Grenze International Journal of Engineering and Technology, January Issue

A Review on Advancements in Contrast Enhancement of Dental X-ray images

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***Abstract*— Dental radiography is essential for diagnosing and planning treatment of dental and alveolar conditions, utilizing modalities like 2D digital X-rays and advanced 3D imaging such as Cone Beam Computed Tomography (CBCT). While low-dose imaging techniques reduce patient radiation exposure, they pose challenges such as increased noise and reduced contrast, which can compromise diagnostic accuracy. This review categorizes contrast enhancement methods into traditional, multiscale, and AI-based approaches, highlighting their strengths and limitations. Traditional methods like Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) are computationally efficient but struggle with noise amplification, while multiscale techniques like Retinex and wavelet-based methods offer better detail preservation at the cost of complexity. AI-based methods, including Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), show significant promise in enhancing low-dose dental images but require substantial computational resources and tailored datasets. Future research should focus on developing hybrid approaches, noise-adaptive techniques, and dental-specific datasets to address the unique challenges of low-dose imaging and improve diagnostic outcomes.**

***Index Terms*— Dental X-ray, Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs).**

I. INTRODUCTION

X-rays are electromagnetic radiations used to produce images. They have high energy and it can penetrate the body tissues by creating shadows or variations [1]. The images produced using X-rays are referred to as Radiographs. Dental radiography involves producing images of intraoral and extraoral structures using X-rays to assist in diagnosis and treatment planning. An ideal radiograph provides comprehensive diagnostic information, enabling accurate identification of dental conditions and facilitating effective treatment strategies [2].
A variety of X-ray images are utilized in the dental field to track and diagnose dental conditions. These imaging modalities include three-dimensional imaging techniques as well as conventional two-dimensional radiographs. Examples of intraoral radiographs include Bitewing X-rays, Periapical X-rays, and Occlusal X-rays. In the category of extraoral radiographs, Panoramic X-rays and Cephalometric X-rays are commonly used [3] [4]. Additionally, advanced imaging techniques such as Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) are also employed for detailed diagnostic purposes [5].

Grenze ID: 01.GIJET.11.1.560

Among the different imaging modalities, Digital X-rays are extensively utilized in the medical field, especially in dentistry, because of their dependability and affordability [6]. Fig. 1 shows sample x-ray images.

Figure 1. Examples of dental x-ray images (Pic courtesy: Menon, Hema & V, Gayathri. [7])

II. Contrast Enhancement and Noise Reduction in Low-Dose Imaging

Various modalities as discussed are available for diagnosis. Dental radiography is essential for diagnosing conditions affecting the teeth and alveolar structures [8]. However, the quality of the chosen modality is crucial for accurate results. Exposure factors, including tube voltage, tube current, and exposure time, along with equipment factors such as focal spot size, grid usage, and X-ray generator design, as well as geometric factors like source-to-object distance and source-to-image receptor distance, play a crucial role in influencing both patient dose and the quality of radiographs. Optimizing image quality by encompassing contrast, density, motion blur, and geometric unsharpness and minimizing patient exposure is key to assessing the selection of exposure parameters. Selecting a radiographic technique often requires striking a balance between different aspects of image quality and radiation exposure [9].
Low-dose imaging techniques are crucial as they help in protecting samples from phototoxicity and radiation damage. However, these techniques face challenges due to Poisson noise and additive Gaussian noise, which degrade image quality by reducing the signal-to-noise ratio, contrast, and resolution [10]. In order to maintain image quality in low-dose imaging, it's essential to focus on enhancing the contrast while reducing noise.

III. Classification of Contrast Enhancement Methods

In the context of contrast enhancement, the methods can be classified into three main categories: Traditional Methods, Multiscale and Adaptive Techniques, and AI (Artificial Intelligence) and ML (Machine Learning)-Based Methods (Fig. 2). Since we are focusing on research published after 2020, our attention is primarily directed towards Multiscale and Adaptive Techniques and AI and ML-Based Methods.

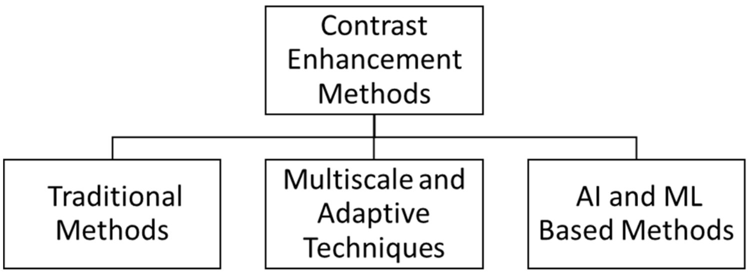

Figure 2. Classification of contrast enhancement methods

A. Traditional Methods

Histogram Equalization
Histogram equalization adjusts the pixel values of an image according to its intensity histogram, resulting in an image with a flattened histogram and uniform intensity distribution. This technique enhances the visibility of image details by utilizing the full dynamic range [11].

Reference [12] explains a method for X-ray image enhancement based on histogram equalization to improve image clarity. First, X-ray images are collected and decomposed using wavelet transform. Then, the histogram equalization method is applied, with an improvement to the standard technique. Finally, a homomorphism filter is used to enhance the brightness of the image.
Experimental results show that this method achieves a visually effective enhancement and demonstrates strong robustness against various types of noise.

Gamma correction
In dental X-ray images, contrast enhancement is crucial because many features like early stages of dental decay or bone abnormalities, may not be easily visible due to the uniform gray scale of the image. Gamma correction helps to improve the visibility of these features by enhancing the contrast of specific regions.
Menon, H.P. et al. [6] proposes an automated system that enhances dental digital X-ray images using methods like Histogram Equalization, Gamma Correction, and Log Transform, based on image quality and statistics and thereby improving diagnostic accuracy.

B. Multiscale and Adaptive Techniques

Contrast Limited Adaptive Histogram Equalization (CLAHE)
Georgieva, V., Mihaylova, A., & Petrov, P., presents an effective approach for enhancing dental X-ray images to aid in the detection of caries. The method involves contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) and morphological processing in which a homomorphic wavelet filter is applied to reduce noise and correct non-uniform luminance distribution.
The experimental results showcase the visual quality and effectiveness of the proposed approach, emphasizing its potential for use in clinical diagnostic applications.
CLAHE limits the contrast amplification in regions where noise is high by introducing a contrast threshold [13].

Multi-Layers of Histogram Equalization Technique
This is a multi-layered approach combining Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). In this approach HE is followed by multiple passes of CLAHE which provided noticeable enhancements, smoothing the cumulative distribution function (CDF) and revealing critical image details. Combining HE and CLAHE yielded high-contrast images with smoother histograms, improving diagnostic visibility. Alkhalid, F. et al. claims the improvement in the contrast (enhances local and global contrast) and clarity of dental X-ray images. In the case of highly noisy images, while CLAHE helps limit noise amplification, it does not specifically focus on noise reduction [14].

CLAHE and Gamma Correction
Omarova, G. et.al [15] proposes a methodology that combines Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gamma Correction. In their findings, the combined method provided better visual contrast enhancement than individual methods. Image quality metrics such as NIQE (Naturalness Image Quality Evaluator) and BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator) were used for assessment. The evaluation showed that the CLAHE method combined with gamma correction lowered the NIQE and BRISQUE scores, suggesting an improvement in image quality. Advantages of the method include improved contrast enhancement, effective noise control, and the ability to adapt to varying image brightness levels.

Fuzzy-Based Histogram Partitioning
A novel fuzzy-based bi-histogram equalization (bi-HE) method [16] for enhancing low-contrast images. Conventional methods often result in brightness shifts and over-enhancement, compromising the natural appearance of images. The fuzzy-based method partitions an image histogram into sub-histograms using the computed threshold and independently equalizes each sub-histogram.
For better adjustment of membership functions to suit varying image conditions, a level-snip clipping process is used. The proposed method avoids over-enhancement and excessive brightness shifts observed in other methods. Objective evaluations (e.g., Peak Signal-to-Noise Ratio, Universal Image Quality) show consistent improvements and subjective tests confirm that the method effectively balances enhancement and natural appearance.
Compared to simpler methods like CHE (Conventional histogram equalization), BBHE (Brightness Preserving Bi-Histogram Equalization), and DSIHE (Dual-Source Intensity Histogram Equalization), the fuzzy-based approach is more computationally intensive due to the need of skewed triangular membership functions and the level-snip process for optimizing the fuzzy threshold.

Multi-Scale Top-Hat Transform Geodesic Reconstruction Algorithm

The algorithm is meant for panoramic radiography. A novel algorithm for local enhancement that preserves the global characteristics of the image is introduced.

This approach combines the classic Top-Hat Transform and Geodesic Reconstruction to extract features related to brightness and darkness. It Fuses extracted features by calculating maxima at multiple scales and adding them to the original image. The algorithm demonstrated effective brightness preservation and improved global contrast. It enhanced the clarity of anatomical features such as enamel, dentin, and root canals, supporting more accurate diagnoses. The disadvantage of the method is the increased noise in some cases, as indicated by lower PSNR (Peak Signal-to-Noise Ratio) scores compared to certain other algorithms [17].

FCLAHE (Fast Contrast-Limited Adaptive Histogram Equalization)

FCLAHE (Fast Contrast-Limited Adaptive Histogram Equalization) is a computationally optimized version of CLAHE (Contrast-Limited Adaptive Histogram Equalization), which is widely used for improving image contrast while preventing over-enhancement. Sang, H. et al.

[18] introduces a high-performance system designed to improve the quality of dental X-ray images in real-time. The system addresses common challenges in dental X-ray imaging, such as difficulty in distinguishing details in both dark and bright regions and the need for high-speed image enhancement to match the requirements of real-time imaging systems.

The FPGA-based system is a promising solution for enhancing the diagnostic quality of dental X-rays, offering High-speed processing and Adaptive enhancement. The work represents a critical step forward in combining hardware acceleration with adaptive image processing for dental imaging.

Wavelet based methods

Wavelet based methods can be used for enhancing digital radiography (DR) images using a multiscale decomposition method. It utilizes Shannon–Cosine wavelet [19] to enhance image details and suppress noise effectively. The method divides the image into high-frequency and low-frequency sub-images for focused enhancement of diagnostically relevant details. It also introduces an adaptive noise-reduction algorithm based on pixel activity, which attenuates noise in smooth areas while preserving critical details in textured regions. The nonlinear gain functions with multiple degrees of freedom dynamically enhances the image contrast, effectively preventing over-enhancement or noise amplification. It demonstrates superior performance over traditional methods such as histogram equalization (HE), contrast-limited adaptive histogram equalization (CLAHE), and single-scale wavelet transforms. The approach achieves improved peak signal-to-noise ratio (PSNR) and comparable structural similarity (SSIM) indices.

Retinex Based Methods

This is an advanced technique for enhancing X-ray images, especially for objects with high absorption ratios, using a Retinex-based global-local contrast enhancement model implemented through deep learning. The process begins with Ray Source Filtering to compress the spectral bandwidth of low-energy X-rays, preventing saturation of low absorptivity objects and enabling single-exposure imaging while preserving both high and low absorption information. The images are then decomposed using Retinex Theory-Based Decomposition into illumination (overall brightness) and reflection (intrinsic details) components through a multi-scale residual decomposition network (Decom-Net) for independent enhancement.

The Enhance-Net model, utilizing a U-Net architecture with global and local attention mechanisms, adjusts illumination globally for uniform brightness and locally for enhanced contrast in finer regions. The Restore-Net model enhances reflection details through anisotropic diffusion filtering and residual dense networks, suppressing noise and avoiding blurring.

Finally, the enhanced illumination and reflection components are fused using pixel-wise multiplication to produce the final image. The proposed method is compared to other techniques like CLAHE and the method demonstrates superior contrast enhancement and detail preservation [20].

C. AI and Machine Learning/ Deep Learning-Based Methods

AI and machine learning techniques have shown immense potential in enhancing medical images. Although studies on dental X-rays remain limited, methods like super-resolution GANs, denoising autoencoders, and Cycle-GANs can be tailored to address the unique challenges of dental radiographs.

These methods enable improved contrast, noise reduction, and edge preservation, enhancing the diagnostic utility of low-dose or low-resolution dental images.

Applying these techniques to dental X-rays could revolutionize image quality, bridging the current research gap.

Denoising Convolutional Neural Networks

A hybrid image contrast enhancement technique combining Discrete Wavelet Transform (DWT) and Denoising Convolutional Neural Networks (DnCNN) [21] to adaptively improve image quality, particularly in challenging lighting conditions. Images captured under varied and low-light conditions often have poor quality due to the limited dynamic range of pixel values. In the proposed hybrid approach DWT is meant for image decomposition and enhanced representation of texture details. It captures multiscale features of the image. DnCNN is used for denoising and adaptive contrast improvement. It is done by eliminating latent information in hidden layers, yielding a cleaner image and focuses on preserving the original texture using a structural similarity index (SSIM)-based lossy method.

Deep Bilateral Learning

Deep Bilateral Learning, a real-time image enhancement technique using a neural network architecture that operates efficiently on high-resolution images. It combines global and local features to enhance image quality adaptively and performs high-frequency operations like tone mapping and detail enhancement in real-time [22]. This technique can be adapted for dental X-rays by performing Real-Time Contrast Enhancement which can improve the diagnostic accuracy by enhancing X-ray contrast in low-dose images and the Real-time processing enables immediate feedback during imaging procedures. When efficient computation is considered, it can be deployed on hardware-limited environments, such as portable or handheld X-ray devices. The method offers significant potential for improving clinical workflows while maintaining diagnostic precision in dental imaging.

Super-Resolution Convolutional Neural Network (SRCNN)

The method is a deep learning-based super-resolution (SR) technique to enhance the quality of dental panoramic radiographs. The methods aim to overcome resolution limitations caused by factors such as equipment variations, patient positioning errors, and inconsistencies in image layers. The study explores several deep learning-based techniques for improving image resolution. The Super-Resolution Convolutional Neural Network (SRCNN) maps low-resolution images to high-resolution ones. The Super-Resolution Generative Adversarial Network (SRGAN) enhances image quality by using adversarial and content loss functions. U-Net combines downsampling and upsampling paths to improve resolution [23]. The potential of deep learning-based SR techniques can revolutionize dental radiography by enhancing image clarity, contrast, and diagnostic utility

Generative Adversarial Networks (GANs)

Lan, L. et al. [24] focuses on the applications of Generative Adversarial Networks (GANs) in medical informatics and biomedical imaging. It provides an overview of the architecture, principles, and diverse GAN models used for generating and enhancing medical data. GANs can be effectively applied to contrast enhancement in dental X-rays by addressing challenges like low-dose imaging and noise. Cycle-GAN can learn mappings between low-contrast and high-contrast dental X-ray images, improving clarity and diagnostic value. Models like Cycle-GAN with gradient consistency loss can ensure edges (e.g., tooth and bone boundaries) remain sharp while enhancing contrast.

The GAN-based enhancement method used for underwater images [25] can be effectively adapted for dental X-ray image contrast enhancement. By leveraging GANs, multi-scale contrast enhancement, noise reduction, and adaptive histogram equalization, the method can significantly improve the clarity, contrast, and detail preservation in dental X-rays. This would make it easier for dental professionals to identify and diagnose conditions such as cavities, fractures, and other abnormalities.

B. Xu et al. [25] addresses the challenges of enhancing deep underwater color images, which often suffer from low brightness, poor contrast, and loss of local details. To improve the quality of such images, an enhancement method based on Generative Adversarial Networks (GAN) shall be used. The method focuses on low-light image enhancement. It restores the original scene information and obtain natural, clear images with complete details and structure. Comparative results show that the method surpasses other enhancement techniques in terms of color preservation, contrast enhancement, and image detail enhancement, improving key image quality indicators.

IV. Evaluation and Comparison of Methods

This section evaluates the contrast enhancement methods discussed, focusing on their strengths and limitations. By systematically comparing their performance, this evaluation provides insights into the most suitable techniques for various applications, such as low-dose imaging. Table I shows advantages, disadvantages and performance of different methods.

When comparing various contrast enhancement techniques, it is important to evaluate them based on several key criteria such as image quality, processing time, robustness to noise, preservation of image details, and computational complexity.
The Contrast-to-Noise Ratio (CNR)[26], Peak Signal-to-Noise Ratio (PSNR)[27], and Structural Similarity Index (SSIM) [28] are critical metrics for evaluating the quality of contrast enhancement methods in image processing, particularly in medical imaging. In Table II, the methods are compared based on three critical parameters: computational efficiency, noise handling, and clinical applicability.

TABLE I. COMPARATIVE ANALYSIS OF CONTRAST ENHANCEMENT METHODS

Category	Advantages	Disadvantages	Performance
Traditional Methods	Simple, fast, widely applicable	Limited adaptability, noise amplification, loss of details	Moderate to good quality, fast processing
Multiscale & Adaptive Methods	Improved local contrast, noise control, detail preservation	Computationally expensive, potential artifacts	High quality, better noise handling, slower processing
AI & ML-Based Methods	Superior image quality, adaptive, detail preservation	High computational cost, data dependency, complex deployment	Best performance, excellent contrast & detail, slow training and deployment

TABLE II. EVALUATION EFFICIENCY, NOISE HANDLING, CLINICAL APPLICABILITY

Category	Efficiency	Noise Handling	Clinical Applicability
Traditional Methods	High efficiency, low complexity	Moderate, risk of amplification	Effective for routine image adjustments
Multiscale/Adaptive Techniques	Moderate to high, scale-dependent	Superior handling of illumination issues	Suitable for specialized, high-precision imaging
AI and Machine Learning	Computationally intensive	Excellent, context-aware filtering	Advanced clinical applications with high customization

The choice of a contrast enhancement method is based on the individual criteria such as real-time performance, noise robustness, and the clinical setting. While traditional methods are efficient, multiscale and AI-based methods offer superior performance in complex scenarios.

V. CURRENT CHALLENGES AND LIMITATIONS

Contrast enhancement methods face many challenges. There is often a trade-off between computational efficiency, noise handling, and preserving fine details or natural appearance. Improving one aspect can compromise another. Clinical workflows require methods that are fast, reliable, and easy to interpret. Different imaging types, such as X-rays, CT (Computed Tomography) scans [29], and MRI (Magnetic Resonance Imaging) s [30], have unique challenges like noise and structural complexity. No single method works well for all of them. Solving these issues needs a mix of traditional, adaptive, and AI-based methods. Innovations in hardware and algorithms are also necessary to improve efficiency and quality.
Radiation exposure poses health risks, particularly for children and individuals requiring frequent imaging. This makes low-dose X-rays significant [31]. But there are challenges and limitations when low-dose X-ray imaging is considered. Traditional methods like Histogram Equalization (HE) and sharpening tend to amplify noise and create artifacts, often obscuring subtle diagnostic details critical in low-dose imaging. These methods also struggle with complex structures and localized intensity variations, making them less effective for applications like dental X-rays. Multiscale and adaptive techniques, such as Multiscale Retinex and wavelet-based methods, offer better noise suppression and detail preservation but are computationally intensive. Additionally, their performance is highly sensitive to parameter tuning, which can result in over-smoothing or edge blurring, further compromising fine details. AI-based methods, including CNNs and GANs, excel in noise suppression and detail retention but face challenges like dependence on large, annotated datasets, high computational demands, and the opaque nature of deep learning models.
Furthermore, AI applications in dental X-rays are underexplored, leading to suboptimal performance in tackling the unique hurdles posed by overlapping structures and subtle features such as micro-cracks. Across all methods, the balance between computational efficiency, noise management, and fine detail preservation remains a critical challenge, compounded by the lack of standardized low-dose X-ray datasets for training and evaluation.

VI. Future Directions

The lack of large, high-quality, annotated datasets for low-dose dental X-rays hinders the training and optimization of AI models. Developing AI models specifically designed for dental X-rays would improve the precision of contrast enhancement and noise reduction while preserving fine anatomical details, leading to more accurate diagnoses, especially for detecting cavities, fractures, and other dental conditions.
Low-dose dental X-rays are often noisy due to reduced radiation exposure, which can significantly degrade image quality. Traditional contrast enhancement methods and AI models need to be adapted to handle this noise without over-smoothing or losing important details. Noise-adaptive techniques would improve the diagnostic value of low-dose images by reducing noise while maintaining or enhancing key features.

III. Conclusion

The choice of contrast enhancement method depends on real-time performance, noise robustness, and the clinical setting. While traditional methods are efficient, multiscale and AI-based methods offer superior performance in complex scenarios. This comparison highlights the importance of selecting the right technique for optimal results in different applications. Future work should focus on further refining these methods to optimize their performance in clinical settings, especially for specialized applications like low-dose dental X-rays, where both noise reduction and fine detail preservation are critical.

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