An Efficient Quality Enhancement Method for Low-Dose CBCT Imaging

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Abstract: - Cone-Beam Computed Tomography (CBCT) is a widely used imaging technique in medical and dental applications. However, low-dose radiation CBCT images are prone to aliasing artifacts, which introduce artifacts in microstructures, degrade image quality, and as a result affect diagnostic accuracy. Existing CBCT image enhancement approaches tend to focus on noise reduction and higher resolution but they fail to address aliasing artifacts. This paper introduces a unique anti-aliasing method specifically designed for low-dose CBCT images. The proposed approach utilizes a Butterworth filter to remove aliasing artifacts in high frequencies, while speckle noise is reduced by a Non-Local Means (NLM) filter. Finally, the overall visual quality is improved by a Laplacian filter which enhances edges while steps are taken to adjust brightness and contrast. Subjective evaluations show that our approach outperforms existing methods by an average of 98.63%, effectively mitigating aliasing without compromising resolution or introducing additional noise, thereby improving the diagnostic reliability of CBCT images and addressing a critical gap in current clinical practice.

Key-Words: - Cone-Beam Computed Tomography, Low-dose radiation imaging, aliasing artifacts, Butterworth filter, Non-Local Means filter, denoising, speckle noise.

Received: March 21, 2024. Revised: August 22, 2024. Accepted: October 6, 2024. Available online: November 11, 2024.

1 Introduction

Cone-Beam Computed Tomography (CBCT) is a crucial imaging technique that provides detailed 3D representations, widely used in medical and dental applications. In dentistry, CBCT offers high-resolution images for precise diagnosis and treatment planning, particularly in orthodontics and implantology. In broader medical imaging, CBCT aids interventional radiologists and radiation oncologists in guiding image-based procedures, offering clear visualization of anatomical structures with lower radiation doses compared to conventional CT. However, CBCT is prone to artifacts that can affect image quality and diagnostic reliability. One of the most common artifacts in CBCT imaging is the aliasing effect, which appears as jagged or stair-step edges across the image, affecting both soft tissue and teeth, [1]. Aliasing arises from under-sampling, where the detector's resolution or the number of projections is insufficient to capture fine details accurately, leading to distortions and false patterns in the reconstructed image. The problem is further amplified in low-dose applications because the signal-to-noise ratio (SNR) is compromised, making it harder to distinguish true anatomical features from artifacts, [2]. Despite the growing use of CBCT in clinical applications, particularly in dentistry and image-guided interventions [3], methods specifically designed to address aliasing in CBCT images are limited.

Numerous studies have been done to develop anti-aliasing techniques, particularly in areas like conventional CT and MRI, [4], [5]. Existing methods in 2D and 3D imaging often rely on strategies such as high-pass filtering, interpolation, or super-resolution techniques, [6], [7]. However, most of these techniques focus on reducing noise or improving resolution without directly targeting the aliasing artifacts, particularly in the unique context of CBCT, where both circular scanning geometries and low-dose constraints add complexity to the challenge, [8], [9]. For example, [10] proposed an anti-aliasing and self-super-resolution algorithm for MR images that requires no external training data. Their approach utilizes high-frequency information from in-plane slices and applies a deep network across different orientations, followed by Fourier burst accumulation to reduce aliasing artifacts and improve image quality. Also, [11], proposed an anti-aliasing approach in their LDCT denoising framework by incorporating BlurPool, which mitigates high-resolution image distortion. This technique helps preserve image sharpness while reducing aliasing, enhancing the overall quality of animal CT images.

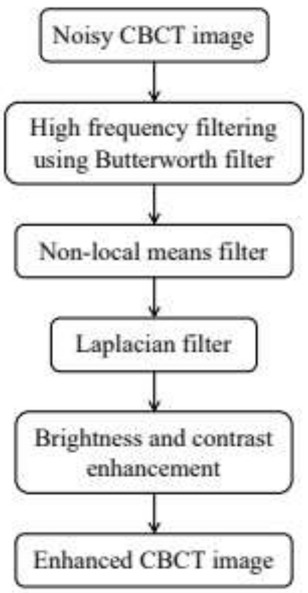

Fig. 1: Flowchart of our proposed method for anti-aliasing, denoising and overall visual enhancement of low-dose radiation CBCT images

In recent years, different techniques have been proposed to enhance the visual quality of CBCT images [12], [13], [14], [15], [16]. For instance, [12] used a Wiener filter to reduce overall noise, followed by a basic 3D Laplacian filter that is used for edge enhancement. Finally, the amplified noise by the sharpening process is removed by a Gaussian filter. Another approach presented in [13] introduces a hybrid filtering method. In this case, a Shepp–Logan phantom and wavelet transform splits the image into low and high-frequency components, while Gaussian noise is added to the image. High and low frequencies are filtered separately using Wavelet thresholding and Wiener filtering, respectively. Further refinement is achieved by anisotropic diffusion. A more recent approach introduced in [14] uses an AI-based diagnosis. A denoising module that is based on a multiscale U-Net-like sparse coding method, improved the visual quality of the CBCT images, leading to improved diagnostic accuracy. In another study presented in [15] proposed a contextual loss-optimized multi-planar 2.5D U-Net model for noise and artifact reduction in CBCT, preserving image sharpness while significantly improving image quality based on both quantitative metrics and qualitative evaluations by dental clinicians. The work in [16] introduced a conditional denoising diffusion probabilistic model that uses a U-Net architecture with residual and attention blocks to transform Gaussian noise into the target CT distribution, conditioned on CBCT images, significantly enhancing image quality. Despite the numerous enhancement techniques developed for CBCT images, there remains a notable gap in both the literature and clinical practice regarding specialized anti-aliasing methods, particularly for low-dose CBCT imaging. This oversight highlights the need for targeted solutions to address aliasing artifacts in these settings.

In this paper, we introduce a novel anti-aliasing method specifically designed to remove aliasing artifacts in low-radiation CBCT images. Our method leverages frequency-domain filtering followed by spatial domain enhancements to improve the visual quality of CBCT images without compromising resolution or introducing additional noise. By addressing the aliasing problem directly, this approach aims to improve the diagnostic utility of low-dose CBCT images, providing clinicians with clearer and more reliable images for patient care.

The rest of this paper is organized as follows: Section 2 details our antialiasing and denoising approach followed by our brightness and contrast enhancement technique. Section 3 presents the experimental results and evaluates our proposed approach against the state-of-the-art methods. Finally, Section 4 concludes this paper.

2 Our Proposed Approach

In this section, we detail the proposed anti-aliasing methodology for low-dose radiation CBCT images, which involves a series of signal processing techniques to effectively remove aliasing artifacts while preserving critical image details. Figure 1 shows the block diagram of our proposed antialiasing method which involves high-frequency artifact suppression (Butterworth filter), noise reduction using a Non-Local Means (NLM) filter, edge recovery by a Laplacian filter, and brightness and contrast enhancement. These steps are detailed in the following subsections.

2.1 High-Frequency Artifact Suppression

Aliasing in CBCT images is primarily caused by under-sampling, leading to high-frequency distortions. To eliminate these artifacts, we apply a 7th-order Butterworth low-pass filter. This type of filter is well-suited for medical imaging because of its smooth frequency response and lack of ripple in the passband and stopband, ensuring that the transition from the preserved low-frequency content to the removed high-frequency noise is gradual. The Butterworth filter can be defined as follows:

$$H(f) = \frac{1}{1 + \left(\frac{f}{f_c}\right)^{2n}} \tag{1}$$

where f_c is the cut-off frequency, and n is the order of the filter (in this case, $n = 7$). By setting the cut-off frequency f_c based on the sampling rate and image resolution, we ensure that frequencies above this threshold, where aliasing predominantly occurs, are thoroughly suppressed. This step is crucial in removing the jagged edges and visual distortions caused by aliasing.

2.2 Noise Reduction using Non-Local Means Filter

While the Butterworth filter removes aliasing artifacts, other noise types, particularly speckle noise, remain present in low-dose CBCT images. To address this, we apply an NLM filter. Unlike traditional filtering methods that rely on local information (e.g., Gaussian smoothing), the NLM filter averages pixels based on similarity across the entire image. This allows for effective denoising while preserving fine image details. The NLM filter is defined by:

$$NL[v](x) = \sum_{y \in \Omega} w(x, y) v(y) \tag{2}$$

where $v(y)$ is the pixel value at location y, and $w(x, y)$ is the weight determined by the similarity between the local neighborhood of pixels around x and y. By leveraging global information, this filter smooths the image while maintaining edges and microstructures, making it particularly effective in reducing speckle noise without blurring the important anatomical structures in the CBCT images.

2.3 Edge Recovery using Laplacian Filter

Noise reduction methods can sometimes result in the loss of sharp edges, which are critical for identifying structures in medical images. To counteract this, we apply a Laplacian filter, which enhances the edges that may have been smoothed during the previous denoising step. Note that the Laplacian filter is a second-order derivative filter which manages to track sudden signal changes, and thus it may be used to effectively detect and sharpen edges. This filter is defined as follows:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{3}$$

where I represents the image intensity. The resulting sharpening of boundaries and edges increases the visibility of fine structures and details, which may have been blurred during the anti-aliasing and denoising processes. The final image appears sharper which in turn leads to better diagnosis.

2.4 Brightness and Contrast Enhancement

Once aliasing and noise have been removed, and edges have been recovered, we apply a brightness and contrast enhancement to further improve image clarity. This step adjusts pixel intensities to optimize the visual quality of the image, ensuring that details are easily discernible without overexposure or underexposure. The enhancement is performed by adjusting the intensity values based on a histogram equalization-like approach:

$$I_{new}(x) = \alpha \cdot (I(x) - min(I)) + \beta \tag{4}$$

where α is the contrast adjustment factor, and β controls the brightness shift. After the adjustment, pixel intensities are clipped to the valid intensity range (typically 0–255 for 8-bit images) to avoid artifacts caused by oversaturation or clipping. This final enhancement step ensures a balanced image with optimal brightness and contrast for improved visual inspection.

3 Results and Discussion

To evaluate the effectiveness of our proposed anti-aliasing technique, we used a 3D CBCT dataset containing 440 2D projections provided by the Department of Dentistry at the University of British Columbia. Figure 2(a) shows the 315th slice of a low-radiation 3D CBCT scan, which highlights significant noise and aliasing artifacts. Figure. 2(b)–(d) compare the denoising results of methods by [12], [13] and [14]. Figure 2(e) presents the outcome of our proposed method, demonstrating superior anti-aliasing and noise reduction performance by fully eliminating aliasing while enhancing the overall visual quality, outperforming the latest signal processing and deep learning-based approaches.

We carried out a subjective test to assess the performance of our proposed method by comparing the visual quality of the CBCT images it enhanced with three state-of-the-art approaches, namely the ones by [12], [13] and [14]. The test involved eighteen participants, including 8 men and 10 women aged between 21 and 35 years. Each participant was shown pairs of CBCT images labeled "A" and "B"—one processed by our method and the other by one of the four comparison methods, [17]. The image placement (left or right) was randomized to avoid bias, and an "equal" option was included for instances where both images appeared to have the same visual quality. Participants were asked to choose the image they found visually superior. This evaluation covered 15 different 2D CBCT images enhanced by both our method and the other four existing methods, ensuring a thorough and reliable analysis. Figure 3 shows the average number of times subjects preferred the visual quality of CBCT images enhanced by our approach over others. On average, our method outperformed [12] by 97.77%, [13] by 98.33%, and [14] by 99.81%.

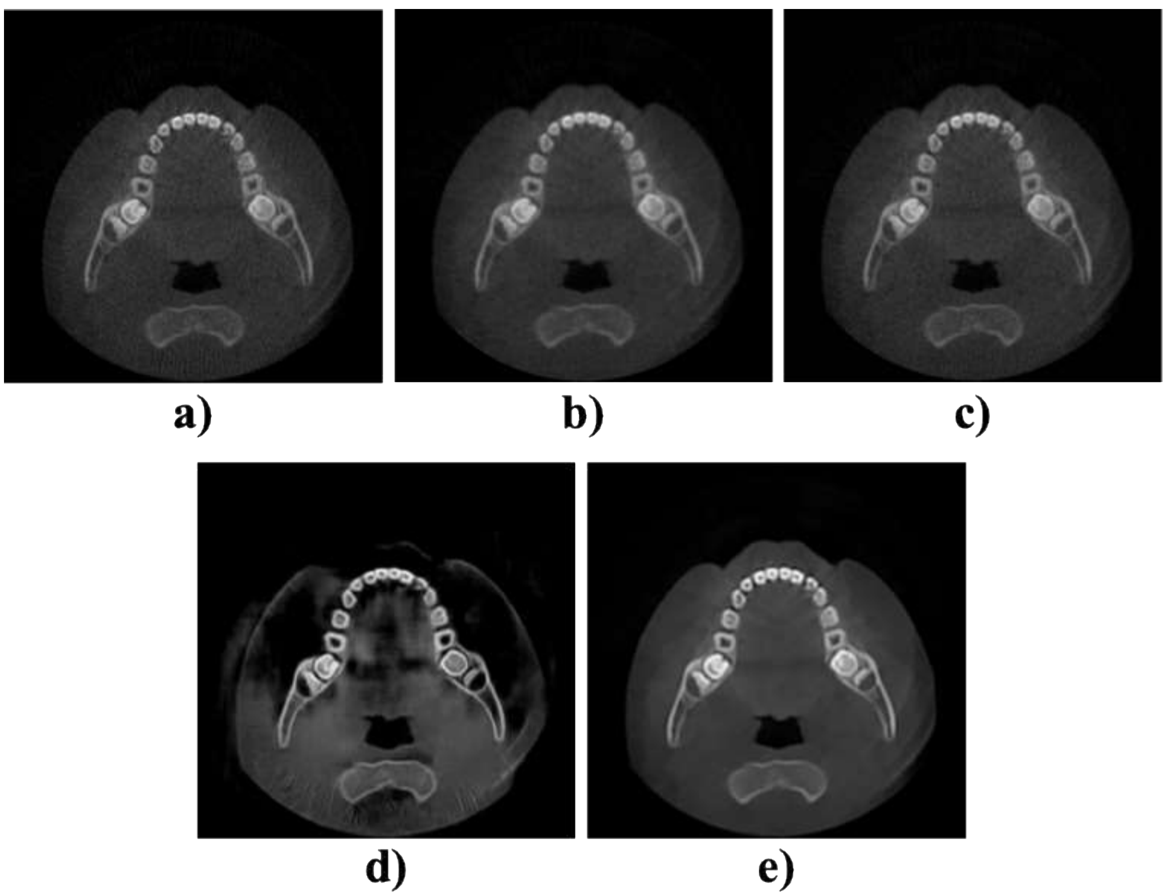

Fig. 2: Denoising and anti-aliasing performance of various methods by using the 315th slice of a 3D noisy CBCT scan: a) noisy low-dose CBCT, b) method in [12], c) method in [13], d) deep learning approach in [14] and e) our proposed anti-aliasing and quality enhancement method

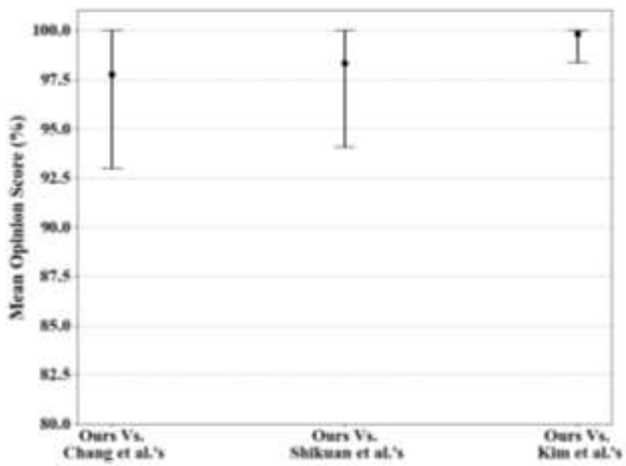

Fig. 3: Preference scores of subjects in mean opinion score (MOS) when comparing the visual quality of CBCT images enhanced by our approach over other methods

4 Conclusion

In this paper, we introduce a novel technique for anti-aliasing and quality enhancement of low-dose CBCT images by combining signal processing methods in both the frequency and spatial domains. Our method began with applying a Butterworth high-pass filter to target high-frequency components where aliasing artifact occurs. This is followed using an NLM filter to reduce the residual noise, such as speckle noise, while preserving edges and globally denoising the image. Next, a Laplacian filter sharpened the image, and we applied brightness and contrast adjustments to further enhance the overall visual quality of low-dose CBCT images. Subjective evaluations demonstrated that our approach outperforms the current state-of-the-art techniques by an average of 98.63%, highlighting its effectiveness in improving the diagnostic reliability of CBCT images for various dental applications.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilized artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Simin Mirzaei led the research, developed the methodology, conducted all experiments and data analysis, and drafted the entire paper.
- Drs. Tohidypour, Nasiopoulos, and Mirabbasi contributed to the present research, at all stages from the formulation of the problem to verifying the final findings and contributed to editing the final versions of the manuscript.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

This research was funded by NSERC and TELUS.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.