UNITED IMAGING

Ultra EFOV

High-Precision Extended Field Reconstruction Technology

Technical White Paper

01
version

Contents

Introduction

Computed tomography (CT) is an essential imaging modality in modern medicine, playing a pivotal role in disease diagnosis, treatment planning, and interventional guidance. However, conventional CT systems are inherently constrained by field-of-view (FOV) limitations, which restrict anatomical coverage and can compromise diagnostic accuracy. The standard scan field of view (SFOV) is dictated by the geometry of the CT detector and source, often failing to accommodate patients with larger body sizes or non-standard imaging positions. These constraints lead to image truncation, geometric distortions, and loss of anatomical information, presenting significant challenges in both diagnostic and therapeutic applications.

To address these limitations, Extended Field of View (EFOV) technology was introduced, leveraging projection extrapolation and optimized reconstruction algorithms to extend anatomical coverage. This advancement represented a milestone in CT imaging, improving visualization beyond the conventional SFOV and enhancing clinical utility.

Despite these improvements, conventional EFOV algorithms exhibited fundamental limitations that hindered their reliability in real-world applications. Truncation artifacts remained a major concern due to incomplete projection data, introducing severe image artifacts along the extended boundary. Additionally, CT number inaccuracies in the extrapolated region compromised quantitative imaging, which is critical for applications such as radiation therapy planning, tumor characterization, and bone density assessment. Geometric distortions and contour discontinuities further degraded image fidelity, particularly in high-precision imaging applications such as orthopedic and cardiovascular assessments.

To overcome these challenges, we developed Ultra EFOV, a next-generation extended-field reconstruction algorithm that integrates deep learning with physics-based modeling. Ultra EFOV was designed to suppress truncation artifacts, improve geometric accuracy, and ensure precise CT number calibration in the extended region. Additionally, it enhances anatomical contour continuity, preserving the natural structure of tissues while mitigating distortion effects.

Ultra EFOV is designed to support various CT scanner models from UIH, ensuring superior image quality across both routine diagnostic imaging and high-precision applications. The algorithm is compatible with systems that expand from an SFOV of 500 mm to an EFOV of 820 mm, as well as those extending from an SFOV of 630 mm to an EFOV of 870 mm. The algorithm's robustness has been rigorously validated across multiple scanner platforms and diverse clinical scenarios, demonstrating strong generalizability and reliability.

This paper provides a comprehensive analysis of Ultra EFOV, detailing its technical principles, workflow, model training process, and multi-scenario validation results. Additionally, we explore its clinical impact, particularly in radiation therapy planning and quantitative imaging applications, where extended-field accuracy is crucial.

Challenges and Limitations of Traditional EFOV Algorithms

Extended Field of View (EFOV) technology was developed to mitigate the inherent field-of-view constraints of standard scan field-of-view (SFOV) by extrapolating projection data, allowing for expanded anatomical coverage. While this approach extends the imaging range beyond the SFOV, conventional EFOV algorithms remain fundamentally limited in their ability to achieve high-precision imaging in complex clinical scenarios. These limitations stem from the inherent assumptions used in projection data extrapolation, resulting in geometric distortions, truncation artifacts, and inaccuracies in CT number calibration, all of which undermine diagnostic accuracy and restrict its applicability in fields such as radiation therapy planning and orthopedic imaging.

A major challenge of traditional EFOV algorithms is their reliance on mathematical models to estimate missing projection data. These methods assume a predictable relationship between truncated and non-truncated regions, which can work effectively in homogeneous anatomical structures. However, this assumption fails in complex cases involving heterogeneous tissues, high-density structures, or large anatomical variations. In regions with bony structures or multi-layered soft tissues—such as the pelvis in obese patients—extrapolation-based reconstruction often leads to geometric distortions and structural inconsistencies, degrading image fidelity and reducing the reliability of quantitative assessments. Moreover, truncation artifacts remain a pervasive issue, particularly along the periphery of the extended field, where limited projection data results in blurred edges, streak artifacts, and anatomical discontinuities. These artifacts obscure critical details and compromise both qualitative visualization and quantitative analysis (Fig. 1).

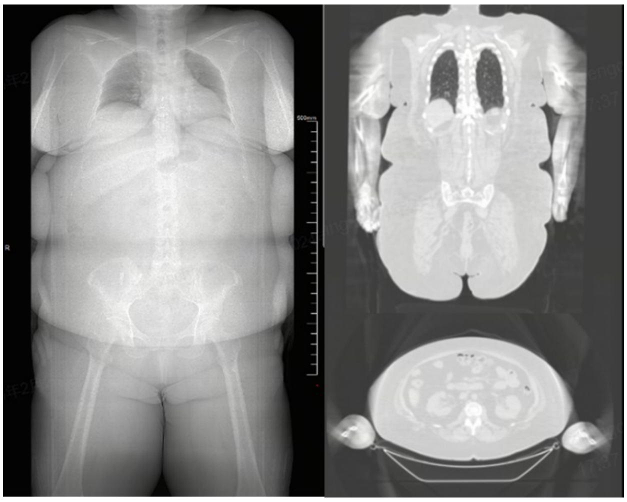

Figure 1: Artifacts in conventional EFOV algorithms affecting extended-field image quality

Another critical limitation of conventional EFOV algorithms is the inaccuracy of CT number (Hounsfield Units, HU) calibration in the extended region, which has direct implications for quantitative imaging applications. Accurate HU values are essential for tasks such as radiation therapy dose calculations, tumor characterization, and bone density analysis. However, because conventional EFOV relies on extrapolated projection data, significant HU deviations frequently occur, particularly in regions containing bone or other high-density structures. The severity of these deviations is further exacerbated when dense materials, such as cortical bone, are located near the X-ray source but outside the SFOV, where beam hardening effects and metal-induced artifacts distort HU values. These inaccuracies introduce uncertainties in dose calculations and tissue characterization, directly impacting radiotherapy planning and orthopedic imaging workflows.

In addition to HU inconsistencies, geometric distortions and contour discontinuities further limit the effectiveness of traditional EFOV algorithms. The reconstructed boundaries in the extended region often lack smoothness and anatomical integrity, creating artifacts that interfere with applications requiring precise anatomical delineation, such as orthopedic surgery planning and radiation therapy contouring. This issue is particularly pronounced when high-density structures within the EFOV remain unconnected to the SFOV, leading to errors in extrapolation and subsequent misalignment of anatomical features. Structural deformations are further exacerbated in cases involving large-body patients or off-center positioning, reducing the reliability of EFOV-based reconstructions in challenging clinical conditions (Fig. 2).

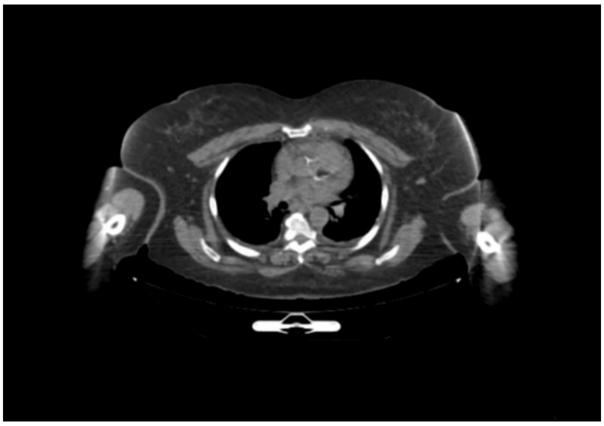

Figure 2: Geometric distortions and contour discontinuities in conventional EFOV algorithms

Despite the advantages of EFOV in extending the imaging field, its inherent limitations—truncation artifacts, HU inaccuracies, geometric distortions, and anatomical discontinuities—severely restrict its reliability in high-precision clinical applications. In radiation therapy, these limitations can compromise dose distribution accuracy, affecting treatment outcomes. In orthopedic imaging, distorted reconstructions can obscure critical bony landmarks, leading to errors in surgical planning. To enhance the clinical applicability of EFOV, future advancements must focus on improving HU consistency, eliminating truncation-induced artifacts, enhancing geometric fidelity, and refining anatomical boundary preservation.

To address these challenges, Ultra EFOV introduces an advanced reconstruction paradigm that integrates deep learning with physics-based modeling. By leveraging deep neural networks trained on diverse anatomical datasets, Ultra EFOV effectively compensates for missing projection data, minimizes truncation artifacts, and preserves geometric accuracy in the extended field. Unlike traditional extrapolation-based methods, Ultra EFOV refines image reconstruction by iteratively correcting residual errors in projection domain data, ensuring more accurate anatomical representation. Through these advancements, Ultra EFOV establishes a new standard for extended-field CT imaging, enabling greater precision in quantitative analysis, improved anatomical continuity, and broader applicability across clinical imaging scenarios.

Ultra EFOV: High-Precision Extended Field Reconstruction Algorithm

The quality of CT imaging plays a critical role in the diagnosis and treatment planning of complex cases. To overcome the limitations of traditional EFOV techniques, Ultra EFOV represents a paradigm shift in extended-field CT imaging by integrating deep learning with physics-based modeling. This hybrid approach systematically addresses the limitations of conventional EFOV by enhancing geometric accuracy, ensuring HU value precision, and effectively suppressing artifacts. This chapter provides a comprehensive analysis of Ultra EFOV's core workflow, model architecture, training methodology, and performance evaluation.

Ultra EFOV Workflow: Synergy of Deep Learning and Physical Modeling

Core Workflow for Ultra EFOV

Ultra EFOV integrates a deep learning-based residual correction framework with conventional projection extrapolation, effectively reducing artifacts and HU inconsistencies. The neural network is trained to iteratively refine the residual errors between truncated and full-FOV reconstructions, progressively enhancing its ability to predict missing data. The fundamental principle of Ultra EFOV is the intelligent processing of projection domain data to mitigate discontinuities that degrade image quality. By integrating optimized filtering during the filtered back projection (FBP) process, Ultra EFOV effectively reduces truncation artifacts, ensuring greater image uniformity and precision.

The algorithm workflow, illustrated in Figure 3, begins with an initial image reconstruction phase where data within the SFOV (Standard Field of View) is separated from the extrapolated EFOV (Extended Field of View) regions. Unlike conventional methods, Ultra EFOV not only leverages truncated region data but also incorporates information from adjacent SFOV areas, using this as a reference for correcting missing projection data. This data fusion strategy compensates for EFOV region deficiencies, providing a robust foundation for deep learning-based refinement.

In the deep learning phase, the algorithm employs convolutional neural networks (CNNs) to extract multi-dimensional features, mapping input anatomical structures to higher-level semantic representations. Specifically, the network generates a residual map, representing artifacts, geometric discrepancies, and HU deviations in the extended region. The residual is iteratively optimized through multi-step learning, and upon convergence, it is integrated with the initial reconstruction to produce a fully corrected image.

By jointly processing SFOV and EFOV data, Ultra EFOV achieves precise anatomical restoration in extended regions while significantly improving HU value consistency. This workflow not only maintains structural continuity across the expanded field but also effectively suppresses truncation artifacts and distortion. Furthermore, because the algorithm exclusively operates on extrapolated regions without modifying the SFOV data, it ensures that the core image quality and HU fidelity within the standard field remain uncompromised, maintaining overall consistency and reliability.

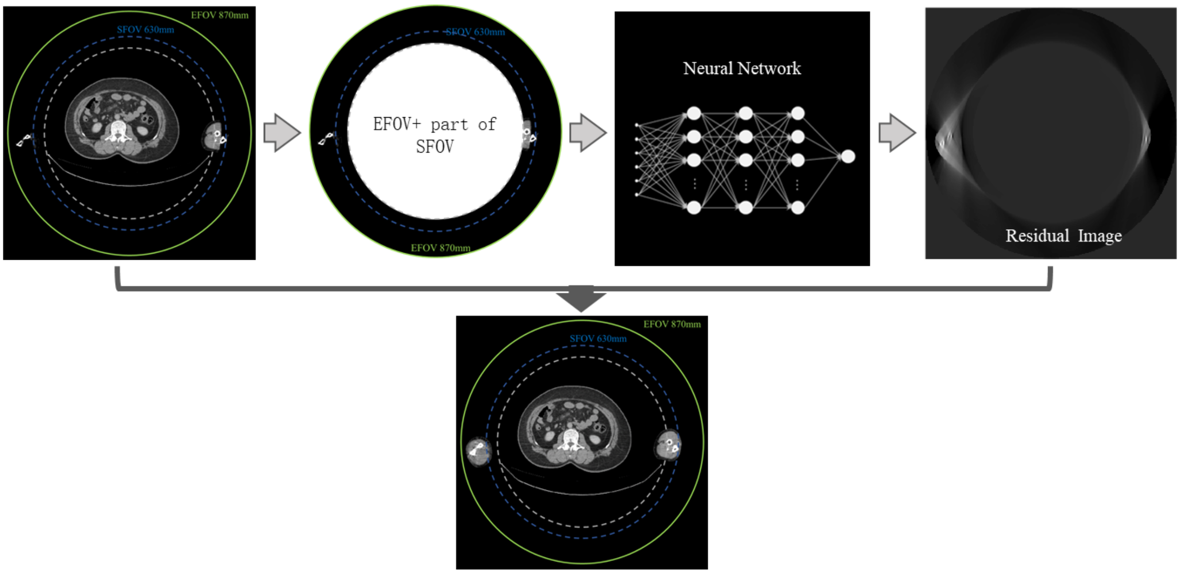

Figure 3: Ultra EFOV Algorithm Workflow

With deep learning at its core, Ultra EFOV bridges the gap between data-driven AI approaches and traditional physics-based reconstruction, overcoming the longstanding limitations of conventional EFOV methods and setting a new benchmark for extended-field imaging.

Large-Scale Data Training and Generalization Performance

To ensure robustness and adaptability across diverse clinical scenarios, Ultra EFOV was trained using a multi-domain dataset of over 500,000 simulated images, spanning varied radiation doses, anatomical structures, and truncation conditions. The training pipeline incorporated contrastive learning to distinguish truncated projection patterns from full-FOV images, enhancing generalization across scanner types and clinical conditions. The dataset includes variations in radiation dose, anatomical structures, and complex imaging conditions such as chest, abdomen, pelvis, and extremities, providing the model with broad exposure to clinically relevant cases. This large-scale training strategy significantly enhances Ultra EFOV's generalization capability, ensuring stable performance across different CT scanners and clinical environments.

During training, the neural network receives input consisting of truncated EFOV data and partial SFOV projections containing truncation artifacts. To guide the learning process, the model also incorporates ground truth images obtained from an extended detector simulation, along with the residual difference between the simulated extended view and truncated data (Residual 1). The algorithm then iteratively generates Residual 2, an estimated correction map, and compares it with Residual 1 to quantify prediction errors. These differences are minimized through backpropagation and iterative parameter optimization, allowing the model to progressively refine its extrapolation accuracy.

This training strategy is based on a contrastive learning framework, where the network continuously learns from discrepancies between complete and truncated data. As the model undergoes multiple training iterations, prediction errors are systematically reduced, ensuring that the final output achieves high-fidelity anatomical reconstruction while eliminating truncation-induced image degradation. Additionally, this method significantly improves overall image uniformity and enhances consistency across the extended region.

Beyond standard cases, Ultra EFOV has been specifically trained to handle challenging clinical scenarios, such as off-center positioning, where conventional EFOV techniques often struggle. By incorporating a diverse set of complex imaging conditions, the model demonstrates exceptional resilience to high-noise, high-truncation datasets, ensuring consistent performance across a broad range of clinical applications. This adaptability makes Ultra EFOV particularly valuable for radiation therapy planning and orthopedic imaging, where precision imaging is essential.

Through its systematic training approach and continuous optimization, Ultra EFOV delivers superior image quality in extended regions while maintaining highly generalized performance across multiple CT platforms. By addressing the fundamental weaknesses of conventional EFOV methods, it establishes a robust and scalable solution for extended-field CT imaging.

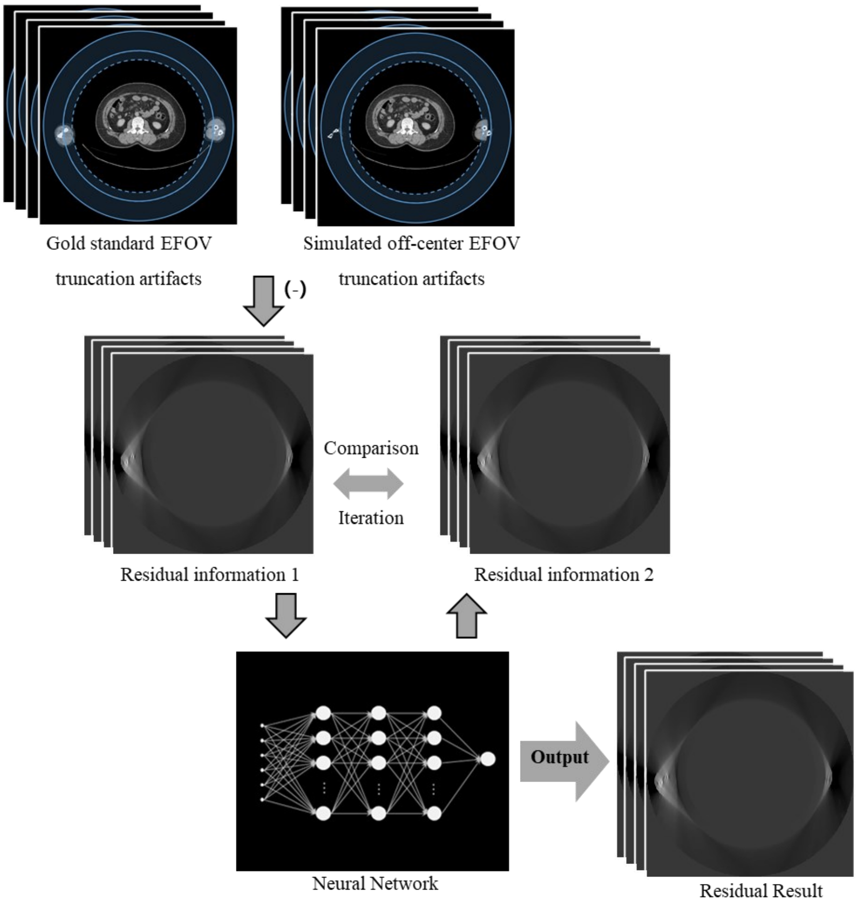

Figure 4: Ultra EFOV Deep Learning Training Process.

Multi-Scenario Validation of Ultra EFOV Performance

The performance of the Ultra EFOV algorithm was comprehensively evaluated through quantitative and qualitative assessments to validate its stability and adaptability across diverse clinical applications. Quantitative evaluation was conducted using water phantoms and electron density phantoms (Model 1472, Gammex Inc.), hereafter referred to as the Gammex phantom, to assess HU accuracy and boundary precision. Qualitative evaluation involved clinical imaging data reviewed by radiology experts to assess improvements in image quality and anatomical consistency.

To ensure cross-platform applicability, validation included multiple CT scanner models within the United Imaging product line, each with distinct physical specifications. These models were categorized as follows: (1) Model 1, featuring a standard field of view (SFOV) of 500 mm and an extended field of view (EFOV) reaching 820 mm; and (2) Model 2, with an SFOV of 630 mm and an EFOV extending to 870 mm. Each model category comprises a series of CT scanners with identical physical parameters, enabling a comprehensive evaluation of Ultra EFOV's performance across different imaging systems.

Evaluation of HU Accuracy

HU (Hounsfield Unit) values are a critical parameter in CT imaging, serving as a key metric for tissue density quantification, which is essential for radiotherapy dose calculations, tumor analysis, and bone density assessments.

To validate Ultra EFOV's HU accuracy, experiments simulated various truncation scenarios by adjusting table height to replicate different degrees of field-of-view limitations. The reference standard (HU_Ref) was obtained from SFOV-based imaging (position 1), serving as the ground truth for comparison.

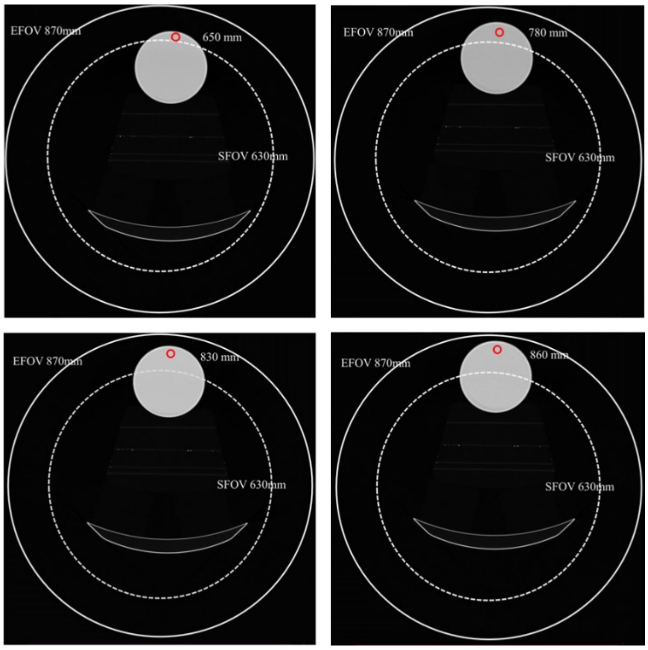

Figure 5: Phantom images under different truncation conditions.

Figure 5 illustrates the phantom imaging results on a CT scanner with an 870 mm EFOV, highlighting four regions of interest (ROIs) across different FOV positions: Position 2 (630–700 mm FOV), Position 3 (700–800 mm FOV), Position 4 (800–850 mm FOV), and Position 5 (850–870 mm FOV).

The Multi-Energy CT Phantom Model 1472 (Figure 6) was used to analyze HU accuracy under different imaging conditions. This phantom consists of both an inner and an outer ring; however, for this study, only the inner ring was used to maintain experimental consistency and focus on HU accuracy and boundary precision. Since the primary objective was to assess EFOV performance rather than external shape variations, the inner ring provided a controlled geometric structure, reducing additional variables that could confound the results. Additionally, the high-density inserts were randomly positioned within the phantom to simulate diverse material distributions and ensure robustness across different imaging scenarios.

The positioning of the Gammex phantom in Model 2 is depicted in Figure 7, illustrating high-density material placement within the SFOV. This setup enabled a controlled evaluation of HU consistency across different truncation scenarios and served as the basis for subsequent boundary precision measurements.

While this study focused on the inner ring configuration, future investigations could explore the effects of the outer ring on EFOV performance, further broadening the understanding of extended-field imaging across varying anatomical representations.

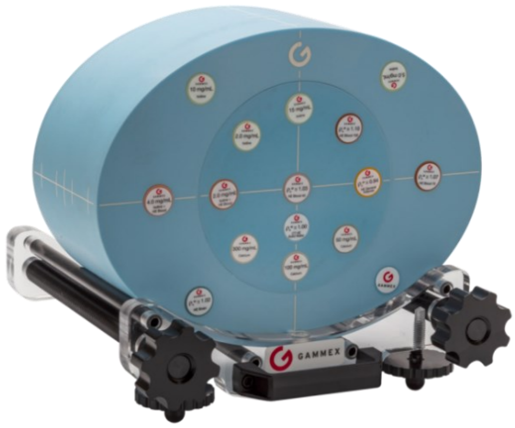

Figure 6: Multi-Energy CT Phantom

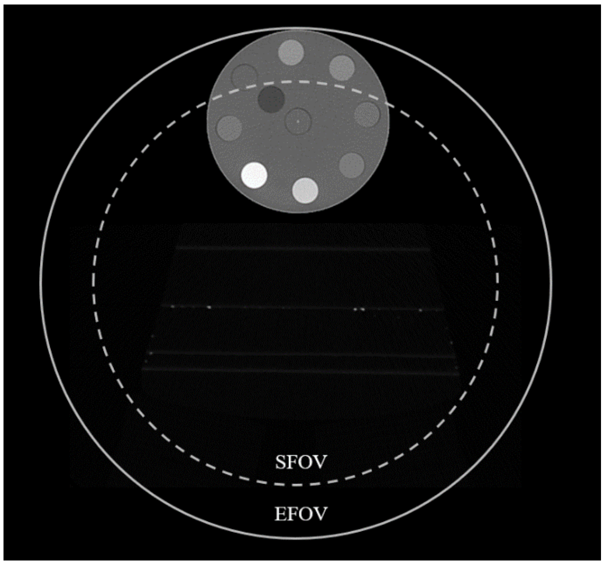

Figure 7： Schematic of Gammex phantom positioning in Model 2

Quantitative Results

HU deviations were measured at multiple positions using both water phantoms and Gammex phantoms. Table 1 summarizes the maximum HU deviations recorded for each scanner model.

Table 1: Maximum HU Deviation (Unit: HU)

Model	Water Phantom	Gammex Phantom
Model 1	2.24	14.3
Model 2	3.4	5.5

For Model 1, the maximum HU deviation was 2.24 HU for the water phantom and 14.3 HU for the Gammex phantom. In Model 2, the maximum HU deviation was 3.4 HU for the water phantom and 5.5 HU for the Gammex phantom.

Assessment of Boundary Precision

Boundary precision is a crucial factor in evaluating geometric distortions within EFOV regions, as it directly impacts anatomical integrity and morphological accuracy. This study analyzed 150 precisely distributed measurement points across the extended field, covering regions from SFOV edges to the EFOV's maximum boundary. This high-density measurement strategy ensured a robust assessment of Ultra EFOV's reconstruction accuracy under various truncation conditions.

Quantitative Results

Boundary accuracy was quantified by measuring the deviation between the reconstructed boundary and the ground truth across six truncation levels. The maximum boundary deviation for each scanner model and phantom type is summarized in Table 2.

Table 2: Maximum Boundary Deviation (Unit: mm)

Model	Water Phantom	Gammex Phantom
Model 1	0.95	0.95
Model 2	1.03	1.03

For Model 1, the maximum boundary deviation was 0.95 mm for the water phantom and 1.03 mm for the Gammex phantom. In Model 2, the maximum boundary deviation was 0.51 mm for the water phantom and 0.63 mm for the Gammex phantom.

Discussion

These results comprehensively validate Ultra EFOV's robustness across multiple imaging dimensions, demonstrating high accuracy in both HU values and boundary precision. The findings highlight the algorithm's effectiveness in EFOV while preserving anatomical fidelity, reinforcing its applicability in high-precision CT imaging scenarios.

Clinical Implications of HU Accuracy

Ultra EFOV effectively controls HU deviations within ±20 HU, ensuring compliance with clinical accuracy requirements for quantitative CT imaging. The deep learning-based model within Ultra EFOV compensates for HU drift at EFOV boundaries, improving the reconstruction of both soft tissue and bony structures. The predefined HU accuracy threshold was set conservatively to guarantee robustness across diverse clinical settings, and experimental validation confirms that observed deviations remain significantly below this threshold.

A notable discrepancy in HU accuracy was observed between Model 1 (820 mm EFOV) and Model 2 (870 mm EFOV), primarily due to differences in the placement of high-density structures within the Gammex phantom. In Model 1, bony structures were positioned closer to the X-ray source, fully within the EFOV, but lacking direct interaction with the SFOV. This configuration intensified beam hardening effects, leading to greater HU deviations. In contrast, Model 2 positioned these structures within or adjacent to the SFOV, thereby reducing artifact severity and improving HU consistency. These findings highlight that HU accuracy is not solely algorithm-dependent but is also significantly influenced by the spatial distribution of high-density materials relative to the SFOV and EFOV regions.

Despite these differences, even in the most challenging scenarios for Model 1, HU deviations remained below 15 HU, which aligns with clinical expectations for extended-field imaging. The maximum observed HU deviation of 14.3 HU is within the acceptable clinical range, ensuring reliable tissue density quantification for radiotherapy planning, tumor assessment, and other quantitative imaging applications. These results further reinforce that HU accuracy remains within clinically acceptable limits, with deviations not exceeding 20 HU, even under extreme imaging conditions.

Boundary Precision and Geometric Fidelity

Ultra EFOV demonstrated high geometric accuracy, as validated by 150-point precision measurements. Unlike conventional EFOV methods, which typically rely on limited spatial sampling, Ultra EFOV's comprehensive approach significantly enhances measurement reliability. The maximum observed boundary deviation remained below 1.04 mm, well within the predefined accuracy threshold. This high-fidelity reconstruction is particularly valuable for applications requiring precise anatomical delineation, such as radiotherapy planning and orthopedic imaging.

The variation in boundary accuracy between Model 1 and Model 2 was further influenced by phantom composition and structure location relative to the SFOV. In Model 1, high-density structures positioned deeper within the EFOV and farther from the SFOV exhibited greater geometric distortion, likely due to beam hardening and metal-induced artifacts. This effect was less pronounced in Model 2, where the positioning of high-density structures within or adjacent to the SFOV enhanced reconstruction accuracy.

Statistical analysis revealed no significant difference in boundary accuracy for water phantoms, suggesting consistent performance across scanner models in homogeneous soft-tissue-equivalent materials. However, in the Gammex phantom, Model 2 exhibited significantly lower boundary deviation than Model 1 ($p=0.038$). This further supports the influence of structure positioning within the SFOV on geometric accuracy, particularly for high-density materials that exhibit strong attenuation effects.

Cross-System Compatibility and Robustness

Ultra EFOV is designed to ensure consistent image quality across different CT scanner models, accommodating a wide range of clinical conditions. Cross-platform validation confirmed that Ultra EFOV maintains stable HU values and geometric fidelity across various configurations, highlighting its strong device-agnostic robustness.

Through extensive multi-system validation, Ultra EFOV has demonstrated reliable performance across diverse clinical applications, including extended-field diagnostics, radiotherapy simulation, and high-precision anatomical imaging. These findings establish Ultra EFOV as a robust, clinically viable solution for overcoming SFOV limitations, ensuring accurate extended-field imaging in routine diagnostics and advanced therapeutic applications.

Clinical Applications Evidence

The clinical validation of the Ultra EFOV algorithm demonstrates its significant advantages in enhancing CT image reconstruction quality, reducing geometric distortions, optimizing HU accuracy, and minimizing artifact interference. Ultra EFOV's enhancements extend beyond image quality improvements, offering clinically meaningful benefits across radiotherapy planning and orthopedic assessments. With boundary deviations consistently below 0.32 mm, the algorithm ensures precise tumor delineation, improves dose calculation reliability, and enables accurate pre-surgical anatomical mapping. To further illustrate its clinical utility, we analyze several typical patient cases that highlight Ultra EFOV's performance in various imaging scenarios.

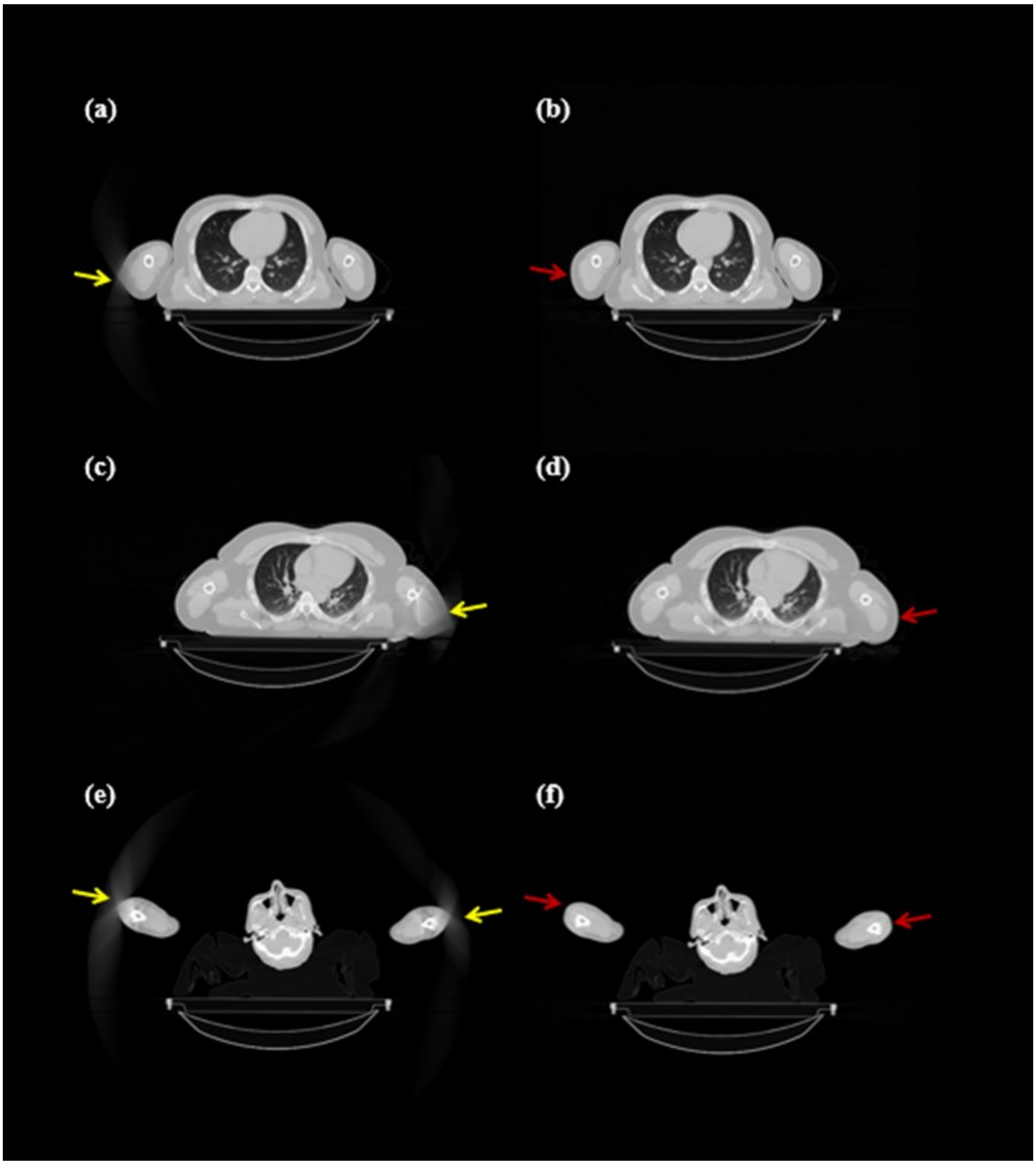

Figure 8 presents three patient cases:

(a) and (b): A large-body patient (height: 190 cm, weight: 102 kg, BMI: 28.25), scanned with an 870 mm field of view using both conventional EFOV and Ultra EFOV reconstructions.

(c) and (d): A second patient (height: 188 cm, weight: 110 kg, BMI: 31.12), also scanned within an 870 mm EFOV, reconstructed using both conventional EFOV and Ultra EFOV algorithms.

(e) and (f): A third patient, where arm elevation resulted in anatomy extending beyond the standard field of view, necessitating EFOV-based reconstruction.

Precision in HU Accuracy: Enhancing Reliability of Quantitative Imaging

HU accuracy is critical in clinical CT applications, particularly in quantitative assessments, such as tumor treatment planning, bone density measurements, and fat composition analysis. By integrating deep learning and physics-based modeling, Ultra EFOV achieves highly precise HU corrections within the extended field, ensuring consistent tissue density representation with SFOV data.

In Figure 8 (a) and (b), the first patient's anatomy extends beyond the 630 mm SFOV. Compared to conventional EFOV, Ultra EFOV reconstruction demonstrates more stable HU values in the extended region, significantly reducing deviations. This precise HU calibration not only improves image visualization but also provides reliable data for subsequent dose calculations and tissue density analyses in radiation therapy and other quantitative imaging applications.

Accurate Anatomical Reconstruction: Reducing Image Distortions

Geometric distortions can compromise anatomical identification, reducing diagnostic accuracy. This issue is particularly problematic in EFOV regions, where conventional EFOV algorithms, constrained by limited projection extrapolation accuracy, can introduce structural deformations that misrepresent the true anatomical morphology.

Ultra EFOV effectively preserves anatomical continuity by enhancing contour consistency and geometric accuracy. In Figure 8 (c) and (d), the second patient, scanned within an 870 mm EFOV, demonstrates how Ultra EFOV more accurately reconstructs the body's outer contour and internal structures, compared to conventional EFOV. By eliminating common geometric distortions, Ultra EFOV improves precision in radiotherapy planning, orthopedic surgery assessment, and other high-accuracy imaging applications.

Artifact Reduction: Enhancing Image Coherence for Stable Image Quality

Truncation artifacts are a well-known issue in extended-field CT imaging, especially in large-body patients, non-standard positioning, or inhomogeneous tissue structures. These artifacts can obscure key anatomical structures, potentially affecting clinical decision-making.

Ultra EFOV effectively minimizes truncation artifacts by employing an intelligent projection data weighting strategy. In Figure 8 (e) and (f), where the patient's elevated arms extended beyond the SFOV, conventional EFOV reconstruction produced visible artifacts, complicating anatomical interpretation. In contrast, Ultra EFOV leveraged SFOV-based photon attenuation learning to accurately correct the extended-region data, resulting in clearer, more natural images and helping clinicians receive more realistic anatomical information.

Multi-Scenario Adaptability: Meeting Diverse Clinical Needs

Ultra EFOV is not limited to radiotherapy simulation but is also widely applicable in general diagnostic CT, including chest and abdominal imaging, and orthopedic assessments. Its high-precision extended field reconstruction capability allows it to maintain stable image quality across different scanner models, regardless of whether operating on 500 mm SFOV (expanded to 820 mm EFOV) or 630 mm SFOV (expanded to 870 mm EFOV).

Furthermore, Ultra EFOV's cross-device adaptability has been validated in multiple real-world clinical cases, further reinforcing its robustness and broad clinical applicability. Whether in diagnostic CT or radiation therapy planning, this algorithm effectively enhances image quality within extended fields, providing clinicians with clearer, more accurate imaging data for improved clinical decision-making.

Conclusion

Ultra EFOV represents a significant advancement in extended-field CT imaging, effectively overcoming longstanding challenges, including geometric distortions, HU inaccuracies, and truncation artifacts. Its high-precision reconstruction capability has led to remarkable improvements in image quality across the extended field, achieving boundary accuracy within ±1.5 mm and HU deviations controlled within ±20 HU. These technical advancements not only enhance anatomical continuity but also ensure the reliability of quantitative analysis within the EFOV region, establishing a solid foundation for high-precision medical imaging.

Clinically, Ultra EFOV has demonstrated exceptional adaptability across various scanner models and complex patient cases. Its stable imaging performance makes it highly applicable in radiotherapy planning, orthopedic imaging, and other medical fields requiring precise anatomical visualization. Particularly in radiotherapy simulation, Ultra EFOV provides highly accurate dose calculations, offering enhanced imaging support for precision radiotherapy.

As medical imaging technology continues to evolve, the application scope of Ultra EFOV is expected to expand further, addressing a broader range of advanced diagnostic needs. Future optimizations will focus on more efficient computational architectures, expanded imaging datasets, and enhanced AI-driven image refinement techniques, ensuring that Ultra EFOV continuously meets the growing demands of clinical imaging. Ultra EFOV marks a transformative advancement in extended-field CT imaging, bridging the gap between deep learning and physics-based reconstruction. By delivering unprecedented anatomical accuracy, the algorithm not only enhances diagnostic precision but also establishes a foundation for next-generation AI-driven medical imaging innovations.

References

1. Hsieh J, Chao E, Thibault J, et al. A novel reconstruction algorithm to extend the CT scan field-of-view. Med Phys. 2004 Sep;31(9):2385-91.

2. Beeksma B, Truant D, Holloway L, Arumugam S. An assessment of image distortion and CT number accuracy within a wide-bore CT extended field of view. Australas Phys Eng Sci Med. 2015 Jun;38(2):255-61.

3. Fonseca GP, Baer-Beck M, Fournie E, et al. Evaluation of novel AI-based extended field-of-view CT reconstructions. Med Phys. 2021 Jul;48(7):3583-3594.

4. Cheung JP, Shugard E, Mistry N, Pouliot J, Chen J. Evaluating the impact of extended field-of-view CT reconstructions on CT values and dosimetric accuracy for radiation therapy. Med Phys. 2019 Feb;46(2):892-901.

5. H. Bruder, C. Suess, K. Stierstorfer. Efficient extended field of view (eFOV) reconstruction techniques for multi-slice helical CT. Proc. SPIE 6913, Medical Imaging 2008: Physics of Medical Imaging. 2008;69132E.

6. American College of Radiology (ACR). CT Accreditation Program Requirements. Available at: https://www.acr.org/Quality-Safety/Accreditation/CT (Accessed September 2024).

7. International Electrotechnical Commission (IEC). IEC 60601-2-44: Medical electrical equipment - Particular requirements for the basic safety and essential performance of X-ray equipment. Available at: https://webstore.iec.ch/publication/26816 (Accessed September 2024).

Shanghai, China
2258 Chengbei Rd., Jiading District, Shanghai, 201807.

Email | info.global@united-imaging.com

Business Consultation | +86（21）- 67076666

After-sales Service | 4006 - 866 - 088

ABOUT UIH

At United Imaging Healthcare, we develop and produce advanced medical products, digital healthcare solutions, and intelligent solutions that cover the entire process of imaging diagnosis and treatment. Founded in 2011, our company has subsidiaries and R&D centers across China, the United States, and other parts of the world. With a cutting-edge digital portfolio and a mission of Equal Healthcare for All™, we help drive industry progress and bold change.

To learn more, visit https://www.united-imaging.com