created smoother colour transitions that are noticeable. In the second set of images, where there are less colour shifts and ripples and smoother pepper surfaces, the denoising network exhibits comparable benefits. The pepper clusters are also recovered with a higher level of precision.

![Fig. 1. Visually observable algorithms for denoising](image)

This graphic depicts the PSNR values and visual impressions of the benchmark and deep learning denoising approaches. Once the clean images have reached their maximum value, Poisson noise is applied to produce noisy images.
Table 1. The average PSNR gain scarcely changes

<table>
<thead>
<tr>
<th>Stride</th>
<th>VST+BM3D</th>
<th>Deep Learning</th>
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<tbody>
<tr>
<td></td>
<td><strong>Time per Image (s)</strong></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>70.74</td>
<td>131.23</td>
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<tr>
<td></td>
<td><strong>Average PSNR</strong></td>
<td>25.09</td>
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<td></td>
<td><strong>PSNR Gain</strong></td>
<td>0.38</td>
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<td><strong>T stat</strong></td>
<td>1.2418</td>
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<td></td>
<td><strong>p-value</strong></td>
<td>0.0004</td>
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Table 1. How stride length impacts processing speed and denoising accuracy. The table below shows how stride size affects calculation time and denoising accuracy. While the average PSNR gain scarcely changes, computation time drastically decreases as the stride size increases.

Effect of Noise Strength:

The effectiveness of the denoising network under various noise levels is further examined in this section. In addition to the initial peak value 4, I also trained one network for the tested peak values of 1, 2, 8, and 16. Poisson noise with peak values of 1 and 2 is more intense than that with peak values of 4; in particular, when peak value 1 is present, noisy pictures have only 2 to 3 brightness levels, which significantly degrades the original image. In contrast to peak value 4, poisson noise with peak values of 8 and 16 is weaker.

![Fig. 2. Visual impression of denoising algorithms with image peak value 2](image-url)
3 Conclusion

Even if there are cutting-edge non-machine learning methods for photo denoising, we often consider whether deep learning may enhance our performance. This study suggests a deep learning denoising network that outperforms conventional benchmark techniques for Poisson denoising statistically significantly. The denoising network may produce a statistically significant PSNR increase of 0.38dB for peak value 4 Poisson noise and even better PSNR gain, for stronger noise. This network has just 6 layers, which is very shallow in comparison to more contemporary designs that make it possible to have more than 50 or 100 layers due to the computer's computing power. Nevertheless, this network can learn the parameters from the data alone and execute Poisson denoising without being explicitly taught the noise properties. The ability of the network to remove noise from other sources, such as random noise or noise with uncertain properties, may be the subject of future study. Future studies may look at how well this architecture fits other image issues like deploring or imprinting.

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