The University of British Columbia

Department of Electrical and Computer Engineering

Keynote Talk

Visual Quality Enhancement of Low-Dose Dental Cone-Beam Computed Tomography (CBCT) Images

Dr. Simin Mirzaei

Date: Oct 29, 2025

Biography

Dr. Simin Mirzaei

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Department of Electrical & Computer Engineering
University of British Columbia
Vancouver, BC, Canada

Research interests are primarily in the area of intelligent digital media, visual information capture and delivery, artificial intelligence in digital media with focus on entertainment, security, autonomous driving, smart cities and health.

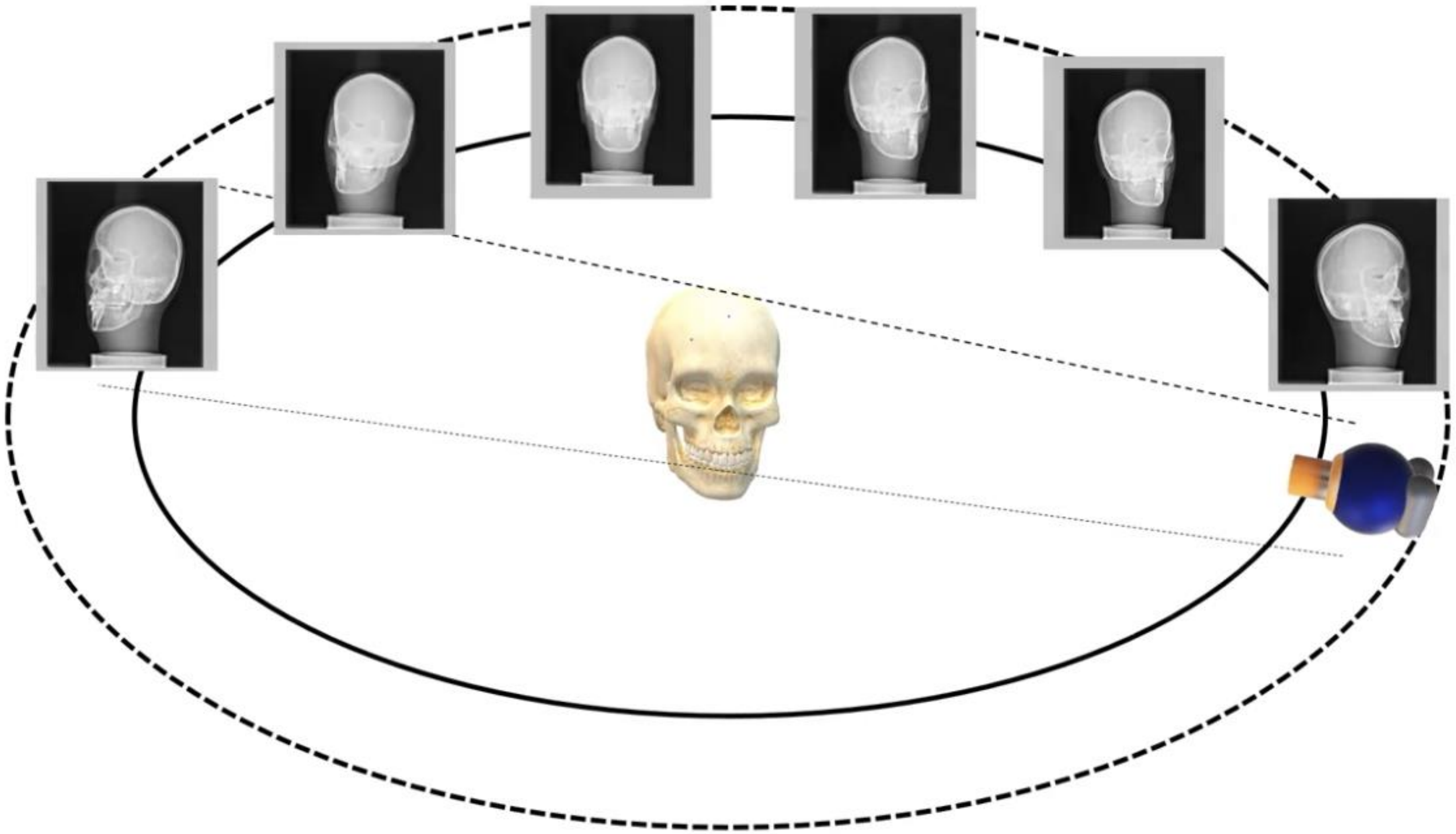
Active member of the Standards Council of Canada (SCC), MPEG, JPEG

Outline

Introduction

Introduction to CBCT Technology

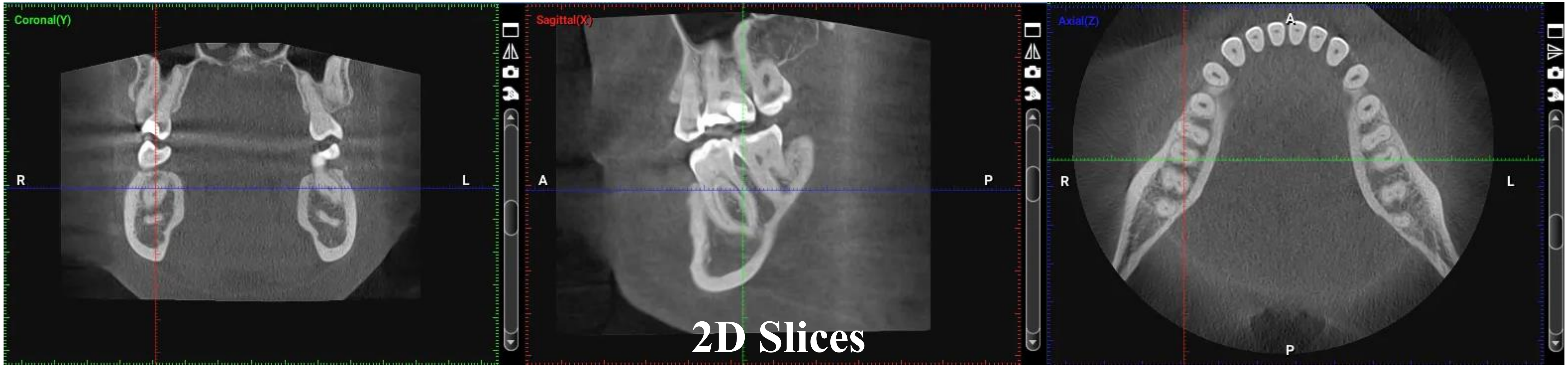
- CBCT: An advanced imaging technique in dentistry and other medical applications



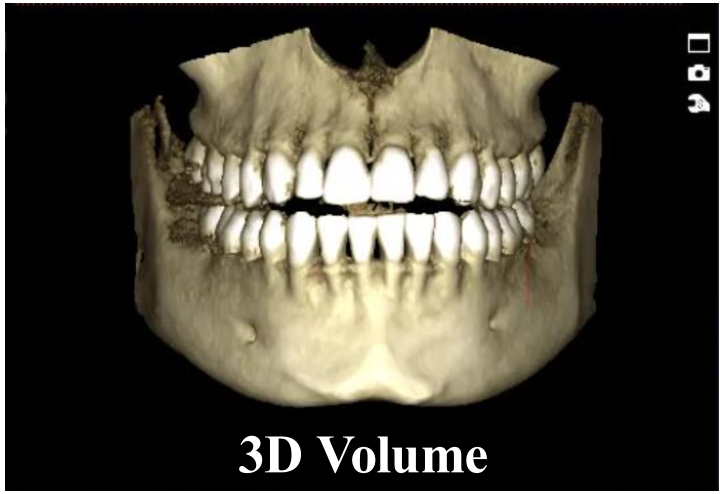
CBCT imaging device

Introduction to CBCT Technology

- CBCT: An advanced imaging technique in dentistry and other medical applications



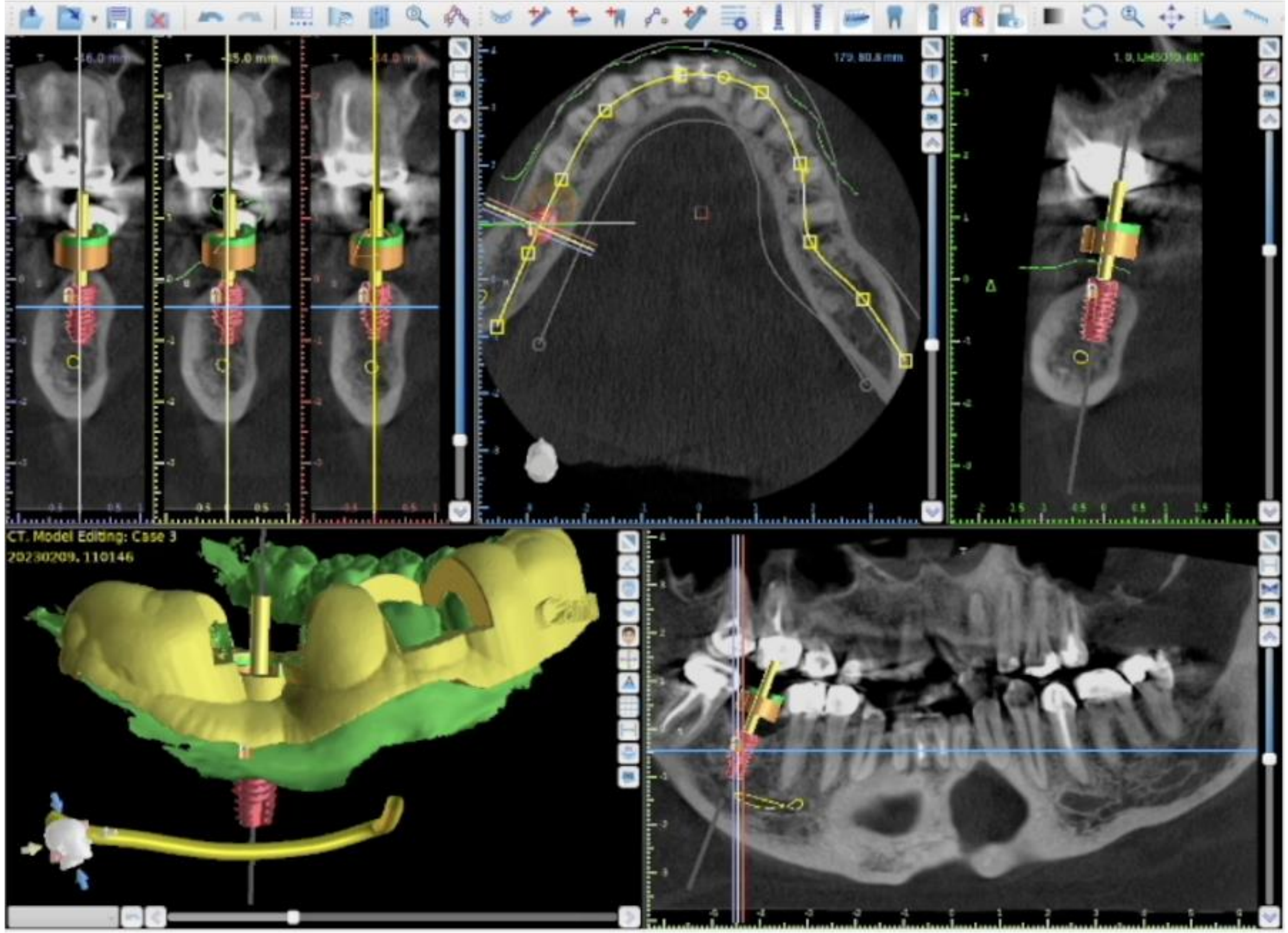
2D Slices



3D Volume

Introduction to CBCT Technology

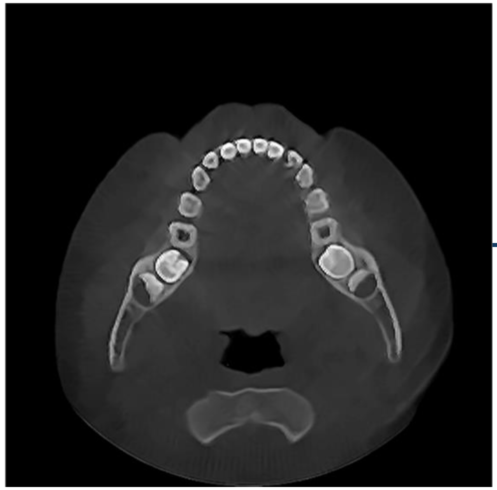
- Implant placement and surgery planning using CBCT images



Challenges, Existing Solutions and Limitations

Challenges

Best image quality possible with high-dose radiation exposure

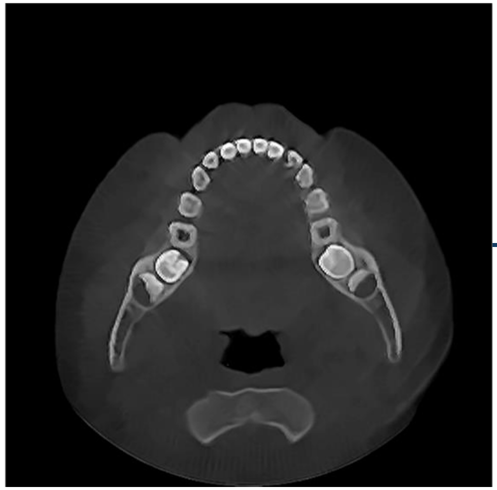


Low level of noise
&
High resolution

higher risk of radiation-induced cancers

Challenges

Best image quality possible with high-dose radiation exposure



Low level of noise
&
High resolution

→ higher risk of radiation-induced cancers

Industry Solution: Lower the radiation exposure for patient safety

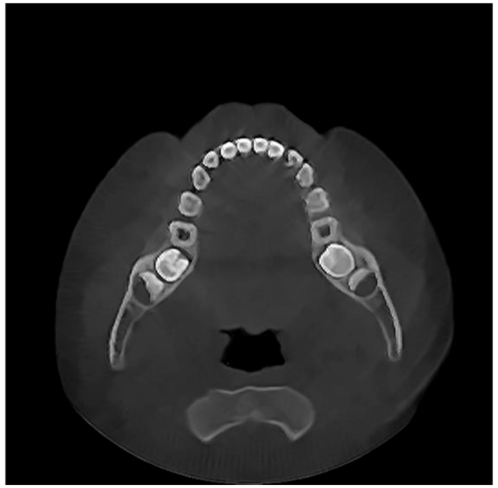
High level of noise
&
Low resolution

→ lower visual quality

Challenges

Ideal Solution?

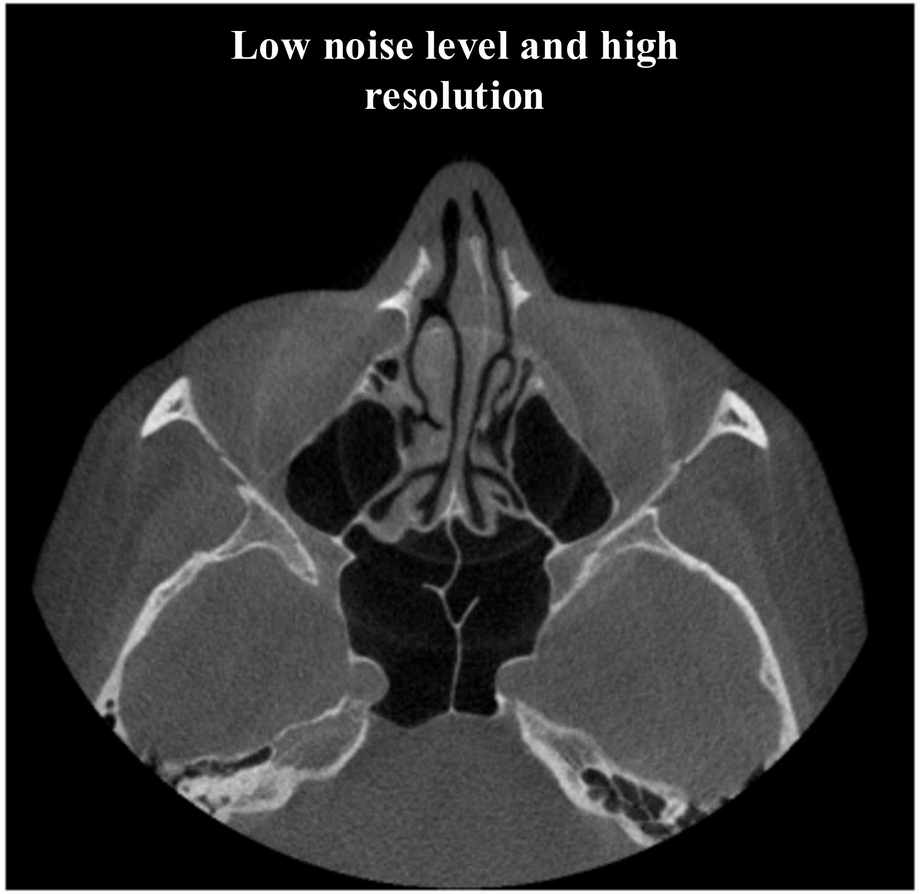
Continue using low radiation exposure for patient safety



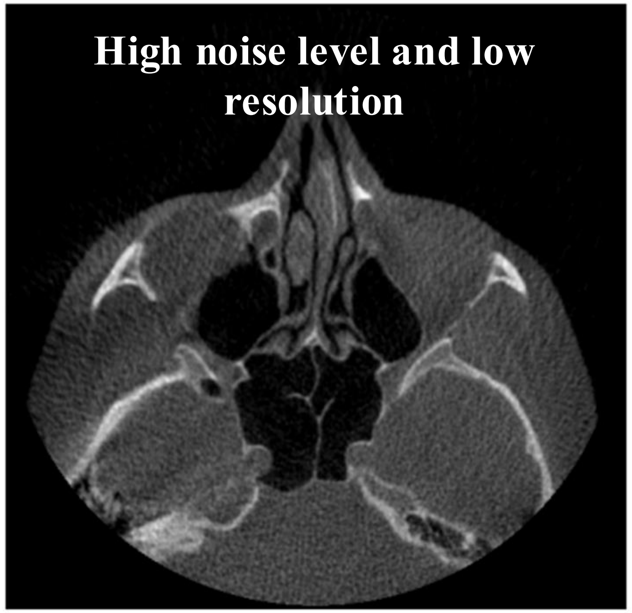
Enhance the quality of the CBCT image to match or surpass that of high-dose radiation

Challenges

High Noise Levels and Low Resolution



High-dose CBCT image



Low-dose CBCT image

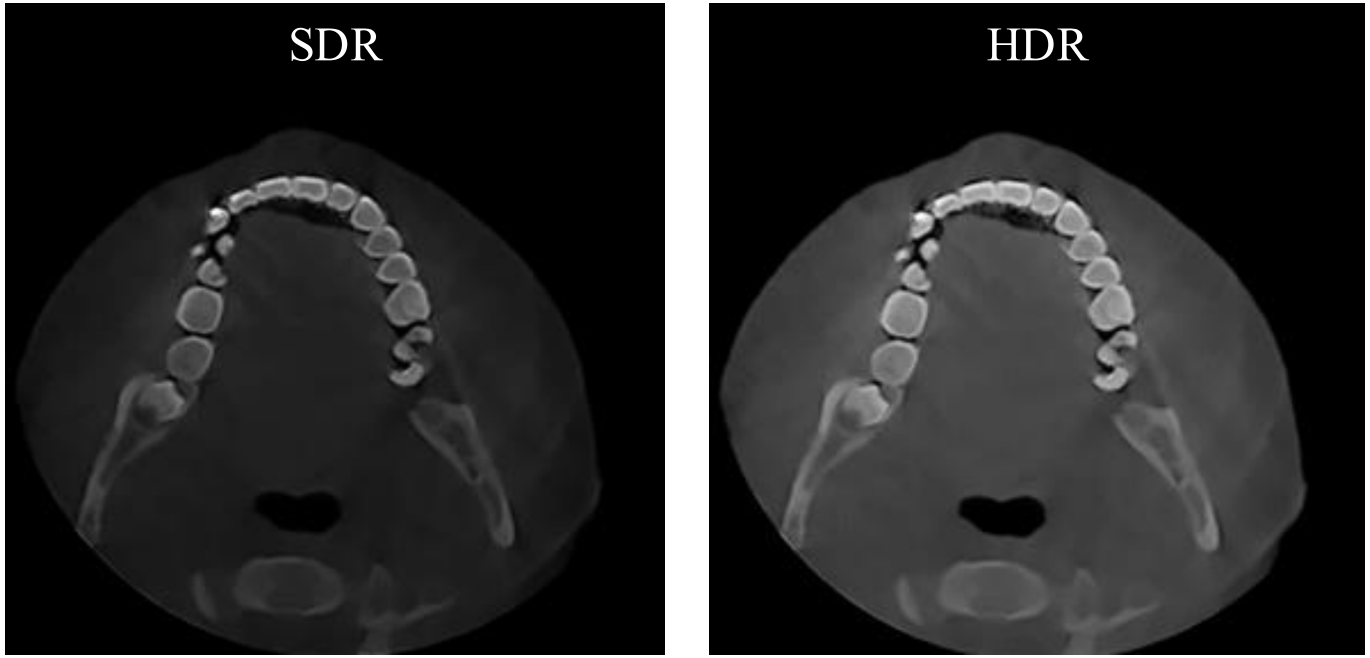
Challenges

High Noise Levels and Artifacts

Examples of low-dose CBCT images

Challenges

Low Brightness and Contrast – Standard Dynamic Range for CBCT (& Medical) Imaging



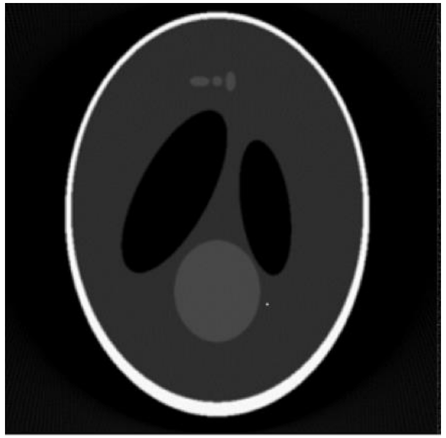
Existing Approaches

State-of-the-Art Methods

Existing Work on Noise Reduction – Signal Processing based

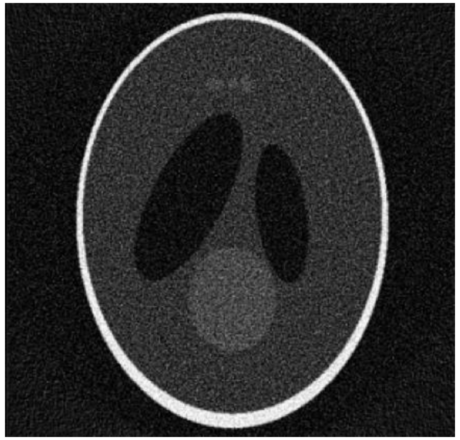
- Li et al. 2019

Not a real CBCT image

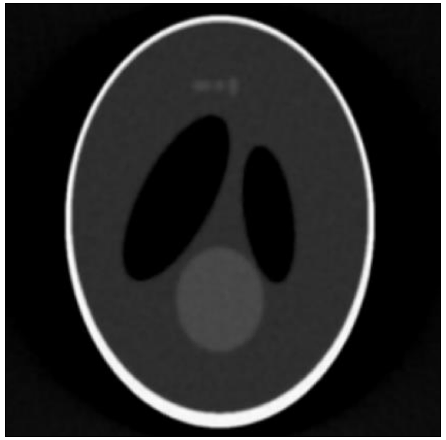


Original

They add fake noise to generate low-dose like CBCT image



Noisy image



Enhanced

Fake noisy image

Yet STILL noisy with smoothed edges

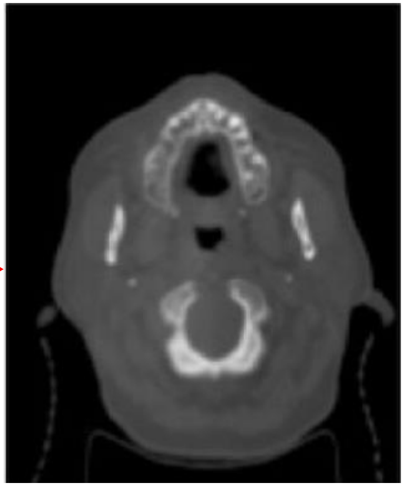
State-of-the-Art Methods

Existing Work on Noise Reduction – Deep Learning based

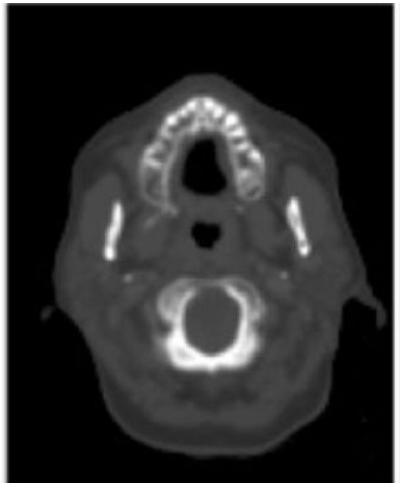
- Zhang et al. 2021

No pairs of low- and high-dose CBCTs for training the NNs

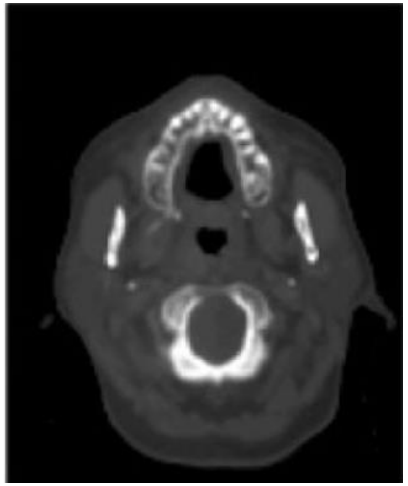
Not real pairs



CBCT (input)



CT (Target)



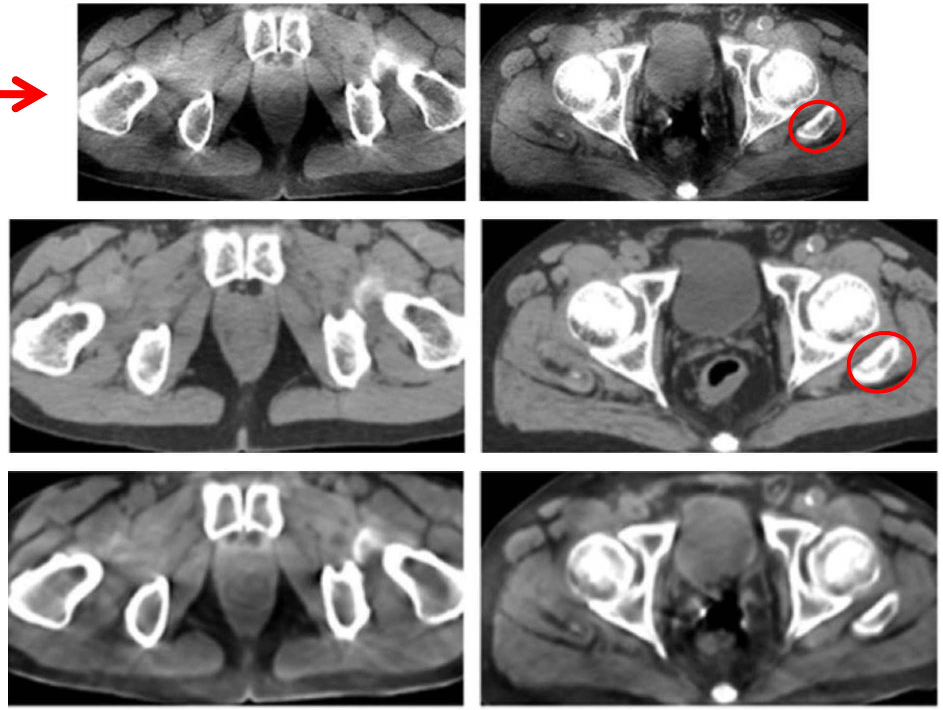
Enhanced

State-of-the-Art Methods

Existing Work on Spatial Resolution Enhancement – Deep Learning based

- Oyama et al. 2018

Not real pairs



Low-dose CBCT

Target CT

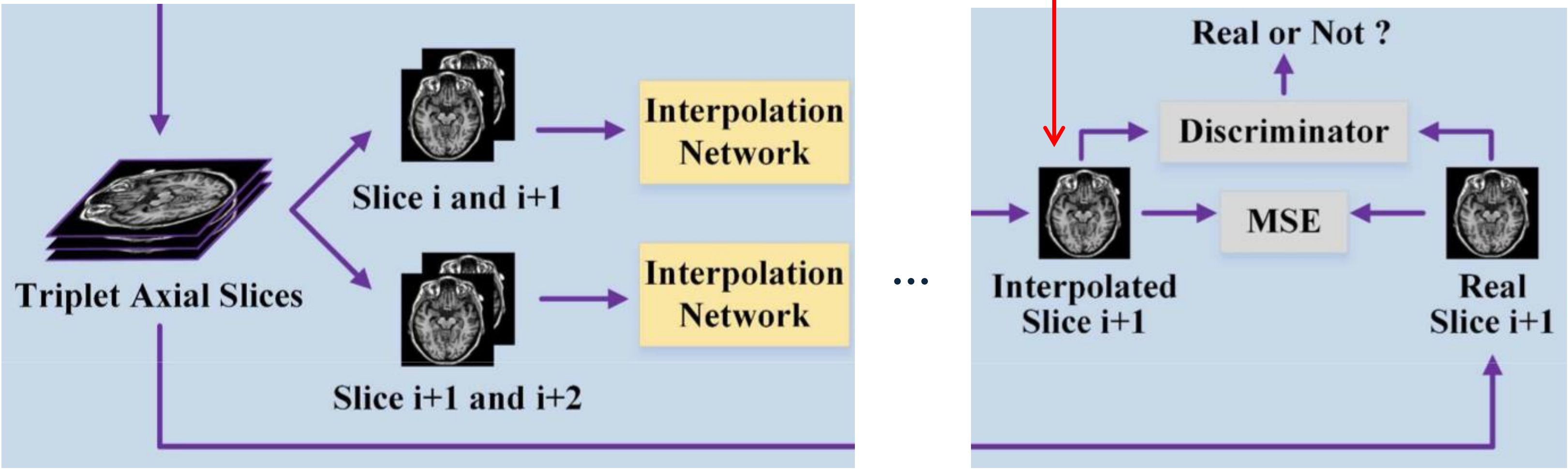
Enhanced CBCT

State-of-the-Art Methods

Existing Work on Spatial Resolution Enhancement (for MRI) – Deep Learning based

- Lu et al. 2021

Use multi-images i, i+1 & i+2 to upscale i+1



Not real pairs
MRI does generalize to CBCT images

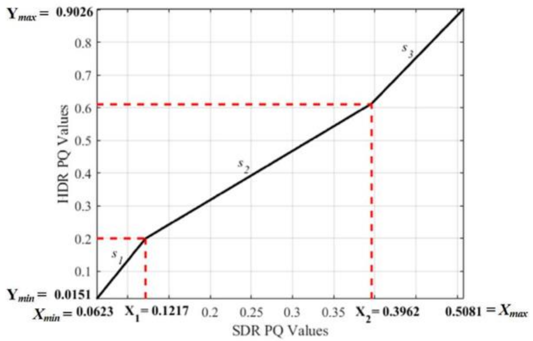
No multi-image super-resolution methods for CBCT images – No paired CBCT dataset

State-of-the-Art Methods

Existing Work on Contrast and Brightness Enhancement of CBCT images

inverse Tone Mapping Operators (iTMOs) for Natural Images – Signal Processing based

- Mohammadi et al. 2021



Method tailored for structures and characteristics of natural images

State-of-the-Art Methods

Existing Work on Contrast and Brightness Enhancement of CBCT images – do not exist

inverse Tone Mapping Operators (iTMOs) for Natural Images – Deep Learning based

- Zhang et al. 2023

SDR image

Again, no real pairs for CBCT images

Target

HDR image

Key Steps for Quality Improvement

1
- **Reduction of Noise and Artifacts**

2
- **Spatial Resolution Enhancement**

3
- **Enhancement of Contrast and Brightness (iTMO)**

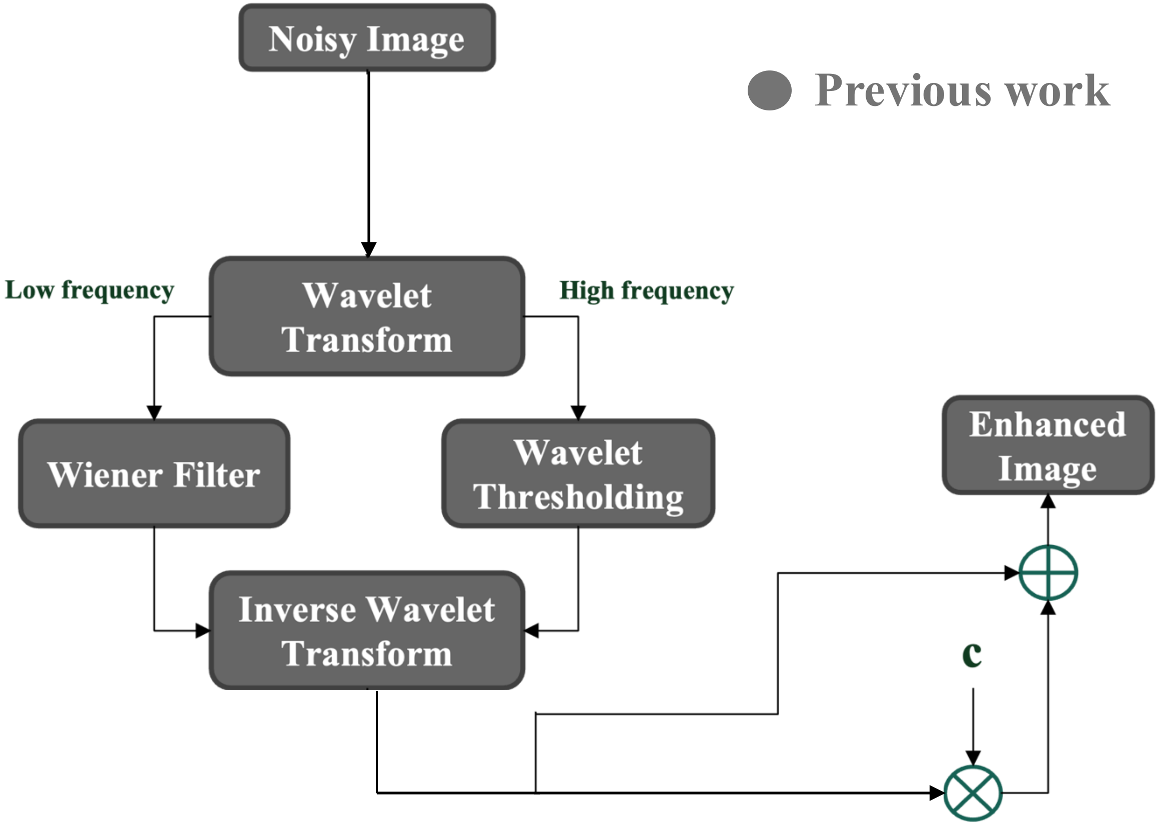
Step 1

“Reduction of Noise and Artifacts”

Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

Gaussian noise in low-dose CBCT: $y = x + n$

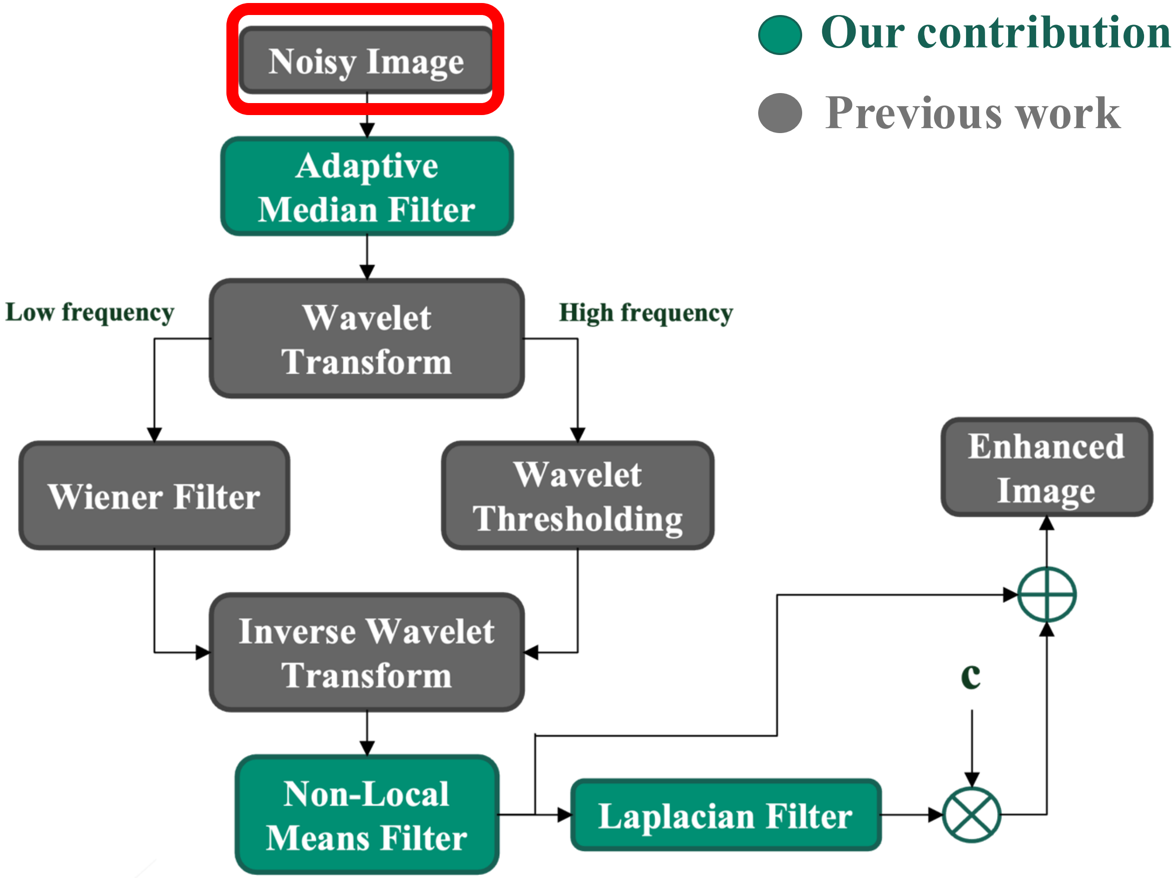


- Previous work

Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

Gaussian noise in low-dose CBCT: $y = x + n$

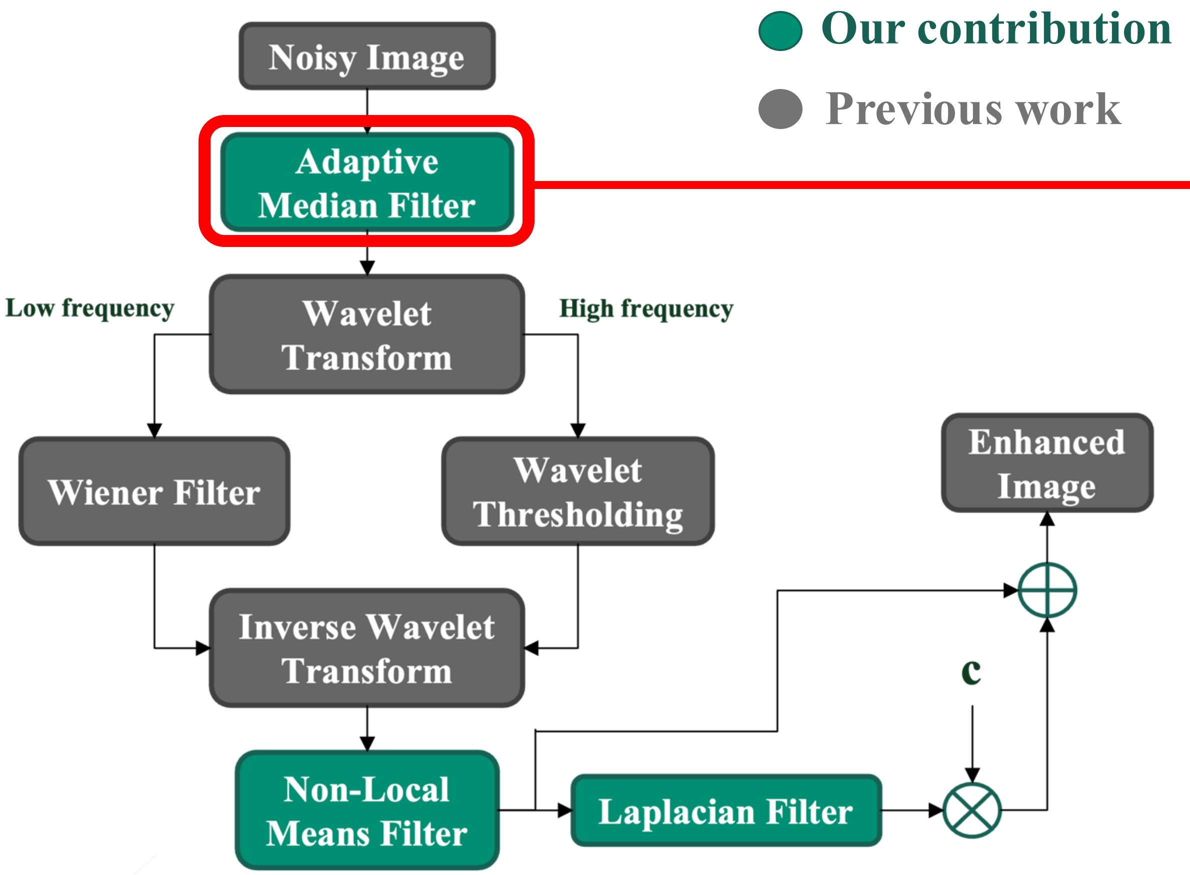


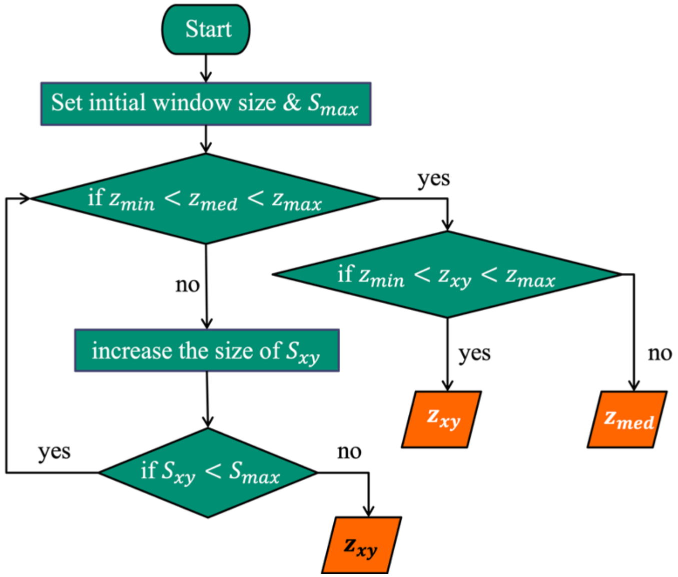
- Our contribution
- Previous work

Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

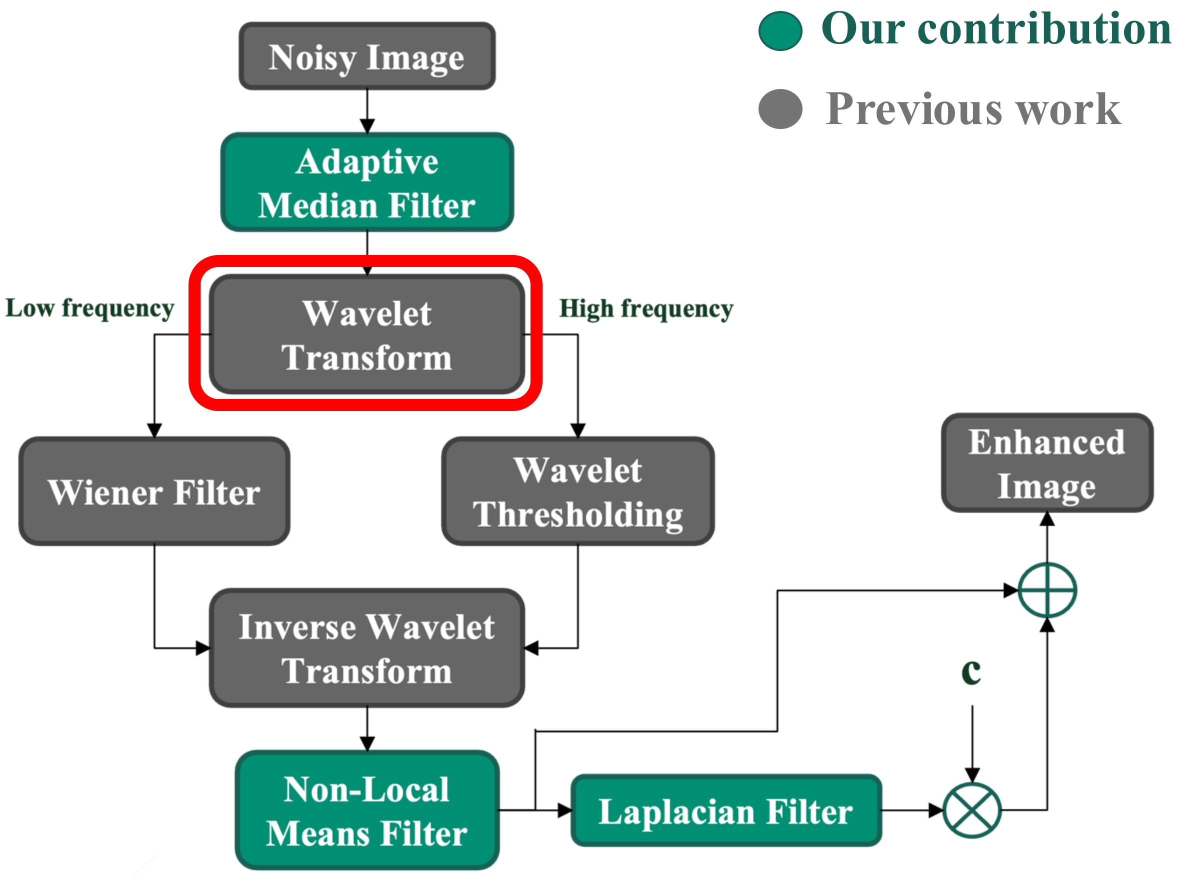
Gaussian noise in low-dose CBCT: $y = x + n$

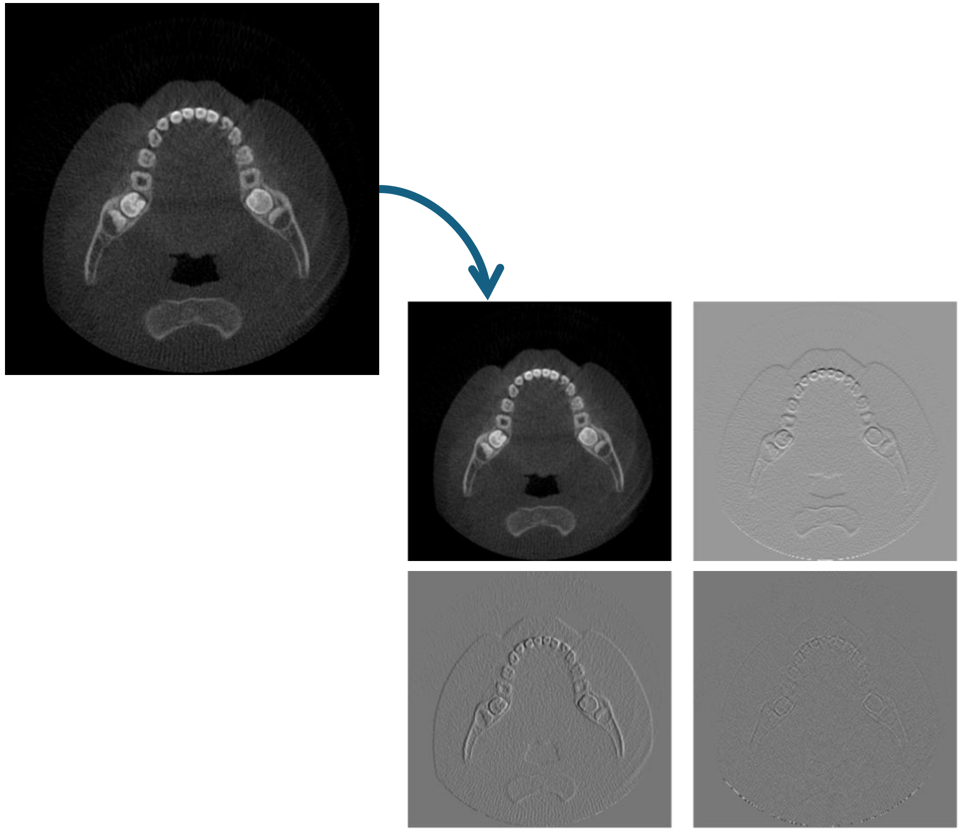




Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

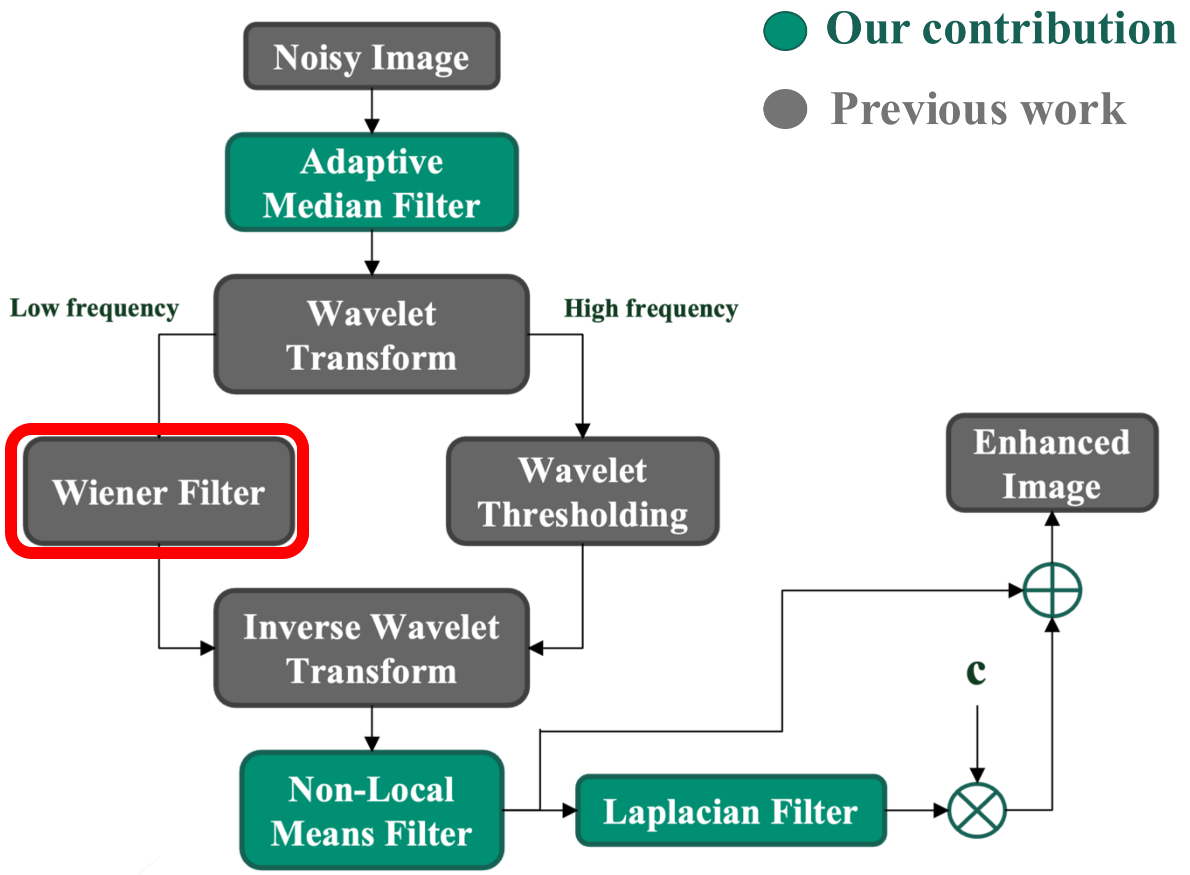




Wavelet decomposition of CBCT image

Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

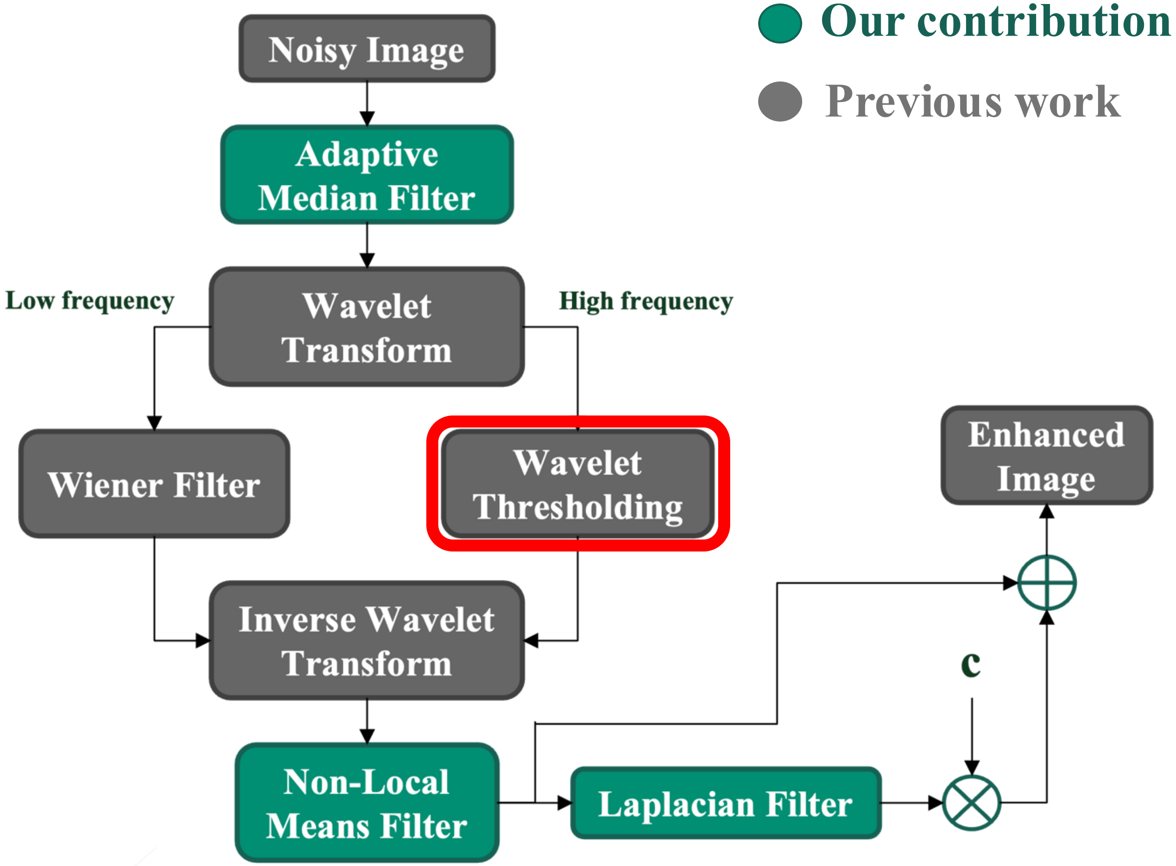


$$I_f(p_i) = \frac{\sigma_l^2}{\sigma_l^2 + v^2}(I_n(p_i) - \mu_l) + \mu_l$$

$$v^2 = \frac{Median(cD)}{0.6745}$$

Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution



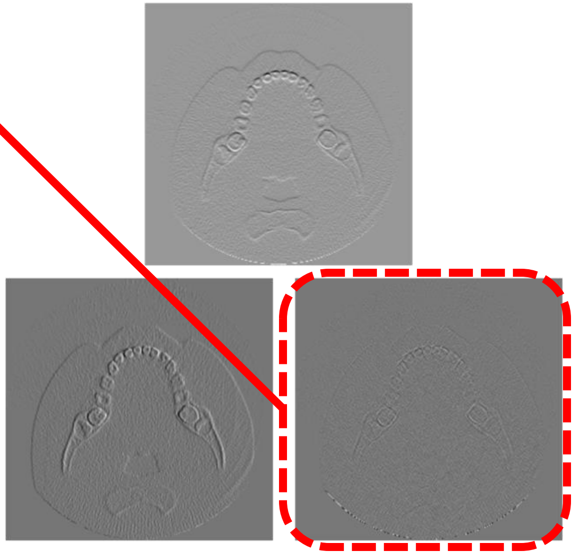
Our contribution

Previous work

$$w_t = \begin{cases} sign(w)(|w| - T), & |w| \geq T \\ 0, & |w| < 0 \end{cases}$$

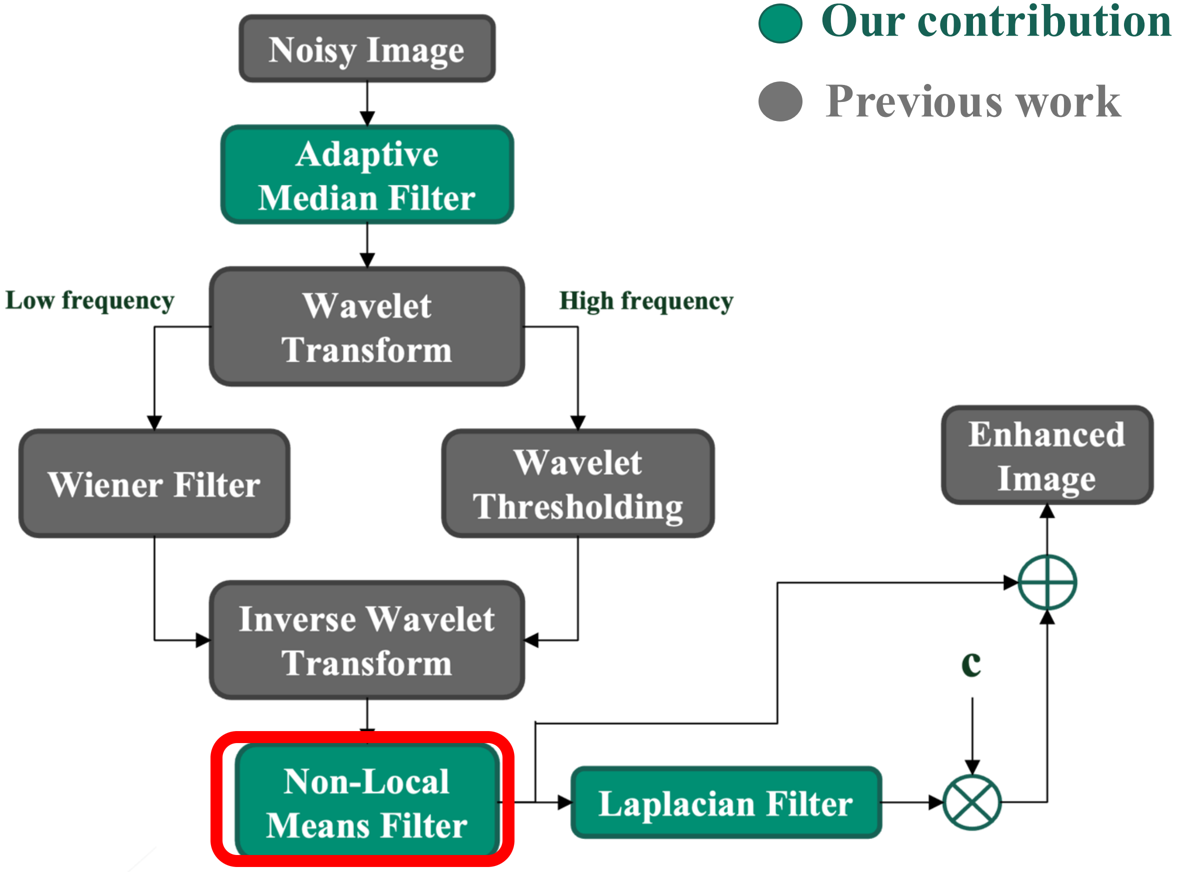
Birge-Massart strategy:

$$\begin{cases} crit(t)_{\min} = \sum c(k)^2 + 2t'\sigma^2(\alpha + \ln\frac{n}{t'}), k \leq t' \\ T = |c(t')| \end{cases}$$

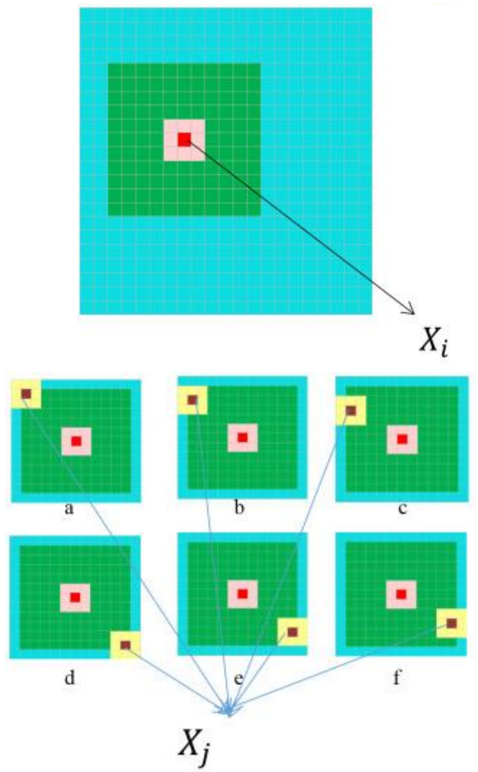


Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

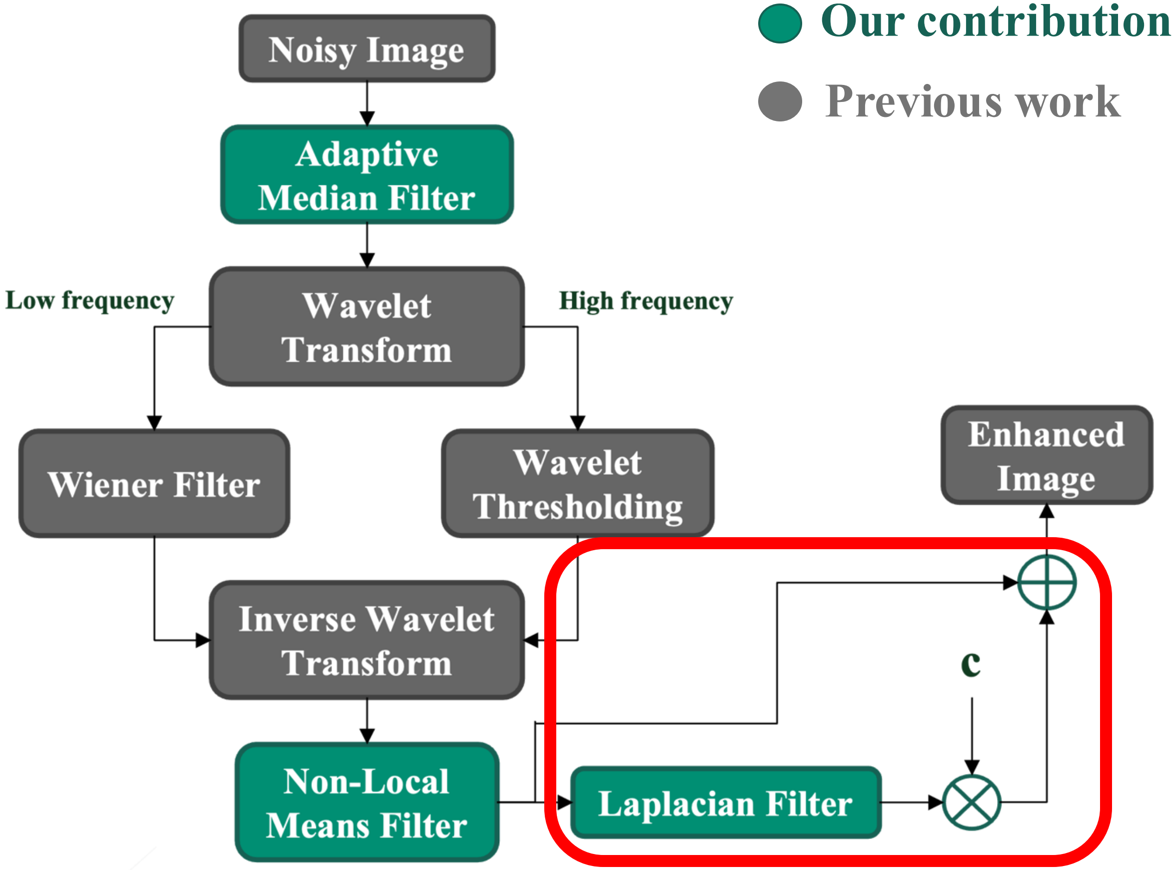


$$I_f(p_1) = \frac{1}{C(p_1)} \sum_{p_2 \in I_n} I_n(p_2) w(p_1, p_2)$$



Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

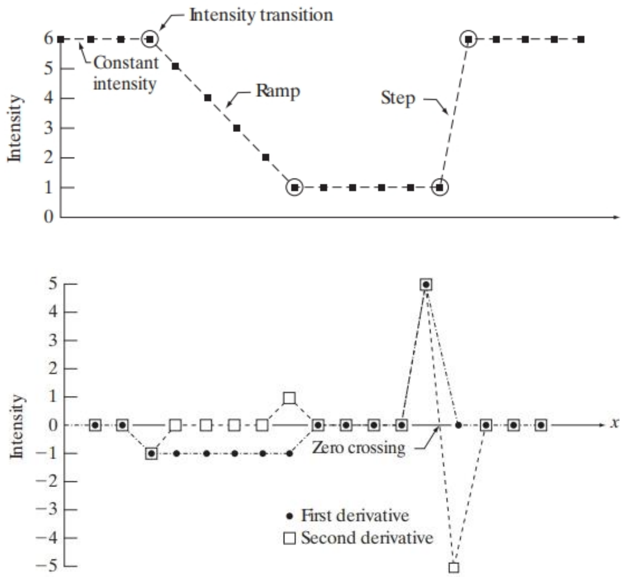


Our contribution

Previous work

$$F = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

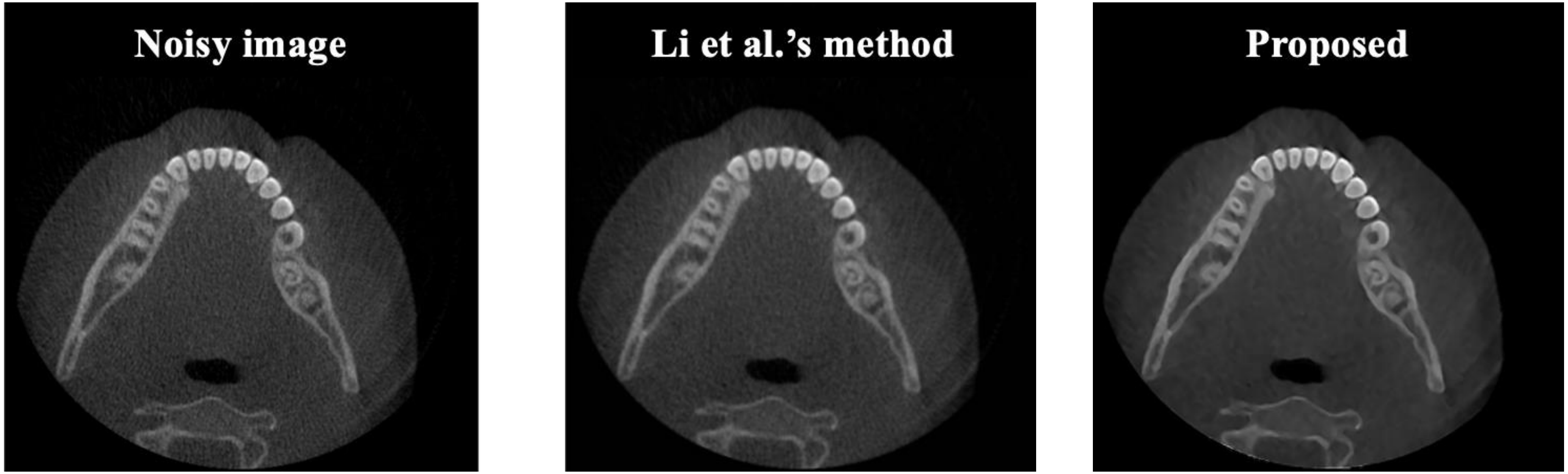
$$I_{sh} = I_c + \underbrace{c(I_c * F)}_{\text{edges}}$$



Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

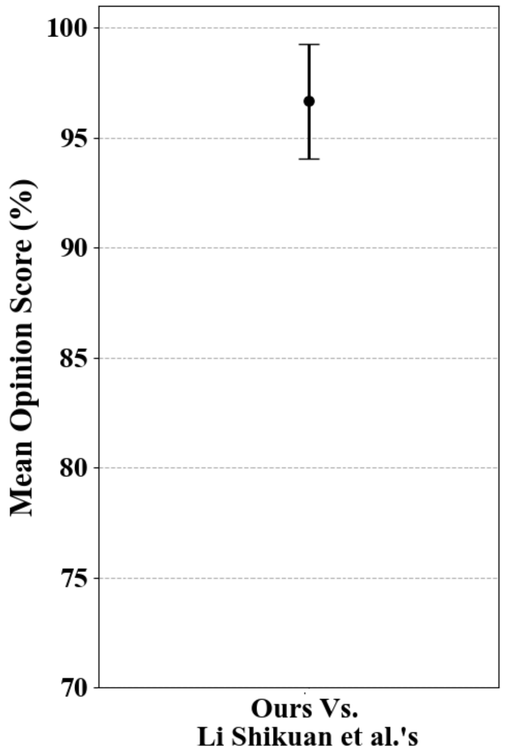
Visual Comparisons



Noise and Artifacts Reduction

Method 1: Denoising – Assuming Gaussian Noise Distribution

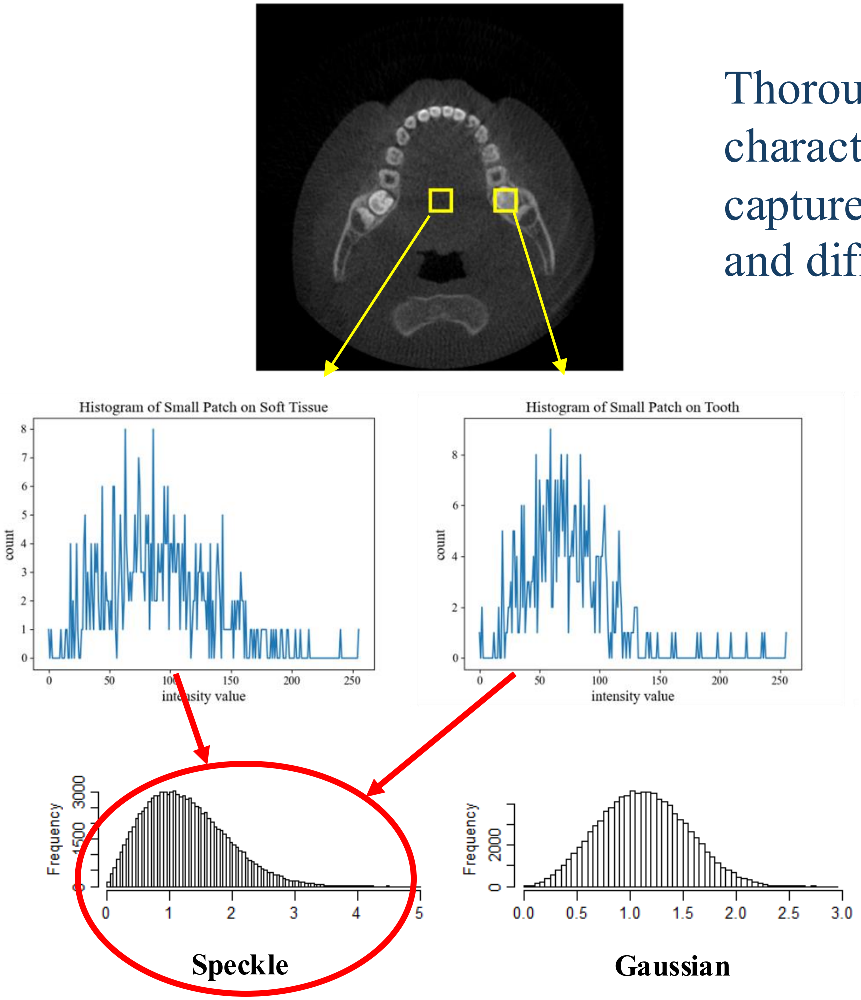
Subjective Evaluations



How many times (%) subjects preferred CBCT images enhanced by our approach over the existing method.

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



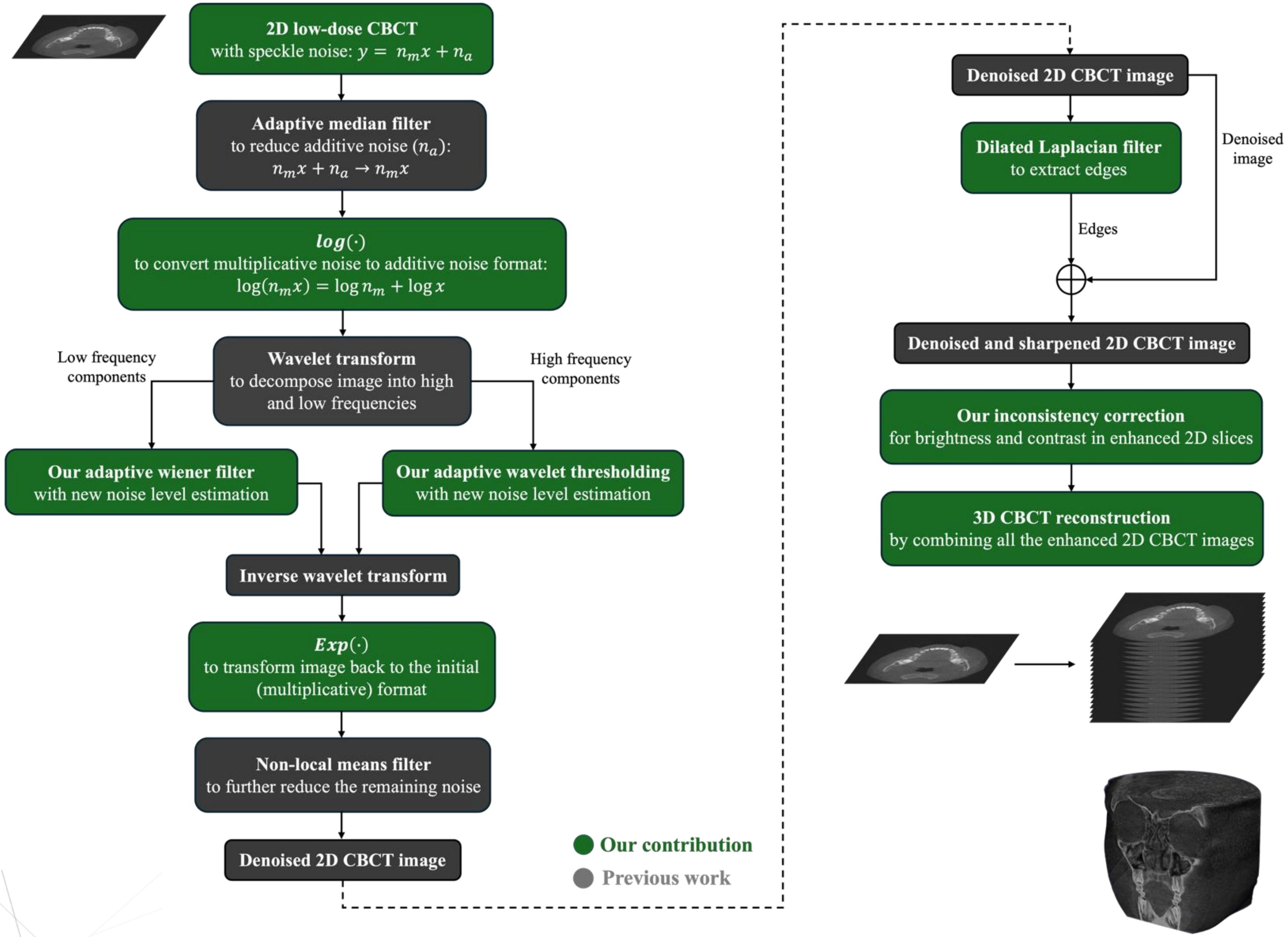
Thoroughly analyzed the noise characteristics in CBCT scans captured at various radiation levels and different tissue structures

speckle noise:

$$y = n_m x + n_a$$

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



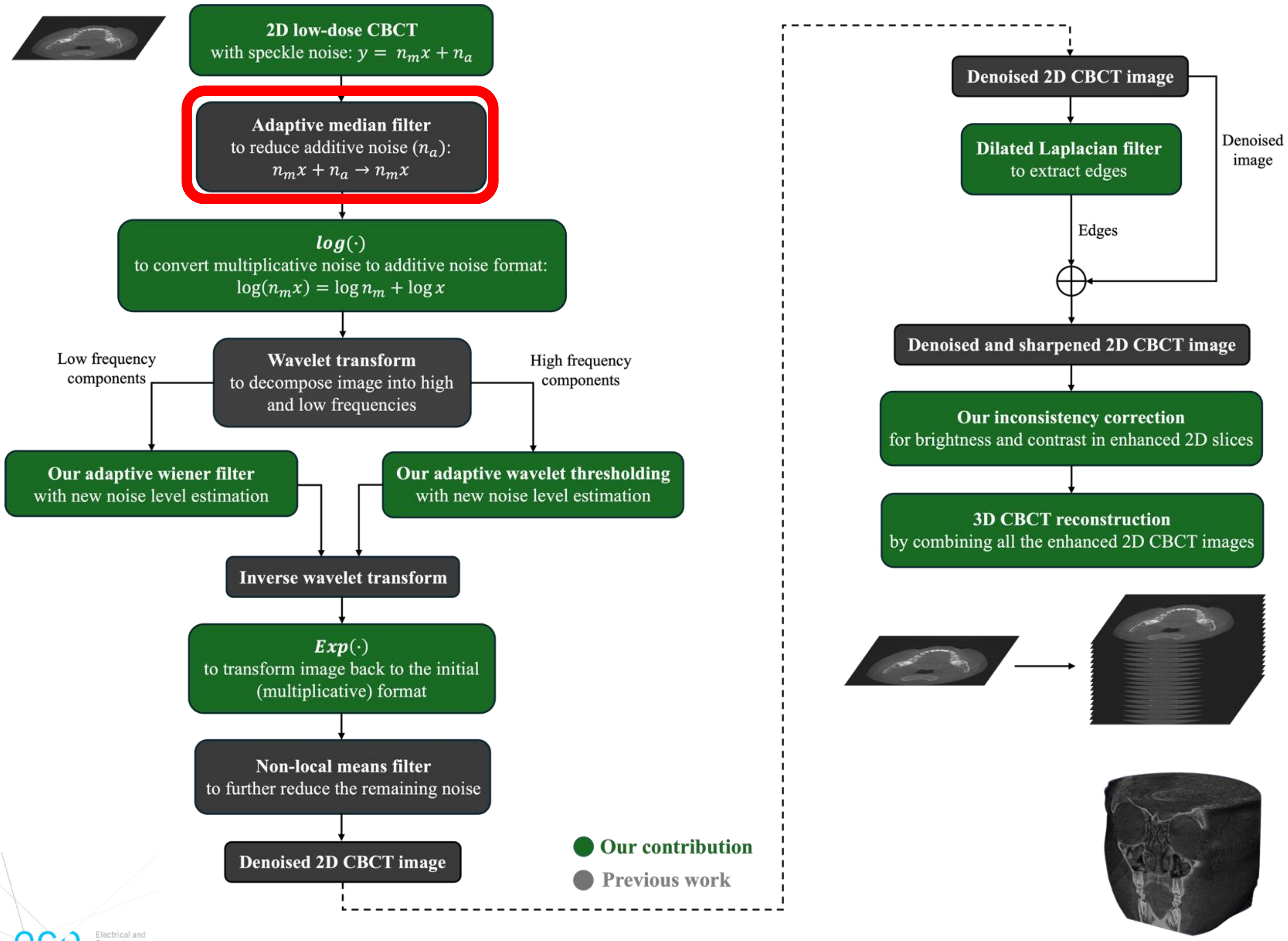
Contributions:

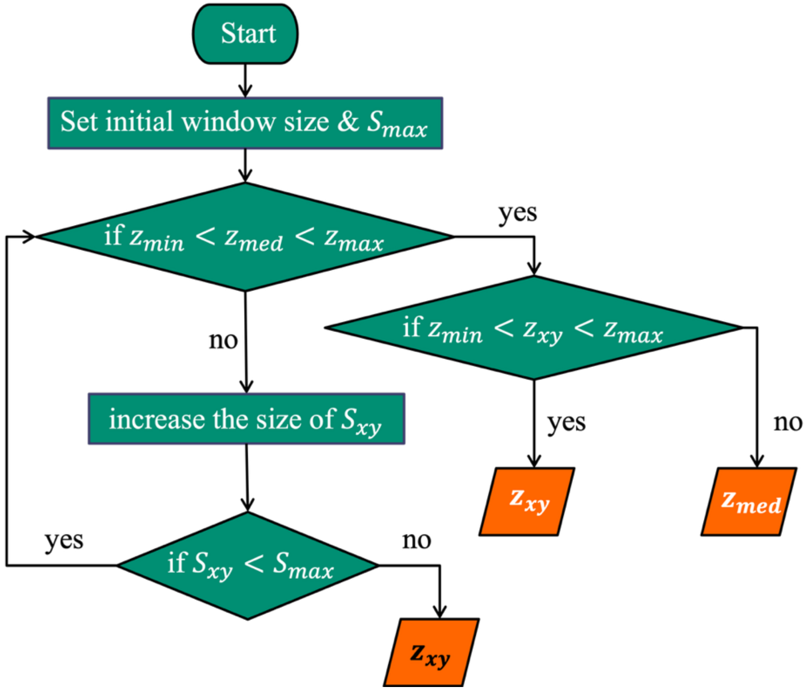
- Identifying speckle noise in CBCT images
- Innovative individual filters, and
- An overall filtering framework in which each individual filter is carefully designed and ordered to form a sequence that achieves optimal denoising of CBCT images

S. Mirzaei, H. R. Tohidypour, P. Nasiopoulos, S. R. Vora, and S. Mirabbasi, "An advanced denoising technique for low-dose CBCT imaging: Enhancing image quality and consumer safety in dental diagnostics," IEEE Transactions on Consumer Electronics, Jan. 2025.

Noise and Artifacts Reduction

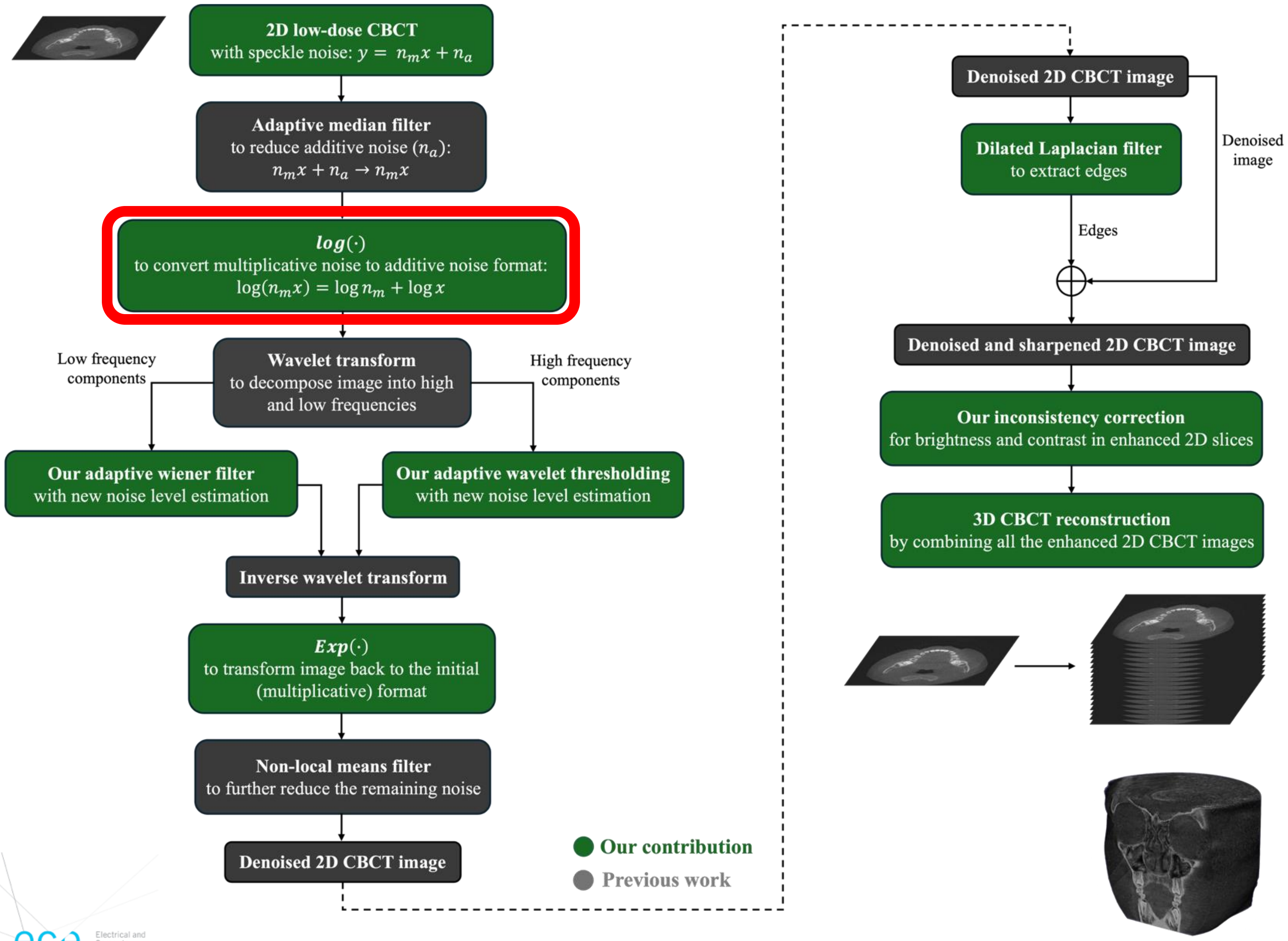
Method 2: Denoising – Assuming Speckle Noise Distribution





Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



Noisy Image: $y = n_m x + n_a$

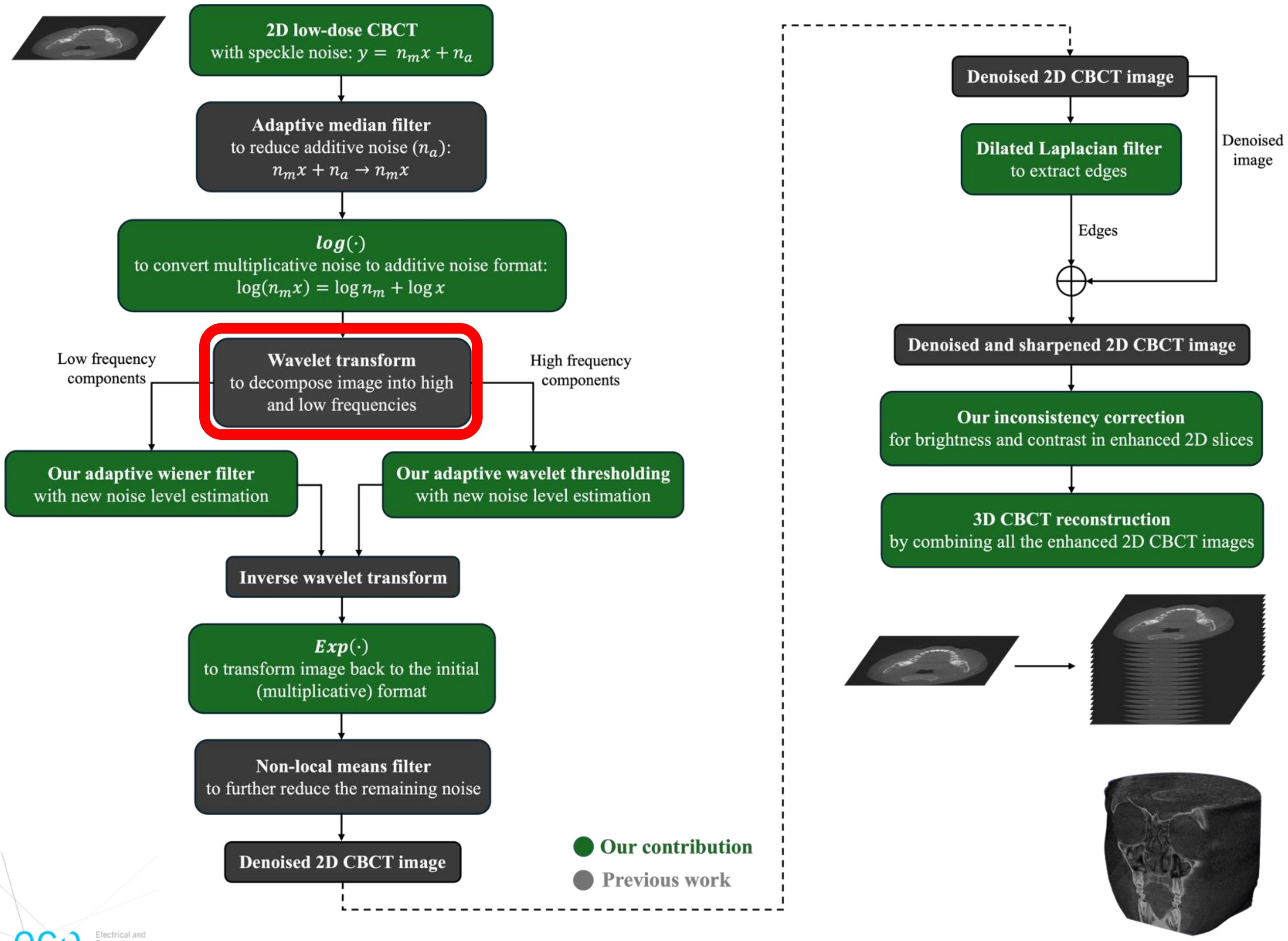
Adaptive median filter: $y' = n_m x$

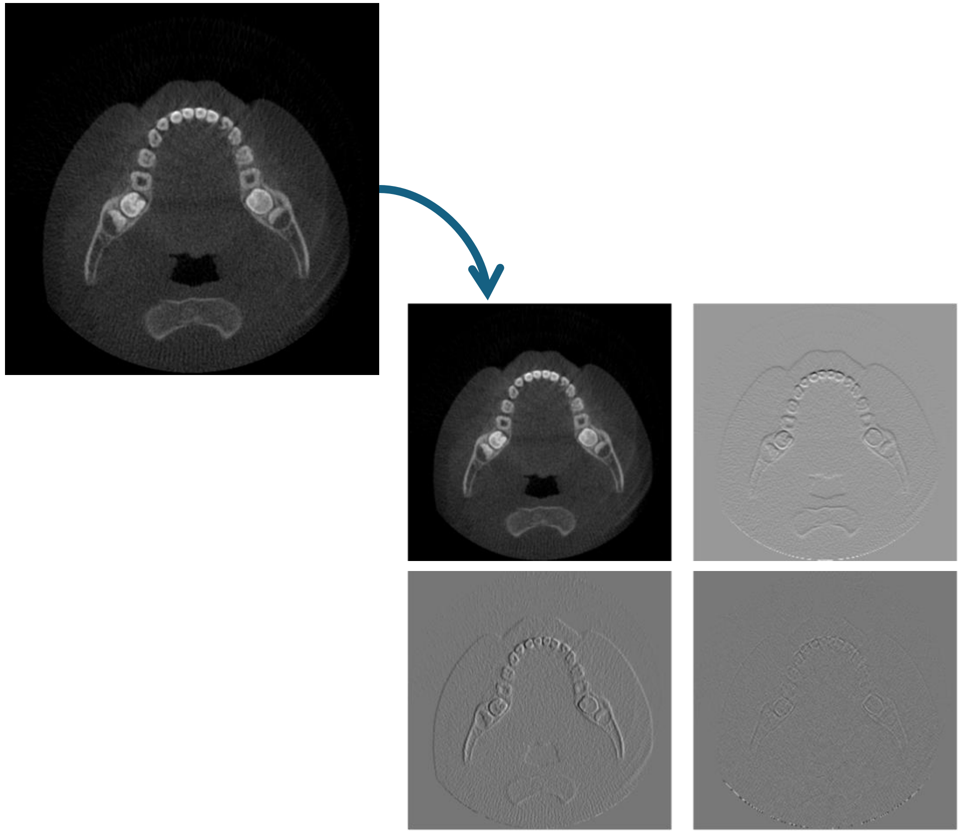
Logarithm: $log\, y' = \log(n_m x) = \log n_m + \log x$

After this step we can use common filters designed for additive noise to remove the multiplicative noise

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

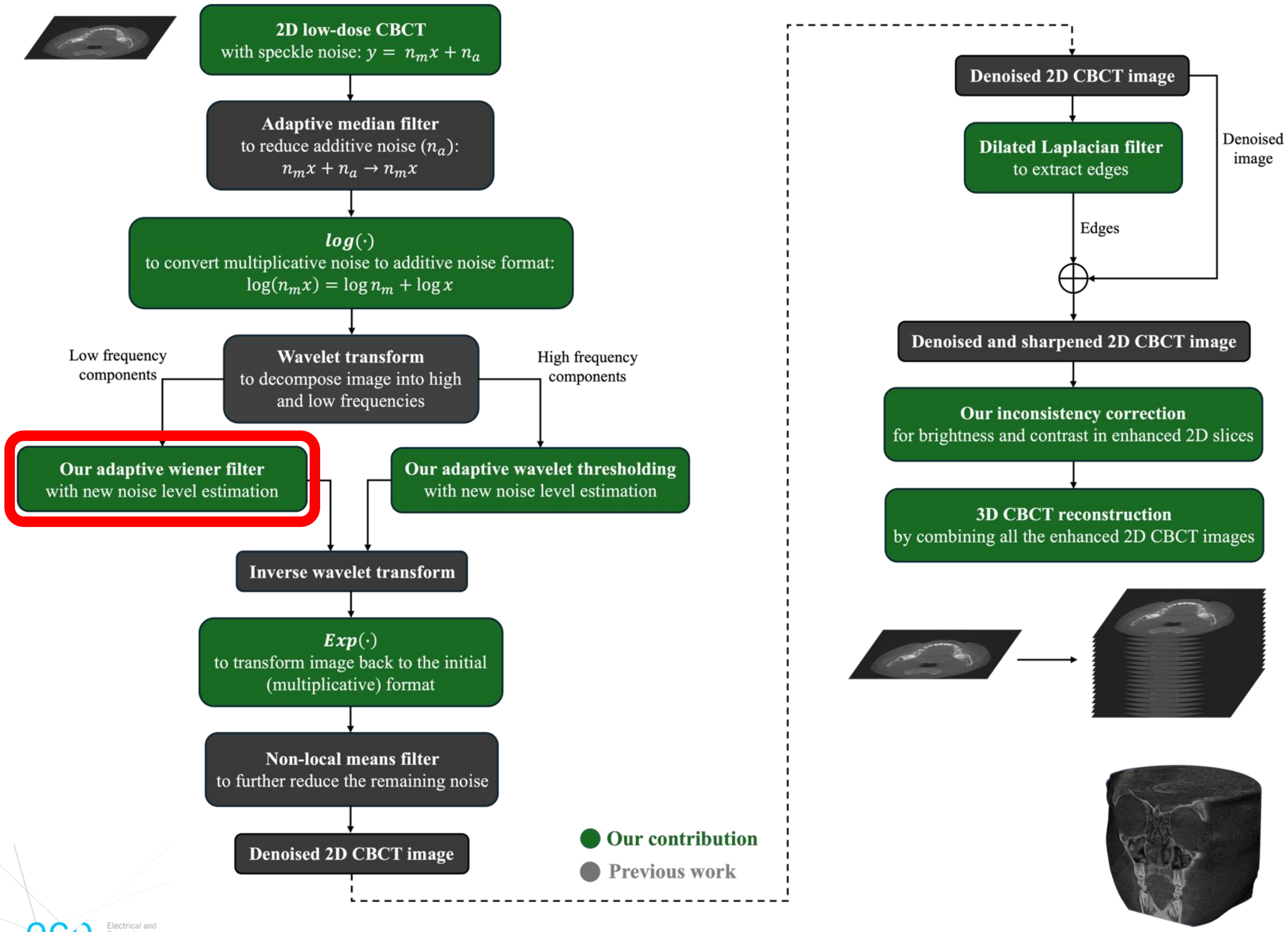




Wavelet decomposition of CBCT image

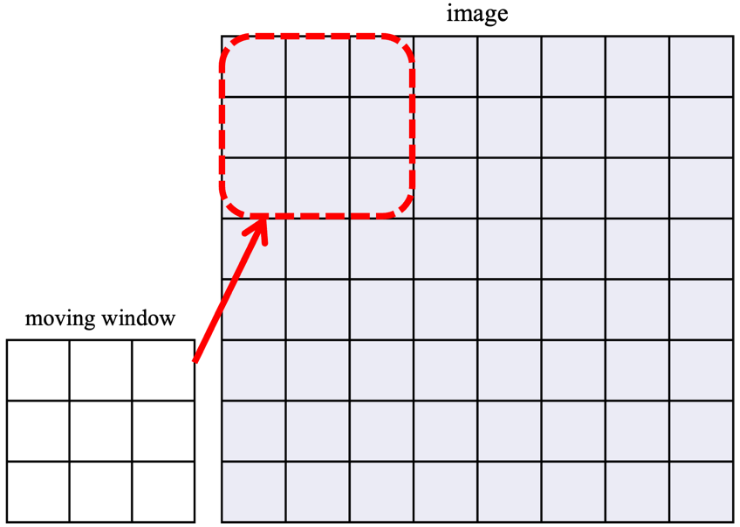
Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



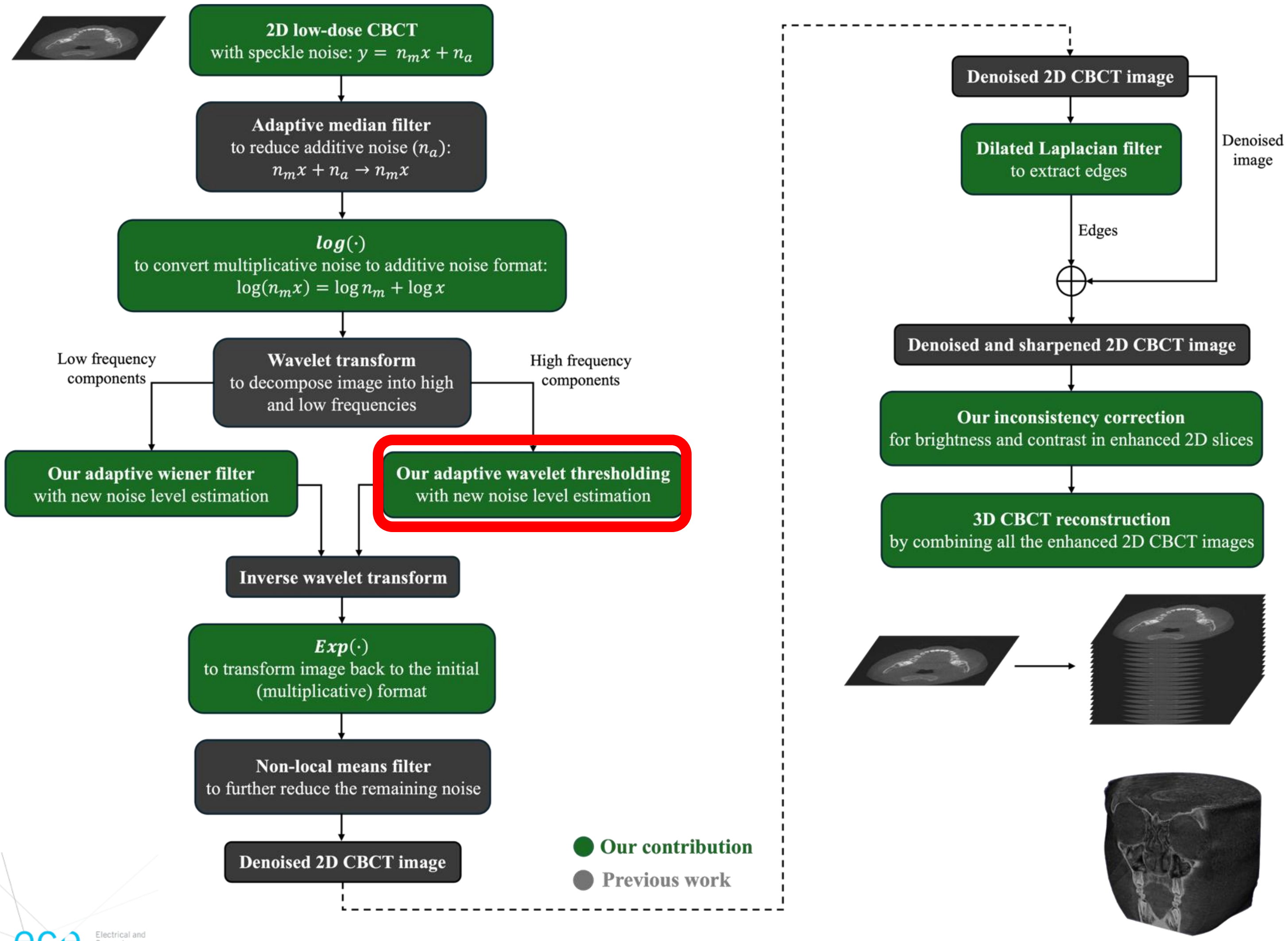
$$I_d = \mu_l + \left(\frac{\max(0, \sigma_l^2 - v^2)}{\max(\sigma_l^2, v^2)}\right)(I_n - \mu_l)$$

$$v^2 = \left(\frac{mean(\sigma_L)}{N}\right) \qquad w = \frac{1}{16}\begin{bmatrix}0.5 & 1 & 0.5\\ 1 & 10 & 1\\ 0.5 & 1 & 0.5\end{bmatrix}$$



Noise and Artifacts Reduction

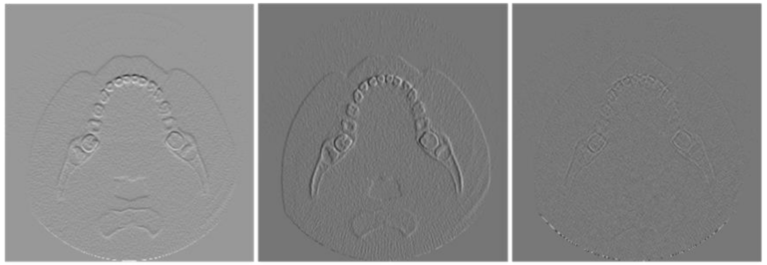
Method 2: Denoising – Assuming Speckle Noise Distribution



$$v_H^2 = \left(\frac{median(|H|)\sqrt{mean(\sigma_L)}}{N/M} \right)^2$$

$$T = \frac{v_H^2}{\sigma_x}$$

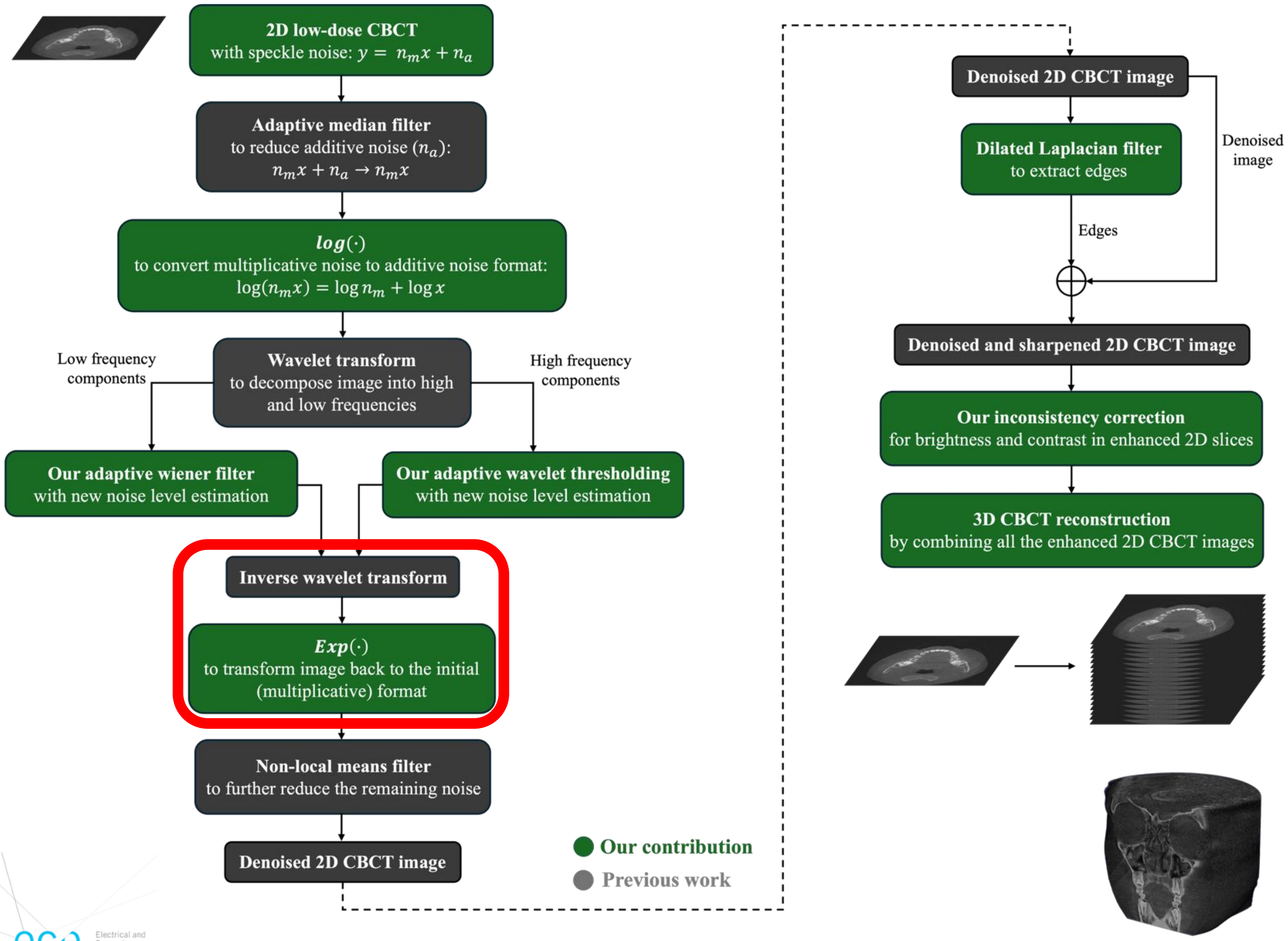
$$\sigma_x = \sqrt{max(\sigma_y^2 - v_H^2, 0)}$$



cH *cV* *cD*

Noise and Artifacts Reduction

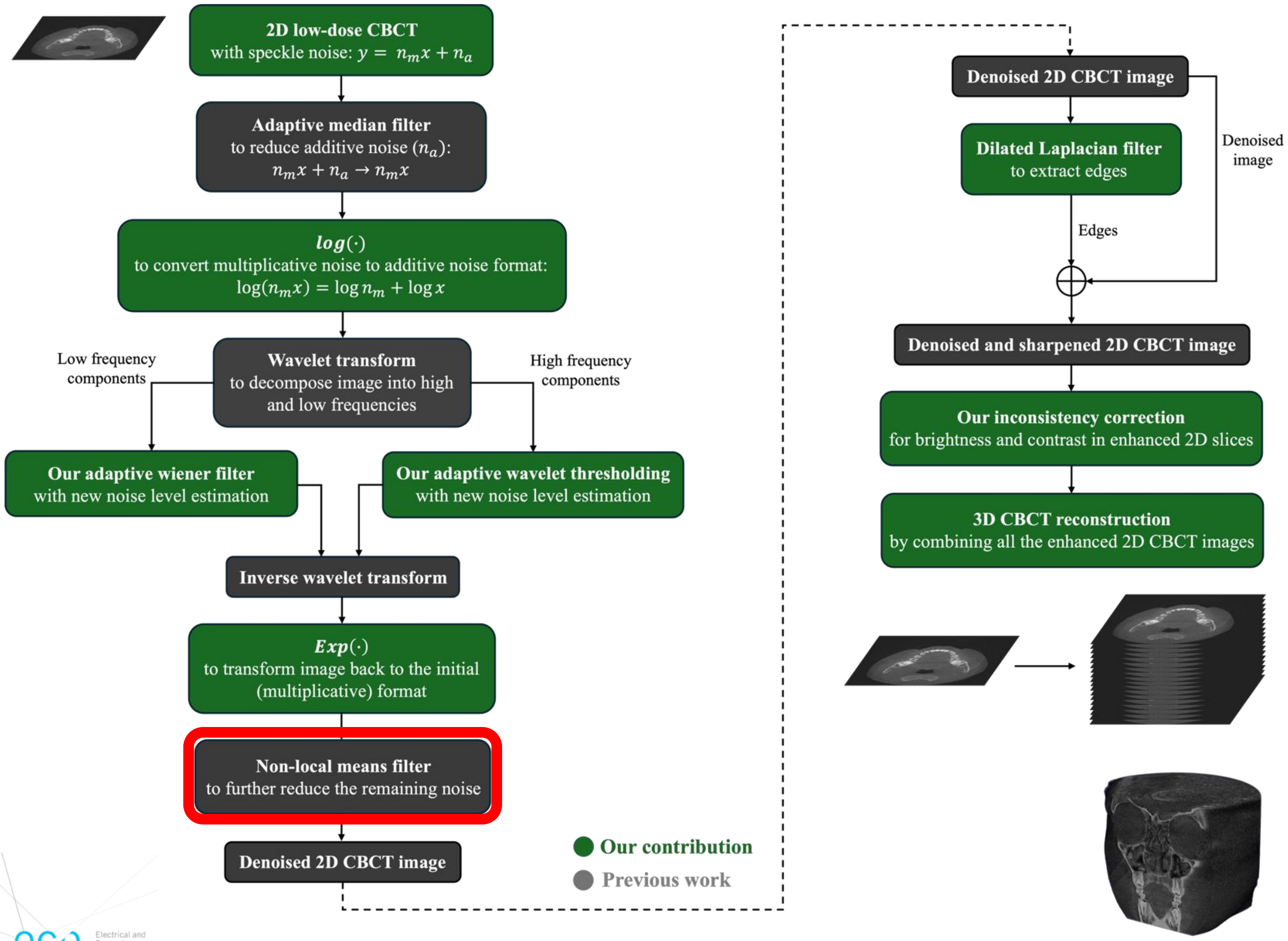
Method 2: Denoising – Assuming Speckle Noise Distribution



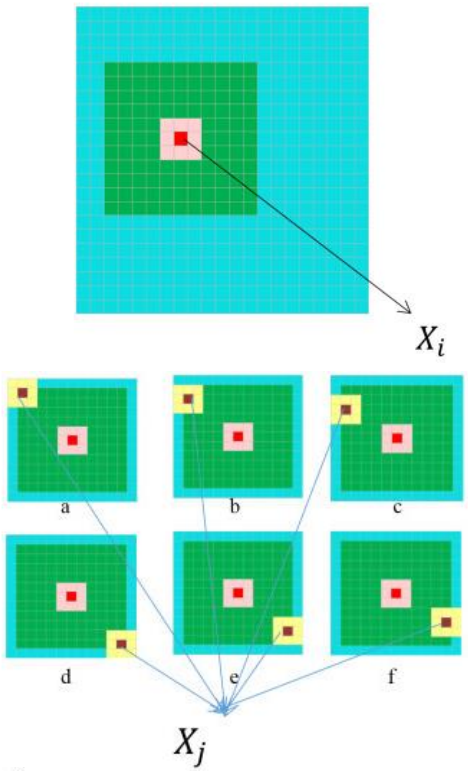
Transfer the image to both **spatial** and **multiplicative noise** domain

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

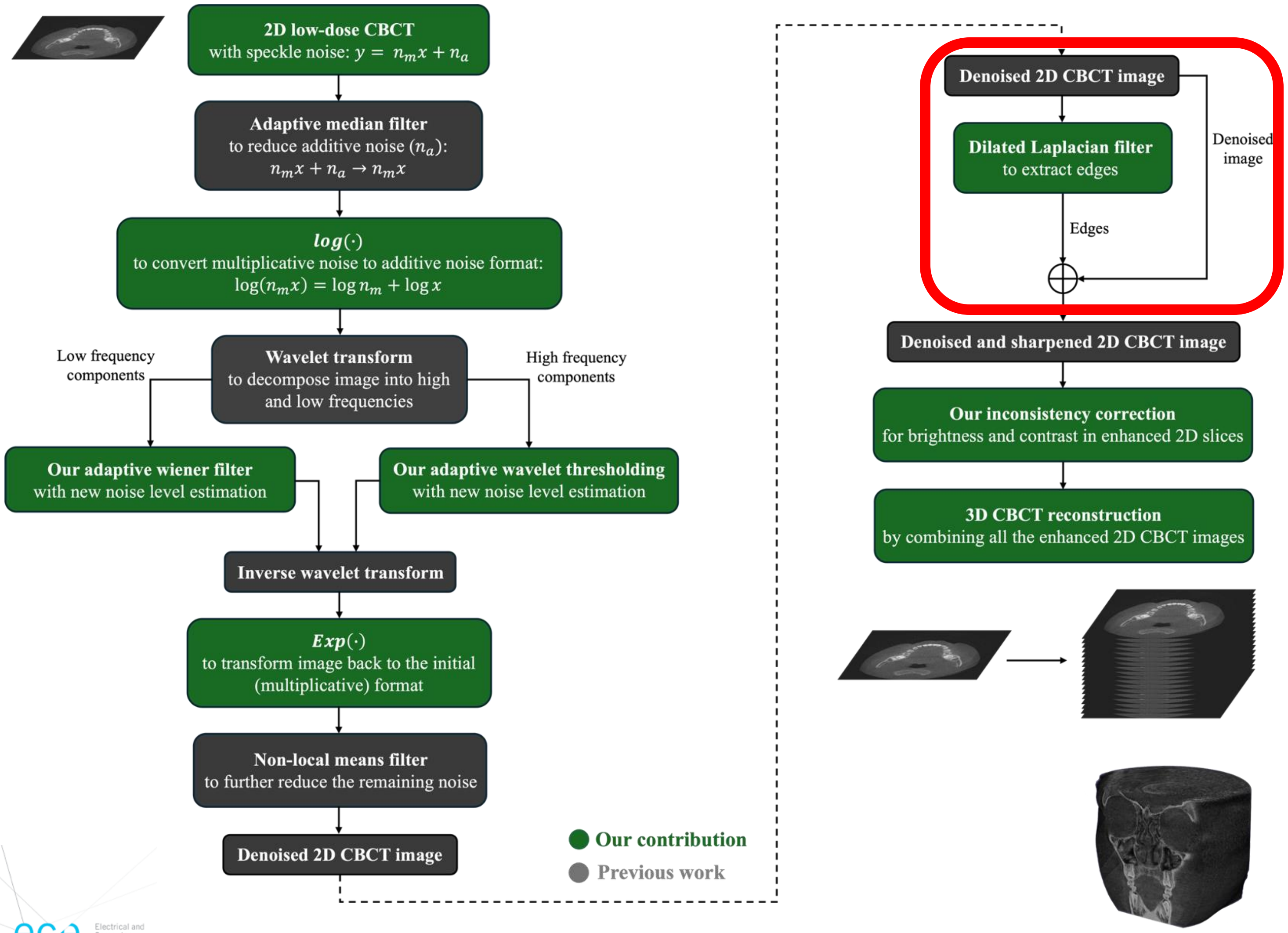


$$I_f(p_1) = \frac{1}{C(p_1)} \sum_{p_2 \in I_n} I_n(p_2) w(p_1, p_2)$$



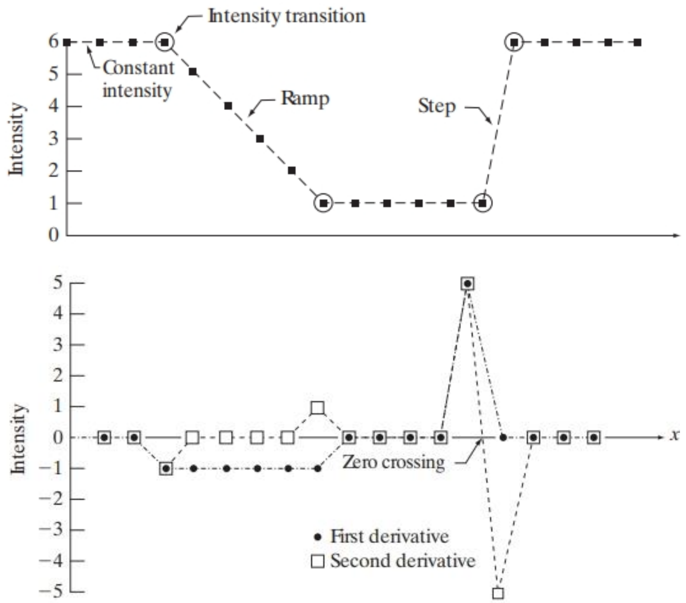
Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



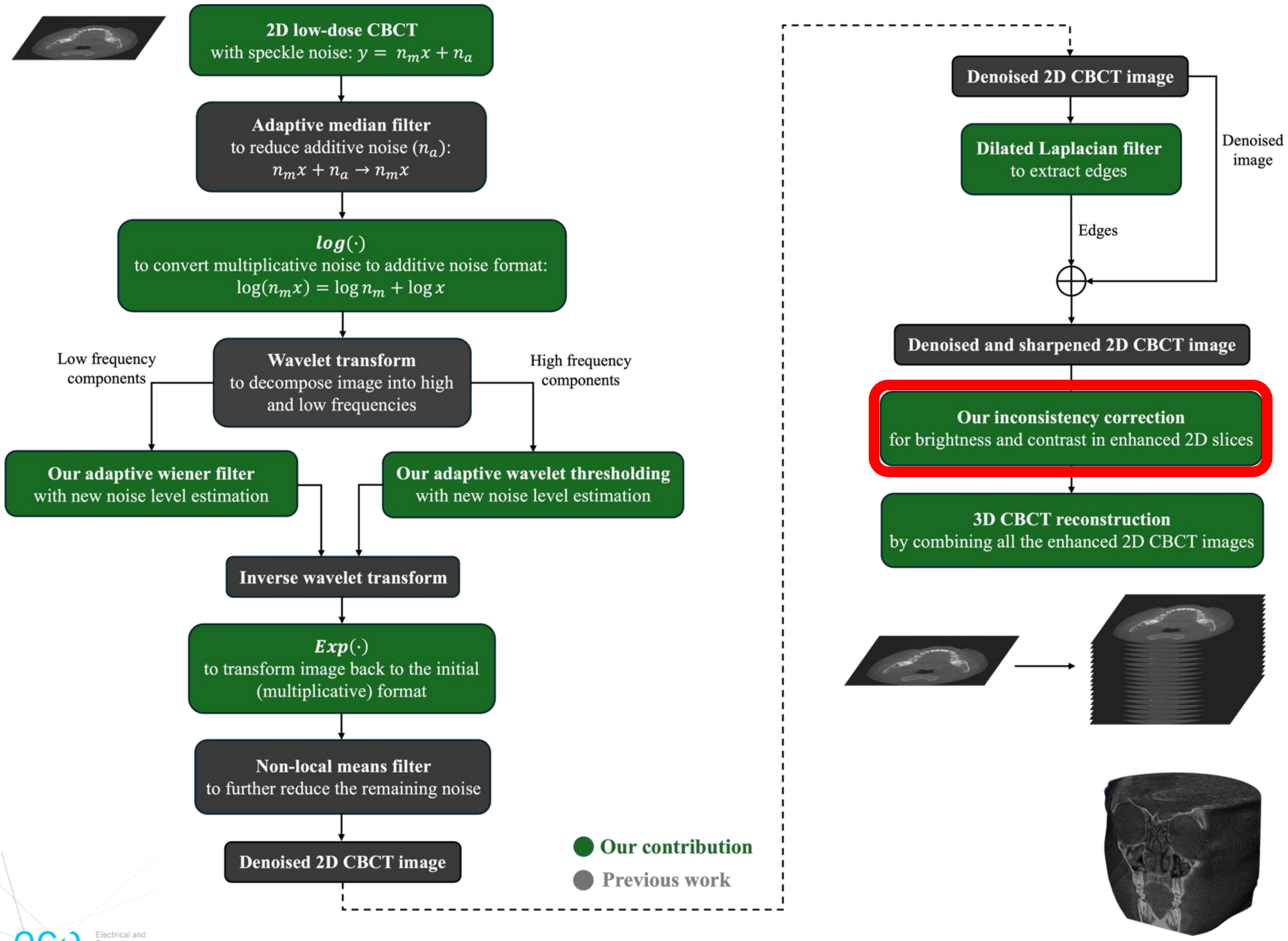
$$F = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & -4 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$I_{sh} = I_c + \underbrace{c(I_c * F)}_{\text{edges}}$$



Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

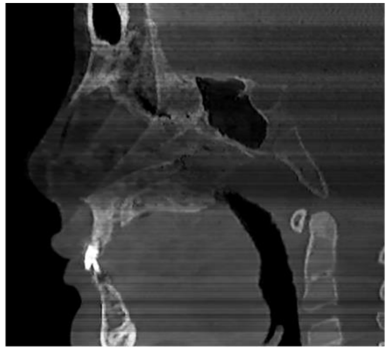


$$r = \frac{mean(I_n - \min(I_n))}{mean(I_f - \min(I_n))}$$

$$I_{n'} = I_n - \min(I_n)$$

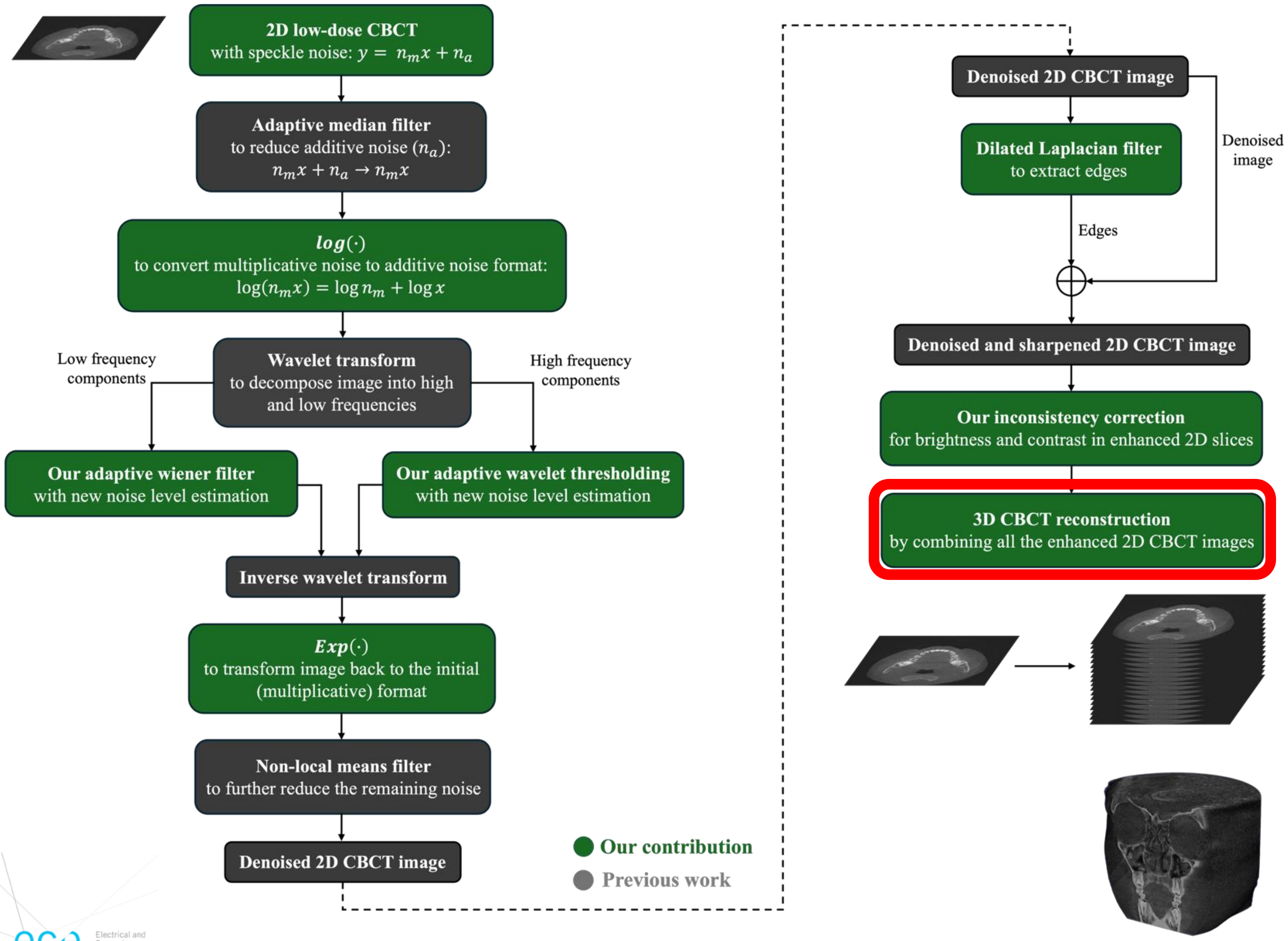
$$I_{f'} = I_f - \min(I_n)$$

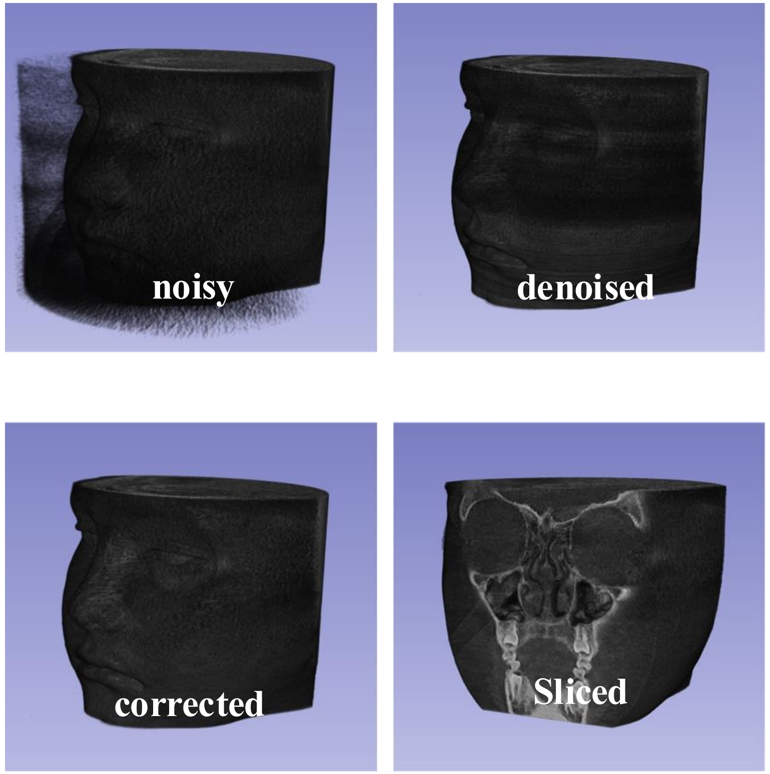
$$I_{out} = \min(\max(rI_{c'}, \min(I_{n'})), \max(I_{n'})) + \min(I_n)$$



Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution



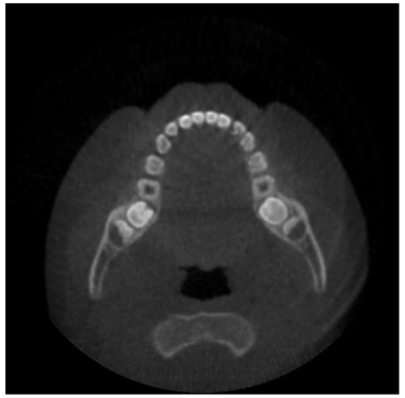


Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

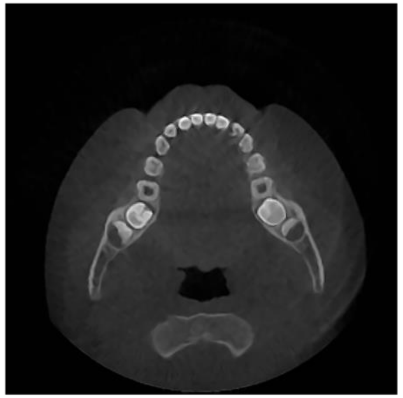
Visual comparisons

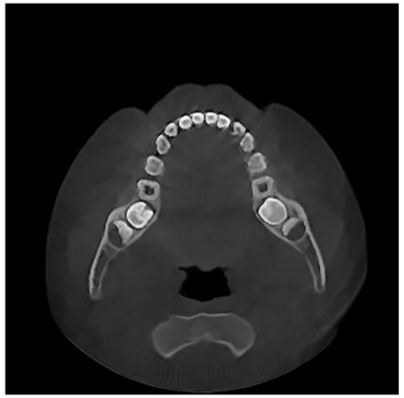

Noisy image


Chang et al.'s


Li et al.'s


Kim et al.'s

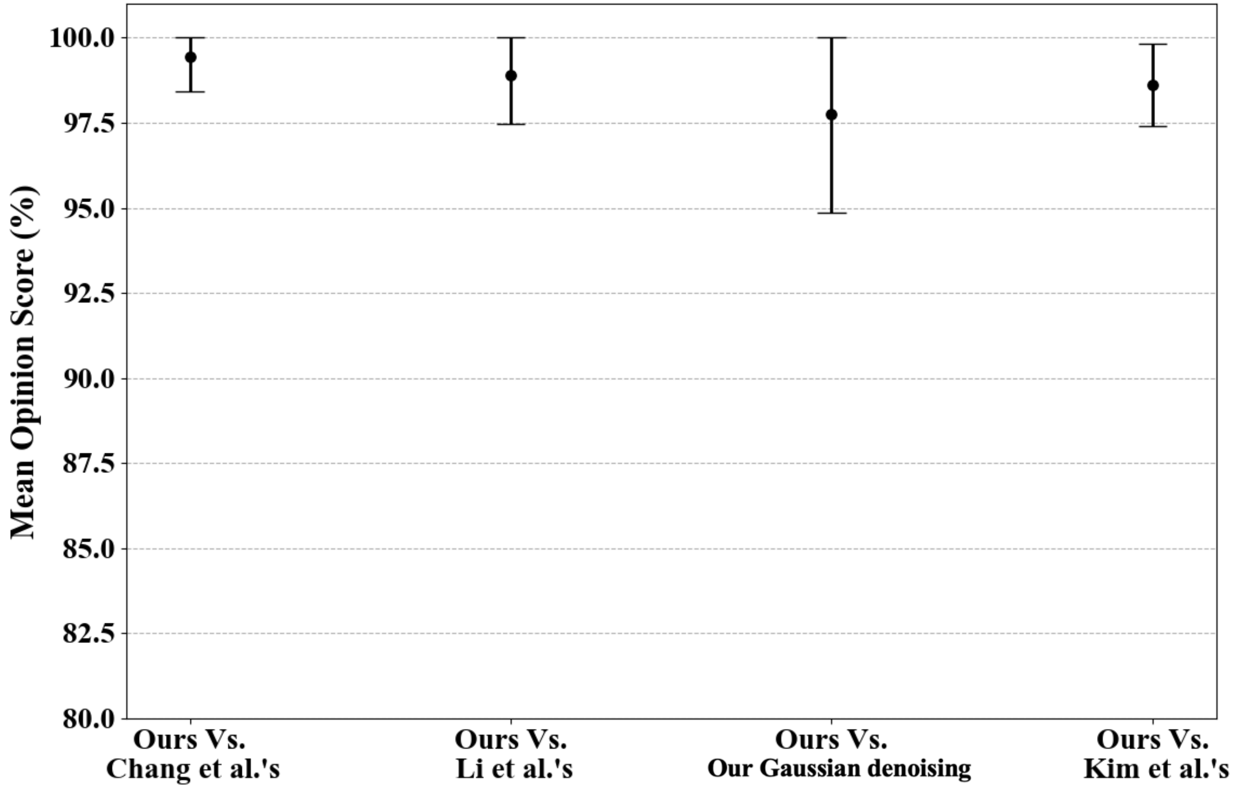

Our Gaussian noise removal method


Our speckle noise removal method

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

Subjective Evaluations



Number of times (%) subjects preferred the visual quality of CBCT images generated by our speckle method over other methods - Mean Opinion Score (MOS)

Noise and Artifacts Reduction

Method 2: Denoising – Assuming Speckle Noise Distribution

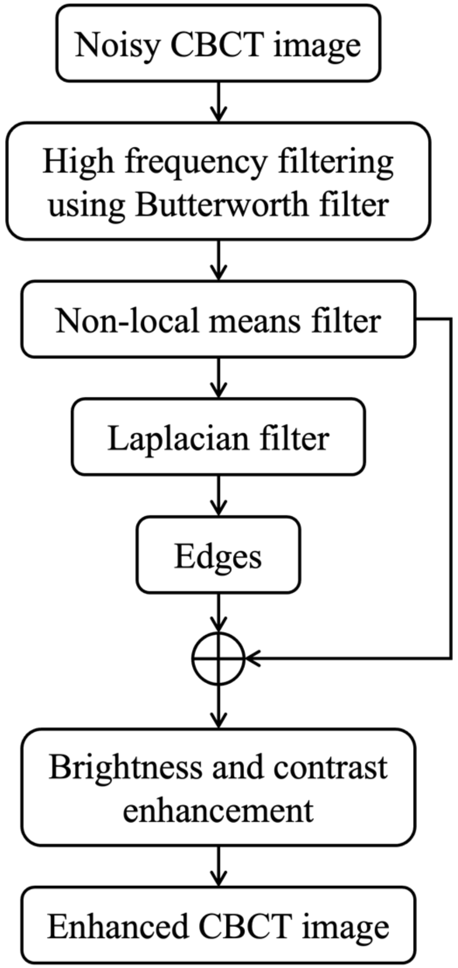
No-Reference Objective Evaluations

BRISQUE and NIQE scores for our method and existing approaches

Techniques	BRISQUE Score	NIQE Score
Noisy Image	50.57	6.14
Chang et al.'s	48.41	5.38
Li et al.'s	48.67	5.65
Mirzaei et al.'s	47.89	4.86
Kim et al.'s	46.24	4.67
Our Method	**44.88**	**3.89**

Noise and Artifacts Reduction

Method 3: Antialiasing Using Frequency and Spatial Domain Filtering



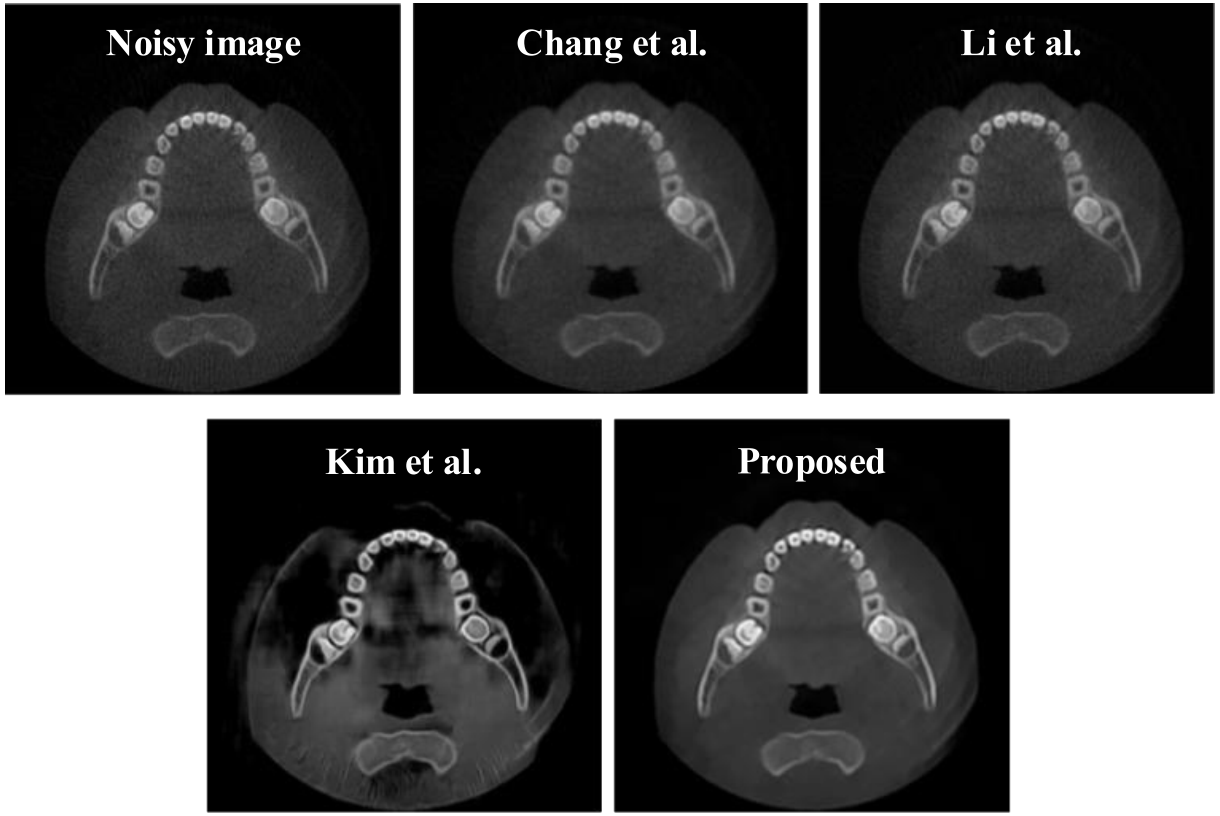
Our Contribution

A filtering framework designed to form a sequence of filtering steps that achieves optimal antialiasing of CBCT images

Noise and Artifacts Reduction

Method 3: Antialiasing Using Frequency and Spatial Domain Filtering

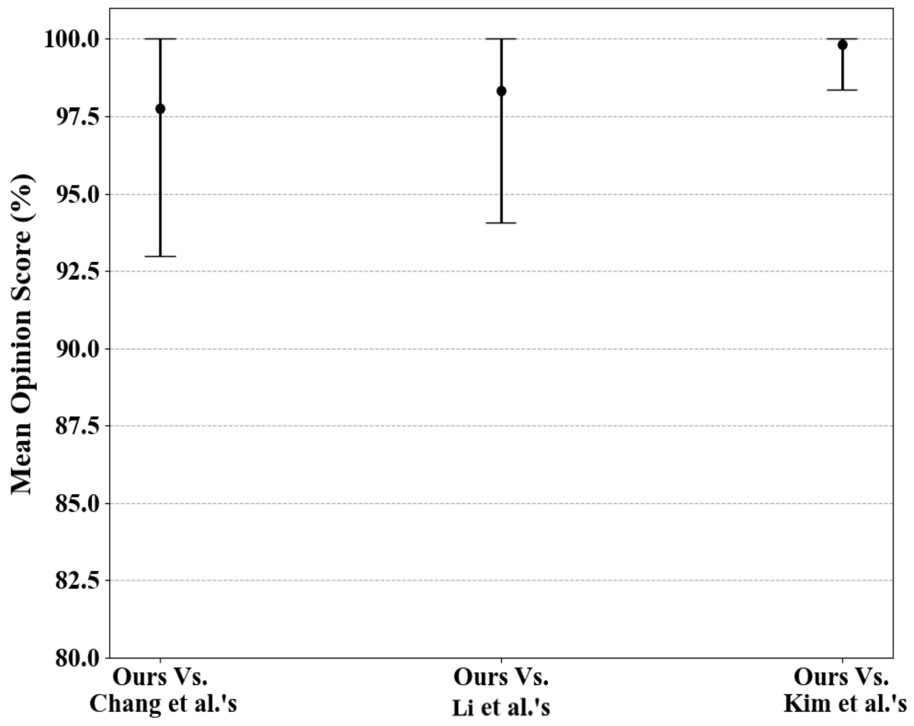
Visual Comparisons



Noise and Artifacts Reduction

Method 3: Antialiasing Using Frequency and Spatial Domain Filtering

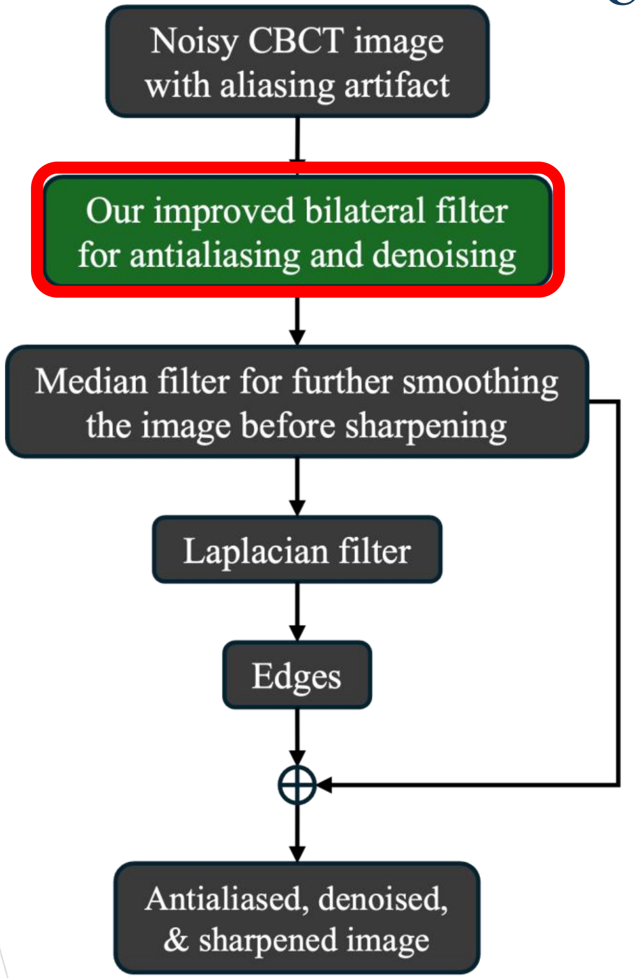
Subjective Evaluations



Number of times (%) subjects preferred the visual quality of CBCT images generated by our approach over other methods - Mean Opinion Score (MOS).

Noise and Artifacts Reduction

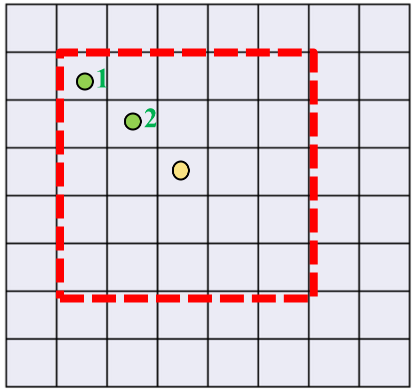
Method 4: Edge-Aware Antialiasing Based on an Enhanced Bilateral Filter



Contribution: Our modified Bilateral filter

Classic Bilateral filter:

$$I_{filtered}(p) = \frac{1}{W_p} \sum_{q \in \Omega} I(q) \cdot \underbrace{exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right)}_{\text{spatial closeness}} \cdot \underbrace{exp\left(-\frac{|I(p)-I(q)|^2}{2\sigma_i^2}\right)}_{\text{intensity similarity}}$$



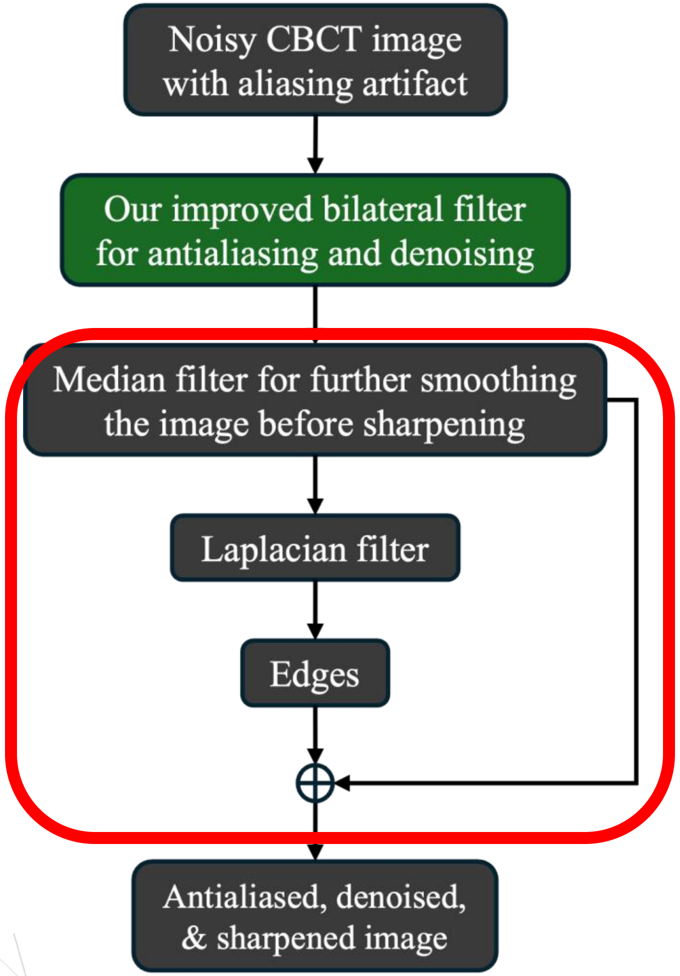
Our Modified Bilateral Filter:

$$I_{filtered}(p) = \frac{1}{W_p} \sum_{q \in \Omega} I(q) \cdot \underbrace{exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right)}_{\text{spatial closeness}} \cdot \underbrace{exp\left(-\frac{|I(p)-I(q)|^2}{2\sigma_i^2}\right)}_{\text{intensity similarity}} \cdot \underbrace{exp\left(-\frac{(\|\nabla I(p)\| - \|\nabla I(q)\|)^2}{2\sigma_g^2}\right)}_{\text{gradient similarity}} \cdot \underbrace{exp\left(-\frac{\left(std(N_p) - std(N_q)\right)^2}{2\sigma_t^2}\right)}_{\text{texture similarity}}$$

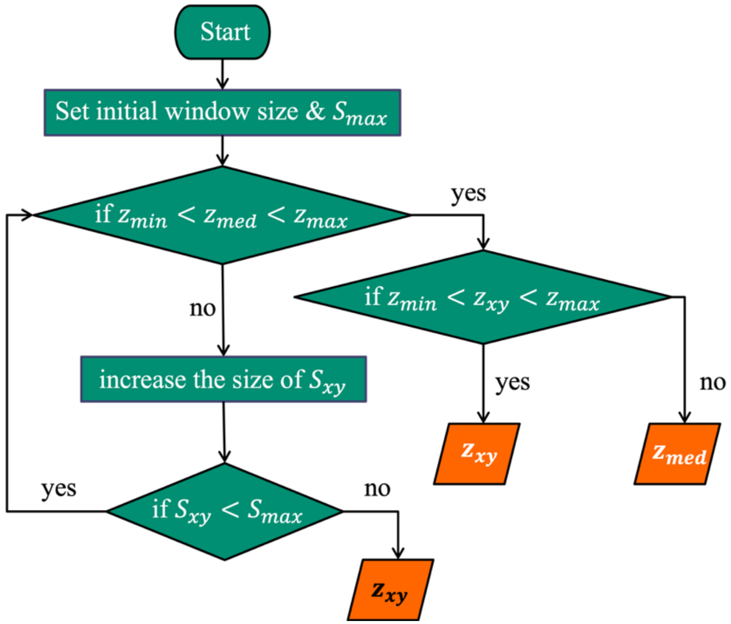
S. Mirzaei, H. R. Tohidypour, S. Mirabbasi, and P. Nasiopoulos, "A novel edge-aware bilateral filter for antialiasing and denoising in low-dose CBCT imaging," in Proc. 2025 IEEE International Conference on Image Processing (ICIP), 2025.

Noise and Artifacts Reduction

Method 4: Edge-Aware Antialiasing Based on an Enhanced Bilateral Filter



Adaptive Median Filter:



Sharpening:

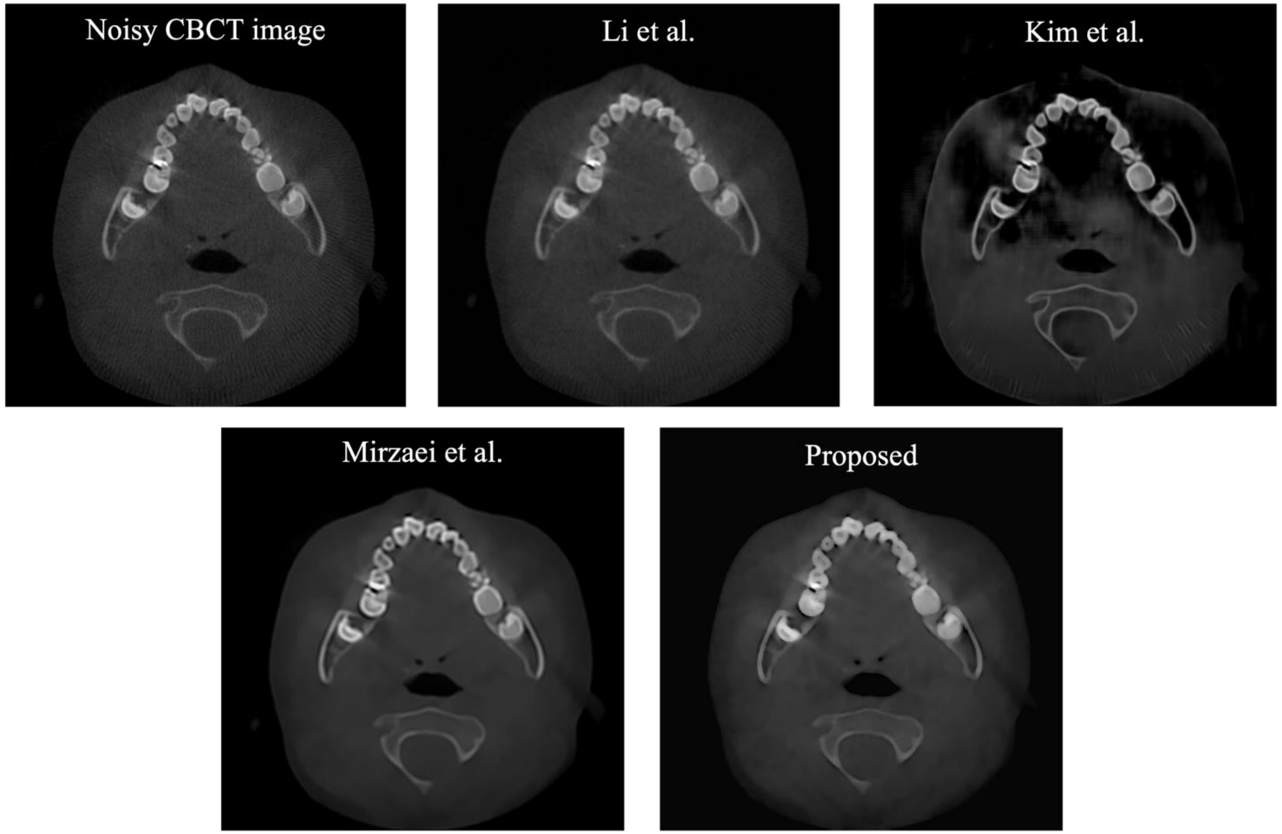
$$F = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$I_{sh} = I_c + \underbrace{c(I_c * F)}_{\text{edges}}$$

Noise and Artifacts Reduction

Method 4: Edge-Aware Antialiasing Based on an Enhanced Bilateral Filter

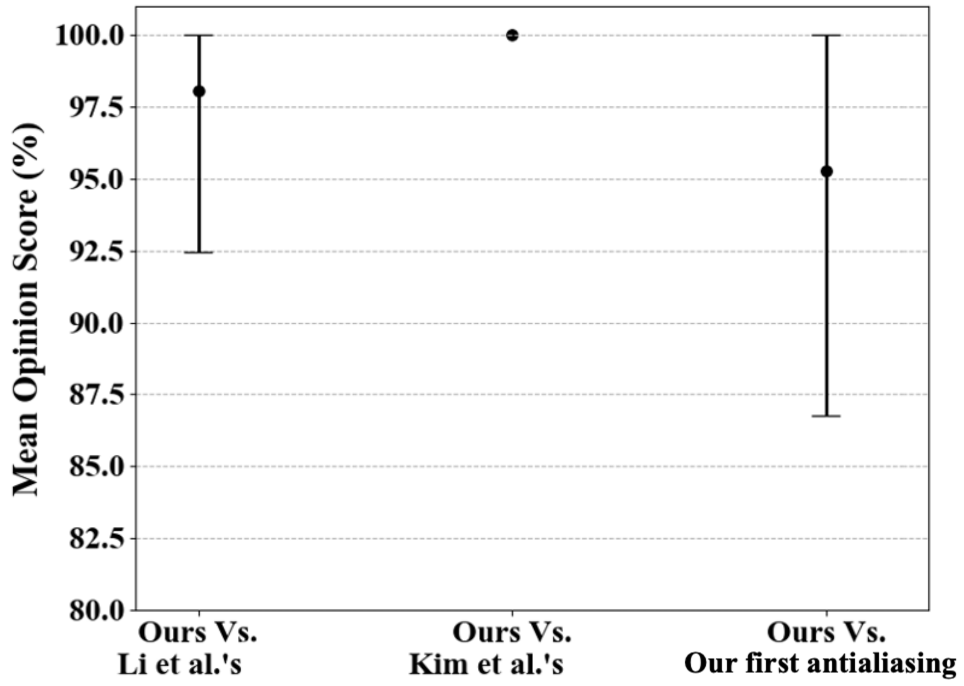
Visual Comparisons



Noise and Artifacts Reduction

Method 4: Edge-Aware Antialiasing Based on an Enhanced Bilateral Filter

Subjective Evaluations

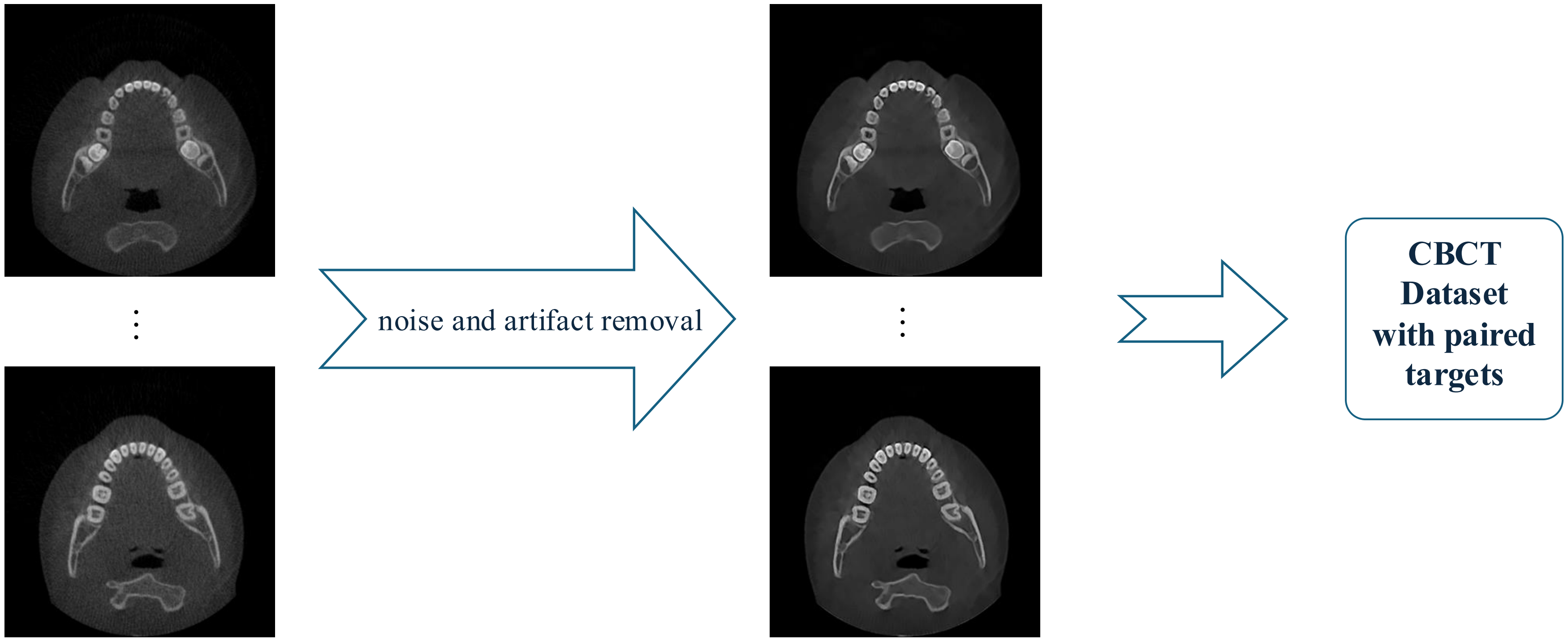


Number of times (%) subjects preferred the visual quality of CBCT images generated by our approach over other methods - Mean Opinion Score (MOS).

Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction

Contribution: Our unique CBCT dataset



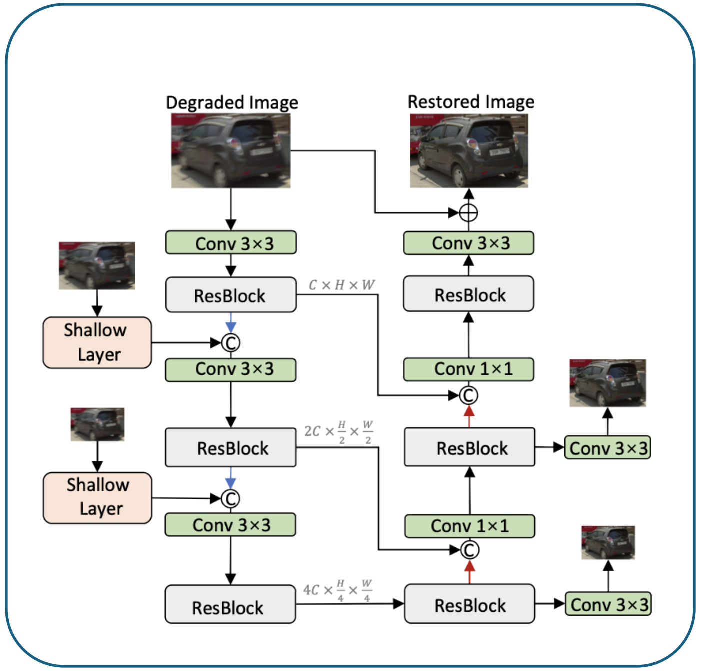
Noisy CBCT images

Produced realistic paired targets

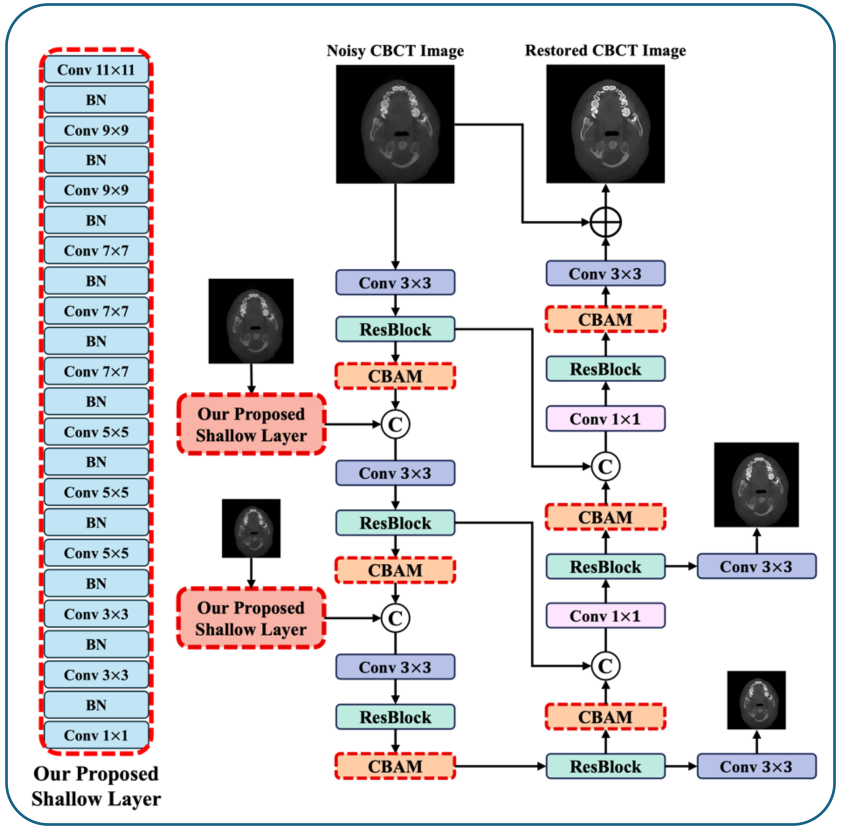
S. Mirzaei, H. R. Tohidypour, S. Mirabbasi, and P. Nasiopoulos, "Learning beyond generated targets: A modified SFNet for CBCT image enhancement," in Proc. 2025 25th International Conference on Digital Signal Processing (DSP), Jun. 2025, pp. 1–5.

Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction



Original SFNet proposed by Cui et al.



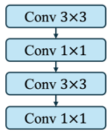
Our improved SFNet

Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction

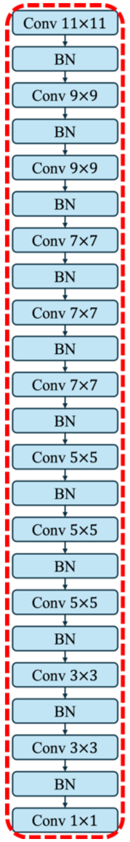
Contributions: Modifications 1 & 2 to SFNet for optimal denoising of CBCT images

1. Improved Shallow Layer for Better Feature Extraction



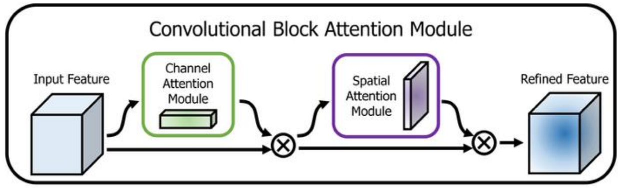
Originial shallow layer

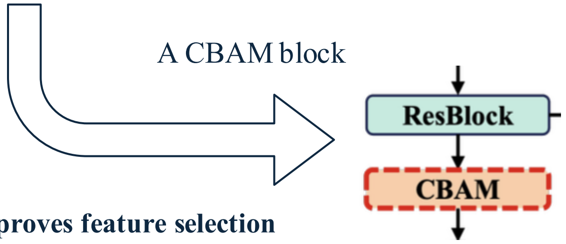
Deeper Convolutional layers + Batch Normalization



Our improved shallow layer

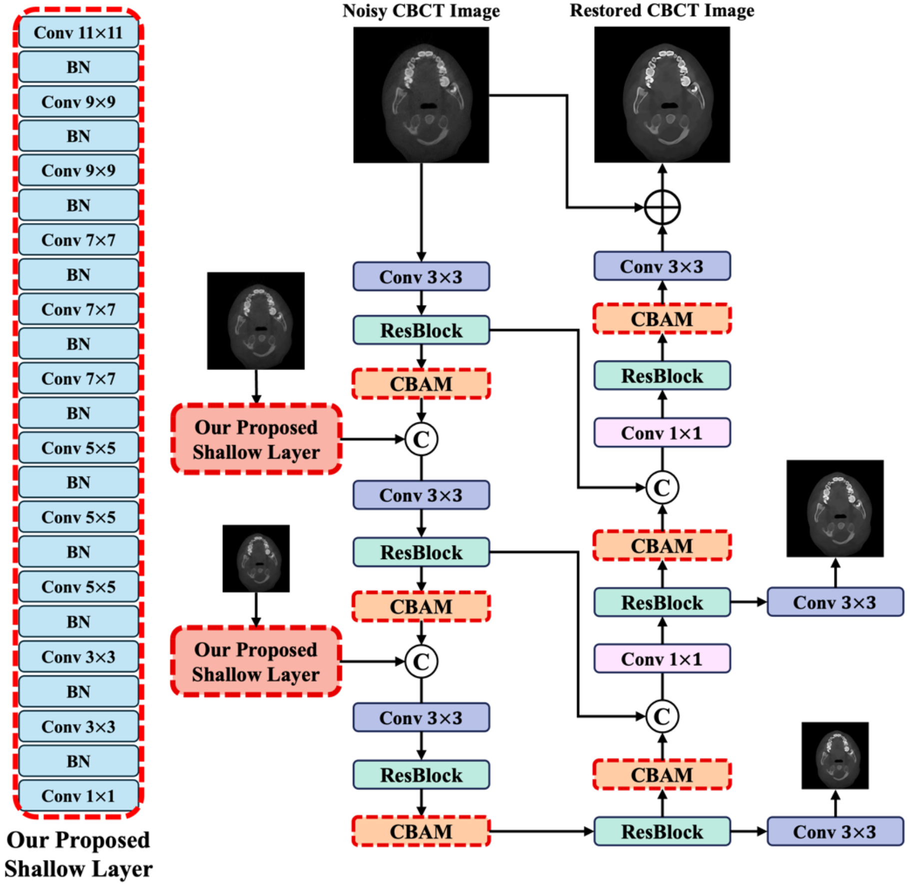
2. Integrating CBAM





Improves feature selection through both channel and spatial domains

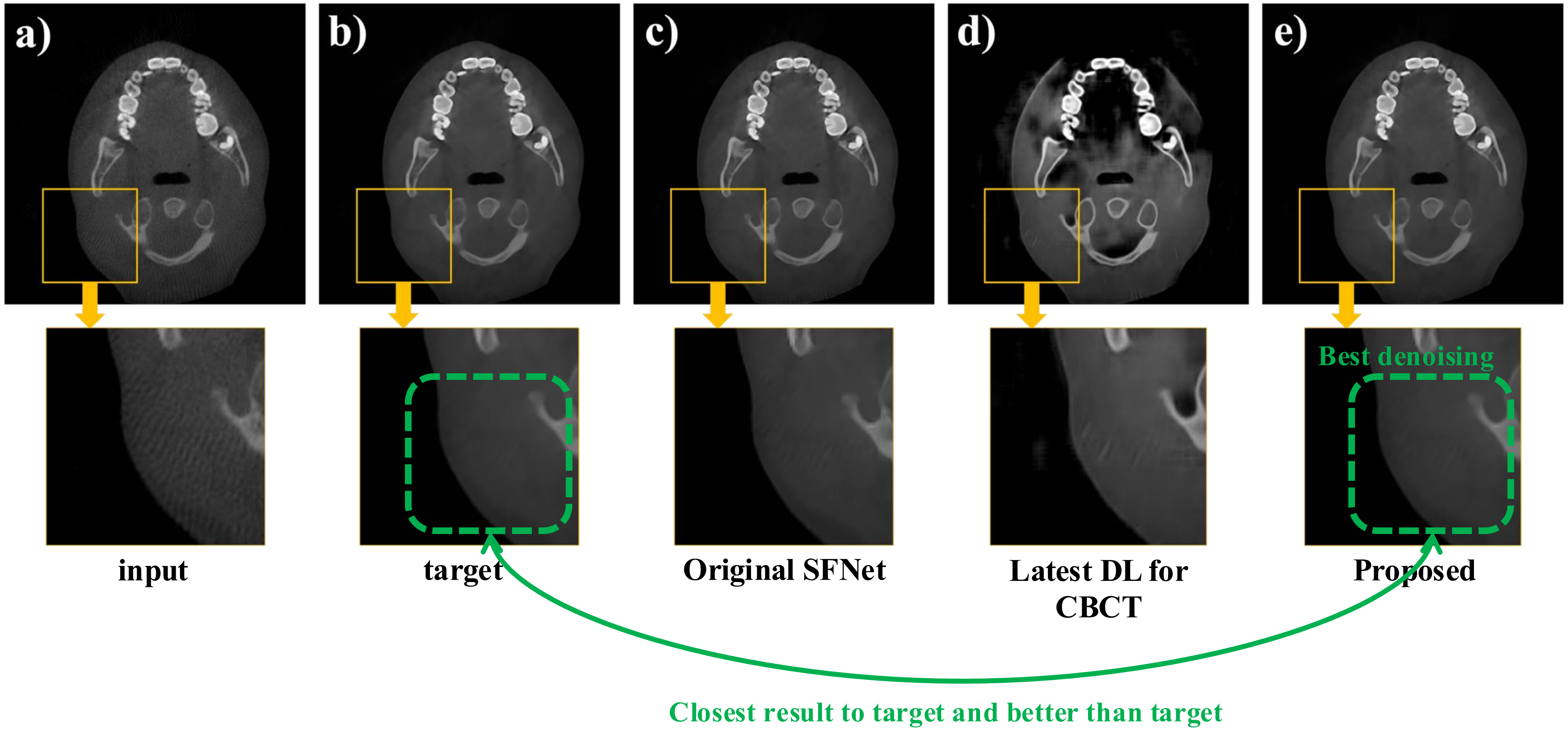
Placement after Residual Block



Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction

Visual Comparisons



Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction

Objective Evaluations

Full-Reference Objective Evaluations:

Methods	Full-Reference Quality Metrics	
	PSNR (dB)	*MS-SSIM*
Original SFNet	44.73	0.9845
The latest DL method	21.21	0.8101
Our modified SFNet	**46.77**	**0.9857**

BEST

No-Reference Objective Evaluations:

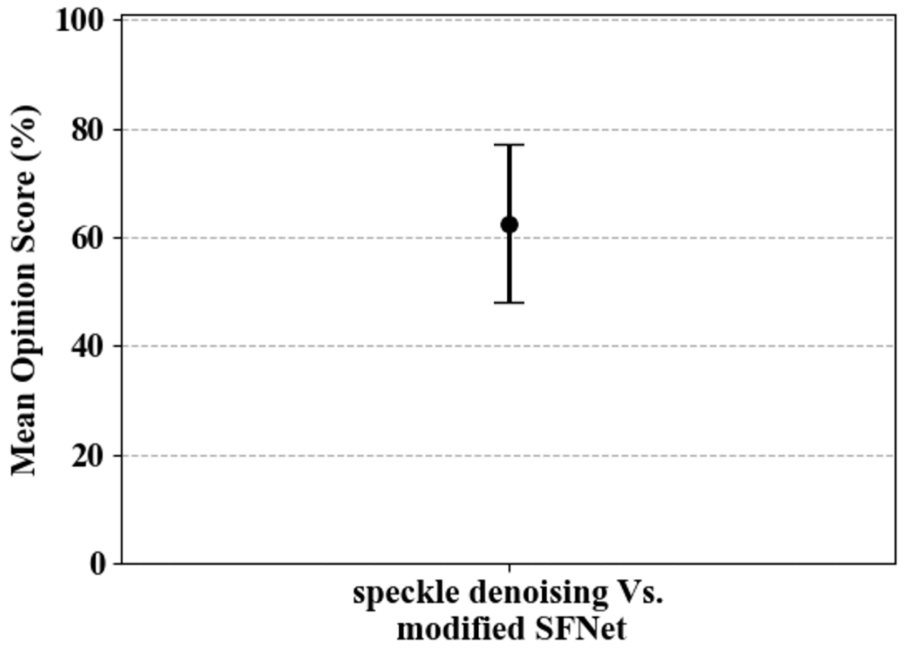
Images	No-Reference Quality Metric *SSEQ*
Noisy CBCT image	2.99
Target (generated by us)	2.14
Original SFNet	2.24
The latest DL method	2.51
Our modified SFNet	**2.10**

BEST

Noise and Artifacts Reduction

Method 5: Proposed Modified Selective Frequency Network (SFNet) for CBCT Noise Reduction

Subjective Evaluations



Best Denoising:
our speckle noise reduction method

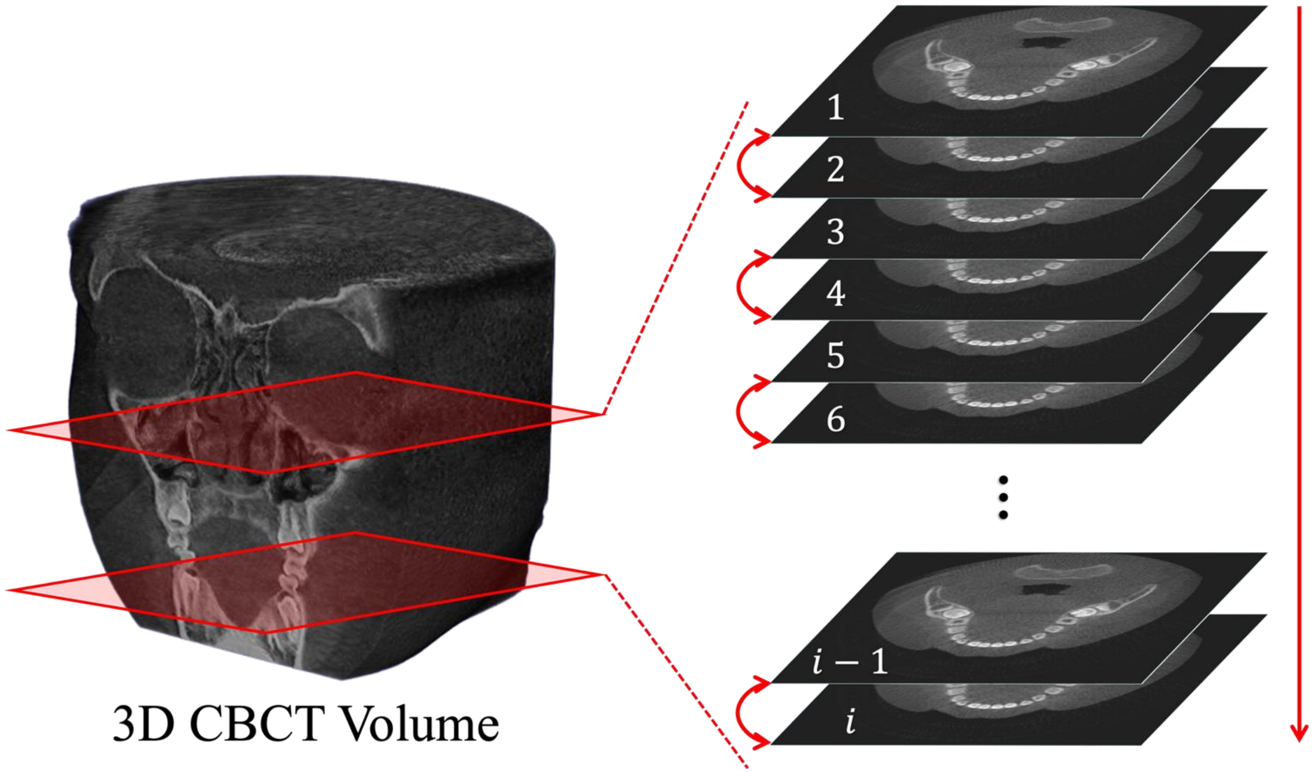
Step 2

"Spatial Resolution Enhancement"

Spatial Resolution Enhancement

Proposed Lightweight StereoMamba for CBCT Resolution Enhancement

Contribution: Leveraging information between adjacent CBCT scans to upscale both scans



Spatial Resolution Enhancement

Proposed Lightweight StereoMamba for CBCT Resolution Enhancement

Results of our comparative analysis of existing Single-Image Super-Resolution (SISR) & Stereo-Image Super-Resolution (SSR) methods

	Method	#S	#Params	PSNR	SSIM
SISR	SwinIR	x2	11.28M	36.32	0.9849
SSR	NAFSSR-T	x2	0.45M	36.72	0.9865
	NAFSSR-S	x2	1.54M	36.65	0.9859
	NAFSSR-B	x2	6.77M	36.47	0.9857
	NAFSSR-L	x2	23.79M	36.08	0.9846
	StereoMamba	x2	7.55M	35.88	0.9840

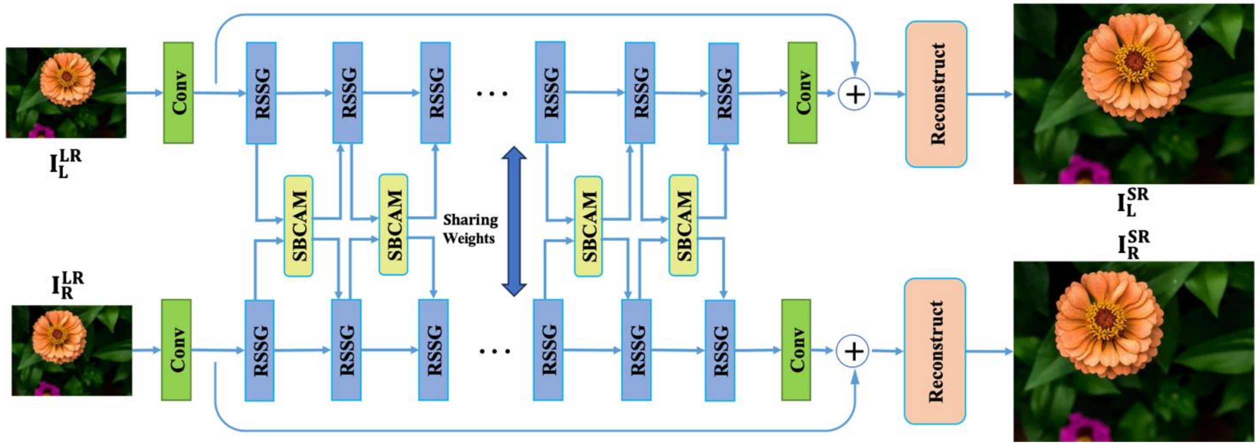
→ **The most promising architecture**
But worst generalizability

Large, complex models tend to overfit when applied to content with much lower complexity

Spatial Resolution Enhancement

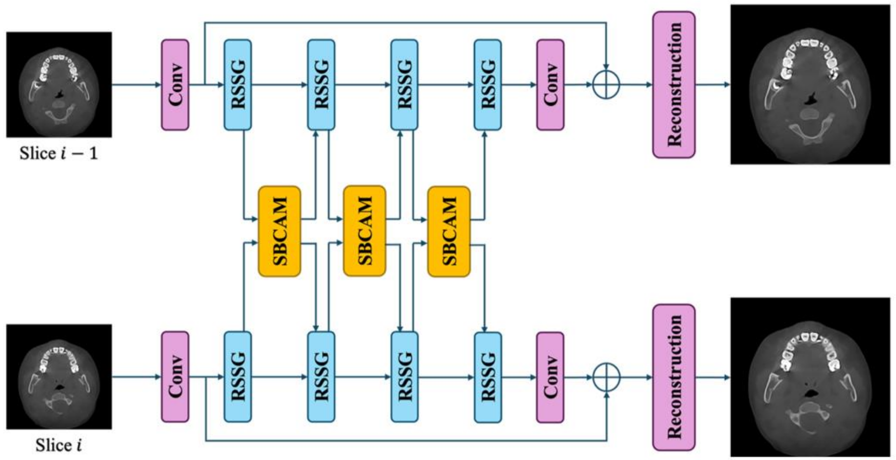
Proposed Lightweight StereoMamba for CBCT Resolution Enhancement

Original StereoMamba:



Contribution: Modifying StereoMamba to optimize upscaling of CBCT images

StereoMamba-Light:



A lightweight version without memorizing dataset-specific details

Spatial Resolution Enhancement

Proposed Lightweight StereoMamba for CBCT Resolution Enhancement

No-Reference Objective Evaluations

NIQE scores for our method and existing approaches

	Method	#S	#Params	NIQE
SISR	SwinIR	x2	11.28M	5.1
SSR	NAFSSR-T	x2	0.45M	4.2
	NAFSSR-S	x2	1.54M	4.5
	NAFSSR-B	x2	6.77M	4.8
	NAFSSR-L	x2	23.79M	5.4
	StereoMamba	x2	7.55M	6.1
	StereoMamba-Light	x2	**0.9M**	**3.7**

Step 3

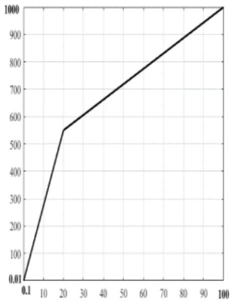
“Brightness and Contrast Enhancement”

Brightness and Contrast Enhancement

inverse Tone Mapping Operator (iTMO)

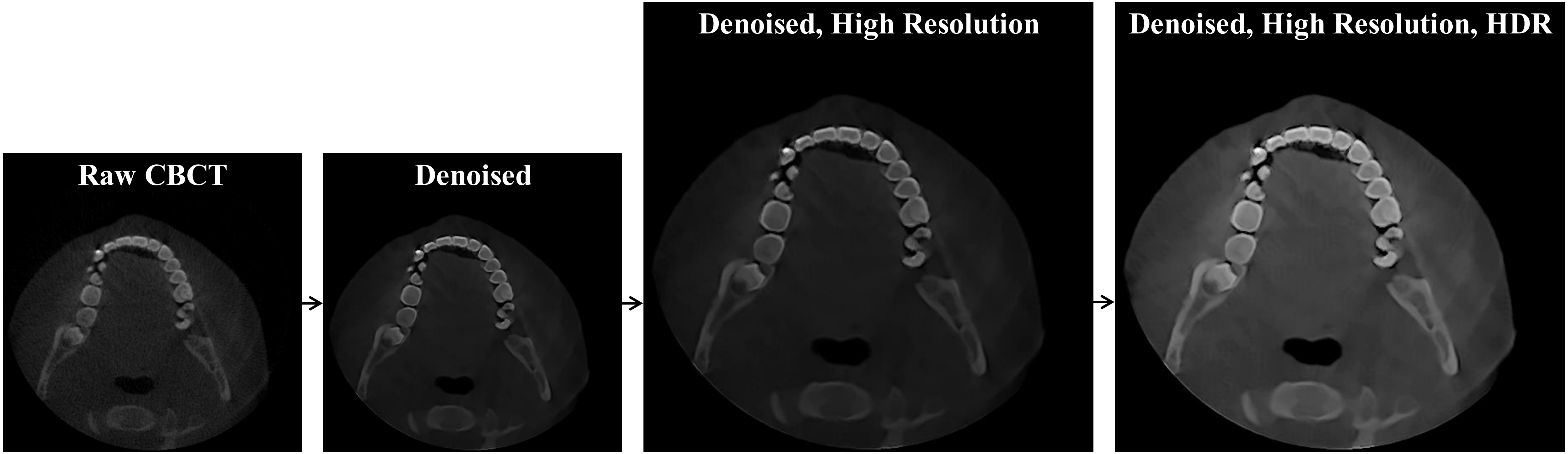
SDR Image

HDR Image



Conclusion

Conclusion



Noisy, Low Resolution, SDR CBCT Image → Denoising → Super Resolution → Inverse Tone Mapping

Thank you