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Scanning procedure optimization for computed tomography and cone-beam computed tomography in cranio-maxillofacial surgeries: a systematic review

M. A. Tsarenko[A,B,D], L. Ye. Kalashnikova[C,E,F]

National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"

A – research concept and design; B – collection and/or assembly of data; C – data analysis and interpretation; D – writing the article; E – critical revision of the article; F – final approval of the article

Keywords:
computer tomography, cone-beam CT, cranio-maxillofacial imaging, scanning parameters optimization, image artifacts, segmentation accuracy, radiation dose reduction, beam hardening correction, scatter artifact mitigation, motion artifact suppression, artificial intelligence in medical imaging, deep learning artifact correction.

Ключові слова:
комп'ютерна томографія, конусно-променева комп'ютерна томографія, краніо-максилофаціальна візуалізація, оптимізація параметрів сканування, артефакти зображення, точність сегментації, зниження дози опромінення, корекція затвердіння променя, усунення артефактів розсіювання, придушення артефактів руху, штучний інтелект у медичній візуалізації, корекція артефактів на основі глибокого навчання.

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Computed tomography (CT) and cone-beam computed tomography (CBCT) are essential imaging tools for visualization in cranio-maxillofacial (CMF) surgery, providing high-resolution, 3D anatomical data for diagnosis, surgical planning, and follow-up. CT offers broader anatomical coverage and soft tissue contrast, while CBCT provides detailed bone imaging at lower radiation doses. However, both modalities are prone to artifacts – beam hardening, scatter, motion, and metal interference – that reduce image accuracy. Optimization of scanning parameters and protocols is essential to balance diagnostic quality with radiation safety. In parallel, deep learning approaches such as convolutional and generative adversarial networks are being explored for artifact suppression and segmentation enhancement.

Aim. The aim of the study is to review and compare CT and CBCT to identify the most optimal scanning parameters for cranio-maxillofacial imaging, ensuring high diagnostic accuracy while minimizing radiation exposure and artifact impact.

Materials and methods. A systematic search of scientific studies was conducted in the PubMed, Scopus, IEEE Xplore, and Web of Science using keywords: CBCT optimization, CT artifact correction, cranio-maxillofacial imaging, and deep learning in CT / CBCT. Inclusion criteria: studies assessing scanning parameters, image quality, artifact correction techniques in CMF contexts. Clinical, *in vitro*, and *ex vivo* studies were included. In total, 85 papers were analyzed.

Results. Optimal parameters – voxel sizes of 0.075–0.125 mm for CBCT and slice thicknesses of 0.50–1.25 mm for CT – improved diagnostic accuracy and segmentation outcomes. CBCT was preferred for bone structures, while CT remained superior for soft tissue and trauma. Traditional correction methods showed Dice gains of 6–15 %. AI-based models demonstrated higher performance, reducing artifacts by up to 70 % and achieving Dice scores up to 0.95. However, clinical adoption remains limited due to regulatory and standardization barriers.

Conclusions. Optimizing scan parameters significantly improves diagnostic performance in CMF imaging. While AI-based artifact correction shows strong potential, integration into clinical workflows requires further validation and regulatory alignment.

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Оптимізація процедури сканування для комп'ютерної томографії та конусно-променевої комп'ютерної томографії в краніомаксилофаціальних хірургіях: систематичний огляд

М. А. Царенко, Л. Є. Калашнікова

Комп'ютерна томографія (КТ) та конусно-променева комп'ютерна томографія (КПКТ) є пріоритетними методами візуалізації в краніомаксилофаціальній (КМФ) хірургії, що дають змогу отримати високоякісні тривимірні анатомічні дані для діагностики, планування операцій і післяопераційного контролю. Порівняно з КПКТ, КТ характеризується розширеним охопленням анатомічних зон і кращою діагностичною інформативністю щодо м'яких тканин, але КПКТ переважає у відтворенні зображення кісткових структур при меншому променевому навантаженні. Обидва методи характеризуються вразливістю до утворення таких артефактів, як затвердіння пучка, розсіювання, рух пацієнта та викривлення через наявність металевих елементів, що знижують точність зображення. Оптимізація параметрів і протоколів сканування є важливою для досягнення балансу між якістю діагностики та радіаційною безпекою. Паралельно досліджують методи глибинного навчання, зокрема згорткові нейронні мережі та генеративно-змагальні мережі, для пригнічення артефактів і покращення сегментації.

Мета роботи – здійснити огляд літератури та порівняти КТ і КПКТ для визначення оптимальних параметрів сканування для краніомаксилофаціальної візуалізації, що забезпечує високу діагностичну точність і мінімізацію променевого навантаження та впливу артефактів.

Матеріали і методи. Систематичний пошук наукових досліджень здійснили в базах даних PubMed, Scopus, IEEE Xplore та Web of Science з використанням ключових слів: CBCT optimization, CT artifact correction, cranio-maxillofacial imaging, deep learning in CT / CBCT. Для відбору релевантних досліджень використано такі критерії: оцінювання параметрів сканування, якість зображення та методи корекції артефактів у КМФ-контексті. До аналізу залучено клінічні, *in vitro* та *ex vivo* дослідження. Загалом проаналізовано 85 робіт.

Результати. Оптимальні параметри, а саме розмір вокселя 0,075–0,125 мм для КПКТ і товщина зрізу 0,50–1,25 мм для КТ, покращували точність сегментації та діагностики. КПКТ більш доцільна для візуалізації кісткових структур, а КТ оптимальна для м'яких тканин і травм. Традиційні методи корекції показали підвищення коефіцієнта Dice на 6–15 %. Моделі на основі ШІ показали вищу ефективність, зменшуючи артефакти до 70 % і досягаючи коефіцієнта Dice до 0,95. Втім, їх клінічне впровадження залишається обмеженим через регуляторні та стандартизаційні бар'єри.

Висновки. Оптимізація параметрів сканування суттєво покращує діагностичні можливості при КМФ-візуалізації. Хоча методи корекції артефактів на основі ШІ характеризуються високою ефективністю, їхня інтеграція в клінічну практику потребує валідації та узгодження з нормативними вимогами.

Сучасні медичні технології. 2026. Т. 18, № 2(69). С. 140-148

This systematic review explores the optimization of scanning parameters and artifact correction strategies in Computed Tomography (CT) and Cone-Beam Computed Tomography (CBCT), with a particular emphasis on applications in cranio-maxillofacial (CMF) surgery. CT and CBCT have become indispensable in producing high-resolution, three-dimensional anatomical models critical for diagnosis, treatment planning, and surgical navigation [1]. However, the accuracy of these models is significantly influenced by parameters such as slice thickness, voxel size, radiation dose, voltage, and reconstruction algorithm – each playing a role in balancing image quality and patient safety [2].

CBCT is widely adopted for dental and CMF procedures due to its superior spatial resolution and lower radiation dose, while CT remains the gold standard for bone, soft tissue imaging and trauma cases [3,4].

Despite these advancements in scanning protocol optimization, imaging artifacts such as beam hardening, scatter, motion, and metal-induced distortions continue to pose challenges, particularly in CBCT [5]. The review categorizes artifact sources into physics-based, patient-related, and scanner-related groups and outlines traditional correction methods (e. g., metal artifact reduction (MAR), iterative reconstruction). In addition, it evaluates recent AI-based solutions, including deep learning models, such as convolutional (CNNs) and generative adversarial networks (GANs), which can significantly enhance artifact suppression, segmentation accuracy, and processing speed [6,7]. Although these methods show great promise – achieving Dice coefficients up to 0.95 – their clinical integration remains limited due to regulatory and generalizability concerns [8,9].

By synthesizing current evidence, the review underscores the importance of parameter standardization and the emergence of hybrid AI-classical frameworks as future directions for improving diagnostic reliability, minimizing radiation, and enabling precise artifact-resilient CMF imaging.

Aim

This study aims to review and compare CT and CBCT to identify the most optimal scanning parameters for cranio-maxillofacial imaging, ensuring high diagnostic accuracy while minimizing radiation exposure and artifact impact.

Materials and methods

A comprehensive literature search was carried out using databases including PubMed, Scopus, IEEE Xplore, and Web of Science, covering publications from 2023 to 2025. Keywords used in the search strategy included: CBCT optimization, CT artifact correction, cranio-maxillofacial imaging, deep learning in CT / CBCT, beam hardening, motion artifact, segmentation accuracy, and AI in medical imaging. Inclusion criteria comprised peer-reviewed studies that: investigated CT or CBCT imaging protocols specifically in CMF surgery; discussed image quality in relation to scanning parameters (e. g., slice thickness, voxel size, kVp, mA); or presented solutions for artifact reduction using traditional or AI-based techniques. Both clinical studies and *in vitro* / *ex vivo* experimental validations were included. In total, 28 papers were analyzed.

Results

CT in CMF imaging. In CMF imaging, CT modalities – CBCT, multidetector CT (MDCT), and Helical CT – play a critical role in anatomical visualization and preoperative planning. These technologies differ in scanning mechanics, reconstruction algorithms, and clinical applications, which directly influence image quality and patient safety.

CT imaging: scanning protocols in CMF. MDCT and its predecessor, Helical (Spiral) CT, represent the principal medical-grade CT technologies employed for high-resolution imaging of both bony and soft tissue structures. These scanner types operate using a fan-shaped X-ray beam and a rotating gantry equipped with detector arrays, capturing volumetric anatomical data in a rapid and continuous fashion. The primary distinction between traditional helical CT and MDCT lies in the number and configuration of detector rows, which directly impacts image resolution, speed, and anatomical coverage. This spiral trajectory allows for volumetric scanning rather than isolated slice acquisition, dramatically reducing scan times and minimizing motion artifacts. However, early helical systems typically featured single or dual detector rows, limiting spatial resolution and increasing reconstruction time. Despite this, helical CT provided the foundation for advanced maxillofacial imaging by enabling 3D reconstructions and multi-planar reformatting, which were significant improvements over older axial-only CT methods. Helical CT is still in use in certain trauma and rural settings but has largely been replaced by MDCT in modern practice [10].

Multidetector CT represents a major evolution of helical scanning. Modern MDCT scanners are equipped with 16, 64, 128, or more detector rows, enabling simultaneous acquisition of multiple slices per gantry rotation. This not only shortens scan duration but also increases z-axis resolution and expands anatomical coverage. For CMF protocols, MDCT systems typically operate in helical mode, acquiring data with a sub-millimeter slice thickness – often 0.50 mm to 1.25 mm – allowing for exceptionally detailed imaging of facial bones, sinuses, orbits, and temporomandibular joints. The thin slices facilitate high-resolution 3D renderings, curved planar reformats (CPR), and virtual surgical planning, which are critical in managing complex fractures, midface reconstructions, tumor resections, and congenital deformities [10].

Scanning parameters for MDCT in CMF applications are largely determined by the protocol. Tube voltage (kVp) typically ranges between 100 kV and 140 kV, and tube current (mA) may vary from 150 to 500 mA, adjusted using automatic exposure control systems based on patient size and region of interest. Pitch factors, defined as the ratio of table feed per rotation to total beam width, are usually optimized between 0.75 and 1.50, balancing scan speed and resolution. The field of view (FOV) for CMF imaging is generally confined to 180–250 mm, sufficient to include the midface and skull base while minimizing radiation to adjacent tissues. Exposure times per rotation range from 0.4 to 1.0 second, and total scan durations for the entire CMF region typically remain under 10 seconds.

Image reconstruction in MDCT relies on sophisticated algorithms. While filtered back projection was standard for decades, modern scanners favor iterative reconstruction techniques that reduce image noise and allow for lower-dose imaging protocols. This is especially relevant in CMF imaging, where repeat imaging may be required in preoperative planning, postoperative evaluation, or orthognathic simulation [10,11]. Furthermore, MAR algorithms are integrated to mitigate the effects of dental restorations or implants, which are common sources of image degradation in the maxillofacial region.

In summary, MDCT has become the gold standard in hospital-based CMF imaging, especially in acute settings where soft tissue contrast, speed, and anatomical range are critical. While Helical CT laid the foundation for volumetric scanning, its role has been largely historical. The multidetector architecture of modern MDCT allows for high-fidelity imaging of complex anatomical zones and supports advanced surgical planning, making it indispensable in trauma, oncology, and complex CMF reconstructive procedures.

CBCT imaging: scanning protocols in CMF. CBCT has become a cornerstone in CMF surgery due to its ability to generate accurate, high-resolution three-dimensional images of the facial skeleton with significantly lower radiation exposure than conventional CT [2]. Unlike CT, which captures sequential axial slices using a fan-shaped X-ray beam, CBCT employs a cone-shaped beam and a flat-panel detector to acquire volumetric data in a single or limited rotational arc [12]. This technique improves imaging efficiency while providing comprehensive 3D datasets for diagnostic and surgical planning.

Notably, CBCT accuracy depends on protocol adherence. Inconsistent settings may result in suboptimal resolution or incomplete visualization of critical structures, compromising surgical planning. Proper immobilization, scout imaging, calibration of rotation arcs, and operator training are essential for reproducibility. Standardized protocols not only improve local accuracy but also enable reliable data integration into virtual surgical planning platforms and 3D-printed surgical guides [13].

Reconstruction of CBCT images is typically performed using the Feldkamp-Davis-Kress algorithm, optimized for cone-beam geometry. Although CBCT has limited soft tissue contrast compared with CT, its spatial resolution (0.075–0.4 mm) makes it the modality of choice for osseous detail in orthognathic surgery, temporomandibular joints diagnostics, midface trauma, and implant planning [4,14].

Comparison of CT and CBCT: key differences in scanning mechanics for CMF imaging. CT – specifically MDCT and helical CT – and CBCT differ significantly in scanning mechanics, detector configurations, and reconstruction strategies. These differences are particularly relevant in CMF imaging, where both high-resolution bone visualization and soft tissue contrast are often required.

MDCT / helical CT employs a fan-beam X-ray system with multi-row detector arrays, allowing continuous volumetric scanning with high temporal and spatial resolution. It provides excellent soft tissue contrast, making it the modality of choice for evaluating complex facial trauma, sinonasal and orbital pathology, head and neck tumors, and vascular anatomy. The flexibility to fine-tune acquisition parameters – such as slice thickness, tube voltage, and tube current – enables tailored imaging for intricate CMF structures like the temporomandibular joint and infraorbital canal. Furthermore, advanced CT protocols such as dual-energy CT and contrast-enhanced helical CT improve tissue characterization and vascular mapping, offering superior diagnostic capability in oncologic and reconstructive planning [12].

In contrast, CBCT uses a cone-shaped X-ray beam and flat-panel detectors, optimized for high-resolution 3D imaging of osseous structures. With isotropic voxel sizes as small as 0.075 mm, CBCT is highly effective for dental implant planning, jaw deformity analysis, fracture detection, and surgical navigation in alveolar, midfacial, and orthognathic procedures [15,16,17]. Additionally, CBCT typically delivers a much lower radiation dose [4,13]. However, CBCT's inferior soft tissue contrast, limited grayscale dynamic range, and higher susceptibility to metal artifacts restrict its utility in soft tissue diagnostics [4].

Another important distinction lies in image reconstruction. MDCT / helical CT often utilizes iterative reconstruction algorithms, which reduce image noise and allow for lower-dose imaging while maintaining clarity [10]. In contrast, CBCT predominantly uses the Feldkamp-Davis-Kress algorithm, which, while computationally efficient, lacks advanced noise correction capabilities and is more prone to artifacts, particularly in areas affected by motion or metallic interference [18].

Ultimately, the choice between MDCT / helical CT and CBCT in CMF imaging should be guided by the specific clinical objective. CBCT is preferred when high spatial resolution of bony anatomy is

Table 1. Comparison of optimal scanning parameters between CT and CBCT for CMF surgeries

Parameter, units of measurement	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	5 × 5 cm (teeth), 10 × 10 cm (jaws)	20 × 20 cm
Reconstruction algorithm	Feldkamp-Davis-Kress	Iterative reconstruction

needed with minimal radiation, while MDCT remains superior for soft tissue evaluation, pathology detection, and comprehensive surgical planning. A structured comparison of optimal scanning parameters between CT and CBCT modalities is presented in *Table 1*, providing practical reference values for clinical application.

Image artifacts and minimization techniques. Image artifacts in CT and CBCT represent distortions or inaccuracies that compromise image quality, hinder accurate segmentation, and reduce the overall diagnostic reliability of the scan. These artifacts arise from physical interactions between X-rays and patient tissues or materials, as well as limitations in imaging geometry and reconstruction algorithms. Although artifacts occur across all imaging modalities, CBCT is particularly susceptible due to its lower radiation dose, narrower detector dynamic range, and greater sensitivity to scattered radiation compared to conventional CT. These factors contribute to a higher prevalence of image degradation in CBCT, often manifesting as streaks, shadows, or distortions that obscure anatomical details or lead to misinterpretation [19]. Understanding the mechanisms underlying artifact formation and applying appropriate correction strategies is therefore essential for ensuring diagnostic accuracy. Artifacts in CT and CBCT are generally categorized into three groups: patient-related (motion or metal), physics-based (beam hardening, scatter, noise), and scanner-related (detector imperfections or calibration errors).

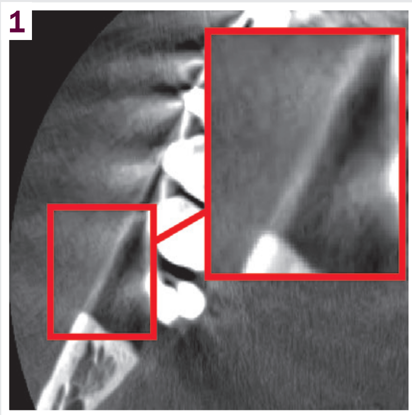
Physics-based artifacts. Physics-based artifacts in CT and CBCT imaging arise from inherent interactions between X-ray photons and matter, leading to distortions such as beam hardening, scatter, and photon starvation, which occurs when dense structures absorb most of the photons before they reach the detector, producing streaking and under-sampling artifacts that degrade image quality.

To mitigate these artifacts, correction strategies are employed. In CT, hardware solutions such as bowtie filters, anti-scatter grids, high-energy spectra, and beam-hardening correction algorithms are standard. In CBCT, hardware filtering is limited, making software-based solutions essential. These include scatter correction algorithms, Monte Carlo-based scatter modeling, and careful optimization of exposure parameters (kVp, mA, voxel size) to balance dose and image quality. Collectively, such techniques are indispensable for diagnostic reliability in high-contrast CMF environments [18].

Scatter artifacts are among the most prevalent and challenging image distortions in CBCT. They arise when X-ray photons are deflected from their original trajectories due to interactions with patient tissues before reaching the detector. These scattered photons overlay the primary signal, resulting in decreased image contrast, blurring, and loss of edge definition (*Fig. 1*, red arrows point to a visual example of scatter artifacts). This issue is significantly more pronounced in CBCT than in conventional CT due to the wide-angle cone beam, larger field of view, and limited collimation – factors that collectively increase the proportion of scatter reaching the detector. The problem is exacerbated in low-dose imaging protocols, where scattered photons contribute disproportionately to signal intensity, thereby degrading diagnostic quality.

To mitigate scatter artifacts, several strategies have been developed. Anti-scatter grids are commonly employed to physically block scattered radiation before it reaches the detector, improving contrast resolution. Additionally, hardware beam collimators help constrain the X-ray beam to the region of interest, reducing off-axis scatter. On the computational side, Monte Carlo-based scatter modeling is widely used to simulate and subtract scattered components from the raw data, enhancing image clarity. More recently, deep learning-based correction techniques – particularly CNNs, residual CNNs, and conditional generative adversarial networks (cGANs) – have shown promising results. CNNs are effective at predicting scatter distribution in the projection domain, while GAN-based models excel at reconstructing scatter-free images in the image domain, often outperforming traditional iterative correction. For example, recent studies reported up to 35 % improvement in CBCT image contrast using CNN-driven correction pipelines, while adversarial models demonstrated strong generalizability across patient anatomies and acquisition protocols [19]. These AI-driven approaches provide real-time, adaptive solutions that dynamically adjust to variable imaging conditions, marking a significant advancement in artifact reduction and image enhancement in CBCT imaging.

Beam hardening is another significant artifact that adversely affects both CT and CBCT imaging quality. It occurs when lower-energy X-ray photons are preferentially absorbed as they pass through dense materials – such as bone or metal implants – while higher-energy photons penetrate more effectively. This differential attenuation leads to non-uniform X-ray absorption, resulting in characteristic dark bands, cupping artifacts, and streaking in reconstructed images. These distortions can obscure anatomical details or simulate pathology, thus compromising diagnostic accuracy. Beam hardening is particularly problematic in maxil-



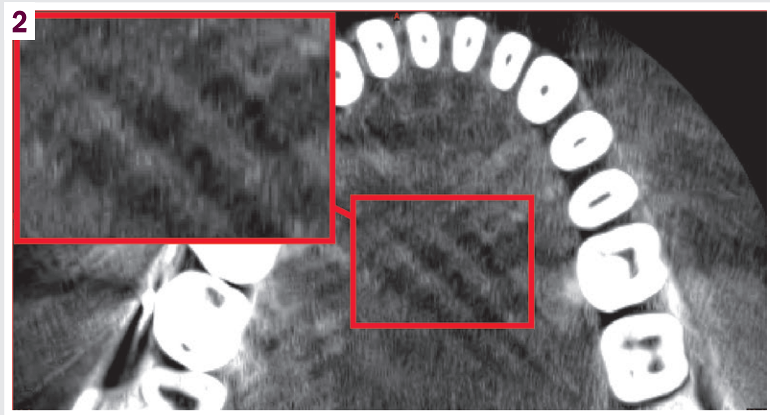


Fig. 1. Zoomed red area contains scatter artifacts example. Personal CBCT lower jaw scans made for dental purposes. Scan key parameters: scanner type – Planmeca / ProMax, Tube Current – 8 mA, kVp – 90 kV, slice thickness – 0.2 mm, slice increment – 0.2 mm, pixel size – 0.2 mm, number of slices – 501, scan date – 17.10.2023.

Fig. 2. Zoomed red area contains beam hardening artifact on CBCT. Personal CBCT lower jaw scans made for dental purposes. Scan key parameters: scanner type – Planmeca / ProMax, Tube Current – 8mA, KVP – 90 kV, slice thickness – 0.2 mm, slice increment – 0.2 mm, pixel size – 0.2 mm, number of slices – 501, scan date – 17.10.2023.

lofacial CBCT imaging, where high-density anatomical regions and dental restorations are common. In fact, segmentation errors of up to 1.5 mm have been reported in CBCT scans affected by this artifact, posing a serious challenge for surgical planning and prosthetic design [8,20]. A representative example of beam hardening effects in CBCT imaging is illustrated in *Fig. 2*, showing streaks and cupping artifacts adjacent to metallic restorations.

Mitigation strategies for beam hardening focus on improving the uniformity of X-ray penetration and enhancing reconstruction fidelity. One common approach is to increase the tube voltage (typically to 100–120 kV), thereby generating higher-energy photons that are less susceptible to selective absorption, reducing the severity of beam hardening. Additionally, beam hardening correction algorithms are applied during image reconstruction to compensate for intensity variations. Among these, dual-energy CT has shown particular promise; it acquires images at two distinct energy levels to distinguish between different tissue types and materials, enabling more accurate attenuation correction [14]. Recent developments have also introduced AI-driven dual-energy reconstruction models, which outperform traditional beam hardening correction methods. For instance, deep learning-based dual-energy CT approaches can significantly reduce beam hardening streaks in CBCT datasets, particularly in regions with dense restorative materials where conventional algorithms fail [8]. These innovations represent a critical step forward in addressing beam hardening artifacts and improving the reliability of CBCT in clinical workflows.

Noise artifacts in CBCT and CT imaging occur primarily when the X-ray dose is insufficient, resulting in random fluctuations in pixel intensity that obscure anatomical detail and degrade overall image clarity.

CBCT systems are particularly vulnerable to noise due to their inherently lower signal-to-noise ratio compared to conventional CT. This limitation becomes especially significant in low-dose protocols, such as those used in pediatric imaging, orthodontic assessments, and routine dental screenings, where minimizing radiation exposure is a clinical priority. In such cases, noise not only reduces image sharpness but can also mask subtle pathologies or anatomical boundaries, compromising diagnostic accuracy.

While increasing the X-ray dose can reduce noise levels, this approach directly conflicts with the principle of radiation dose optimization, particularly in vulnerable populations. As a result, alternative noise-reduction strategies are essential. Recent advancements in AI-driven denoising techniques have demonstrated remarkable potential in overcoming this challenge. These models – including CNNs, residual U-Nets, and GAN-based architectures – are capable of selectively suppressing noise while preserving fine structural details, offering a superior balance between image quality and radiation safety. For example, it is reported that a CycleGAN-based denoising approach improved CBCT image clarity by up to 60 %, enabling diagnostic-quality reconstructions from low-dose acquisitions without increasing patient exposure. Deep learning methods have been shown to consistently outperform traditional filters and iterative reconstruction, achieving better preservation of edge sharpness while simultaneously reducing stochastic noise. Such innovations represent a transformative step in CBCT imaging, making high-fidelity visualization more accessible and safer for a broader range of clinical applications.

Patient-based artifacts. Patient-based artifacts in CT and CBCT imaging result from factors intrinsic to the patient, including involuntary movement, anatomical variations, and the presence of metallic implants, all of which can distort the reconstructed image and compromise diagnostic accuracy. Motion artifacts are especially common in CBCT due to its typically longer scan times compared to conventional CT. Even minor patient movements during image acquisition can lead to blurring, streaking, or double-image formation, which impairs the visualization of anatomical structures and reduces spatial accuracy. This issue is particularly critical in pediatric imaging, scans involving unco-

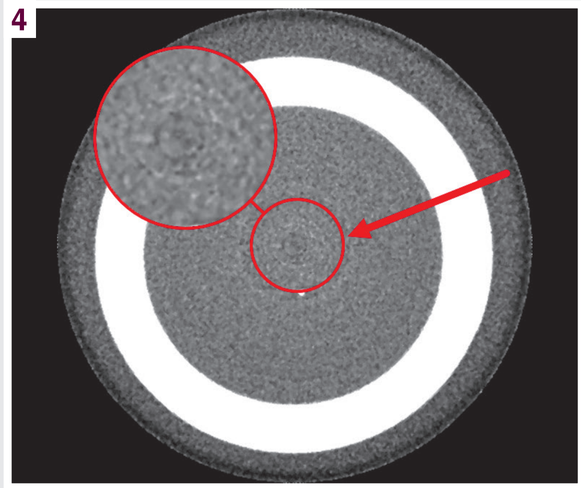


Fig. 3. Red arrows point to motion artifact. Adapted from [22].

Fig. 4. Red arrow points to a ring artifact. Adapted from [22].

operative or medically complex patients, and cases requiring extended exposure durations.

In addition to movement, anatomical heterogeneity – such as dense cortical bone, air-filled sinuses, and soft tissue transitions – can introduce attenuation mismatches that cause subtle inconsistencies in image reconstruction. These structural variations may alter X-ray absorption unpredictably, leading to artifacts that resemble pathology or mask real findings.

Metal artifacts represent another significant challenge, frequently encountered in CBCT due to the high prevalence of dental restorations, orthodontic appliances, and surgical implants in the CMF region. These materials induce severe streaking, dark bands, and signal voids, primarily due to beam hardening and photon starvation, which distort surrounding anatomy and complicate segmentation or surgical planning.

To mitigate patient-based artifacts, several techniques are employed. These include shortened acquisition protocols to reduce motion susceptibility, patient immobilization strategies such as bite blocks and head stabilizers, and the use of MAR algorithms to restore image integrity near metallic structures. Furthermore, motion correction software and emerging AI-driven artifact suppression models offer promising avenues to further enhance image quality, especially in complex or compromised scanning conditions [6]. When combined, these strategies are essential for optimizing the diagnostic reliability of CBCT imaging across diverse patient populations.

Motion artifacts represent a significant challenge in both CT and CBCT imaging, occurring when the patient moves during data acquisition *(Fig. 3)*. Such motion results in blurring, double contours, streaking, and overall degradation of image quality, which can severely impair diagnostic accuracy. This problem is especially pronounced in CBCT, where longer scan times – often exceeding 10–20 seconds – make the modality more susceptible to involuntary movements such as breathing, swallowing, or tremors. In contrast, CT typically operates with shorter scan durations and higher acquisition speeds, making it relatively less prone to this issue. Motion artifacts are particularly problematic in neurological imaging, dental CBCT scans, and pediatric applications, where maintaining patient stillness can be difficult or unpredictable.

Traditional mitigation strategies focus on reducing scan duration – typically to 3–6 seconds for CBCT and 5–10 seconds for CT – along with patient immobilization techniques, such as bite blocks in dental imaging or head restraints in neurosurgical applications. While these methods are partially effective, they do not eliminate motion-related distortions, especially in cases involving uncooperative patients or complex anatomical regions.

Recent advances in artificial intelligence have introduced more sophisticated and robust solutions. For example, a prototype motion correction reconstruction algorithm for interventional CBCT, showing substantial improvements in motion artifact suppression [8]. Similarly, a time-resolved CBCT reconstruction method using spatiotemporal Gaussian models, significantly reducing streaking and respiratory-motion artifacts [21]. More recently, a review highlighted AI-based motion compensation frameworks in CT and CBCT reconstruction, emphasizing the integration of deep learning into real-time motion prediction and correction pipelines [9]. These dynamic approaches integrate motion estimation into the reconstruction process, resulting in a reduction of motion-induced artifacts and substantial improvements in overall image clarity. Collectively, these AI-driven techniques mark a transformative step in enhancing the reliability and diagnostic utility of CBCT and CT imaging, particularly in challenging clinical scenarios where patient motion is unavoidable.

Scanner-based artifacts originate from inherent limitations within the imaging system itself, including detector performance issues, hardware miscalibrations, and imperfections in reconstruction algorithms. These artifacts are particularly evident in CBCT due to its compact system design and reliance on simpler hardware compared to conventional CT. Common scanner-based artifacts include ring artifacts, truncation artifacts, and limited FOV artifacts.

Ring artifacts, frequently encountered in CBCT, arise from defective or miscalibrated detector elements. These faults manifest as concentric rings or circular distortions in the reconstructed image, degrading diagnostic accuracy. While such artifacts are now rare in modern CT systems – due to robust detector calibration and advanced iterative reconstruction algorithms – they remain a concern in CBCT, particularly in older or lower-end systems.

Truncation artifacts occur when part of the patient's anatomy lies outside the detector's FOV, leading to incomplete data acquisition and causing bright halos or edge distortions in the final image. This is especially problematic in CBCT, where the limited scan volume and small detector array may fail to capture larger anatomical structures, such as the full craniofacial skeleton or jawline in dental imaging.

Limited-FOV artifacts are closely related and refer to image data loss at the periphery, where regions outside the detector coverage are not reconstructed, resulting in cut-off anatomy or inconsistent gray levels near the edges. These effects can hinder clinical interpretation and reduce measurement accuracy, particularly in surgical planning or orthodontic applications.

Mitigation strategies for scanner-based artifacts include rigorous detector calibration protocols and the implementation of extended-field-of-view algorithms that extrapolate beyond the scanned region to recover lost information. Deep learning-based correction models are also being integrated into CBCT workflows, offering data-driven reconstruction improvements that can effectively suppress scanner-induced distortions. In CT imaging, the use of optimized detector arrays and iterative reconstruction techniques has largely minimized the prevalence of these artifacts, making them significantly less pronounced than in CBCT systems. As CBCT technology continues to evolve, addressing scanner-based artifacts remains a key priority to ensure consistent image quality and clinical reliability.

Ring artifacts are a notable image distortion, particularly prevalent in older CBCT systems or devices with inadequate detector calibration *(Fig. 4)*. These artifacts appear as concentric circular bands superimposed on the reconstructed image and are caused by individual detector elements that consistently record inaccurate intensity values due to malfunction or miscalibration. The repetitive nature of these errors across the rotational scan leads to circular anomalies centered around the axis of rotation. This artifact is especially disruptive in applications requiring high anatomical precision, such as craniofacial reconstruction, sinus evaluation, and orthognathic surgical planning, where even minor inaccuracies in segmentation can lead to clinical misinterpretation. To address ring artifacts, detector calibration procedures and flat-field correction techniques are routinely employed. These methods aim to normalize the detector's response by compensating for gain and offset inconsistencies across all pixels, thereby minimizing the appearance of rings in the reconstructed volume.

Partial volume artifacts are another common source of image distortion in CBCT imaging, occurring when a single voxel encompasses multiple tissue types due to limited spatial resolution. This results in averaged or blended intensity values within the voxel, inaccurately representing the true anatomical structures. The artifact leads to blurred boundaries, false density readings, and reduced contrast between adjacent tissues – posing a significant challenge in applications requiring precise delineation, such as dental root analysis, implant planning, and bone – tissue interface evaluations.

This effect is generally more pronounced in CBCT than in CT, largely due to the larger voxel sizes and lower detector sensitivity employed in many CBCT systems, particularly when operating under low-dose protocols. In contrast, CT systems typically offer finer control over slice thickness and detector resolution, allowing better discrimination between tissues.

Mitigation strategies focus on enhancing spatial resolution. In CBCT, reducing voxel size – ideally to the range of 0.075–0.125 mm – can significantly reduce partial volume effects, especially in high-detail regions such as the alveolar ridge or cranial sutures [5]. For CT, optimal slice thickness typically falls within 0.50–1.25 mm, depending on the clinical context. Additionally, the application of high-pass spatial filters during post-processing can improve edge definition and compensate for blurring caused by partial volume averaging. These filters emphasize high-frequency components of the image, thus enhancing the visibility of small anatomical structures [23].

Recent studies have confirmed that reducing voxel size in CBCT improves diagnostic accuracy in fine-detail imaging tasks. For example, S. Murat et al. (2025) demonstrated that smaller voxel sizes significantly improved CBCT-derived measurement accuracy compared to micro-CT [24]. Similarly, highlighted voxel size has been identified as a major determinant of registration accuracy in facial imaging, while AI-based CBCT resolution enhancement models have been proposed to reduce partial volume artifacts and improve image clarity in dental and endodontic applications [25].

As imaging demands increase in precision-driven fields like CMF surgery and endodontics, minimizing partial volume artifacts remains a critical factor in optimizing CBCT image quality and ensuring accurate clinical outcomes.

Impact of artifacts on segmentation accuracy. This issue is especially pronounced in CBCT imaging, which is inherently more susceptible to artifacts due to its lower radiation dose, limited detector dynamic range, and wider cone beam geometry. The presence of such artifacts can substantially impair segmentation accuracy, with soft tissue boundaries being particularly vulnerable because of low contrast resolution and beam-related distortions. One notable example is beam hardening and scatter artifacts, which cause non-uniform attenuation and result in blurred or artificially altered tissue boundaries. In maxillofacial CBCT studies, segmentation errors of up to 1.5 mm have been reported in artifact-prone regions, a significant margin that can compromise the clinical accuracy of surgical or prosthetic interventions [26].

Metal artifacts, commonly encountered in dental and orthopedic imaging, present an additional challenge. High-density restorations, implants, and surgical hardware cause severe streaking and signal voids that obscure the surrounding bone and soft tissues. This distortion can lead to mislocalization of implants, inaccurate bone delineation, and compromised preoperative planning. In radiation therapy, segmentation errors caused by artifacts can translate into inaccurate dose mapping, risking underdosing of the target or unintended exposure to surrounding critical structures,

Table 2. Comparison of traditional vs AI-based artifact correction techniques in CT and CBCT imaging

Feature	Traditional methods	AI-based methods	Citations
Accuracy (Dice)	0.65–0.80 depending on filter type and modality (MAR, beam hardening correction)	0.85–0.95 using deep learning (CNN, GAN, b-MAR) on CBCT datasets	[24,25,26]
Processing time	~1–5 min per scan using conventional iterative reconstruction or MAR filters	0.5–2.0 min (depending on GPU capacity); real-time possible in some cases	[22]
Clinical readiness	Fully integrated into major CT / CBCT systems; FDA (Food and Drug Administration) cleared	Mostly experimental; limited FDA/CE (Conformité Européenne) approvals; general-purpose AI correction not yet widely cleared	–
Artifact coverage	Optimized for one type (e.g., beam hardening or motion)	Can learn multiple artifact patterns simultaneously (motion + noise + beam hardening)	[22,25]
Scalability	Vendor-dependent; tuned to scanner models	Highly scalable across platforms, but robustness to patient anatomy and diverse scanners remains a challenge	–

thereby affecting both treatment efficacy and patient safety [25].

Recent advances in deep learning have introduced AI-driven segmentation models that substantially improve robustness against artifacts. Automated 3D segmentation frameworks such as nnU-Net v2 have demonstrated strong performance in CBCT datasets, achieving reliable detection of fine structures with Dice similarity coefficients (DSC) >0.90 even in artifact-rich scans [27]. Similarly, multi-algorithm comparisons in CMF imaging confirmed that AI-based CBCT segmentation consistently outperforms manual and semi-automated methods, particularly in complex anatomical zones [20]. More advanced strategies, including deep ensemble learning and hybrid multi-structure segmentation pipelines, have further improved accuracy for surgical planning tasks, reducing variability and increasing reproducibility across patient datasets [28].

Comparison of traditional and AI-based artifact correction techniques. Traditional artifact correction techniques in CT and CBCT imaging – such as beam hardening filters, MAR algorithms, and iterative reconstruction – have been widely used in commercial scanners for years. These methods typically address a single artifact type and offer moderate segmentation accuracy, with Dice coefficients ranging from 0.65 to 0.80 depending on the anatomical region and imaging modality *(Table 2)*.

In contrast, AI-based correction methods, particularly deep learning approaches using convolutional neural networks and generative adversarial networks, demonstrate significantly higher segmentation precision, often achieving Dice scores between 0.85 and 0.95 on benchmark datasets *(Table 2)*. These methods excel at modeling complex, overlapping artifacts such as scatter and motion simultaneously and can reconstruct missing anatomical details around metal implants more effectively than traditional techniques.

Processing time is also markedly improved. AI models, when executed on modern GPUs, can produce corrected scans in under 2 minutes, with some achieving near real-time performance.

Challenges and future directions. Despite their promising capabilities, AI-based artifact correction techniques remain underutilized in routine clinical practice. Many models have been validated only in controlled, retrospective, or single-vendor environments, limiting their generalizability. Furthermore, current AI systems often target individual artifact types, while in real-world clinical imaging, multiple artifacts frequently co-occur – interacting in ways that simple single-mode correction cannot resolve. Another barrier is regulatory approval, as most models have not undergone the multi-center clinical validation and safety testing required for integration into FDA- or CE-cleared diagnostic platforms.

To overcome these limitations, future research must prioritize large-scale, multi-institutional validation across diverse patient anatomies, scanner models, and imaging protocols. The development of hybrid or multi-task AI frameworks, capable of simultaneously correcting multiple artifact types, will be essential for practical deployment. Additionally, user-friendly integration into existing Picture Archiving and Communication System and imaging software platforms is needed to ensure smooth clinical adoption without disrupting established radiology workflows.

By addressing these challenges, AI-based artifact correction can transition from an experimental innovation to a clinical standard, enabling safer, faster, and more accurate diagnostic imaging across a wide range of applications in medicine and surgery.

Conclusions

1. The diagnostic effectiveness of cranio-maxillofacial imaging with CT and CBCT is largely determined by the adjustment of scanning parameters and reconstruction algorithms. Optimization of these parameters ensures high image quality and patient safety.

2. Nevertheless, imaging artifacts remain a significant obstacle. In CT and CBCT, such artifacts can decrease segmentation accuracy by up to 30 %, thereby complicating diagnostic evaluation.

3. Conventional correction methods (e. g. iterative reconstruction, beam-hardening filters, and metal artifact reduction algorithms) improve segmentation accuracy by only 6–15 %. These approaches are generally tailored to individual artifact types and demonstrate limited effectiveness in complex or combined scenarios.

4. Artificial intelligence–based correction methods, including convolutional neural networks and generative adversarial networks, show improvements in segmentation accuracy of up to 30 %. These techniques can simultaneously address multiple artifact sources and enable real-time reconstruction. However, AI-based algorithms remain at an experimental stage; their clinical effectiveness, reliability, reproducibility, and generalizability are still under investigation and require further validation.

Prospects for further research. Future research should focus on the development of hybrid correction frameworks that integrate validated AI models with conventional reconstruction approaches, with particular emphasis on ensuring clinical reliability and regulatory compliance.

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Information about the authors:

Tsarenko M. A., Postgraduate Student, Department of Biomedical Engineering, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute".
ORCID ID: 0009-0004-8719-094X
Kalashnikova L. Ye., PhD, Associate Professor, Department of Biomedical Engineering, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute".
ORCID ID: 0000-0002-4809-5446

Відомості про авторів:

Царенко М. А., аспірант каф. біомедичної інженерії, Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського».
Калашнікова Л. Є., канд. біол. наук, доцент каф. біомедичної інженерії, Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського».

Mykola Tsarenko (Микола Царенко)
mykola.tsarenko94@gmail.com

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