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CardioBoost

Cardiac-Specific Deep Learning

Training Algorithm

Technical White Paper

01

version

Contents

Introduction

Cardiovascular diseases remain a paramount concern in global clinical practice, with their accurate assessment and diagnosis heavily reliant on high-quality cardiac imaging modalities. Computed tomography (CT), as the cornerstone of non-invasive cardiac evaluation, provides exceptional visualization of cardiac anatomy and coronary arteries. However, achieving optimal radiation dose reduction while maintaining diagnostic efficacy under the ALARA (As Low As Reasonably Achievable) principle persists as a critical challenge in cardiac CT imaging.

United Imaging Healthcare’s (UIH) proprietary CardioBoost algorithm represents a cardiac-optimized deep learning reconstruction breakthrough. Leveraging a three-dimensional neural network architecture trained on multimillion datasets covering dedicated optimization for coronary stents, plaques, and microvascular structures, this innovative solution overcomes conventional cardiac imaging limitations. Integrated into the reconstruction pipeline, CardioBoost enables simultaneous achievement of noise suppression, enhanced low-contrast detectability (LCD), and preserved spatial resolution under low-dose conditions, establishing new benchmarks for cardiac CT image quality.

This technical whitepaper systematically reviews the evolution of cardiac reconstruction algorithms, provides in-depth analysis of CardioBoost's technological innovations in low-dose denoising and LCD enhancement, and demonstrates its clinical value through phantom validation studies and real-world applications.

Cardiac CT Image Reconstruction

Reconstruction algorithms play a pivotal role in enhancing CT image quality. Over decades, significant research efforts have been dedicated to advancing cardiac CT reconstruction methodologies, with the ultimate goal of obtaining diagnostically superior cardiac images while adhering to stringent low-dose scanning protocols.

Challenges in Cardiac Reconstruction

CT cardiac imaging is the most challenging clinical application of CT technology. Its technical difficulties are mainly reflected in two aspects: it demands extremely high temporal resolution to overcome motion artifacts caused by the rapid heartbeat, and it requires accurate display of the delicate structures of the cardiovascular system, as the morphological characteristics of lesions are crucial for clinical diagnosis.

At present, the technology faces a dilemma. Shortening the scanning time is the main way to improve temporal resolution when the mechanical performance limits the rotation speed of the gantry. However, this reduces the effective data volume, leading to a marked increase in image noise, which is unfavorable for presenting the delicate structures of the heart. To suppress noise interference, existing solutions often require a significant increase in radiation dose. Yet, the increase in dose is not proportional to the increase in effective data volume.

Therefore, developing a new reconstruction algorithm that can simultaneously reduce image noise and radiation dose while maintaining spatial resolution has become the core research focus in cardiac CT imaging.

Algorithms for Cardiac Image Reconstruction

To obtain high - quality clinical CT cardiac images, experts have continuously explored and proposed various image reconstruction algorithms to address these challenges.

The filtered back projection (FBP) is a basic image reconstruction algorithm and cannot resolve the conflict between image noise and spatial resolution [1]. With FBP reconstruction, using a lower frequency kernel and thicker slice thickness can help reduce image noise, but at the expense of decreased spatial resolution. Unfortunately, the aforementioned methods' adverse effects in cardiac imaging are unacceptable.

Hybrid iterative reconstruction (HIR) is based on FBP technology, using iterative de-noising in both the projection and image domains to reduce streak artifacts and image noise [2], thus enhancing cardiac imaging. However, due to FBP's inherent properties, the benefits of HIR are limited as the dose decreases. Moreover, a high level of iterative weighting often results in "plastic" or "blotchy" images, which could negatively impact cardiac image quality and diagnostic accuracy [3].

Model - based iterative reconstruction (MBIR) addresses previous - generation algorithm limitations by incorporating complex system models and multiple iterations [1,5]. This fundamentally eliminates data noise and benefits high - quality cardiac imaging. However, it has a huge computation workload, taking too long for image reconstruction. Furthermore, MBIR employing heavy iterative weighting can generate 'plastic' or 'blotchy' artifacts in reconstructed images [3] and fails to meet clinical cardiac imaging needs.

Recently, deep learning technology has been increasingly utilized and has demonstrated its potential in various application fields, including medical imaging. Deep learning is an end-to-end data-driven method that uses a large amount of data to train neural networks, enabling them to automatically learn patterns and rules of data [7,8]. In recent years, deep learning has demonstrated its capabilities in CT imaging reconstruction for noise and artifact reduction, particularly in cardiac imaging. By training with numerous typical clinical images, the deep learning-based CT image reconstruction method can suppress noise while preserving the natural noise texture. Moreover, by specifically training on clinical images with coronary stents, calcified plaques, and other special features in CT cardiac imaging, the algorithm can better focus on these scenarios, improving image quality.

UIH has consistently focused on the development and application of cutting-edge technologies to break through the bottleneck of traditional CT image reconstruction methods. Inspired by the deep learning technology, UIH presents a deep learning-based CT images reconstruction method — CardioBoost.

CardioBoost: Excellent Deep Learning Reconstruction Engine

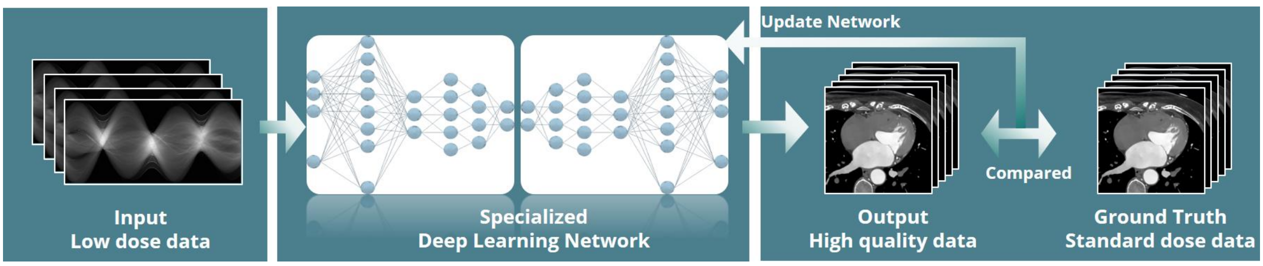
UIH has consistently emphasized the development and application of cutting-edge technologies. Driven by research and development in deep learning technology, UIH has introduced CardioBoost to achieve high-quality reconstructed images, particularly in low-dose scans. With millions of diverse data-sets and a specialized network design, CardioBoost facilitates efficient workflow in a wide range of clinical scenarios.

Precise Training Process of CardioBoost

The workflow of the CardioBoost proposed by UIH is illustrated in Figure 1. Two data-sets were comprised of a normal dose data-set and the simulated low dose data-set. Then, the deep learning network is trained to extract semantic information from images to reconstruct high-quality images, especially in low-dose scans. Finally, the trained deep learning network of CardioBoost can be easily integrated into the routine clinical workflow.

During each training cycle, all simulated low dose images are randomly shuffled and input to the network. A dedicated loss function quantitatively measures the pixel-wise discrepancy between the network's output and the ground truth clean image. This error metric drives the optimization process through backpropagation with adaptive gradient descent, systematically adjusting network parameters to minimize reconstruction errors. Millions of parameters in the deep learning network are tuned through back propagation, reducing the difference between the network output and normal dose images.

Then, a large amount of real low-dose data-set not used in training is applied to validate the algorithm, ensuring its robustness and accuracy.



[Figure 1] The training process of the CardioBoost

Millions Various Data-sets for Driving CardioBoost

Data provides rich information and features, aiding deep learning models in learning more complex patterns and relationships. Sufficient data is essential for the model to achieve better universality, robustness, and subsequently, higher accuracy.

The training data-set for CardioBoost includes approximately millions pairs of normal dose images and simulated low dose images. Based on the normal dose data-set, a low dose simulation algorithm is applied to create the corresponding low dose data-set. As described in references[9,10], the low dose simulation algorithm considers noise produced by low dose tube current, including photon noise and electronic noise.

By utilizing the low dose simulation, a massive training data-set is generated without scanning the same patient twice with normal dose and low dose respectively. Additionally, the mismatch of paired training data can be entirely avoided.

CardioBoost's dataset uses tissue - recognition classification, identifying hundreds of tissues across the chest and abdomen, including plaques and heart valves, to boost model robustness and tissue contrast.

Notably, to cater to diverse cardiac clinical scenarios and maintain universality, the dataset employs targeted augmentation strategies specializing in stents, plaques, and small vessels, thereby improving the algorithm's performance in these key cardiac scanning scenarios.

Specialized Deep Learning Network Design

CT provides three - dimensional (3D) cardiac imaging data. Cardiac image analysis based on volumetric data offers more comprehensive and accurate diagnostic information for clinical practice. CardioBoost uses 3D data processing to learn the entire cardiac CT dataset and understand the continuous 3D - spatial representation of anatomical structures. Consequently, CardioBoost ensures the uniformity and consistency of 3D images while effectively suppressing noise in axial images.

The extraction of semantic information at different levels is crucial for image reconstruction. To prevent performance degradation caused by information loss as network depth increases, CardioBoost utilizes a dense connection method with varying depth information. This approach effectively prevents information loss, thereby completing more accurate reconstruction tasks by combining more information.

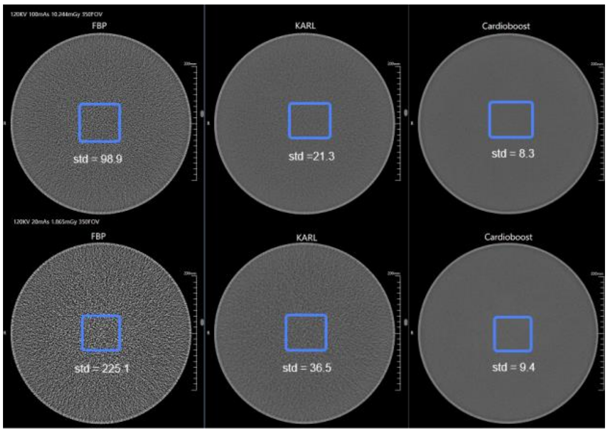
Phantom Validation

Phantom studies were performed to objectively assess CardioBoost's performance in noise reduction, LCD improvement and high spatial resolution enhancement, particularly under lower radiation dose.

Excellent Performance in Noise Reduction

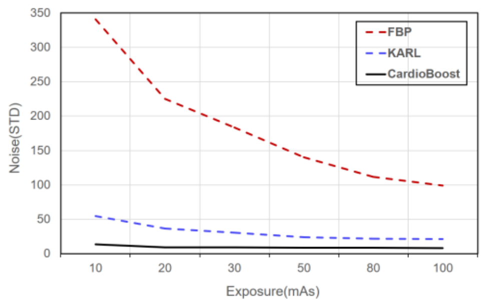
A 320mm diameter water phantom was scanned to evaluate CardioBoost's performance in noise reduction. The water phantom was scanned with 120 kV at various dose levels from 10 mAs up to 100mAs. Phantom images under different dose levels were reconstructed by FBP, KARL (a hybrid iterative reconstruction method developed by UIH), and CardioBoost.

Noise level is defined as the standard deviations (STD) of the Hounsfield Unit (HU) values within the region-of-interest (ROI)~~.~~ As illustrated in Figure 2, CardioBoost demonstrates the best noise reduction capability compared with FBP and KARL at both dose levels.

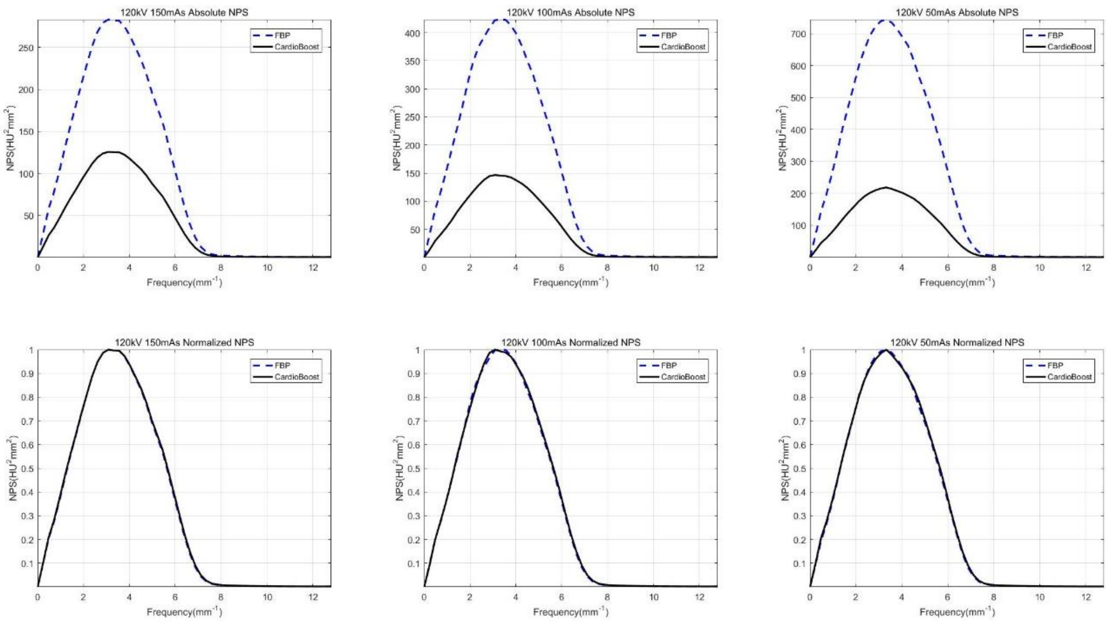


[Figure 2] The reconstructed images and STD values of the 320 mm water phantom under different reconstruction methods and dose levels.

Additionally, images reconstructed by three different methods were used to calculate the image noise in the central ROI at each dose level. Figure 3 presents the image noise with FBP, KARL and CardioBoost. From the noise curves we observe that CardioBoost exhibits the minimal noise level compared with FBP at all dose levels, particularly at low dose levels.



[Figure 3] Curves of noise with dose for different reconstruction method.



***[Figure 4]** Curves of noise power spectrum （NPS）for different reconstruction method.*

The basic principle of noise power spectrum (NPS) measurement is based on Fourier transform, which transforms signals to the frequency domain for measurement and analysis. It can describe the noise frequency variations in reconstructed data and fully considers the effects of factors such as reconstruction, filtering, and post-processing on noise correlation. This makes it a relatively comprehensive method for noise evaluation.

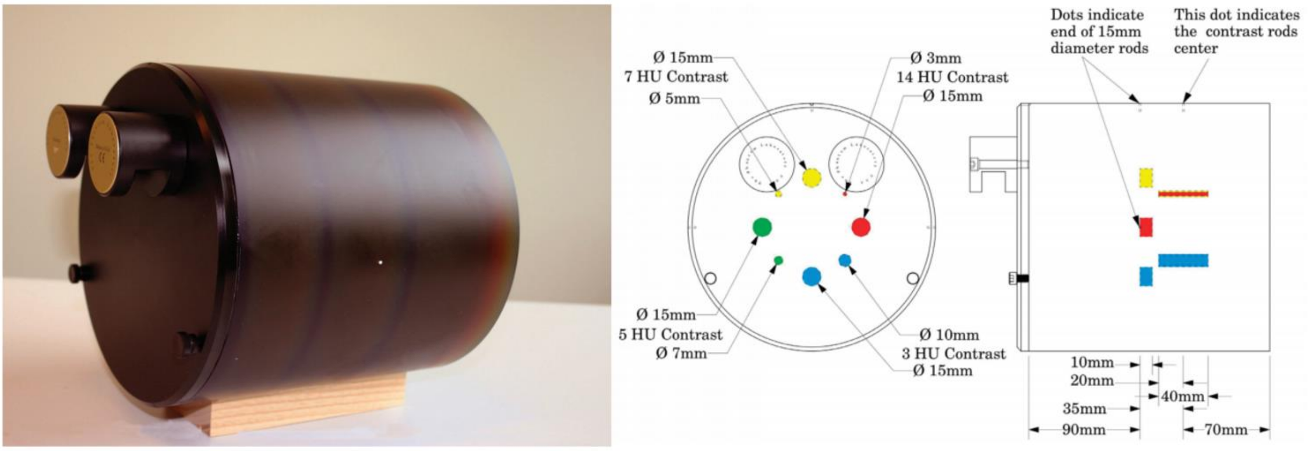
From the absolute NPS curve, CardioBoost noise enhanced when scanning dose decreased but better than FBP. From the normalized NPS curve, CardioBoost image noise peak are similar when scanning dose varied and the peak of CardioBoost NPS curve is similar as the peak of FBP.
From the noise spectrum power curves of Figure 4, the peak of CardioBoost NPS is similar as the peak of FBP which showed that noise pattern of CardioBoost is similar to FBP.

LCD Improvement under Low Dose Imaging

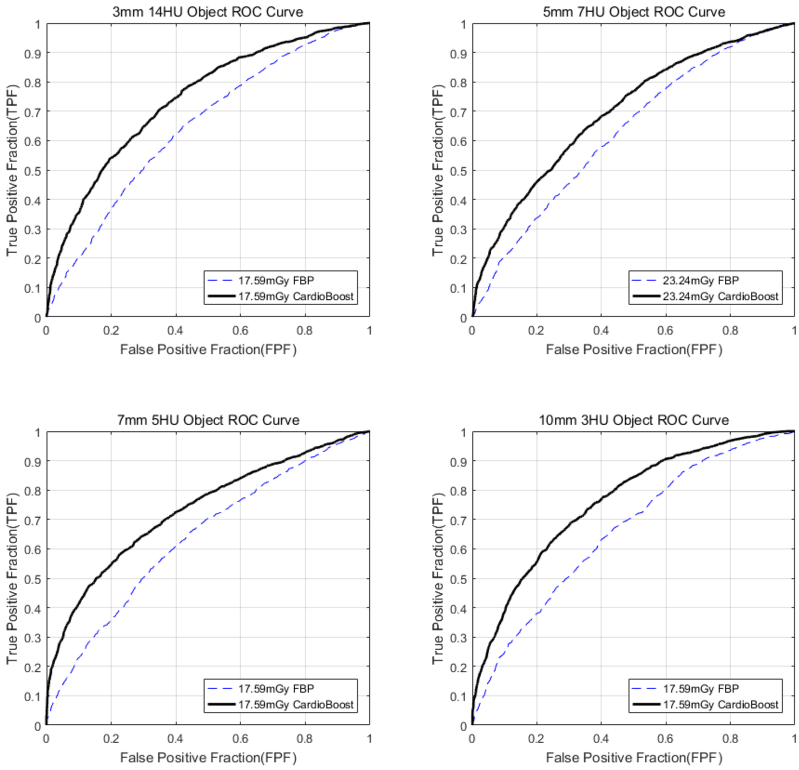
LCD is often regarded as a critical indicator of image quality, especially under low dose imaging, as it reflects the detectability of low contrast objects, which may represent early-stage lesions in clinical scenarios.

The quantitative evaluation of LCD improvement under low dose is based on task-based method with a model observer [11], as recommended by the Joint MITA-FDA CT Image Quality Task Group.

We used a model observer LCD evaluation method [11] to evaluate the capability of CardioBoost for dose reduction and LCD improvement. A CCT189 MITA CT IQ low contrast phantom (The Phantom Laboratory, Salem, NY) was used for evaluation, as shown in Figure 5. It contained four rods with different diameters and contrasts. The phantom was scanned with 120 kVp at different dose levels ($CTDI_{vol}$ = 4.16/2.50 mGy). Images were reconstructed using FBP and CardioBoost. The Channelized Hotelling Observer (CHO) [12] was used to assess the LCD. The Receiver Operating Characteristic (ROC) curves and the Area Under the ROC Curve (AUC) values were calculated to compare the LCD performance between FBP and CardioBoost.



[Figure 5] CCT189 MITA CT IQ low contrast phantom, which contains 4 rods with different diameter and contrast.

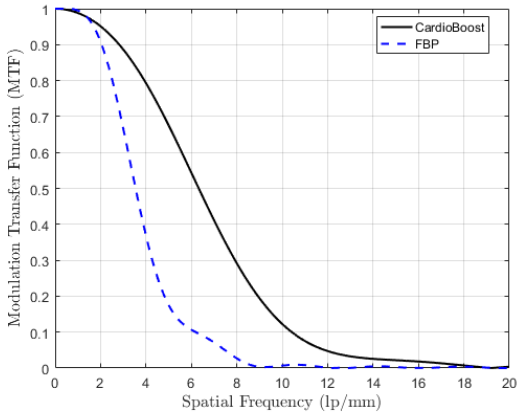


[Figure 6] The ROC curves and AUC values of FBP and CardioBoost at the same dose. Higher true positive fractions and AUC values indicate better LCD performance.

From the ROC curves and AUC values shown in figure 6, it is apparent that CardioBoost shows better LCD performance than FBP at the same dose.

High Spatial Resolution Improvement under Low dose Imaging

To assess the spatial resolution properties of CardioBoost results, we scanned the Catphan 700 phantom with 100 kV at 100 mAs, namely 9.968 mGy CTDIvol dose. The phantom images were reconstructed using FBP and CardioBoost in 512x512 matrices. The Modulation Transfer Function(MTF) of the reconstructed images in Figure 7 demonstrate that CardioBoost exhibits higher spatial resolution and less noise compared with FBP under the same scanning conditions.



[Figure 7]. *MTF curves for different reconstruction method.*

Clinical Applications Evidence

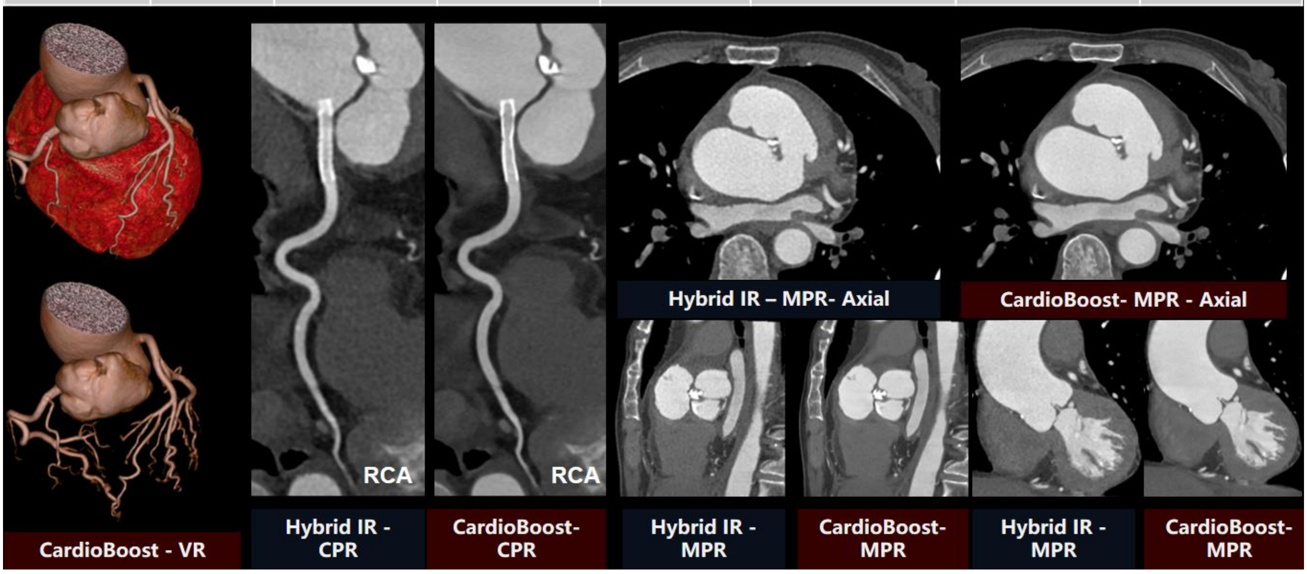
The following clinical cases subjectively evaluate CardioBoost's effectiveness in clinical applications, demonstrating its ability to produce high-quality CT images

CardioBoost in Cardiac Coronary Stents

Figure 8 illustrates a case where KARL and the proposed CardioBoost technology are utilized for cardiac scanning. The patient was scanned at 100 kV, 102 mAs, with $CTDI_{vol}$ = 8.00 mGy and effective dose 1.57 mSv.

CardioBoost significantly reduces image noise and enhances image contrast. In this clinical case of congenital bicuspid aortic valve and pseudoaneurysm, the images reconstructed by CardioBoost show clearer valve details. Compared to KARL, CardioBoost also provides a clearer display of the lumen within the stent.

Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Axial	100	102	512×512	0.25	0.5	8.00	1.57

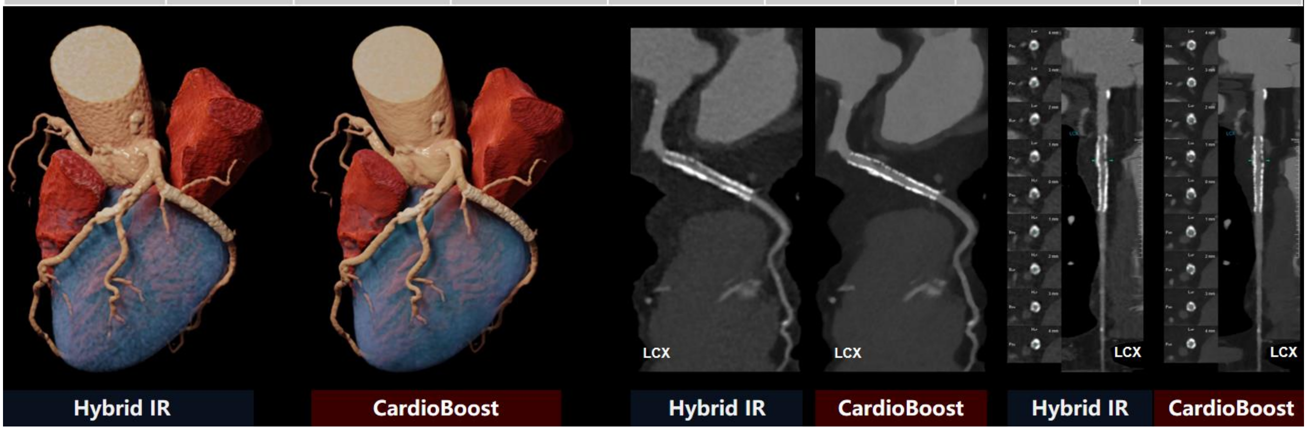


[Figure 8] Cardiac images reconstructed using KARL and CardioBoost. Compared with the traditional KARL, CardioBoost clearly shows the valve and the lumen within the stent.

Figure 9 shows another example of a heart stent scan using KARL and CardioBoost techniques. The patient was scanned at 100 kV, 635 mAs, with CTDIvol = 13.1 mGy and effective dose 4.05 mSv.

Compared with KARL, CardioBoost reconstructed images had lower noise, higher signal-to-noise ratio (SNR) in lumen, and better contrast, which could clearly show the hyperplasia of stent intima.

Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Helical	100	635	512×512	0.25	0.5	13.1	4.05



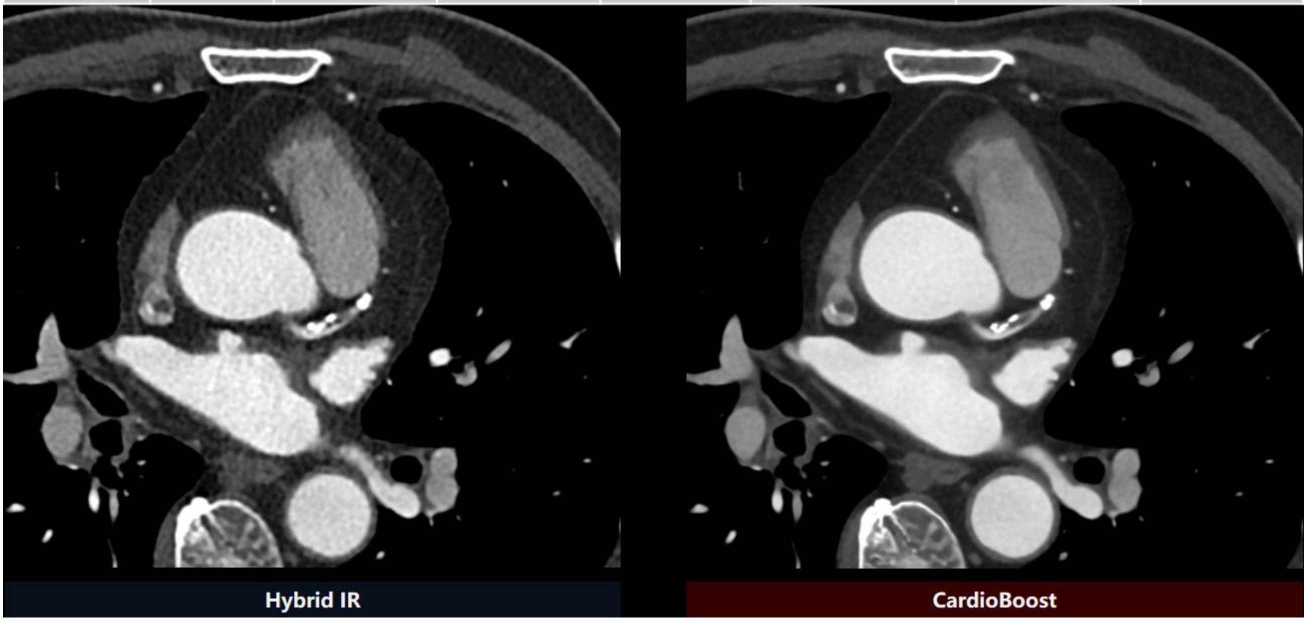
[Figure 9] Cardiac images reconstructed using KARL and CardioBoost. Compared with the traditional KARL, CardioBoost clearly shows hyperplasia of the intima of the coronary stent.

CardioBoost in Cardiac Coronary Plaques

Figure 10 presents a cardiac calcification plaque scanning case using KARL and CardioBoost. The patient was scanned at 120 kV, 89 mAs, with CTDIvol = 16.01 mGy and effective dose 3.85 mSv.

Apparently, CardioBoost can reduce image noise and enhance image contrast. Compared with KARL images, CardioBoost images exhibit a higher SNR, and the boundaries of mixed plaques, particularly soft plaques, are more clearly defined, thus boosting diagnostic confidence.

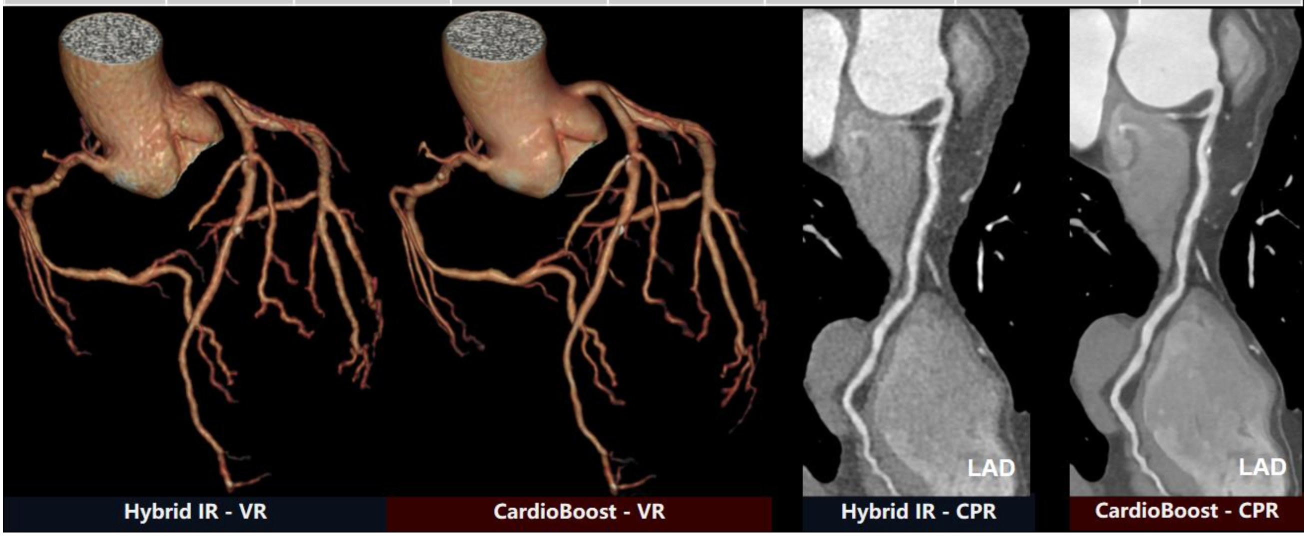
Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Axial	120	89	512×512	0.25	0.5	16.01	3.85



[Figure 10] Cardiac images reconstructed with KARL and CardioBoost. Compared with traditional KARL, CardioBoost has a better SNR and shows clearer mixed plaque boundaries.

Figure 11 presents a cardiac scanning case with soft plaques. The patient was scanned at 100 kV, 133 mAs, with CTDIvol = 12.61 mGy and effective dose 2.47 mSv. It's apparent that CardioBoost significantly reduces image noise. Additionally, the contrast of coronary soft plaque is more obvious in images reconstructed with CardioBoost.

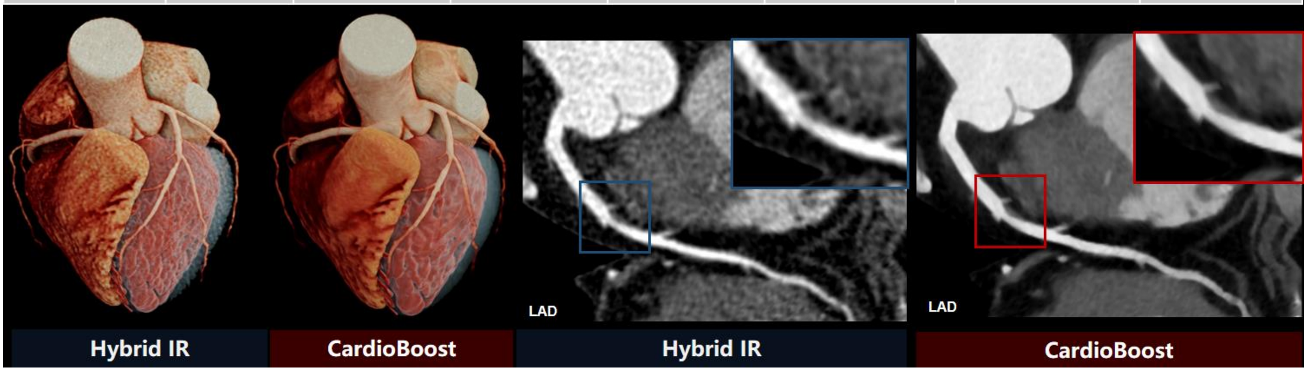
Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Axial	100	133	512×512	0.25	0.5	12.61	2.47



[Figure 11] Cardiac images reconstructed with KARL, CardioBoost. In comparison to the traditional KARL, CardioBoost provides clearer display of soft plaques.

Figure 12 presents a cardiac non-calcified plaque scanning case. The patient was scanned at 100 kV, 673 mAs, with CTDIvol = 12.09 mGy and effective dose 3.54 mSv. CardioBoost significantly reduces image noise, providing clear vessel boundaries, high imaging contrast, and clear display of Left Anterior Descending (LAD) non-calcified plaques.

Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Helical	100	673	512×512	0.25	0.5	12.09	3.54



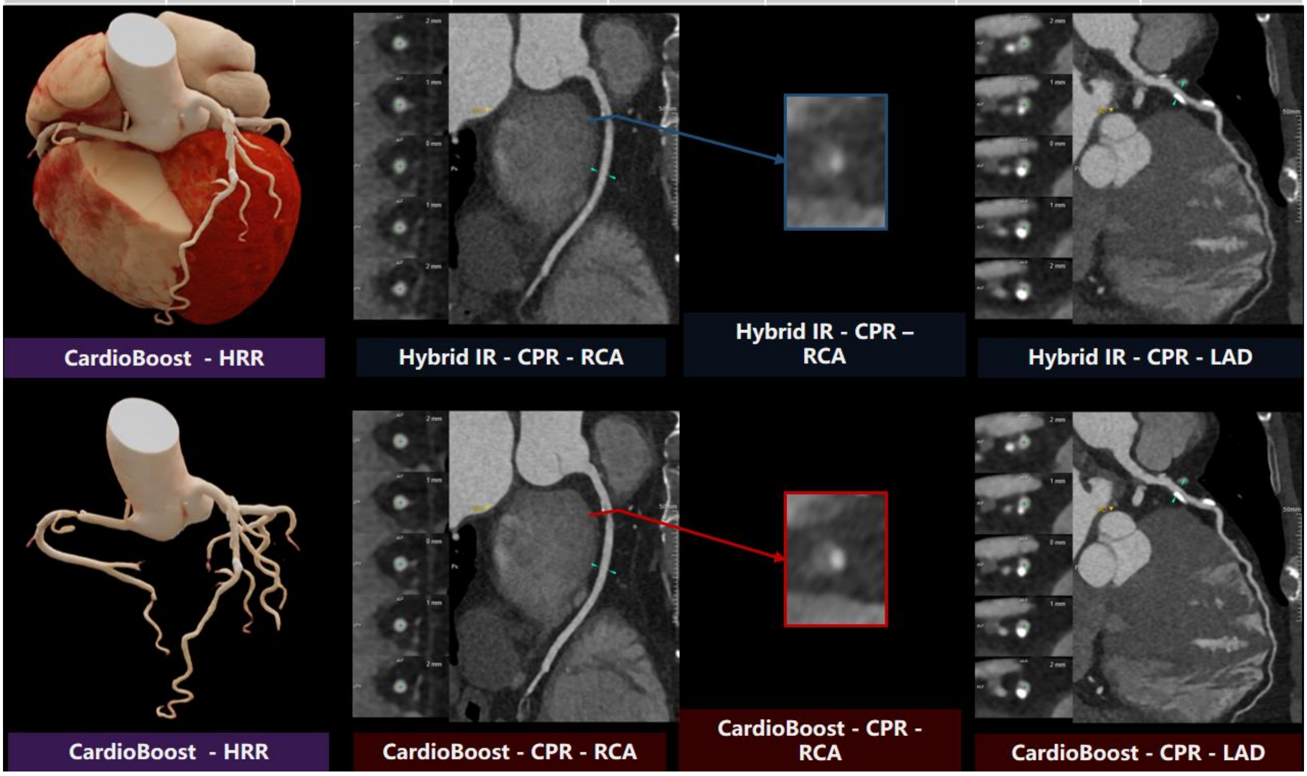
[Figure 12] Cardiac images reconstructed with KARL, CardioBoost. In comparison to the traditional KARL, CardioBoost significantly reduces image noise, providing clear vessel boundaries, high imaging contrast.

CardioBoost in Low Dose Coronary Imaging

Figure 13 presents a low dose cardiac scanning case. The patient was scanned at 80 kV, 148 mAs, with CTDIvol = 7.81 mGy and effective dose 1.53 mSv.

This shows CardioBoost can still boost imaging contrast at low doses, with CPR images displaying clearer blood vessel boundaries and more distinct contrast between mixed plaques and the vessel lumen.

Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
CorCTA Axial	80	148	512×512	0.25	0.5	7.81	1.53



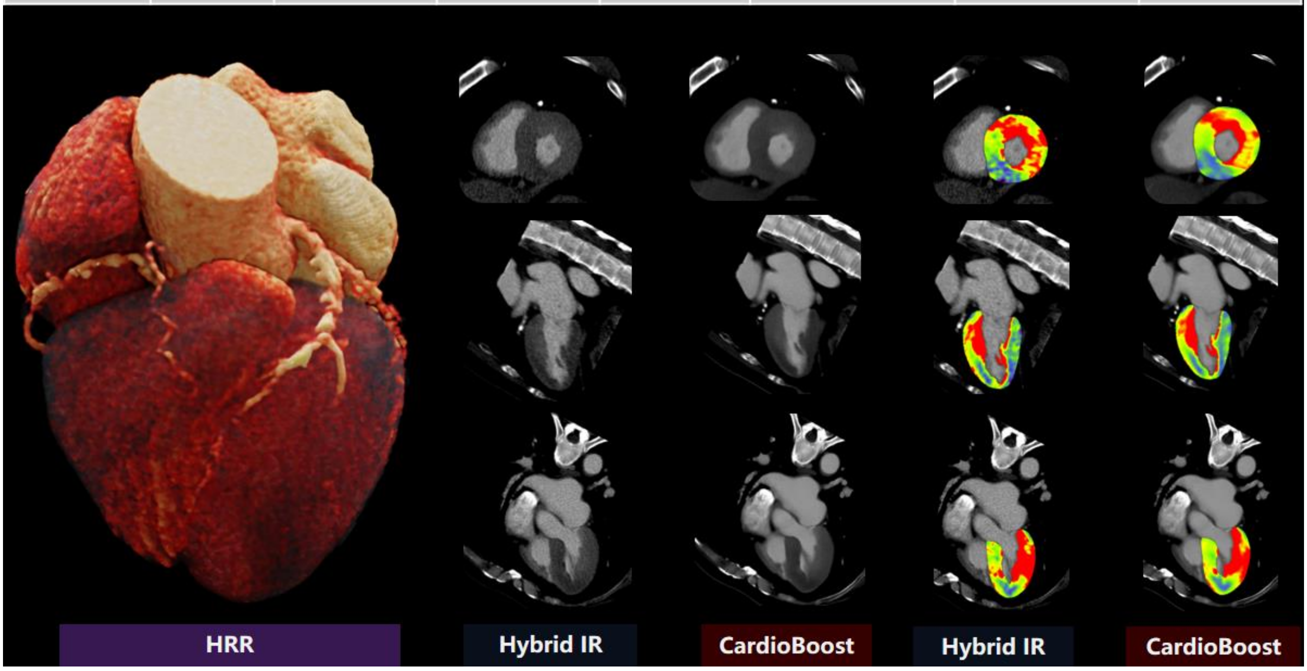
[Figure 13] Cardiac images reconstructed with KARL, CardioBoost. In comparison to the traditional KARL, CardioBoost still provides better imaging contrast at low doses.

CardioBoost in Myocardial Perfusion

Figure 14 presents a myocardial perfusion examination utilizing KARL and CardioBoost. The patient was scanned at 70 kV, 177 mAs, with CTDIvol = 19.7 mGy and effective dose 3.86 mSv.

CardioBoost effectively reduces radiation dose while significantly lowering image noise and enhancing tissue contrast, resulting in diagnostically acceptable image quality.

Scan Type	kV	mAs	Matrix	Rotation time(s)	Slice Thickness(mm)	CTDIvol(mGy)	Effective dose(mSv)
Myocardial Perfusion	70	177	512×512	0.25	0.5	19.7	3.86



[Figure 14] *Cardiac images reconstructed with KARL, CardioBoost. In comparison to the traditional KARL, CardioBoost significantly lowering image noise and enhancing tissue contrast.*

Conclusion

CardioBoost, based on a 3D deep learning neural network architecture, is meticulously designed using millions of datasets to create a superior model with greater universality, robustness, and accuracy.

Objective results from phantom validation and subjective results from clinical evidence show that, compared to the traditional HIR method, CardioBoost can obtain high - quality cardiac scanning images, significantly reduce image noise, and acquire high - resolution images at low doses. It also delivers outstanding performance in stents and plaques.

Reference

1. Willemink MJ, Noël PB. The evolution of image reconstruction for CT – from filtered back projection to artificial intelligence. Eur Radiol 2019;29(5):2185–2195.
2. K. Minamishima, K. Sugisawa, Y. Yamada, M. Jinzaki, Quantitative and qualitative evaluation of hybrid iterative reconstruction, with and without noise power spectrum models: a phantom study, J. Appl. Clin. Med. Phys. 19 (3) (2018) 318–325
3. L.L. Geyer, U.J. Schoepf, F.G. Meinel, J.W. Nance Jr., G. Bastarrika, J.A. Leipsic, N. S. Paul, M. Rengo, A. Laghi, C.N. De Cecco, State of the art: iterative CT reconstruction techniques, Radiology 27(August(2)) (2015) 339–357,
4. Z. Yu, J. Thibault, C.A. Bouman, K.D. Sauer, J. Hsieh. Fast model-based X-ray CT reconstruction using spatially nonhomogeneous ICD optimization. IEEE Trans Image Process, 20 (2011), pp. 161-175
5. Tamura A, Mukaida E, Ota Y, Kamata M, Abe S, Yoshioka K. Superior objective and subjective image quality of deep learning reconstruction for low-dose abdominal CT imaging in comparison with modelbased iterative reconstruction and filtered back projection. Br J Radiol 2021;94(1123): 20201357.
6. Koetzier LR, Mastrodicasa D, Szczykutowicz TP, et al. Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects. Radiology. 2023;306(3):e221257.
7. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436–444.
8. Willemink MJ, Koszek WA, Hardell C, et al. Preparing medical imaging data for machine learning. Radiology 2020;295(1):4–15.
9. Stanislav Žabić, Wang Q , Morton T , et al. A low dose simulation tool for CT systems with energy integrating detectors[J]. Medical Physics, 2013, 40.
10. Frush D P , Slack C C , Hollingsworth C L , et al. Computer-simulated radiation dose reduction for abdominal multidetector CT of pediatric patients.[J]. Ajr American Journal of Roentgenology, 2002, 179(5):1107-13.
11. Computed tomography image quality (CTIQ): low-contrast detectability (LCD) assessment when using dose reduction technology, NEMA/MITA WP 1-2017
12. Yu, Lifeng, Leng, et al. Prediction of human observer performance in a 2- alternative forced choice low-contrast detection task using channelized Hotelling observer: Impact of radiation dose and reconstruction algorithms[J]. Medical Physics, 2013.

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