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OPTIMIZATION OF SCANNING PARAMETERS FOR CT AND CBCT: A SYSTEMATIC REVIEW

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Abstract- *computed tomography (CT) and cone-beam computed tomography (CBCT) have revolutionized medical imaging by providing high-resolution, three-dimensional (3D) anatomical models for diagnostics, treatment planning, and surgical simulation. The accuracy of these models is highly dependent on scanning parameters such as slice thickness, spatial resolution, radiation dose, voltage, exposure time, and reconstruction algorithms. While optimized parameters can enhance image quality and segmentation accuracy, suboptimal settings may introduce artifacts, reduce anatomical fidelity, and compromise clinical outcomes [1]. CBCT is widely used in dentistry and maxillofacial surgery due to its lower radiation dose and high spatial resolution, whereas CT is preferred for comprehensive anatomical evaluations due to its superior soft tissue contrast [3]. The choice of scanning parameters requires balancing image clarity and patient safety. Studies have shown that an optimal slice thickness of 0.075–0.125 mm in CBCT and 0.5–1.25 mm in CT yields the best segmentation results [4]. Radiation dose must also be carefully adjusted; 0.1–0.3 mSv is typically sufficient for CBCT, while 2–5 mSv is recommended for CT [5]. Voltage settings of 80–100 kV (CBCT) and 100–120 kV (CT) help reduce beam hardening artifacts while maintaining contrast. Tube current should range between 4–10 mA for CBCT and 50–300 mA for CT to optimize noise reduction [6]. One of the major challenges in CT imaging is the presence of artifacts, including scatter artifacts, beam hardening artifacts, motion artifacts, and partial volume artifacts. Scatter artifacts degrade image quality due to unintended radiation deflection and can be mitigated using anti-scatter grids and beam collimation techniques [7]. Beam hardening artifacts, caused by differential X-ray absorption in dense structures, can be corrected using higher voltage settings and advanced reconstruction algorithms [4]. Motion artifacts, resulting from patient movement, can be minimized by reducing exposure time and employing motion correction software [3]. Partial volume artifacts, which affect the accuracy of tissue segmentation, can be addressed by reducing voxel size and applying high-pass filters. Traditional artifact reduction techniques such as high-pass filters, metal artifact reduction (MAR) algorithms, dual-energy CT (DECT), and Monte Carlo simulations have been widely implemented, but their effectiveness is often limited [8]. Recent advancements in Artificial Intelligence (AI)-based artifact correction have introduced new, data-driven methods that surpass conventional approaches in speed, accuracy, and adaptability [9]. This review provides a comprehensive analysis of CT and CBCT scanning parameters and typical artifacts, summarizing the optimal settings for different clinical applications. By refining scanning protocols and employing advanced artifact reduction techniques, the accuracy and reliability of anatomical models can be significantly improved, ensuring better diagnostic and therapeutic outcomes [10].*

Keywords: *CT; CBCT; segmentation accuracy; scanning parameters; image artifacts; radiation dose; scatter artifacts; beam hardening artifacts; motion artifacts; partial volume artifacts; metal artifacts; ring artifacts; noise artifacts; reconstruction algorithms; image quality; dose optimization; artifact minimization.*

INTRODUCTION

Computed tomography (CT) and cone-beam computed tomography (CBCT) have revolutionized medical imaging by enabling precise three-dimensional (3D) reconstruction of anatomical structures. These technologies are widely utilized in fields such as dentistry, maxillofacial surgery, orthopedics, and radiology. By providing detailed imaging with high spatial resolution, CT and CBCT play an essential role in diagnosing conditions, guiding surgical interventions, and improving patient outcomes. However, the accuracy of 3D anatomical models heavily depends on scanning parameters, including spatial resolution, radiation dose, slice thickness, and artifact minimization strategies. The careful selection and optimization of these parameters are crucial for achieving the best possible image quality while ensuring patient safety by minimizing radiation exposure.

CT imaging typically employs a fan-shaped X-ray beam combined with a multi-row detector array, making it highly effective for whole-body scans and soft tissue analysis. On the other hand, CBCT utilizes a cone-shaped X-ray beam and a flat-panel detector, allowing for a more focused and lower-dose imaging approach, particularly advantageous in dental and maxillofacial applications. Despite these benefits, both modalities face challenges related to imaging artifacts, which can compromise diagnostic accuracy and treatment planning. Addressing these challenges is crucial, as errors in image reconstruction or segmentation can lead to misdiagnosis and suboptimal treatment decisions. Given the increasing reliance on imaging for clinical decision-making, optimizing scanning protocols is not only a technical necessity but also a critical factor in improving healthcare outcomes and patient safety.

With continuous advancements in imaging technology, there is a growing interest in refining scanning protocols and developing new strategies for artifact reduction. Artificial intelligence (AI)-driven correction techniques have emerged as promising tools for enhancing image clarity and segmentation accuracy.

The goal of the review is to evaluate how scanning parameters have been selected and justified in previous studies to improve the accuracy of anatomical models in CT and CBCT imaging. Across the literature, researchers have adopted varying strategies depending on clinical needs, anatomical regions, and equipment capabilities. For example, authors have proposed thinner slice thicknesses and smaller voxel sizes for enhanced bone segmentation, while higher voltage settings are commonly used to minimize beam hardening artifacts in the presence of dense structures. These parameter choices reflect efforts to balance image clarity, segmentation accuracy, and radiation safety. In addition to summarizing scanning protocol decisions, this review also examines artifact reduction techniques—particularly the growing application of AI-based correction models. While recent studies have demonstrated the potential of deep learning for mitigating artifacts such as scatter, motion, and noise, there remains considerable skepticism regarding their clinical readiness. Many AI models have only been validated in experimental or retrospective settings, and their generalizability, regulatory approval, and integration into real-world clinical workflows remain open challenges. As such, this review critically explores both the reported successes and current limitations of AI-driven approaches, with the goal of informing future research and guiding evidence-based decisions in medical imaging practic

I. COMPUTED TOMOGRAPHY IN MEDICINE

Computed Tomography (CT) and Cone Beam Computed Tomography (CBCT) are widely utilized imaging modalities that rely on X-ray-based techniques for producing detailed anatomical images. While CT has been the standard imaging method in medical diagnostics, CBCT has gained prominence in dental and maxillofacial applications due to its costeffectiveness and lower radiation dose. The fundamental differences between these modalities lie in their scanning mechanics, acquisition techniques, and reconstruction methods, which influence their spatial resolution, image quality, and clinical applicability. Understanding these differences is crucial for selecting the most appropriate imaging technique based on diagnostic requirements and anatomical regions

1.1 CT IMAGING: SCANNING MECHANICS AND METHODS

CT imaging employs a fan-shaped X-ray beam and a multi-row detector array that rotate around the patient to capture multiple projections, which are then reconstructed into cross-sectional images. The scanning process can be performed in helical (spiral) mode or axial (step-and-shoot) mode. Helical CT, where the X-ray source continuously rotates while the patient moves through the scanner, is widely used for whole-body imaging due to its speed and ability to acquire volumetric data.

Axial CT, which captures individual slices sequentially, is used when higher spatial resolution is required, such as in brain imaging [26]. The optimal scanning parameters for CT vary depending on the clinical application but generally include a slice thickness between 0.5 and 5 mm to balance image resolution and radiation dose. The radiation dose typically ranges from 2 to 10 mSv, with lower doses applied for extremities and higher doses for thoracic or abdominal imaging .
[25]. The voltage applied in CT scans usually falls between 100 and 140 kV, while the tube current ranges from 150 to 500 mA, depending on the patient's size and diagnostic needs.

Exposure times range from 0.5 to 2 seconds per rotation, which enables fast image acquisition and reduces motion artifacts. The field of view (FOV) in CT imaging varies from 250 to 500 mm, allowing it to accommodate a wide range of anatomical regions, from localized studies to full-body imaging. Reconstruction of CT images is performed using filtered back projection (FBP) or iterative reconstruction (IR) algorithms, with IR being the preferred method due to its ability to reduce noise and optimize image quality at lower radiation doses. Advanced CT technologies, such as dual-energy CT (DECT), enable better tissue differentiation by acquiring images at two different X-ray energy levels, making it particularly useful in soft tissue imaging and contrast-enhanced studies [27]

1.2. CBCT IMAGING: SCANNING MECHANICS AND METHODS

CBCT differs from CT in its scanning mechanics, employing a cone-shaped X-ray beam and a flat-panel detector (FPD) that captures volumetric data in a single or limited rotational arc. Unlike CT, which reconstructs images from multiple slices, CBCT captures an entire 3D dataset in a single scan, making it highly efficient for localized imaging. This scanning technique is particularly beneficial for dental and maxillofacial imaging, as well as orthopedic applications where high spatial resolution is required [25].

CBCT scanners operate at lower tube voltages, typically between 70 and 120 kV, and use significantly lower tube currents, ranging from 5 to 20 mA, contributing to their reduced radiation dose. The total radiation dose for CBCT imaging varies between 0.05 and 1.2 mSv, significantly lower than CT, making it a safer option for repeated imaging, especially in pediatric and dental applications [24]. The slice thickness in CBCT, determined by the voxel size, generally ranges from 0.075 to 0.4 mm, providing high spatial resolution essential for detailed bone structure visualization. However, the longer exposure times, typically between 5 and 20 seconds, can increase susceptibility to motion artifacts compared to CT.

The field of view in CBCT varies from 50 to 250 mm, making it ideal for small anatomical regions such as the teeth, jaw, and temporomandibular joint but less suited for full-body imaging. Reconstruction in CBCT is performed using the Feldkamp-Davis-Kress (FDK) algorithm, optimized for cone-beam projection data. While CBCT provides excellent spatial resolution, its soft tissue contrast is significantly lower than CT due to the absence of advanced reconstruction techniques such as iterative reconstruction [27]

1.3. COMPARISON OF CT AND CBCT: KEY DIFFERENCES IN SCANNING MECHANICS

CT and CBCT differ significantly in their scanning mechanics, acquisition parameters, and reconstruction methods, each offering advantages suited to different clinical applications. CT employs a fan-beam X-ray system with multi-detector arrays, enabling rapid image acquisition and superior soft tissue contrast, making it the preferred modality for medical imaging of the brain, thorax, abdomen, and cardiovascular system [26].

The ability to adjust parameters such as slice thickness, voltage, and current allows CT to optimize imaging for different anatomical regions, including motion-prone structures such as the lungs and heart. In contrast, CBCT uses a cone-beam X-ray system that captures a volumetric dataset in a single scan, making it particularly advantageous for high-resolution bone imaging in dental, maxillofacial, and orthopedic applications [25].

CBCT also delivers a significantly lower radiation dose than CT, making it a safer option for frequent imaging; however, its limited ability to differentiate soft tissues restricts its use in broader medical applications. Another key difference is the reconstruction methodology: CT scanners increasingly use iterative reconstruction techniques to enhance image quality and reduce radiation dose, while CBCT predominantly relies on the Feldkamp-Davis-Kress algorithm, which lacks the noise-reducing benefits of iterative reconstruction [27]

Furthermore, CT scanners incorporate advanced imaging techniques such as dual-energy scanning, perfusion imaging, and contrast-enhanced studies, whereas CBCT remains primarily focused on high-resolution static anatomical imaging. The choice between CT and CBCT depends on clinical requirements, with CT being the better option for soft tissue imaging and full-body scans, while CBCT is superior for detailed bone assessments with minimal radiation exposure.

Table 1 **Comparison of optimal scanning parameters between CT and CBCT**

Parameter	Optimal CBCT Values	Optimal CT Values
Slice Thickness (mm)	0.075–0.125	0.5–1.25
Radiation Dose (mSv)	0.1–0.3	2–5
Voltage (kV)	80–100	100–120
Tube Current (mA)	4–10	50–300
Exposure Time (s)	3–6	5–10
Field of View (FOV)	5×5 cm (teeth), 10×10 cm (jaws)	20×20 cm
Reconstruction Algorithm	Iterative Reconstruction	Iterative Reconstruction

2. IMAGE ARTIFACTS AND MINIMIZATION TECHNIQUES

Image artifacts are distortions in CT and CBCT scans that degrade image quality, compromise segmentation accuracy, and impact diagnostic utility. These artifacts arise due to the physical properties of X-ray interactions, interactions with tissues and materials, limitations in scanning geometry, and reconstruction algorithms. While artifacts are present in all medical imaging modalities, CBCT is particularly prone to image degradation due to its lower radiation dose, limited detector dynamic range, and increased sensitivity to scattered X-ray interference compared to conventional CT [1].

The presence of artifacts in CBCT can significantly affect image interpretation and diagnosis, making it essential to understand their origins and implement correction techniques. Artifacts in CT and CBCT imaging can be classified into three main categories: patient-based artifacts, physics-based artifacts, and scanner-based artifacts.

2.1 PHYSICS-BASED ARTIFACTS

Physics-based artifacts are caused by the fundamental interactions between X-ray photons and matter, which lead to distortions such as beam hardening, and scatter. Beam hardening occurs when lower-energy X-rays are preferentially absorbed as the beam passes through dense structures such as bones or metal implants, resulting in streaking, cupping, and dark bands in the reconstructed images. This effect is more significant in CBCT than CT because CBCT uses a polychromatic X-ray spectrum without energy filtering, exacerbating differential attenuation artifacts [1].

X-ray scatter, another major source of image degradation, occurs when X-rays deviate from their original path due to interactions with tissues, causing blurring and contrast reduction. Scatter is more problematic in CBCT due to the wider X-ray beam angle and larger field of view, leading to higher noise levels and loss of contrast [16].

Photon starvation, which occurs when X-ray photons are completely absorbed before reaching the detector, results in streaking artifacts in areas of high attenuation, such as dense bones and metal implants. Minimization techniques for physics-based artifacts include the use of beam-hardening correction algorithms, anti-scatter grids, bowtie filters, and high-energy X-ray spectra in CT to reduce differential attenuation. In CBCT, the implementation of scattered radiation correction techniques, Monte Carlo-based scatter modeling, and optimized exposure parameters can improve image quality and reduce noise [9].

SCATTER ARTIFACTS

One of the most common types of artifacts is scatter artifacts, which occur due to the deflection of X-ray photons as they interact with tissue before reaching the detector. In CBCT, this effect is more pronounced because of the wide-angle X-ray beam and the lack of collimation, which allows scattered radiation to overlay the primary image, reducing contrast and sharpness. Scatter artifacts are particularly problematic in low-dose imaging protocols, where scattered photons significantly influence intensity variations. To reduce scatter artifacts, anti-scatter grids can be used to block scattered radiation before it reaches the detector. Additionally, hardware beam collimators are effective in limiting radiation spread and reducing scattered rays. Computational techniques such as Monte Carlo simulations have been integrated into reconstruction algorithms to estimate and remove scattered signals mathematically. Recent AI advancements have introduced deep-learning-based scatter correction methods, such as the model developed by [6], which improved CBCT contrast by 35% by predicting and eliminating scattered signals more accurately than conventional methods.

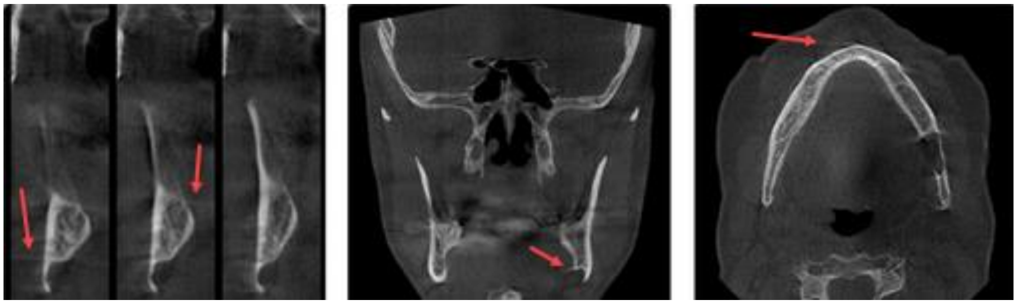

Figure 1: Scatter artifact [32]

BEAM HARDENING ARTIFACTS

Another significant artifact that affects CT and CBCT imaging is beam hardening, which occurs when low-energy X-rays are absorbed more rapidly than higher-energy ones, leading to non-uniform attenuation through dense structures such as bone or metal implants. This results in dark bands and streaks in high-density areas, causing false intensity variations that distort anatomical structures. Beam hardening can significantly impact maxillofacial CBCT scans, where segmentation errors of up to 1.5 mm have been reported in regions affected by this artifact. A key mitigation strategy is increasing the tube voltage (typically 100–120 kV), which helps generate higher-energy X-rays that penetrate tissues more uniformly, reducing the differential absorption effect. Another effective approach is the use of beam hardening correction algorithms, including Dual-Energy CT (DECT) reconstruction, which utilizes X-rays at two different energy levels to differentiate between materials and correct for attenuation distortions. [11] proposed an AI-driven dual-energy reconstruction model that significantly reduced beam hardening streaks, particularly in CBCT scans where conventional correction techniques had limited success.

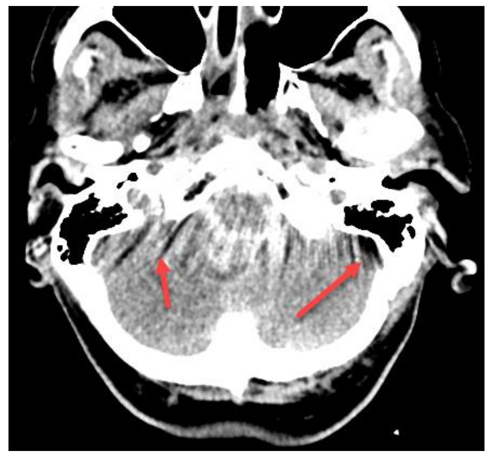

Figure 2: Beam hardening artifact [30]

NOISE ARTIFACTS

Noise artifacts arise when the X-ray dose is too low, resulting in random variations in pixel intensity that degrade image clarity. CBCT is more prone to noise due to its lower signal-to-noise ratio (SNR) compared to CT. Noise artifacts are particularly problematic in low-dose imaging protocols, such as pediatric imaging and orthodontic CBCT scans, where radiation exposure must be minimized. Increasing the X-ray dose can reduce noise but at the expense of higher radiation exposure, which is not always an ideal solution. AI-based denoising models have shown exceptional effectiveness in restoring lost detail while preserving fine anatomical structures. [13] developed an AI-powered denoising model that improved CBCT image clarity by 60%, allowing low-dose scans to achieve diagnostic-quality resolution without increasing patient radiation exposure.

2.2. PATIENT-BASED ARTIFACTS

Patient-based artifacts arise from movement, anatomical structure variations, and metal implants, all of which can distort the reconstructed images. Motion artifacts are common in both CT and CBCT but are more pronounced in CBCT due to longer scan times. Patient movement during image acquisition causes blurring, streaking, or double image formation, reducing the accuracy of anatomical structures.

This is particularly problematic in CBCT scans of uncooperative patients, pediatric imaging, and cases requiring long exposure times. Additionally, anatomical variations such as dense bone structures, air-filled cavities, or soft tissue changes can create attenuation mismatches, leading to image inconsistencies. Metal artifacts, caused by dental restorations, orthopedic implants, or surgical hardware, introduce severe streaking and dark bands due to beam hardening and photon starvation [9].

Strategies to minimize patient-based artifacts include the use of faster acquisition protocols, motion correction algorithms, metal artifact reduction (MAR) techniques, and patient immobilization strategies such as bite blocks and head stabilizers in CBCT scans.

MOTION ARTIFACTS

Motion artifacts present another major challenge in CT and CBCT imaging, arising when a patient moves during scanning, leading to blurring, double edges, and streaking in reconstructed images. This issue is particularly severe in CBCT due to its longer scan time compared to CT, making it more susceptible to involuntary motion such as breathing or swallowing. Motion artifacts are particularly problematic in neurological imaging, dental CBCT scans, and pediatric imaging, where patient cooperation is difficult.

Conventional mitigation techniques include shorter exposure times (3–6 seconds for CBCT and 5–10 seconds for CT) and patient immobilization techniques, such as bite blocks in dental imaging or head restraints in neurosurgical imaging. However, AI-based motion artifact correction models have proven to be far more effective. [7] introduced a real-time AI motion correction algorithm that predicts movement patterns and adjusts image reconstruction dynamically, reducing motion-induced errors by 50%, thereby significantly enhancing image clarity.

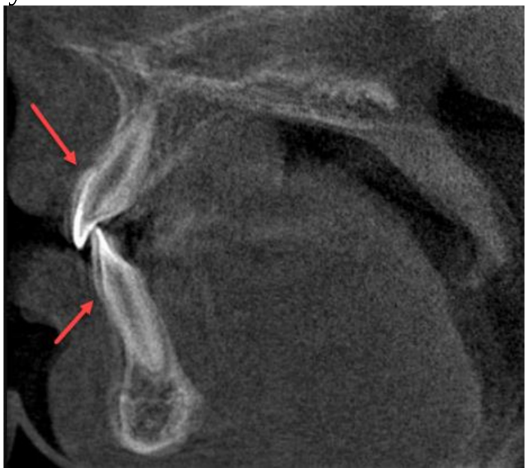

Figure 4: Motion artifact [34]

METAL AND CERAMICS ARTIFACTS

Metal artifacts are among the most visually disruptive distortions in CT and CBCT, commonly seen in dental, orthopedic, and neurosurgical imaging due to metal implants, dental fillings, or prosthetic devices. These high-density objects absorb a large portion of the X-ray beam, leading to streak artifacts, dark bands, and signal voids that obscure anatomical details. The presence of metal artifacts is particularly problematic in radiotherapy planning, where accurate dose calculations are crucial, and in post-surgical evaluations, where bone healing around implants must be carefully assessed.

One effective method for reducing metal artifacts is increasing the tube current (mA) and voltage (kV), which allows more X-rays to penetrate metal objects, minimizing streaking. Additionally, Metal Artifact Reduction (MAR) filters and iterative reconstruction techniques have been used to improve visualization in metal-affected areas. [8] developed a Bayesian Metal Artifact Reduction (b-MAR) model, which achieved a 70% reduction in dental implant artifacts, enabling clearer visualization of surrounding bone structures.

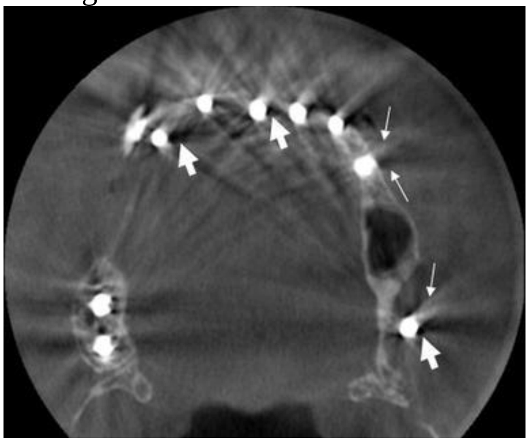

Figure 5: Metal artifacts [33]

2.3. SCANNER-BASED ARTIFACTS

Scanner-based artifacts are introduced due to limitations in the imaging system, detector performance, and reconstruction algorithms. These artifacts include ring artifacts, truncation artifacts, and limited-field-of-view (FOV) artifacts. Ring artifacts, commonly seen in CBCT, arise when individual detector elements are miscalibrated or defective, leading to circular patterns on the reconstructed images. This issue is less common in modern CT scanners due to better detector calibration and iterative reconstruction methods. Truncation artifacts occur when the patient's anatomy extends beyond the scanner's field of view, leading to incomplete image data reconstruction and bright halo effects in CBCT images. Limited-FOV artifacts are especially problematic in CBCT, where smaller detectors often fail to capture the full anatomical structure, causing data loss at the image edges. Correction strategies for scanner-based artifacts include the use of enhanced detector calibration protocols, deep-learning-based image correction methods, and extended-field-of-view algorithms in CBCT to reduce truncation effects and restore missing image data. In CT, iterative reconstruction techniques and optimized detector configurations have significantly improved artifact suppression, making scanner-based artifacts less prominent compared to CBCT [16].

RING ARTIFACTS

Ring artifacts are another issue, particularly in older CBCT scanners or systems with imperfect detector calibration. These artifacts manifest as concentric circular bands in images due to faulty or uncalibrated detector elements, causing consistent recording of incorrect intensity values. This effect disrupts segmentation accuracy, making it particularly problematic in craniofacial reconstruction and sinus imaging. Mitigation strategies include detector calibration techniques and flat-field correction methods, which normalize variations across the detector to minimize ring formation. AI-based detector correction models, such as those developed by [25], have further enhanced artifact reduction by detecting and correcting non-uniform detector response patterns.

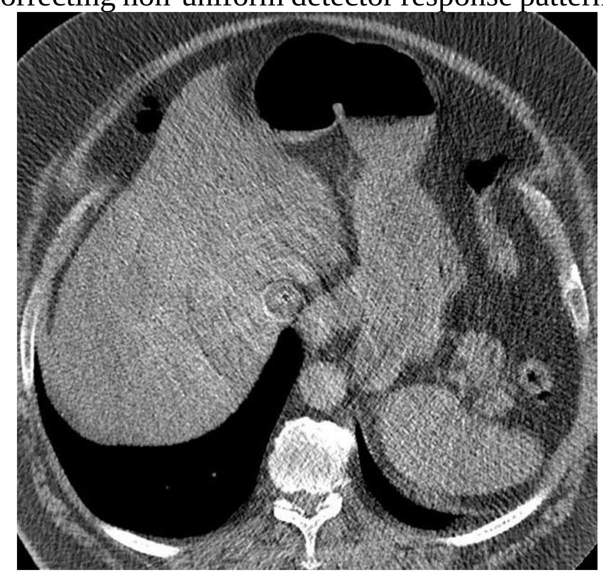

Figure 6: Ring artifacts[31]

PARTIAL VOLUME ARTIFACTS

Another common artifact in CBCT is the partial volume artifact, which occurs when a single voxel contains multiple tissue types due to limited spatial resolution. This results in blended density values, inaccurately representing the scanned anatomy and making it difficult to distinguish between adjacent structures. The effect is more severe in CBCT compared to CT, as CBCT often has larger voxel sizes in some settings, reducing spatial resolution. To mitigate this issue, reducing slice thickness can improve spatial resolution, with optimal values ranging from 0.075–0.125 mm for CBCT and 0.5–1.25 mm for CT. High-pass filters have also been used to improve edge detection and compensate for density blurring, helping to restore image sharpness. [4] demonstrated that voxel size reduction in CBCT significantly reduces segmentation error, leading to more precise anatomical modeling

2.4. AI-BASED ARTIFACT CORRECTION IN CT AND CBCT IMAGING.

Recent advancements in Artificial Intelligence (AI)-based artifact correction have significantly improved image quality in CT and CBCT. One of the most impactful techniques is deep-learning-based scatter correction, which reduces scatter artifacts that degrade image contrast in CBCT. [6] introduced a CNN-based scatter correction method that improved CBCT contrast by 35%, demonstrating a substantial enhancement in image clarity.

Additionally, AI-driven beam hardening correction has become a vital tool in artifact minimization, addressing streak artifacts caused by low-energy X-ray absorption. Developed a GAN-based beam hardening model that improved soft tissue differentiation by 40%, significantly enhancing anatomical accuracy in CBCT imaging. Another key area where AI has made significant advancements is real-time motion artifact suppression. Patient movement during image acquisition distorts image reconstruction, and traditional correction methods often fall short. [7] introduced an AI-powered motion correction model that reduced motion-induced errors by 50%, effectively restoring image quality without the need for repeated scans. Similarly, machine learning for metal artifact reduction (MAR) has revolutionized how metal implants are visualized in CBCT and CT. Metal artifacts create severe streaking that obscures anatomical structures, but AI models can now reconstruct missing details that would otherwise be lost. [8] proposed b-MAR, an AI-driven MAR technique that reduced dental implant artifacts by 70%, making metal-dense areas more distinguishable for diagnostic purposes. Lastly, AI-powered noise reduction has become essential in optimizing low-dose imaging. Lowering radiation exposure is critical for patient safety, but it often results in increased noise and reduced image clarity. To combat this, developed an AI-based denoising model that improved CBCT image clarity by 60%, making low-dose images comparable in quality to full-dose scans. By integrating these AI-driven correction methods into modern imaging workflows, CT and CBCT scans can now achieve superior image clarity, enhanced segmentation accuracy, and reduced radiation exposure, making AI an indispensable tool in medical imaging.

Despite these achievements, clinical implementation of AI-based artifact correction remains limited. Most models are evaluated in controlled or retrospective settings, and their performance across different scanners, patient anatomies, and imaging protocols is not yet fully validated. Moreover, these models often target single artifact types, whereas clinical images frequently contain a combination of overlapping distortions. Regulatory approval for clinical use is another barrier, as many AI correction algorithms lack the necessary multi-institutional validation and safety evaluation required for integration into routine diagnostic workflows.

To address these limitations, future research must focus on large-scale clinical validation across diverse patient populations and imaging systems. Development of hybrid AI frameworks that can simultaneously correct for multiple artifact types will be crucial for practical application. Additionally, user-centered integration of AI tools into existing clinical platforms is necessary to facilitate adoption without disrupting established workflows. Such advances are essential for transitioning AI-based artifact correction from experimental innovation to everyday clinical reality.

2.5. IMPACT OF ARTIFACTS ON SEGMENTATION ACCURACY

Artifacts in computed tomography (CT) and cone-beam computed tomography (CBCT) imaging significantly affect the accuracy of anatomical segmentation. Artifacts arise due to limitations in X-ray physics, patient movement, and the constraints of image reconstruction algorithms. These distortions degrade the quality of medical images, making it difficult to accurately segment anatomical structures, particularly for applications requiring high precision, such as implant planning, surgical navigation, and volumetric analysis [9].

Studies have demonstrated that the presence of artifacts can reduce segmentation accuracy by up to 30%, particularly in CBCT imaging, which is more prone to distortions due to its lower radiation dose and detector sensitivity [10]. In the case of soft tissue segmentation, artifacts can cause significant errors in boundary definition, leading to incorrect volume calculations. For instance, in studies evaluating maxillofacial CBCT images, segmentation errors were found to be as high as 1.5 mm in regions affected by beam hardening and scatter artifacts [12].

The presence of metal artifacts in dental and orthopedic imaging can lead to inaccurate localization of implants and bone structures, ultimately affecting treatment planning. In radiation therapy applications, segmentation inaccuracies due to artifacts can result in incorrect dose calculations, potentially impacting the efficacy and safety of the treatment [14]

CONCLUSIONS

The accuracy and reliability of anatomical models derived from CT and CBCT imaging are deeply influenced by optimized scanning parameters. An ideal balance between image quality and patient safety requires careful adjustments in slice thickness, radiation dose, voltage, exposure time, and reconstruction algorithms. For CBCT, optimal parameters include a slice thickness of 0.075–0.125 mm, a radiation dose of 0.1–0.3 mSv, and a voltage range of 80–100 kV. In contrast, CT imaging achieves optimal results with a slice thickness of 0.5–1.25 mm, a radiation dose of 2–5 mSv, and a voltage range of 100–120 kV.

One of the significant challenges in CT and CBCT imaging is the presence of artifacts, which can severely affect segmentation accuracy and diagnostic interpretation. Studies have shown that artifacts can reduce segmentation accuracy by up to 30%, with CBCT being particularly susceptible due to its lower radiation dose and detector sensitivity. Common artifacts such as beam hardening, motion artifacts, scatter artifacts, and metal artifacts must be carefully managed through advanced correction techniques. AI-driven approaches, including deep-learning-based denoising, motion correction, and metal artifact reduction, have demonstrated substantial improvements over conventional methods.

However, it is important to acknowledge that many of these AI techniques have not yet been widely implemented in clinical practice. While the experimental results are promising, further validation is needed to confirm their robustness across different imaging scenarios. Most studies are limited to narrow datasets or simulation-based evaluations and have not undergone full regulatory evaluation for routine clinical deployment.

The integration of AI in medical imaging represents a transformative step forward in reducing artifacts, refining segmentation accuracy, and optimizing imaging protocols. Future directions should prioritize clinical trials, hybrid models that address multiple artifact types simultaneously, and user-friendly implementation strategies that fit within existing workflows. Additionally, standardizing scanning parameters and correction techniques across various clinical settings remains a crucial step in ensuring diagnostic consistency and safety.

By leveraging these technological innovations and refining both scanning protocols and correction methods, medical imaging can continue to evolve, delivering higher precision, better surgical planning, and safer patient care across a wide range of medical disciplines.

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ОПТИМІЗАЦІЯ ПАРАМЕТРІВ СКАНУВАННЯ ДЛЯ КТ І КПКТ: СИСТЕМАТИЧНИЙ ОГЛЯД

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Анотація - *комп’ютерна томографія (КТ) та конусно-променева комп’ютерна томографія (КПКТ) революціонізували медичну візуалізацію, забезпечуючи високоточні тривимірні (3D) анатомічні моделі для діагностики, планування лікування та хірургічної симуляції. Точність цих моделей значною мірою залежить від параметрів сканування, таких як товщина зрізу, просторове розрішення, доза опромінення, напруга, час експозиції та алгоритми реконструкції.*

Оптимізовані параметри можуть підвищити якість зображень та точність сегментації, тоді як неоптимальні налаштування можуть спричиняти артефакти, знижувати анатомічну точність та негативно впливати на клінічні результати. КПКТ широко використовується в стоматології та щелепно-лицевій хірургії завдяки нижчій дозі опромінення та високій просторовій роздільній здатності, тоді як КТ переважно застосовується для комплексної анатомічної оцінки через кращу контрастність м’яких тканин. Вибір параметрів сканування має забезпечувати баланс між чіткістю зображення та безпекою пацієнта. Дослідження показали, що оптимальна товщина зрізу 0.075–0.125 мм у КПКТ та 0.5–1.25 мм у КТ забезпечує найкращі результати сегментації. Доза опромінення також має бути ретельно скоригована: для КПКТ зазвичай достатньо 0.1–0.3 мЗв, тоді як для КТ рекомендовано 2–5 мЗв. Значення напруги 80–100 кВ для КПКТ і 100–120 кВ для КТ допомагає зменшити артефакти затвердіння променя, зберігаючи контрастність.

Однією з головних проблем у візуалізації КТ/КПКТ є наявність артефактів, включаючи розсіювальні артефакти, артефакти затвердіння променя, артефакти руху та часткові об’ємні артефакти.

Цей огляд містить комплексний аналіз параметрів сканування КТ і КПКТ, узагальнює оптимальні налаштування для різних клінічних застосувань. Завдяки покращенню протоколів сканування та використанню сучасних методів зниження артефактів можна значно підвищити точність і надійність анатомічних моделей, що забезпечить кращі діагностичні та терапевтичні результати.

Ключові слова: *КТ; КПКТ; точність сегментації; параметри сканування; артефакти зображень; доза опромінення; артефакти розсіювання; артефакти затвердіння променя; артефакти руху; часткові об’ємні артефакти; металеві артефакти; кільцеві артефакти; шумові артефакти; алгоритми реконструкції; якість зображення; оптимізація дози; мінімізація артефактів.*