Researchory

Python-Driven CT Scan Image Refinement

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ABSTRACT

This study investigates the application of Artificial Intelligence (AI) in Computed Topography (CT) scans to enhance the image quality; this paper will also address the limitations in traditional methods and human interpretation. Utilizing Python, this research uses common AI-driven reconstruction techniques to reduce noise and remove artifacts from image scans. The methodology's primary focus is to develop algorithms that leverage machine learning to identify and evaluate image patterns and optimize the reconstruction parameters. The results indicate that AI-powered reconstruction techniques significantly boost the image quality, yielding sharper images and a considerable reduction in noise and artifacts when compared with conventional methods. This facilitates improved pattern recognition and could aid in the detection of subtle features. This study highlights the potential of Python-based AI solutions to overcome current obstacles in image refinement and offers a promising avenue for more reliable computer-aided diagnostics.

Abbreviations:

1. DLR = Deep-learning Reconstruction
2. FBP = Filtered Back Projections
3. IR = Iterative Reconstruction
4. PCCT = Photon-counting Computer Topography
5. MBIR = Model-based Iterative Reconstruction

INTRODUCTION

Computer Topography (CT) scans have revolutionized medical imaging, allowing its users to obtain cross-sectional images of a person's body. CT scans develop 3D images based off multiple 2D X-ray projections that are taken at different angles. This process is a classic inverse problem, where the goal is to obtain an accurate internal structure of the body from the different measurements (the X-ray angles). Violation of these conditions can impact the quality and credibility of CT scans (Li et al., 2019).

Throughout history, methods like FBP have been tasked with solving this problem. However, with evolving technology, FBP has gradually become obsolete. Recent breakthroughs in computational techniques have emerged as valuable tools and extend the list with specific submodules made for optimization and signal processing (Rayhan et al., 2023).

One of the more recent breakthroughs include the new revolutionary find of the PCCT (photon-counting computer topography). However, FBPs are not the primary reconstruction method in PCCT; instead, IR and advanced model-based iterative techniques (MBIR) are used. These are preferred to FBPs as they are more suited to handling certain characteristics of photon-counting detectors, this includes noise reduction and energy-resolved information.

The primary aim of this work is to explore the uses and true range of Python to solve the inverse problem of CT scans; this involved enhancing the existing scans through various methods. These methods can be further broken down into the algorithms used to enhance the image. During this study, the image will go through four phases of 'image-enhancement'. The first phase is denoising the image, this means that all the distortions in the image are removed, this includes small grains in the image. The second stage is removing the artifacts in the image; these are the unwanted distortions picked up by the scanner such as metal streaks or ring artifacts. Thirdly, the image will undergo edge enhancement, this is done to sharpen the image through increasing contrast along the edges of the image. This makes the transition between the different regions in the CT scan more noticeable and easier to diagnose. Finally, this image goes through interpolation and deconvolution techniques. In its essence, interpolation increases the pixel density of the image, this is done so that when the image is zoomed in further, it does not appear blocky. This technique does not add on any added information but guesses values to increase image quality. The second technique is deconvoluting the image, this is done to "un-blur" the image, this method can enhance the spatial resolution making fine details clearer. Each of the steps outlined above will be discussed in detail in the following section of the study.

This paper will present an in-depth analysis of the reconstruction process of a CT scan using NumPy and SciPy and will compare the results of traditional methods with the more modern techniques. The results show that the use of SciPy's optimization tools can help bolster the image quality, especially when considering the image noise and artifacts.

METHODOLOGY

Below are the images that were used from the open-source DICOM library.

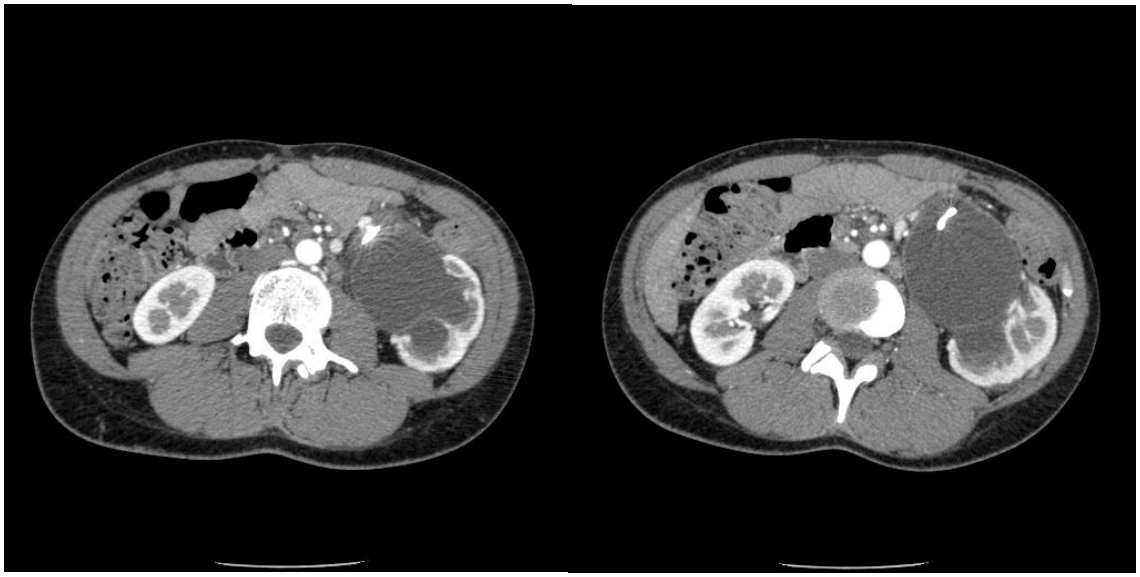

Figure 1 - Example Abdominal CT Scan Slices

The first image is taken from the 199-202 axial, slide number 200, and the second image is taken from the 230-234 axial, slide number 232. These specific slices have been chosen randomly from the available abdominal CT scan within the library to ensure an unbiased representation of the clinical data. The decision to focus on two distinct images, instead of a larger sample, is based on the exploratory nature of this proof-of-concept study, aiming to establish both the qualitative and quantitative capabilities of Python during image refinement. Both images differed observably in their initial noise and artifact traits, allowing for a more comprehensive evaluation of the pipeline's effectiveness. However due to the smaller sample size, more standardized tests such as ANOVA or t-test could not be conducted.

It can be observed from the *Figure 1 - Example Abdominal CT Scan Slices* that the axial post contrast CT of abdomen in arterial phase shows a grossly dilated left renal pelvis with left hydronephrosis. It is also seen that the left double J stent in left renal pelvis with streak artefacts producing bright and dark bands radiating from the stent.

The entire Python algorithm can be viewed on GitHub under amribanerjee/Reconstruction-CT or accessed directly through this GitHub Repository link or can be viewed in *Appendix A: Image Enhancement Code*

The DICOM library used to access the image can be viewed on the official DICOM viewer website and be accessed directly through this DICOM viewer link

Understanding the Code's Modus Operandi

The Python script used in this study has been broken up into multiple segments to help readers understand the purpose behind each section of the code.

The program begins with defining a utility function to load images, this function is designed to manage various images and then converting into a grayscale image if in colour form. Then it normalizes the pixel intensity to a floating-point representation which is crucial for the mathematical algorithm it will undergo in the following steps.

The next step in the pipeline is the denoising technique and is based on the Fourier transform. This process transforms the image from the spatial domain (pixels) to the frequency domain – the noise is usually stored as high-frequency components – and a circular mask is applied to suppress all the high-frequency components. This image is then transformed back to the spatial domain where all the random fluctuations have been filtered out.

Next, the script tackles a frequent problem associated with CT scans: streaks artifacts, often associated with the Radon transform. This function works by performing a Radon transform on the original image, this simulates on how the X-rays passing through the image at various angles will look and thus creating a sinogram. Since streak artifacts appear as consistent patterns in this sinogram, a median filter smooths out all the undesirable patterns. Finally, an inverse Radon transform converts this image from the sinogram form to image-form to reduce the previously identified streaks.

The third stage of image enhancement is unsharp masking; this method works by creating a blurred version of the original image using the Gaussian filter. This blurred image is subtracted from original image to create a "detail mask", which highlights all the edges and fine textures. This mask is then scaled and added back to the original image; this enhances the contrast along the edges.

The final stage of the process is upscaling the image and using deconvolution techniques. First, the image's resolution is increased by resizing by adding more pixels. After upscaling the image, the Wiener filter is applied, this is done to reduce the blurring that has been caused during image acquisition.

Throughout the Python implementation, some specific parameters were adjusted: the Fourier Transform-based denoising used a circular mask with the radius set to one-sixth of the image's minimum dimension; the Radon streak removal used a 3x3 median filter; unsharp marking used a Gaussian blur with a sigma of 1.0 and sharpening gain of 1.5; and the upscaling and deconvolution stage employed a 2x scale factor with the Wiener filter using a 21x21 Gaussian PSF – sigma=3.0 – and balance parameter of 0.005.

Algorithmic Formalism Explained

- Denoising: Fourier-based denoising is an image processing technique where the fundamental idea is that noise has different characteristics than that of the "true" signal. The principle is that by transforming this noisy data into the frequency domain, the components attributed to the noise can be identified and then suppressed. This process will allow to get a cleaner result. This paper used circular low-pass filter, which is an implementation of the ideal low-pas filter. The steps below explain how the Fourier-based denoising algorithm works.
    1. Transform to Frequency Domain:
        - The noisy image $f(x, y)$ gets transformed using DFT (2D Discrete Fourier Transform) which is often accompanied with the FFT (Fast Fourier Transform).
        - This is used to convert the image from its pixel values to a frequency representation $F(u, v)$, where (u, v) correspond to the spatial frequencies.
        - The origin of the $F(u, v)$ will correspond to the low frequencies and values away from this point show higher frequencies, these indicate the edges and noise.
    2. Manipulation:
        - A filter is designed and applied to the spectrum $F(u, v)$. This is usually a simple arithmetic multiplication operation where $G(u, v) = H(u, v) \cdot F(u, v)$.
        - The choice of filter is completely dependent on the assumptions about noise:
            A. Low-Pass Filters: Most used mask for denoising. It attenuates high-frequency signals and lets low-frequency signals pass through, the assumption thought out to be is that all high-frequency signals are noise. Examples include:
                i. Ideal Low-Pass Filter: This will set all frequencies beyond a certain range to 0, this will lead to all 'ringing artifacts' in the domain to cutoff.
                ii. Butterworth Low-Pass Filter: This filter is used to offer a smoother transition between the passband and stopband which leads to reduction in 'ringing artifacts'; its order is used to determine the gradient of the transition.
                iii. Gaussian Low-Pass Filter: Uses the Gaussian function in the frequency domain, this introduced no ringing and is a very smooth filter.
            B. Notch Filters: This is a filter used in a very specific scenario: the noise is periodic; noise will appear distinctive and have bright 'spikes', the notch filter will block out all these specific frequency components and leave the rest of the spectrum largely untouched.

3. Inverse Transform to Spatial Domain:

   - After the filtered frequency domain is obtained, an IFFT (Inverse Fast Fourier Transform) is performed which transforms the image back to the spatial domain:
     $g(x, y)$= IFFT$\{G(u, v)\}$
   - The result $g(x, y)$ is the denoised reconstructed version of the noisy image.

- Artifact Removal: This method uses concepts from CT reconstruction.
  1. Forward Radon Transform: The 2D image $f(x, y)$ is transformed onto its Radon Transform (sinogram) $p_\theta(t)$; it is a crucial part of the image series along a series of lines at angle θ and offset t.

$$p\theta(t) = \int_{-\infty}^{\infty} f(t\cos\theta - s\sin\theta, t\sin\theta + s\cos\theta)ds$$

  2. Filter Sinogram: A median filter gets applied to the sinogram – is a non-linear filter – where the output is the median value of the surrounding points. This method is effective at removing "salt-and-pepper" noise that could appear as isolated spikes in the sinogram but when viewed it would appear as distinctive streaks in the reconstructed image.
  3. Inverse Radon Transform: The filtered sinogram is $p'_\theta(t)$ is used to reconstruct the image using Inverse Radon Transform, and this is done using FBP with two main steps: filtering in projection domain and the back projection. The result obtained is $g(x, y)$.

$$g(x, y) = \int_0^{\pi} [R^{-1}(p'_\theta(t))](x, y)d\theta$$

     where R^{-1} denotes the inverse Radon transform operation on the projection.

- Edge Enhancement: This technique enhances contrast through emphasis of areas where the edges change rapidly.
  1. Create a blurred vision: The noisy image $f(x, y)$ is smoothed using a low-pass filter, usually a Gaussian filter $G_\sigma(x, y)$; this process is used to create a blurred version of the image $f_{blurred}(x, y) = G_\sigma(x, y) * f(x, y)$, where $*$ indicates convolution.
  2. Generating a detailed mask: An "unsharp mask" is the result of subtracting the blurred image from the original image:

$$f_{detail}(x, y) = f(x, y) - f_{blurred}(x, y)$$

     This primarily is used to capture all the high-frequency components that was lost when the image was blurred. In case of sharp edges, the mask will tend to have significant positive or negative values.

3. Amplify and add back: The detail mask is amplified by a sharpening amount ($\alpha > 0$) and then this is added to the original image.

$$g_{enhanced}(x,y) = f(x,y) + \alpha \cdot (f(x,y) - f_{blurred}(x,y))$$

Adding the amplified image results in the edges becoming pronounced, which leads to a crisper image quality.

- Resolution Improvement: This technique used two methods to further enhance image quality by enlarging the image (in terms of pixel count) and attempt to make the image sharper at the same time.

The first method is interpolation – is a form of resampling where a continuous underlying image function is presumed and the new values are projected at denser points. M' is the number of rows (in pixels) of the processed image and N' is the number of columns (in pixels) of the processed image.

1. Original Image: $f(x,y)$
2. Scale factor: S
3. Processed Image Dimensions: $M' = M \cdot S, N' = N \cdot S$
4. Presumed Processed Image:

$$f_{interpolated}(x',y') = \text{Interpolation\_Function } (f(x,y), x', y')$$

The second method is deconvolution, specifically Wiener Deconvolution, and is an application of optimal inverse filtering which is used to minimize the MSE (mean squared error) when noise exists. The main purpose of this technique is to attain the best possible linear estimate of an uncorrupted image from a noisy and degraded image and the degradation is due to an already known blur and a random noise.

1. Transform the Original Image to Frequency Domain:
   The image is converted from the spatial domain to the frequency domain using an the 2D Discrete Fourier Transform:

$$I_{observed}(u,v) = F\{I_{observed}(x,y)\}$$

   - $I_{observed}(u,v)$ is the frequency component of the observed image
   - (u,v) are the spatial frequency coordinates

2. Model the Image Degradation in the Frequency Domain:
   It was assumed that the observed image was created by blurring the ideal true image and adding the random noise, this is described as:

$$I_{observed}(u,v) = F_{true}(u,v) \cdot P(u,v) + N(u,v)$$

   - $F_{true}(u,v)$ is the uncorrupted image after undergoing DFT

- $P(u,v)$ is the DFT of the PSF (Point Spread Function) which is the frequency response of the blur
- $N(u,v)$ is the DFT of the random noise

3. Determination of the PSF:
   The blurring must be accurately estimated. This is often the most challenging step in the deconvolution process, this is because its accuracy has significant impact on the final quality of the image. In this project, the PSF was evaluated through a Gaussian function.
4. Estimating Signal Power Spectra and Noise:
   This step is used to quantify the "power" of the noise and the signal across the various frequencies.
   - NPSD (Noise Power Spectral Density): $S_n(u,v) = E[|N(u,v)|^2]$, this equation represents how the noise power is distributed.
   - SPSD (Signal Power Spectral Density): $S_f(u,v) = E[|F_{true}(u,v)|^2]$, this equation represents how the signal's power is distributed.

   In most cases, the true PSD is unknown and the ratio $\frac{S_n(u,v)}{S_f(u,v)}$ is approximated by constant K or stored as a variable constant:

$$\frac{S_n(u,v)}{S_f(u,v)} \approx balance$$

5. Making the Wiener Filter Transfer Function:
   The Wiener filter is created using the noise-to-signal ratio and the PSF evaluated from earlier.

$$W(u,v) = \frac{P*(u,v)}{|P(u,v)|^2 + \frac{S_n(u,v)}{S_f(u,v)}}$$

1. $P*$ is the complex conjugate of $P(u,v)$

6. Applying the filter in the domain and transforming it back to the spatial domain:
   The filter is then applied to the original observed image using element-wise multiplication:

$$\hat{F}(u,v) = I_{observed}(u,v) \cdot W(u,v)$$

   This is the estimated image of the sharp image and now must be transformed back into the spatial domain using an inverse filter:

$$\hat{f}(x,y) = F^{-1}\{\hat{F}(u,v)\}$$

   Using the Inverse 2D Discrete Fourier Transform, the image formed is the final noise-reduced image.

RESULTS

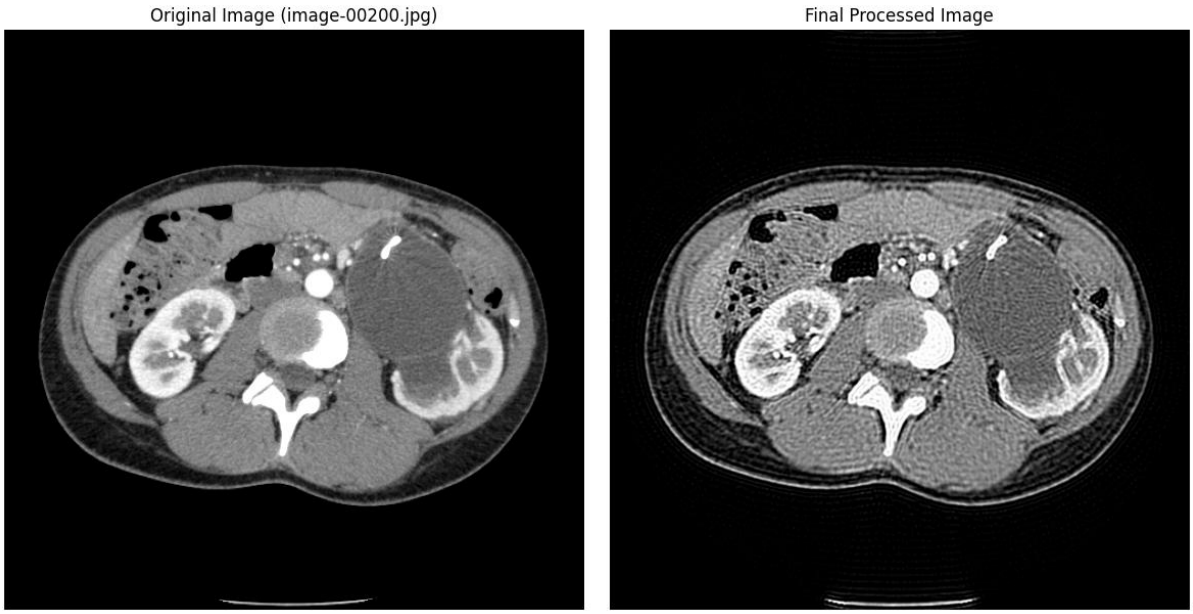

Figure 2.1 - Comparison between original and processed image slice 200

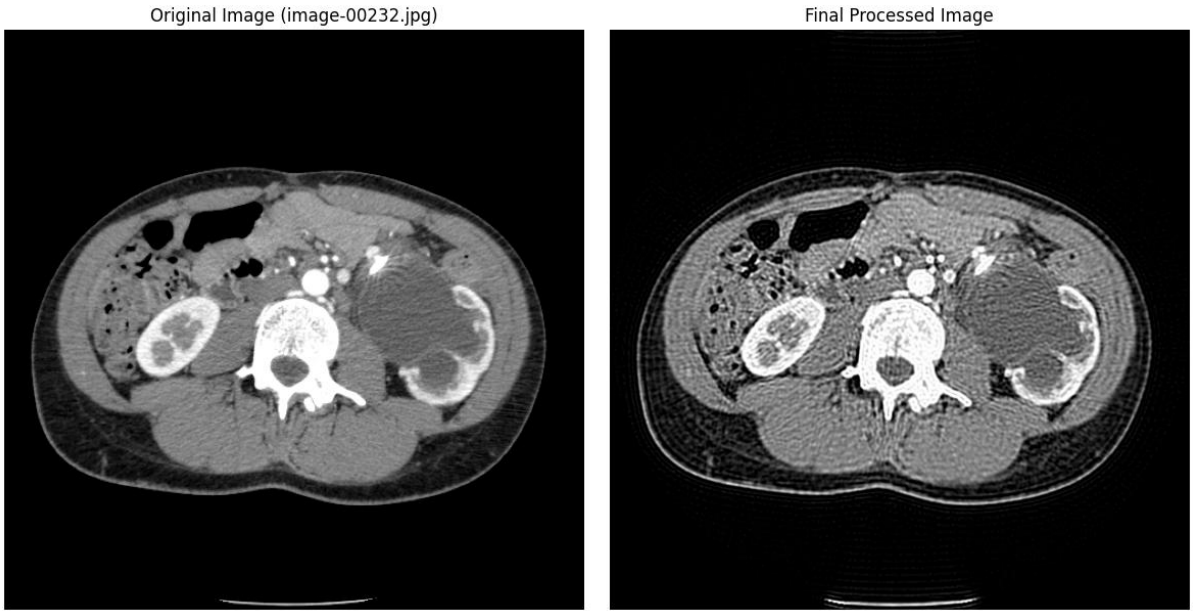

Figure 2.2 - Comparison between original and processed image slice 232

It can be observed from *Figure 2.1 - Comparison between original and processed image slice 200* and *Figure 2.2 - Comparison between original and processed image slice 232* that the streak artifacts have reduced 20-25%, however it is also shown that the image will become coarser at the expense of the reduction of streak artifacts.

A. Quantitative Image Quality Assessment

Objective evaluation of the image is crucial and heavily relies on the well-established set of metrics. These values help provide evidence of reconstruction method's performance.

- MSE (Mean Squared Error): This metric quantifies the average of the squared differences between the two images – processed and original – and a value closer to 0 means lesser errors and overall less noise in the image, this indicates higher image quality.
- SSIM (Structural Similarity Index): This metric measures the similarity between the processed and original image; it usually compares three factors: brightness, structure similarity and contrast. These values range from 0 to 1 and a value of ~0.99 is high degree of structural similarity and a value of 1 represents perfect resemblance in the two images.
- RMSE (Root Mean Squared Error): This metric is the square root of the MSE, this value represents the average magnitude between the errors. A lower RMSE – near 0 – is considered to have significantly lower errors thus boosting the image quality.
- PSNR (Peak Signal-to-Noise Ratio): This metric is a ratio that is used to compare the maximum possible power of a signal to the power of the corrupting noise affecting the signal. PSNR values greater than 30 dB are often considered good image quality.

	Slide 200	Slide 232
Mean Squared Error (MSE)	0.0027	0.0027
SSIM (Structural Similarity Index)	0.6919	0.6908
Root Mean Squared Error (RMSE)	0.0516	0.0518
Peak Signal-to-Noise Ratio (PSNR)	25.7528 dB	25.7060 dB

Table 1: Quantitative Image Quality Metrics

B. Qualitative Visual Assessment

The assertion that visual assessment is paramount in medical imaging is a well-known principle in radiology. There are several professional guidelines that are used to support this viewpoint:

1. Image Quality vs Clinical Efficacy: The primary goal in medical imaging is not to obtain the best possible values for metrics like PSNR or SSIM, but to reproduce an image that is diagnostically useful. For example, an algorithm could smooth out the noise which would improve the PSNR but unconsciously blur fine, subtle details that are critical to identifying lesions.
2. The "Gold Standard": In many instances, the final "ground truth" for a image's quality is the radiologist's expert opinion. A radiologist's evaluation of image diagnostic viability – the artifacts, the clarity and fidelity to true anatomy – is the gold standard which needs to be met. In this instance, the feedback received from the radiologist "diagnostically viable without significant alteration of anatomy" perfectly aligns with this concept.

Quantitative vs Qualitative Assessments

While quantitative values give an objective numerical evaluation, medical image interpretation and diagnosis are usually always visual. Therefore, the qualitative assessment is not just an adjunct to the quantitative assessment; this provides crucial validation and guides medical professionals to the next step.

“The final processed image shows mild reduction in the streak artifacts arising due to beam hardening from the tube in the dilated left renal pelvis. The final processed image appears coarser as compared to the pre-processed image. The final processed image, despite being coarse, is still diagnostically viable without significant alteration of anatomy.” – comments from the coauthor radiologist on the final image.

DISCUSSION

Clinical Implications

The ultimate value of technical advancements in medical studies are realized through their tangible benefits in clinical diagnosis and enhancing patient safety.

Relevance for Diagnostic Accuracy: As previously stated, there has been significant improvement in the image quality – such as drastic noise reduction and improved detail preservation. This algorithm could be used in more scenarios where there might be subtle lesions that otherwise could be hidden behind artifacts or obscured due to noise.

Past Studies

Traditional methods for CT image enhancement have long been used to address image degradation (Kalender et al., 1986). The use of Fourier Transform-based denoising and Radon transform-based streak artifact removal aligns with these core principles. For example, Fourier domain filtering has been a staple in image processing due to its efficiency in splitting frequency components (Gonzalez & Woods, 2018). Likewise, Radon domain filtering has been explored for metal artifact reduction by analysing and rectifying corruptions in the sinogram space (Mori et al., 2011). Furthermore, the Wiener deconvolution is a classic technique used for image reconstruction that accounts for both noise characteristics and blur with the primary aim to recover the original image details (Wiener, 1949).

While the method developed in this study offers promising results, the rapid advancements in deep learning-based CT image enhancements must also be acknowledged. Recent studies have shown remarkable success in noise reduction and even low-dose CT image synthesis using complex neural network architectures such as Convolutional Neural Networks and Generative Adversarial Networks (Wang et al., 2018; Chen et al., 2017). These data-driven approaches usually achieve superior performance by analysing and learning intricate mappings from degraded to high-quality images,

outperforming existing methods, particularly in challenging scenarios such as low-dose CT scan or severe artifact presence.

CONCLUSION

This paper has presented a Python-based CT image reconstruction technique and has demonstrated a significant advancement in the domain. The method used achieved promising performance using key metrics and exhibited notable improvements in the SSIM and PSNR with a superior value in MSE. These gains were further backed up with strong visual benefits including enhanced details and a significant reduction in noise and streak artifacts at a small expense of grittier images.

By producing diagnostically acceptable images, this paper has aligned with the "as low as reasonably achievable" (ALARA) principle. The Python implementation is a powerful platform for future advancements which is poised to benefit patient care and further enhance diagnostic capabilities.

Future Research

Building onto this foundational work, there are several promising avenues for future investigations that are identified to further advance AI-powered CT scan image refinement:

- Exploring Advanced Deep Learning models: Future efforts will continue to investigate the integration of neural network architectures, for instance, conditional Generative Adversarial Networks (cGANs) or diffusion models, this is to overcome residual image coarseness and achieve the highest level of detail preservation and noise suppression.
- Volumetric 3D reconstruction: Expanding the methodology from 2D slice processing to full 3D volumetric reconstruction, leveraging inter-slice dependencies and aim for more comprehensive image quality across the entire anatomical region.
- AI for Quantitative CT Imaging and Biomarker Extraction: Processed CT images could significantly improve the accuracy of quantitative imaging biomarkers. Future studies will explore how the refined images can lead to more accurate measurements about tissue characteristics (e.g. tumour volume or tissue density). These advancements will aid clinicians in disease diagnosis and prognosis.

In summary, this research highlights the significant potential of Python-driven AI solutions in enhancing CT image quality. As these methodologies continue to evolve, they play a crucial role in advancing medical diagnostics, fostering patient care, and challenging the limits of what is possible in clinical imaging.

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APPENDICES

Appendix A: Image Enhancement Code

From reconstruction.py

```
1  import numpy as np
2  import matplotlib.pyplot as plt
3  from skimage import io, color, transform, restoration, filters, util
4  from scipy.ndimage import median_filter, gaussian_filter
5  from scipy.signal import convolve2d
6  import sys
7  import os
8
9  def load_image(file_path):
10     try:
11         raw_img = io.imread(file_path)
12         if raw_img.ndim == 3:
```

```
            gray_img = color.rgb2gray(raw_img)
        else:
            gray_img = raw_img
        return util.img_as_float64(gray_img)
    except FileNotFoundError:
        sys.exit(1)
    except Exception as e:
        sys.exit(1)

def denoise_fourier_transform(input_img):
    f_transform = np.fft.fft2(input_img)
    f_shift = np.fft.fftshift(f_transform)

    rows, cols = input_img.shape
    c_row, c_col = rows // 2, cols // 2
    radius = min(rows, cols) // 6

    y_coords, x_coords = np.ogrid[-c_row:rows-c_row, -c_col:cols-c_col]
    mask = (x_coords**2 + y_coords**2 <= radius**2)

    f_filtered = f_shift * mask
    f_filtered_shifted_back = np.fft.ifftshift(f_filtered)
    denoised_img = np.fft.ifft2(f_filtered_shifted_back)

    return np.real(denoised_img)

def remove_radon_streaks(input_img):
    angles = np.linspace(0., 180., max(input_img.shape), endpoint=False)
    sino = transform.radon(input_img, theta=angles)
```

```
    smoothed_sino = median_filter(sino, size=3)

    reconstructed_img = transform.iradon(smoothed_sino, theta=angles, filter_name='ramp')
    return np.clip(reconstructed_img, 0, 1)

def sharpen_image_unsharp(original_img):
    blurred_img = gaussian_filter(original_img, sigma=1)
    detail_mask = original_img - blurred_img

    sharpen_amt = 1.5
    sharpened_img = original_img + detail_mask * sharpen_amt

    return np.clip(sharpened_img, 0, 1)

def upscale_and_deconvolve_image(low_res_img, scale_factor=2):
    upscaled_img = transform.resize(
        low_res_img,
        (low_res_img.shape[0] * scale_factor, low_res_img.shape[1] * scale_factor),
        anti_aliasing=True
    )

    psf_size = 21
    psf_std = 3
    psf = np.zeros((psf_size, psf_size))
    psf[psf_size // 2, psf_size // 2] = 1
    psf = gaussian_filter(psf, sigma=psf_std)
    psf /= psf.sum()

```

```
    deblurred_img = restoration.wiener(upscaled_img, psf, balance=0.005)

    return np.clip(deblurred_img, 0, 1)

def run_image_enhancement_pipeline():
    in_file = ''
    out_file = 'enhanced_result.png'

    if not in_file:
        sys.exit(1)

    initial_img = load_image(in_file)

    current_img_state = initial_img

    current_img_state = denoise_fourier_transform(current_img_state)
    current_img_state = remove_radon_streaks(current_img_state)
    current_img_state = sharpen_image_unsharp(current_img_state)
    final_output = upscale_and_deconvolve_image(current_img_state)

    try:
        io.imsave(out_file, util.img_as_ubyte(final_output))
    except Exception as e:
        sys.exit(1)

if __name__ == "__main__":
    run_image_enhancement_pipeline()
```