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A Review of Enhancement Techniques for Cone Beam Computed Tomography Images

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ABSTRACT

Cone Beam Computed Tomography (CBCT) has emerged as a valuable imaging modality for various medical applications due to its ability to provide three-dimensional information with minimal radiation exposure. However, CBCT images often suffer from inherent limitations, such as increased noise, artifacts, and reduced spatial resolution. This paper presents a comprehensive review of image processing techniques employed to enhance the quality of CBCT images, addressing the challenges posed by acquisition hardware and image reconstruction algorithms. The review covers a range of preprocessing and post-processing methods, including denoising, artifact correction, and resolution improvement techniques. These methods encompass various mathematical algorithms, machine learning approaches, and hybrid models, which aim to mitigate the imperfections present in CBCT data while preserving diagnostically relevant information. Additionally, this paper discusses the application of deep learning methods, convolutional neural networks, and generative adversarial networks in CBCT image enhancement. These advanced techniques have shown promise in tackling the complex nature of CBCT data and optimizing image quality.

Introduction

Modern CBCT equipment generates superb, high-resolution, three-dimensional images of the oral anatomy, simplifying and confirming dental implant planning and surgical placement. The diagnostic landscape is continuously evolving due to the introduction of new technology in dentistry, which enables dentists to diagnose in three dimensions [1]. Since the development of CBCT, patients have profited from improved diagnosis and treatment planning, as well as eventually safer and more predictable procedures. As computers and scanning technology have advanced, it has emerged as a crucial diagnostic tool for researchers and practicing dentists in the quickly evolving field of digital dentistry. Additionally, CBCT's use in periodontics, endodontics, orthodontics, temporomandibular joint diseases, airway assessment, and oral and maxillofacial surgery have been extensively documented recently [2][3].

Considering the same objectives, the required radiation dose for CBCT is less than that of CT. The existence of grey level non-uniformities in reconstructed CBCT images is a contributing factor to the creation of artifacts [4]. These distortions may cause image deterioration and result in incorrect or misleading diagnoses. It is anticipated that healthcare conventional practices will be both disrupted and transformed by artificial intelligence (AI) [5][6] .The adoption of medical technology has historically been led by radiation oncology, a tradition that necessitates knowledge of both the theoretical and practical elements of a specific technology. In addition to providing a pictorial essay explaining the numerous CBCT defects and artifacts, this article may aid in understanding the factors contributing to CBCT image deterioration. Therefore, the purpose of this study is to provide a broader understanding of state-of-the-art deep enhancement techniques used in cone-beam CT (CBCT) image. It also seeks to provide a summary of discoveries that are clinically relevant and constructive suggestions for further research.

CBCT WORKING MECHANISIM

Cone Beam Computed Tomography (CBCT) expands upon the basic ideas of conventional CT scanning. With CBCT, the patient is exposed from one side while an image detector rotates around the patient to measure the attenuated X-rays on the other side [7] (see Fig. 1). Exposure can be either continuous or pulsed during the rotating scan; pulsed exposure is increasingly used in dental CBCT to shorten effective exposure times and lower patient doses [8].

The X-ray attenuation follows the fundamental physics laws of radiation dose and the atomic makeup of the patient's anatomy in the field of view (FOV). Compton scattering and the photoelectric effect are two significant interactions that regulate the fundamental equilibrium for contrast representation in the images. While photoelectric effect is the main source of visual contrast, when X-ray photon energy increases, its contribution decreases significantly. When tube voltages increase, there is a corresponding decrease in picture contrast. Simultaneously, the impact of scattering grows, accompanied by a spectrum shift towards higher-energy X-rays. [9]..

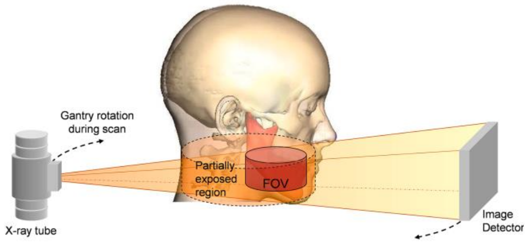

Figure 1 Illustrates the fundamental principle of a CBCT scan [10].

The reproduction of 3D image is the key to CT imaging in the computational space. To solve the numerical opposite issue, this strategy intends to reason the three-layered guide of material-explicit lessening values inside the patient from the x-beam shadow signals recorded during openness. Customarily, standard CBCT scanners have depended on customary logical reproduction techniques, which are established on the guess of the Radon reverse change at first presented by Feldkamp et al. in 1984 [11].Iterative reconstruction techniques have gained popularity recently due to their ability to improve image quality and minimize artefacts [12].

This strategy shows potential in mitigating a major CBCT challenge: the standard CBCT C-arm type gantry design's vulnerability to motion artefacts as a result of the scan time [13], which is relatively long. Artificial intelligence (AI)-based deep learning (DL) techniques represent a new development in picture reconstruction [14]. By utilizing large datasets of standard clinical or technical phantom images, these state-of-the-art methods address the reconstruction issue and produce improved image quality [14]. However, using AI-based reconstruction techniques has several challenges. The learning data must be sufficiently representative and span a wide range of patient anatomy and contrast occurrences. This ensures that the reconstruction method may be applied to any imaging circumstance and produces reliable and accurate image quality for every patient [15].

CBCT scanners employ a special exposure geometry to guidon x-ray beam in the direction of the specific dental area inside the scan field of view

(FOV) in the shape of a cone or pyramid. In this context, a "cone" is a beam where the diameters are about equal in the axial (x, y) directions but not in the vertical (z) directions (see Fig. 1). Modern CBCT scanners include flat-panel detectors (FPD), which are arranged as a pixel matrix composed of amorphous silicon thin-film transistors (TFT) or complementary metal-oxide semiconductors (CMOS) in order to gather the visual signal [15]. Both TFT and CMOS indicator innovations work based on the backhanded transformation idea. Here, consumed x-beams are first changed in the locator's glimmer layer into light photons. Following that, photodiodes ingest these photons and read the whole photodiode pixel grid. This technique makes a solitary crude information projection picture from a particular precise course, which is then joined with different projections from the CBCT crude information [16].

The shine material that changes x-beam energy into light photons is either thallium-doped cesium iodide (CsI:Tl) or terbium-actuated gadolinium oxysulfide (Gd_2O_2S:Tb). Nowadays, FPD innovation, which is replacing obsolete picture intensifier (II) or charge-coupled gadget (CCD) based finders ,offers various imaging benefits, including high spatial goal, an expansive powerful scope of sign levels, a smooth plan, and a successful imaging chain [17]. These benefits are additionally upgraded by CMOS innovation, which gives significantly higher goal, quicker picture readout, and lower electronic clamor contrasted with existing shapeless silicon indicator models. This creation opens the chance of additional enhanced sweeps and further developed clinical picture quality [18].

The projection x-ray raw data must pass through several pre-processing steps before it can be utilized to reconstruct images. These pre-processing procedures take into account various features of the exposure settings and detector in order to address certain restrictions. Fixing the detector's dark current issues and pixel defects and gain utilizing offset and gain correction are important changes [17]. This fast-rotating CBCT scan yields a high frame rate of raw data projections. However, this increased speed may cause certain signals from the previous projection image to appear in the readout of the subsequent image. To address this potential latent picture signal, any residues from the projection image data are removed using afterglow correction [18].

Exposure factors are features of the x-ray beam, including the x-ray spectrum (which depends on the tube voltage and beam pre-filtration), the size of the focal spot, the focus-to-detector distance, and the scatter distribution at the detector surface (which depends on the patient geometry, scan, and spectrum). These parameters influence the sharpness of the image and the tube output. Additionally, the detector response, which is dependent on the specific design of the detector and readout electronics, and other physical aspects of the scan are taken into account when evaluating exposure [19].

Compared to multi-slice CT scanners, one of the main financial benefits of CBCT technology is reduced x-ray output requirements. Dental panoramic x-ray scanners and CBCT scanners usually run at comparable x-ray tube current and spectrum output levels [10]. Like panoramic equipment, the installation footprint for CBCT requires a minimal space, regardless of the presence of a cephalate. As a result, making the switch from panoramic to CBCT imaging does not need significant changes to dental offices. In contrast to the supine sleeping position, many CBCT gantry designs allow patients to be positioned in a standing or sitting position, which helps to minimize the equipment footprint [20].

The architecture of vertical CBCT gantries frequently resembles that of panoramic equipment, possibly combining both features (such as cephalometric imaging). In addition, they have sophisticated digital detectors, workstations for picture processing and reconstruction, and related software. Comprehensive upgrades are not necessary because the electrical supply and heating, plumbing, and air conditioning (HPAC) requirements for CBCT scanners match those of panoramic x-ray equipment [20]. As a critical component of optimizing medical exposure, medical imaging using x-rays stresses minimizing the exposed anatomical region in accordance with radiation safety standards. Restricting the exposure volume improves image quality while also adhering to safety regulations. This is especially important for dental CBCT imaging, since most current scanners come equipped with the capability to choose different FOV sizes [21].

This also effects the patient's radiation exposure and enables indication-specific optimization of the imaging FOV. The voxel size utilized in picture acquisition is also determined by user adjustments made to the FOV size and image quality settings. According to sampling principles, the observed spatial resolution is directly related to the collected voxel size. Comparing to larger voxel sizes, smaller voxels offer a more accurate portrayal of minute details in dental structures, however they require greater radiation dose to retain the same signal-to-noise ratio (SNR). The square root of the relative voxel volume drops and the relative dosage increase needed to maintain SNR are inversely related, according to Poisson statistics. For example, halving the dose with the same picture noise is possible with a four times bigger voxel volume [21].

One of the vital advantages of CBCT imaging is its capacity to produce a great 3D perception and multi-planar reformats of volumetric image information. This capacity is improved by the making of isotropic or almost isotropic image information, where the voxel aspects are generally equivalent in each of the three bearings (x, y, and z). Isotropic imaging information works with the translation and investigation of the multifaceted 3D life systems of the jaw district by offering steady picture quality autonomous of the bearing where the reformatted cuts are anticipated [21].

When 3D image information has been post-handled, there are a plenty of different applications past cross-sectional perspectives. Among these choices are reciprocal multiplane projections of the temporomandibular joint, virtual all-encompassing perspectives (bended multiplane reformat), cephalometric, and customary dental perspectives. All CT imaging procedures, including CBCT for dentistry, are innately mathematically exact. This proposes that the reproduced pictures precisely portray the 3D x-beam constriction circulation of the item without including wandering projection calculation or differing amplification proportions of superimposed structures along the focal bar pivot, rather than conventional dental imaging or the obtained crude information projections of CBCT (before reproduction). Hence, straight estimations can be made reliably and precisely utilizing multiplane CBCT picture information [22].

Truncation impacts, which are brought about by FOV comparative with the total encompassing life structures, further debilitate the low-contrast goal of CBCT (see Fig. 1). Either the patient's constricting designs are inside or outside the FOV, the rotating x-beam pillar goes through them all during CBCT checks. Subsequently, highlights outside the FOV cause signal misfortunes in the crude information projection pictures that are gotten, which appear as difference irregularities in the images that are recreated. Truncation relics show as a piece of lighter-than-anticipated dark scale voxels on the edge of the FOV in the event that they are not changed [23]. The lesser number of raw-data projections (usually hundreds) in dental CBCT as opposed to multi-slice CT acquisitions (usually thousands of projections) is another factor reducing the precision of soft-tissue contrast. However, the unique feature of dental CBCT is its crisp 3D depiction of bony tissues; hence, efforts are being made to improve image reconstruction techniques and scanner hardware to overcome the poor contrast of soft tissues [22].

IMAGE PRODUCTION

The creation of a CBCT image involves three crucial steps: 1. X-ray generation, 2. X-ray detection, and 3. Image reconstruction The x-ray producing and detecting specifications found in CBCT systems that include proprietary changes to these parameters [24].

X-Ray Generation

1. Patient Stabilization: Three patient positions are available with cone-beam machines: supine, standing, and seated. Immunization of the patient's head is essential to avoid image degradation from head movement, regardless of orientation [25].
2. X-ray Generator: Each projection image produced by scan rotation is the result of successively capturing attenuated x-ray rays. Even though it is theoretically simple, continuous radiation emission exposes patients to more radiation. When pulsed x-ray beams are timed to coincide with detector sampling, the exposure duration is cut in half, considerably reducing the radiation dose to the patient. Certain devices (including Accustom, CB Mercu-Ray, Iluma Ultra Cone, and PreXion 3D) expose users to radiation continuously, which causes fluctuations in dosimetry. According to the ALARA principle, patient size should be taken into account while adjusting exposure variables [26].
3. Volume of Scan (Field of View): FOV or scan volume dimensions are determined by the size, shape, beam projection geometry, and collimation capacity of the detector. The FOV form can be spherical or cylindrical (NewTom 3G, for example). Collimation restricts the amount of x-rays that reach the target area. A CBCT unit's maximum FOV height is used to classify it: Small volume (5 cm), Inter-arch (7–10 cm), Maxillofacial (10–15 cm), Single arch (5-7 cm), and Craniofacial (>15 cm). Long-range FOV scanning is difficult because large-area detectors are expensive. Bio image registration or mosaicking, which combines information from two different scans, and offsetting the detector location to scan half of the patient's ROI in each offset scan are two methods. [27].

Figure (2) clarifies the CBCT unit classification based on FOV. This classification is crucial in establishing the range and suitability of CBCT scans. Big FOV scans (Figure 2.A) are very useful for cephalometric analysis since they include the complete craniofacial skeleton. Medium field of view (FOV) scans (Figure 2.B) provide a balanced image for in-depth analysis by concentrating on imaging particular areas, such as the mandible, maxilla, or both. Focused or restricted field of view scans (Figure 2.C) offer high-resolution pictures in constrained areas, facilitating a more thorough examination of particular interest areas. The data from several focused FOV scans are combined to create stitched scans (Figure 2.D), which superimpose numerous images to create bigger regions of interest. This method, referred to as "stitching," improves coverage overall and advances a more thorough comprehension of the body being studied. The image highlights how important FOV categorization is for customizing CBCT imaging to meet each patient's unique diagnostic requirements [28].

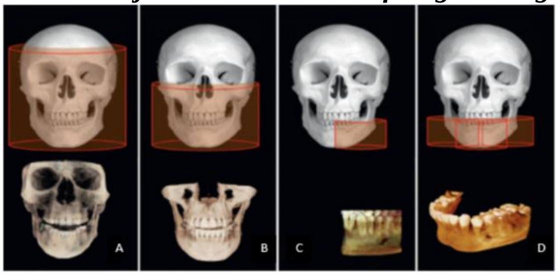

Figure 2: CBCT Unit Classification Based on FOV [28]

X-ray Detection

Based on the type of the x-ray detector, CBCT units can be divided into two groups: flat-panel detectors (FPDs) and Image Intensifier Tube/Charge-Coupled Device (IIT/CCD) units. In the IIT/CCD arrangement, a fiber optic coupling connects an x-ray IIT to a CCD, resulting in larger, bulkier devices that generate spherical volumes, or circular base image areas. By using a solid-state sensor panel connected to an x-ray scintillator layer as an indirect detector, FPDs, on the other hand, creates rectangular volumes. Although both technologies are used, FPDs are the preferred choice for modern CBCT devices because of their improved dynamic range and performance. Generally based on cesium iodide scintillators on amorphous silicon transistors, FPDs provide benefits over IIT/CCD systems, including higher resolution and no geometric aberrations [17].

The pixel size and detector matrix have an impact on voxel size, which is a critical factor in determining spatial resolution in CBCT imaging. For the best diagnostic quality, resolution and dose must be balanced because smaller pixels improve resolution but may also increase image noise. The focal spot size and the geometric arrangement of the x-ray source affect geometric sharpness, which affects spatial resolution. Bit depth determines the grayscale, or the system's capacity to display small contrast changes. Detectors having a bit depth of 12 or higher are used in modern CBCT systems, providing a broad range of grayscale to accurately represent attenuation [29].

Image Reconstruction

The reconstruction process in CBCT involves two stages, as depicted in Figure 3 [15]:

1. Preprocessing Stage: After multiple planar projection images are acquired, this stage is carried out at the acquisition computer. These images are adjusted for intrinsic pixel flaws, changes in detector sensitivity, and unequal exposure. Frequent image calibration is essential to fixing these flaws.
2. Reconstruction Stage: The reconstruction computer is used for the ensuing data processing procedures. The photos that have been rectified are then transformed into a sonogram, which is a composite image made up of several projection images. The vertical axis in a sonogram indicates projection angles, and the horizontal axis shows individual rays at the detector. The Radon transformation creates the sonogram, with each row denoting a distinct projection angle. Multiple sine waves with different amplitudes are combined to create the sonogram, which shows objects projected onto the detector at constantly shifting angles. The filtered back-projection algorithm is used to rebuild the final image from the sonogram; the Feldkamp algorithm is a popular option. Once all slices are reconstructed, they are integrated into a single volume for visualization.

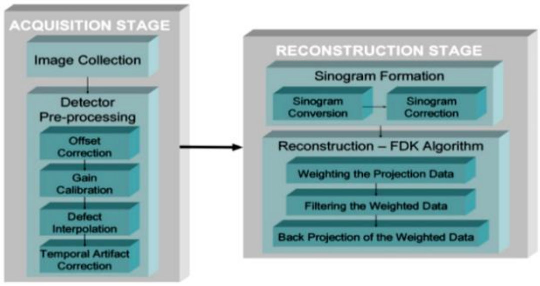

Figure 3: Image acquisition and reconstruction [28]

Reconstruction times vary according to hardware specifications (processing speed, data throughput from acquisition to reconstruction computer), software used (reconstruction algorithms), and acquisition parameters (voxel size, picture field size, and number of projections). In clinical settings, prompt reconstruction, ideally less than five minutes, is crucial to enhancing patient flow [28].

RELATED STUDIES

There are numerous studies that have employed various approaches to enhance the quality of CBCT images. Sisniega et al. (2015), for example, discussing the limitations of traditional CT imaging for traumatic brain injury diagnosis, and introduces cone-beam CT imaging as a promising alternative [30]. The difficulties with cone-beam CT imaging, such as veiling glare, lag, scatter, and beam hardening artefacts, are discussed by the writers. This paper's primary contribution is a thorough framework for artefact correction that combines beam hardening, lag, and veiling glare corrections with an incredibly quick GPU-accelerated MC scatter correction technique.

Sisniega et al. (2015) also reported that the proposed framework achieves high accuracy in artifact correction, resulting in improved image quality and diagnostic accuracy. Specifically, the authors reported that the proposed framework reduced scatter artifacts by up to 90%, beam hardening artifacts by up to 80%, and veiling glare artifacts by up to 70%. Additionally, according to the authors, the framework increases the precision of CT imaging in the diagnosis of traumatic brain injury, especially when it comes to the low-contrast imaging task of detecting tiny parenchymal bleeding, which calls for a high level of picture uniformity and contrast resolution. It is crucial to remember that the accuracy of the framework could be impacted by a number of variables, including the particular imaging technology and the subject being photographed [30].

Moreover, Ferreira et al. (2015) evaluated the accuracy of various CBCT enhancement filters in detecting vertical root fractures (VRFs) in teeth with and without metal posts [31] . In order to compare the various filters' diagnostic values (sensitivity, specificity, and accuracy), statistical analysis was employed in this study. The findings demonstrated that the filter chosen had an impact on the diagnosis's accuracy. In terms of precision, the sharpen-mild filter proved to be better than the sharpen filter; nonetheless, there was no significant difference between the two filters. The investigation also discovered that the accuracy of the diagnosis was not considerably impacted by the teeth's metal supports. Nevertheless, in teeth with metal posts, the addition of enhancement filters did not increase the diagnostic's accuracy.

Thakur et al. (2016) studied the quality improving of the dental CBCT images by reducing noise and enhancing contrast and brightness [32] . Three stages make up the creators' proposed strategy: histogram extending for brilliance improvement, versatile middle channel for sound decrease, and Bi-Histogram Adjustment method with bowing initiation capability for contrast upgrade. The examinations performed on an uproarious low differentiation CBCT picture are introduced in the review. The results show the adequacy of the proposed technique in bringing down commotion and further developing brilliance and difference. PSNR (top sign to-commotion proportion) and SSIM (primary similitude list) values for Improved with Bowed Character, Versatile Middle Channel, and Gamma Histogram Adjustment at various gamma values (0.1-0.9). The subsequent picture quality was surveyed utilizing the most elevated SSIM worth of 0.9999 for Improved with Twisted Personality and a gamma worth of 0.4. In the paper's decision, the future extent of study is examined. This remembers researching the recommended calculation for various picture modalities and elective sound decrease channel methods.

Yang et al. (2016) also studied the picture quality of CBCT, shading-corrected CBCT, and virtual monoenergetic CT (VMCT), which was created by synthesizing CBCT and planning MDCT, utilizing an electron density phantom [33] . As demonstrated by the results, shading-corrected CBCT and original CBCT were found to have lower image quality than VMCT in terms of contrast-to-noise ratio (CNR) and Hounsfield unit (HU) integrity. The study found that, without requiring an increase in dose or scan duration, the suggested strategy of utilizing planned MDCT to realize VMCT for picture quality improvement in on-board CBCT is workable and efficient. The authors proposed that improving the on-board CBCT picture quality can help with daily patient setup and adaptive dose delivery, allowing for more assurance in the precision of radiation therapy patient treatment.

Liang et al. (2017) described the problem of ring artifacts in CT images, which can occur due to various factors such as non-uniformity of the detector, beam hardening, and scatter [34]. The suggested technique entails estimating and removing the ring artefact component from the image iteratively until convergence is reached. The outcomes demonstrate how well the suggested technique works to eliminate ring artefacts while maintaining image structure. Through the use of both simulated and actual data, the authors assess their method and demonstrate its practicality and attractiveness for radiation therapy guided by CBCT. Nevertheless, there are a number of drawbacks to the suggested approach, including the requirement for prior knowledge of the ring artefact pattern and the possibility of overcorrecting the image.

Additionally, Kida et al. (2018) proposed a new method for improving the image quality of CBCT using a deep convolutional neural network (DCNN) [35]. The meaning of CBCT in picture directed radiation therapy (IGRT) was featured by the creators. By and by, in light of the fact that to the remaking's utilization of shortened and disperse polluted projections, it has serious concealing antiquities. To tackle this issue, the creators made a DCNN strategy that gains an immediate planning from the first CBCT pictures to the matching arranging CT (pCT) pictures, bringing about excellent CBCT pictures. Utilizing a dataset of 20 head and neck malignant growth patients who had CBCT and pCT checks, they evaluated the DCNN approach. A complete variety (television) strategy and a conventional separated back projection (FBP) technique have been contrasted with the recommended technique. The differentiation to-commotion proportion (CNR) and underlying comparability record (SSIM) upsides of the DCNN approach were more prominent than those of the other two strategies, showing predominant picture quality. Between the fat (109) and muscle (57) Hamis Feld Units (HU), there was a tremendous distinction in the RMSD of the SNU between the pCT and the first CBCT. One clarification could be that there is a higher proportion of fat than muscle near the skin's surface. The fat locale is where concealing relics are all the more unmistakably seen accordingly. On the other hand, negligible varieties were noted in the RMSD of the SNU between muscle (11) and fat (13) HU and the RMSD of the ROIm's mean pixel values between muscle (14) and fat (11) HU for the I-CBCT.

Mik et al. (2018) also presents a method for classifying tooth types on dental cone-beam CT images using a DCNN [36] . The authors suggested employing rectangular areas of interest (ROIs) that encircle a tooth from an axial slice to classify teeth into seven kinds using a DCNN-based approach. They used a dataset of 1,000 CBCT images to train and test their algorithm, and they were able to classify tooth types with 91.5% accuracy. Additionally, the authors looked into how data augmentation affected classification performance and discovered that using samples with various contrasts and rotations increased classification accuracy overall. They come to the conclusion that their suggested approach may prove to be an invaluable resource for dentists in the identification and management of dental issues.

Kida et al. (2019) proposed a method for enhancing the image quality of CBCT using deep neural networks based on CycleGANby translating [37]. A deep neural network called CycleGAN is capable of learning the translation mappings between two unpaired and misaligned image domains. The suggested method can generate high-quality images with better soft-tissue contrast, less noise, and less artefacts when CBCT images are planned fan-beam CT images. Five distinct models with the same structure and hyper-parameters were used to test the methodology. Less than 10 HU of allowable variability was shown by the results. The results imply that the suggested technique may be a helpful one for improving CBCT pictures in medical imaging .The fact that the suggested approach was only tested on a small number of cases and its applicability to additional circumstances was not completely assessed presents one possible drawback of this study.

Sorkhabi (2019) presented a new methodology for evaluating alveolar bone density using 3-D deep CNNs of CBCT images [38]. The authors stress the need of precisely classifying alveolar bone density when planning dental implant therapy and provide a technique that can effectively capture the bone's trabecular pattern. The suggested method produced an average precision score of 84.63% and 95.20% in hexagonal prism and cylindrical voxel forms, respectively. The study comprised 207 surgery target locations and 83 patients. Classification of alveolar bone was completed in 76 milliseconds.

Hatvani (2019) likewise introduced another way to deal with working on the goal of dental CT examines. The creators note that current super-goal methods for three dimensional pictures are either computationally wasteful or require a huge data set of realized low-goal and high-goal picture matches. Conversely, their tensor-factorization-based approach offers a quick arrangement without the utilization of realized picture matches or severe earlier suppositions [39] . A low-resolution image is broken down into a series of basis images using the tensor factorization method, and a high-resolution image is then rebuilt using the basis images.

The authors propose that their methodology could be extended to other domains including remote sensing and surveillance, in addition to various forms of medical imaging.

Yun et al. (2019) proposed a new method for automatically reconstructing high-contrast panoramic images from dental cone-beam CT data [40]. The three essential strides of the proposed technique are picture age, picture upgrade, and dental curve thickness recognition. The creators fragment the dental curve and decide its thickness in the dental curve thickness distinguishing proof stage utilizing a profound learning-based philosophy. The picture union stage utilizes this data to make an all-encompassing picture with insignificant curios and great differentiation. To make an all-encompassing picture, a few CT cuts are joined in the picture blend process. To deliver a great picture, the creators utilize a clever technique that records for the dental curve's thickness and the X-beam source's area. To additional increment the all-encompassing picture's quality, various picture handling strategies are applied in the last step of the picture improvement process. These techniques incorporate sound decrease, contrast extending, and histogram leveling. To deliver an excellent picture, the creators utilize a clever technique that records for the dental curve's thickness and the X-beam source's area. To additional increment the all-encompassing picture's quality, various picture handling methods are applied in the last stage, picture upgrade. These techniques comprise of sound decrease, contrast extending, and histogram leveling.

Moreover, Puvanasuntharajah et al. (2021) conducted a systematic review study of the PubMed and Web of Science databases [41]. Out of the 382 papers they found, 40 fulfilled the necessities for incorporation and were added to the audit. The picked papers were partitioned into two essential gatherings: research-based Blemish techniques and business Blemish strategies. The creators found that utilizing Blemish strategies on CT sweeps can improve the norm of RT treatment arranging. In any case, because of downsides like the consideration of extra mix-ups (like different ancient rarities) or the disintegration of picture quality (like obscuring), none of the explored or recommended Blemish approaches was completely satisfactory for RT applications. The concentrate additionally saw that, contingent upon the specific methodology utilized, the impact of Blemish approaches on CT Hounsfield Unit esteems and shaping of locales of interest varied. It reached the resolution that more review is expected to resolve the issues with Blemish strategies in clinical imaging.

Zhuoran Jiang et al (2021) presented a method for improving the quality of under-sampled CBCT projections using a CNN [42]. The under-sampled CBCT projections were made better by the suggested approach, which employed a CNN. High-quality CT scans of the same patient serve as the training set for the network. The network then reconstructs the under-sampled CBCT projections using these earlier images as a guide, producing images with higher quality and lower noise. The technique could lower imaging dose and increase radiation therapy planning precision.

An extensive literature evaluation of deep learning (DL) techniques for enhancing CBCT image quality in the context of adaptive radiation treatment (ART) was carried out by Rusanov et al. in (2022) [43]. The review summarizes the key findings of publications published between January 2018 and April 2022, focusing on study design and deep learning methodologies. The authors draw attention to the difficulties in using CBCT imaging for online ART, such as noise, low soft-tissue contrast, and image artefacts. The several DL techniques for creating synthetic CTs and the projection domain techniques used in the literature on CBCT correction were also covered. In addition, the review highlights gaps in the research by summarizing clinically relevant objectives related to dosimetry accuracy and image quality.

Abbate et al. (2022) also presented a study on the condylar remodeling (CR) that occurs in response to forces and stress acting on the temporo-mandibular joint after orthographic surgery [44]. The objective of the research is to examine and evaluate, both statistically and qualitatively, the adaptation mechanisms that take place in CR after maxillary displacement. The study analyses the morph oologic and densitometry changes in the condyles of twelve patients who underwent orthographic surgery using 3D imaging, digital modelling, and workflow technologies. The study's findings revealed several statistically significant changes in the parameters under investigation. A decrease in bone density was observed in all individuals ($p = 0{,}002$ per side). The study sheds light on the processes of reshaping following orthographic surgery and emphasizes the value of taking into account a variety of factors when researching chronic pain. The research also highlights the promise of digital modelling, workflow, and 3D imaging technologies in the field of orthographic surgery.

Jiang et al (2022) proposed a new approach to improving image quality in CBCT using deep learning techniques [45]. The suggested technique produces high-quality CBCT images in the projection domain and increases scatter estimate accuracy by utilizing several spectral CT labels along with the Pix2pix GAN algorithm. The difficulties with CBCT imaging, such as low contrast-to-noise ratio and scatter contamination, are demonstrated in this work. To convert scatter-contaminated projections to scatter signals, a deep learning model was trained using the Pix2pix GAN technique in the suggested method. According to the authors, the suggested technique generates high-quality CBCT pictures in the projection domain and accomplishes correct scatter estimate.

Kang et al (2023) presented a method to enhance the quality of CBCT images while preserving their structural information [46]. A cluster wise contrastive learning-based GAN model that makes CT-like pictures from CBCT pictures was proposed by the creators. Utilizing a clever blend of misfortunes and a component extractor pre-prepared on their preparation dataset, the researchers prepared their model on unpaired CT and CBCT datasets. Utilizing different measures, they evaluated the nature of the pictures created and found that their model delivered CT-like pictures that were observably better compared to those delivered by various standard models. The creators call attention to that their technique is computationally productive, doesn't need matched CT and CBCT datasets, and jelly the primary data of the info CBCT pictures, among different benefits over existing methodologies.

Ryu et al (2023) proposed a system that is used to improve the image quality of CBCT scans [47]. Multi-stage enlistment methodology and an organization design including a completely thought-out shortfall capability and a multi-planar 2.5D U-Net-based network. Curios that are trying to fix with a solitary planar organization can be eliminated utilizing the multi-planar methodology. They utilize three 2.5D single-planar U-Nets that are found the middle value of over the three created volumes. The U-Nets are prepared in the pivotal, coronal, and sagittal bearings, separately. This technique has the advantage of diminishing streaking relics, which are apparent in the two directions yet can be trying to distinguish in one. They utilized both quantitative and subjective techniques to survey the adequacy of their proposed procedure. While the subjective appraisal uncovered discernibly higher scores for antiquities, clamor, goal, and generally picture quality, the quantitative measures affirmed predominant quality in the result photographs when contrasted with the first CBCT.

RESULTS AND DISCUSSIONS

CBCT, which provides three-dimensional information with low radiation exposure, has become a vital imaging modality in a variety of medical and industrial applications. However, low contrast, noise, and artefacts are common problems with CBCT pictures that affect the accuracy and reliability of diagnosis and treatment planning. A range of augmentation strategies have been put out in the body of existing work to address these problems. This article offers a comprehensive and well-evaluated summary of the most current advancements in CBCT image enhancing methods. The strategies that were found can be categorized into four main groups: (1) methods based on filtering; (2) methods based on histograms; (3) methods based on models; and (4) methods based on deep learning. Every category has distinct advantages and disadvantages, and the choice of method depends on the particular use and properties of CBCT images. Although filtering-based techniques like wavelet and median filtering are notable for their ease of use and computational efficiency, their ability to retain image edges and features may be limited.

While histogram-based techniques like contrast stretching and equalization might enhance image contrast, they also run the risk of adding noise and artefacts. By taking into account previous knowledge and restrictions, model-based techniques like statistical and iterative reconstruction can enhance the quality of the image; however, they may necessitate additional processing resources and skill. Convolutional neural networks (CNNs) and generative adversarial networks (GANs), two deep learning-based techniques, have demonstrated encouraging outcomes in CBCT picture improvement. These techniques are capable of adapting to various imaging modalities and situations, as well as learning the intricate and nonlinear correlations between the input and output images. But they also need a lot of training data, and they could be sensitive to the variety and caliber of the data.

In general, the particular application and the trade-off between processing resources and image quality determine which CBCT image enhancement technique is best. Subsequent investigations ought to concentrate on crafting more resilient and effective methodologies that can tackle the constraints of existing approaches and enhance the therapeutic usefulness of computed tomography imaging.

Table 1. The Comparisons between state-of art studies

Ref. No.	Year	Method	ROI and Noise Type	Results
[30]	2015	Ultra-fast GPU-accelerated MC scatter correction method	Traumatic brain injury diagnosis	90% Reduces of scatter artifacts
[31]	2015	Statistical analysis to compare the diagnostic values	Vertical root fractures in teeth	95% Reduces of scatter artifacts
[32]	2016	Adaptive median filter, bi-Histogram equalization, and histogram stretching	Noisy low contrast CBCT image	Noise reduction, contrast enhancement,
[33]	2016	Electron density phantom	Virtual monoenergetic CT	Shading-corrected CBCT with 94%
[34]	2017	Iteratively estimating and subtracting the ring artifact	CBCT image	Rising from 87.12% to 95.50%
[35]	2018	Deep convolutional neural network	Head and neck cancer	CBCT, reducing from 216 to 11 HU for one parameter and from 247 to 14 HU for another.
[36]	2018	Deep convolutional neural network	Enclose a tooth from an axial slice	91.5%
[37]	2019	Deep neural networks based on CycleGAN	Improved soft-tissue contrast	84.63% and 95.20%
[38]	2019	3-D Deep convolutional neural network	Alveolar bone density	84.63 %

[39]	2019	Tensor-factorization	Low-resolution dental CT scans	PSNR:1.2 dB for LRTV and 1.5 dB for TF-SISR.
[40]	2019	Deep learning to segment the dental arch and detect its thickness.	Thickness of the dental arch	Mean:11.03 ± 2.46
[41]	2021	Hounsfield Unit values	Commercial MAR methods	SSIM: 0.8262 CTart: 0.2382 PSNR for CTcor: 22.1685 dB
[42]	2021	Convolutional neural network	Under-sampled CBCT projections	PSNR 37.02±1.930
[43]	2022	Deep learning methods	Image artifacts, noise, and limited soft-tissue contrast	MAE: 32.70 ± 7.26 vs. 42.04 ± 8.84 HU
[44]	2022	Condylar remodeling	Temporo-mandibular joint	Mean loss of 32.8%
[45]	2022	Deep learning techniques Pix2pix GAN algorithm	Head and abdominal	PSNR at 30.49 dB
[46]	2023	Batchwise contrastive learning-based GAN model using various metrics	Structural information of the input CBCT images	PSNR at 25.863±2.073
[47]	(2023)	Deep learning methods for artifact removal in dentistry	Axial, coronal, sagittal directions, and three generated volumes	MAE decreased from 142.6 to 138.1

CONCLUSION

Although, CBCT is a useful imaging technique for a range of industrial and medical applications, it has low contrast, noise, and artefacts. This review study has compiled and examined the most current developments in CBCT image improvement techniques based on covering model-based, filtering-based, histogram-based, and deep learning-based approaches. The best technique will depend on the particular application and the properties of the CBCT pictures. Every type of approaches possesses pros and cons of its own. Although filtering-based techniques are straightforward and computationally inexpensive, they cannot be sufficient enough at maintaining the image's edges and features. While histogram-based techniques can enhance image contrast, they also run the risk of adding noise and artefacts. By utilizing restrictions and past information, model-based approaches can enhance the quality of the images; nevertheless, they can necessitate greater processing power and experience. In CBCT image augmentation, deep learning-based techniques have demonstrated encouraging results; nevertheless, they need a large training data and may be sensitive to the caliber and variety of the data. Overall, the precision and dependability of diagnosis and treatment planning have increased because to developments in CBCT image enhancing techniques. Nevertheless, stronger and more effective approaches are still required to overcome the shortcomings of the existing strategies and raise the therapeutic usefulness of CBCT imaging. Subsequent investigations have to concentrate on crafting methodologies that can adjust to diverse imaging scenarios and modalities, and that can be incorporated into therapeutic procedures.

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