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Zero-Reference Structural–Frequency Constrained Deep Learning Framework for Diagnostic-Safe Contrast Enhancement of Clinical Medical Images

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Abstract

We introduce SFC-ZRNet, a zero-reference deep learning framework designed specifically for safe and reliable contrast enhancement in medical imaging. Unlike traditional histogram-based techniques, which may unintentionally alter anatomical structures, our method is developed with a strong emphasis on preserving diagnostic integrity. The framework explicitly measures and restricts structural distortion, ensuring that critical anatomical boundaries and lesion characteristics remain intact during enhancement. The proposed network is built on a multi-scale convolutional neural architecture and is guided by carefully designed objective functions. These include a structural distortion loss that combines edge-preservation and boundary-displacement constraints, as well as a modality-aware spectral loss to maintain frequency consistency across different imaging types. This design allows the model to enhance contrast while minimizing structural alterations that could compromise clinical interpretation.Extensive evaluation on ultrasound, MRI, CT, and X-ray datasets demonstrates that SFC-ZRNet consistently improves image quality. The method achieves higher PSNR, SSIM, and entropy values compared to conventional approaches, indicating superior contrast and fidelity. Importantly, it records the lowest Boundary Displacement Measure (BDM) among the compared methods, with approximately a 30% reduction relative to CLAHE, confirming improved structural preservation. The model is computationally efficient, requiring approximately 31 milliseconds to process a 256×256 image on a GPU, and contains only around 2.9 million parameters, making it lightweight and suitable for real-world clinical deployment. As a zero-reference framework, SFC-ZRNet eliminates the need for paired ground-truth enhanced images, enabling practical implementation across diverse clinical imaging protocols without additional annotation requirements.

Keywords - SFC-ZRNet, CNN, ultrasound, MRI, CT, X-ray, SSIM, PSNR, and CLAHE.

1. Introduction

Medical imaging forms the backbone of modern clinical diagnosis, treatment planning, and translational biomedical research. Over the past few decades, imaging technologies have evolved from basic anatomical visualization to advanced multimodal and molecular imaging systems capable of capturing both structural and functional information simultaneously. This progression has significantly improved diagnostic precision in fields such as oncology, neurology, and cardiovascular medicine by enabling clinicians to observe not only tissue morphology but also underlying physiological and biochemical processes.

Ultrasound imaging, originally established as a safe and non-invasive diagnostic modality, has expanded well beyond conventional applications. It is now widely used in point-of-care diagnostics and molecular imaging research. However, despite its accessibility and real-time capabilities, ultrasound imaging is inherently limited by low contrast and speckle noise. These degradations arise primarily from acoustic scattering and wave–tissue interactions, which reduce visual clarity and obscure subtle pathological features.

Magnetic Resonance Imaging (MRI), which transformed soft-tissue visualization through its sensitivity to proton relaxation properties, also exhibits contrast variability. Signal intensity in MRI depends on tissue relaxation mechanisms and the administration of contrast agents, leading to differences in image appearance across protocols and institutions. Computed Tomography (CT), while offering excellent structural detail, is affected by noise artifacts, particularly in low-dose acquisition settings where radiation exposure must be minimized. Similarly, hybrid and molecular imaging modalities integrate targeted functional information, yet their diagnostic value still depends heavily on effective post-acquisition image enhancement to ensure interpretability.

Conventional contrast enhancement techniques, such as Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE), operate by redistributing pixel intensity values. Although these approaches can improve visual contrast, they do not account for anatomical structures. As a result, they may inadvertently distort lesion boundaries, amplify noise, or exaggerate edges, potentially compromising clinical interpretation.

Deep learning-based enhancement methods have demonstrated substantial improvements in image restoration and quality enhancement. However, most supervised models rely on paired datasets consisting of low-quality and corresponding high-quality “ground-truth” images. In real-world clinical settings, such ground-truth enhanced images rarely exist. Imaging parameters differ across scanners and institutions, and patient-specific physiological variations further influence contrast characteristics. These factors limit the feasibility and generalizability of supervised learning approaches and may introduce institutional bias.

Zero-reference learning offers an alternative by eliminating the need for paired training data. Instead, it optimizes intrinsic image quality measures directly from the input image. While promising, most existing zero-reference methods are designed for natural images, where degradations are primarily

illumination-related. Medical imaging, however, is governed by complex physics-based acquisition mechanisms. For example, ultrasound contrast is shaped by acoustic scattering and microbubble dynamics; MRI contrast depends on proton relaxation behavior and contrast agent interactions; and molecular imaging relies on targeted biochemical mechanisms. Applying natural-image assumptions or generic spectral priors to such data may suppress clinically significant textures or introduce artificial structural features.

A notable limitation in current enhancement research is the absence of explicit quantification of diagnostic structural distortion. Common metrics such as PSNR and SSIM evaluate pixel-level similarity but fail to capture clinically critical changes, such as anatomical boundary displacement or subtle lesion deformation. These undetected structural alterations may have significant implications for diagnosis.

In response to these challenges, the present study proposes a clinically adaptive zero-reference enhancement framework specifically designed for medical imaging. The framework is guided by three core objectives:

1. To preserve anatomical authenticity during contrast enhancement.
2. To explicitly quantify and constrain structural distortion.
3. To incorporate modality-aware frequency constraints aligned with the physics of image acquisition.

By integrating structural safety mechanisms with adaptive enhancement strategies, this approach aims to bridge the gap between computational image optimization and clinical reliability.

2. Literature Review

Medical image contrast enhancement has evolved from conventional intensity redistribution techniques to advanced deep learning–based frameworks; however, maintaining diagnostic safety across diverse imaging modalities remains a persistent challenge. Early spatial-domain approaches such as Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) improve global and local contrast by redistributing pixel intensities [26,27]. Although computationally efficient, these techniques operate without structural awareness and may unintentionally amplify noise or distort subtle anatomical boundaries, potentially influencing clinical interpretation.

A fundamental limitation of many traditional and natural-image–based enhancement strategies lies in their inability to account for modality-specific image formation physics. In ultrasound imaging, image texture and contrast are largely governed by acoustic wave scattering and microbubble interactions, leading to characteristic speckle patterns and signal variability [5–12]. In Magnetic Resonance Imaging (MRI), contrast depends on proton relaxation mechanisms and contrast agent dynamics, resulting in protocol-dependent variability across scanners and institutions [14–18]. Similarly, multimodal and molecular imaging systems rely on targeted tracer accumulation and functional contrast mechanisms that differ significantly from structural imaging principles [1–4]. These modality-driven physical processes generate frequency and texture characteristics that are fundamentally distinct from natural scene images, limiting the applicability of generic enhancement assumptions.

To address these complexities, physics-informed filtering and denoising approaches have been introduced. While such models attempt to integrate knowledge of acquisition mechanisms, they often rely on constrained assumptions about noise distributions or imaging parameters, which may reduce robustness in heterogeneous clinical environments.

The adoption of supervised deep learning, particularly convolutional neural networks (CNNs), has significantly improved performance in applications such as low-dose CT restoration and MRI enhancement [22]. Furthermore, adversarial learning strategies have enhanced perceptual realism and visual quality in reconstructed images [23]. Despite these advancements, supervised frameworks require paired low- and high-quality training datasets. In routine clinical workflows, true "ground-truth" enhanced images rarely exist, and variability in imaging protocols, scanner hardware, and patient-specific physiology may introduce bias and limit generalization.

Zero-reference learning has emerged as an alternative paradigm that eliminates the need for paired supervision by optimizing intrinsic image quality measures directly from the input image [21]. Although promising, most zero-reference models are primarily designed for natural images and assume illumination-driven degradations. They typically do not incorporate modality-specific spectral characteristics or explicitly constrain structural distortion inherent in medical data.

Structural similarity measures and frequency-domain representations have been explored independently in restoration research [24,25,28], yet few studies combine explicit structural distortion quantification with adaptive frequency regularization within a unified zero-reference framework. Moreover, commonly used evaluation metrics such as PSNR and SSIM, while useful for assessing pixel-level similarity and perceptual structure, do not directly quantify clinically significant changes such as anatomical boundary displacement or subtle lesion deformation.

In summary, although considerable progress has been achieved in classical image processing techniques [26,27], physics-aware modeling [5–18], and deep learning–based enhancement methods [21–23], the literature still lacks a comprehensive zero-reference framework that simultaneously preserves anatomical integrity, adapts to modality-specific frequency behavior, and remains computationally practical for real-world clinical deployment. This gap motivates the development of structurally and spectrally constrained enhancement strategies tailored specifically to the demands of diagnostic medical imaging.

3. Related Work

3.1 Medical Imaging Contrast Mechanisms

Modern medical imaging increasingly relies on multimodal strategies that integrate structural and functional information to improve disease characterization and diagnostic confidence [1], [3]. Rather than capturing only anatomical morphology, contemporary systems aim to represent physiological and molecular processes simultaneously.

In ultrasound imaging, particularly in molecular and targeted imaging applications, contrast is influenced by microbubbles and nanobubbles designed to bind specific biomarkers [8], [9], [12], [13]. These agents

alter acoustic scattering behavior, resulting in distinctive texture and frequency characteristics. Similarly, in Magnetic Resonance Imaging (MRI), contrast agents enhance tissue differentiation by modulating proton relaxation properties [15], [18]. These relaxation-driven mechanisms create signal variations that depend on tissue composition, imaging parameters, and contrast dynamics.

Because each modality is governed by distinct physical principles, the resulting images exhibit modality-specific spectral distributions and texture patterns. These intrinsic frequency characteristics must be considered when designing enhancement frameworks, particularly in safety-critical diagnostic applications.

3.2 Deep Learning for Medical Image Enhancement

CNN-based restoration networks have shown strong performance [19], [22]. Generative adversarial networks (GANs) have been used for low-dose CT enhancement [23]. However, GAN-based models may hallucinate features and lack diagnostic safety guarantees.

Zero-reference frameworks such as Zero-DCE [21] optimize exposure without paired supervision but are tailored to natural scenes.

3.3 Research Gap

Despite progress in both classical and deep learning–based enhancement methods, several limitations remain:

- Existing zero-reference models are not specifically designed for medical imaging physics and modality-dependent signal behavior.
- Structural distortion is rarely quantified explicitly, leaving the risk of subtle anatomical deformation unmeasured.
- Frequency constraints, when applied, are typically generic and not adapted to modality-specific spectral characteristics.

These limitations highlight the need for a clinically adaptive, structurally constrained zero-reference enhancement framework.

4. Proposed Methodology

Framework Overview

- We propose SFC-ZRNet, a fully convolutional encoder–decoder network inspired by U-Net–like architectures. The model takes a single-channel clinical image—such as an ultrasound frame or an MRI slice—as input and predicts a lightness adjustment map. This map is combined with the original image to produce an enhanced output.
- To handle wide dynamic range variations, the enhancement process is applied iteratively, typically for 8–12 steps. This gradual refinement allows smooth contrast improvement while minimizing abrupt structural changes.

Multi-Scale Feature Extraction

- The network employs convolutional layers with batch normalization and ReLU activation functions to extract hierarchical features at multiple spatial scales. Skip connections facilitate gradient propagation and preserve fine spatial details that are essential for anatomical integrity.
- The architecture is intentionally lightweight, containing approximately 2.9 million parameters. It achieves fast inference, requiring roughly 31 milliseconds to process a 256×256 image on a GPU. This efficiency makes the framework suitable for real-time or near-real-time clinical applications.

Curve-Based Enhancement Strategy

- At each iteration, the network predicts a per-pixel adjustment parameter, denoted as $\alpha(x, y)$. This parameter defines a smooth light-curve transformation applied to the current image estimate:

$$I_{t+1}(x,y)=I_t(x,y)+\alpha(x,y)\cdot(I_t(x,y)-I_t(x,y)^2),$$

This formulation, inspired by Retinex-based exposure adjustment strategies, enhances mid-tone contrast while avoiding harsh clipping or over-amplification. The transformation is monotonic and smooth, ensuring gradual contrast improvement without introducing abrupt intensity discontinuities.

Diagnostic Structural Distortion Quantification

A central contribution of this framework is the explicit quantification of structural preservation.

- **Edge Preservation Index (EPI):**

The EPI compares gradient magnitudes between the input and enhanced images to assess whether structural edges are maintained during enhancement.

- **Boundary Displacement Measure (BDM):**

BDM evaluates the average displacement between anatomical boundaries in the input and enhanced images. By penalizing deviations, the framework prevents unintended anatomical deformation or artificial sharpening.

- These structural constraints ensure that contrast enhancement does not compromise clinically relevant morphology.

Modality-Aware Frequency Constraint

- To preserve modality-specific spectral characteristics, the framework incorporates a frequency-domain regularization term. The Fast Fourier Transform (FFT) is used to decompose images into low-, mid-, and high-frequency components.

- A frequency consistency loss is defined as the weighted difference between corresponding frequency bands of the input and enhanced images:

$$L_{freq} = \sum w_i ||F_i^{input} - F_i^{enhanced}||$$

The weights (wi) are selected according to the imaging modality, allowing the framework to adapt to modality-dependent spectral properties.

Unified Loss Function

All objectives are integrated into a unified loss formulation:

$$L_{total} = \alpha L_{exposure} + \beta L_{smooth} + \gamma L_{EPI} + \delta L_{BDM} + \eta L_{freq}$$

This composite loss balances exposure optimization, smoothness regularization, structural preservation, and frequency consistency. Importantly, the framework operates entirely without paired supervision, making it suitable for diverse clinical datasets where ground-truth enhanced.

5. Experiments

We evaluate on four clinical datasets: ultrasound liver scans, brain MRI (T1-weighted), low-dose CT (abdomen), and chest X-ray. For each, we split into 80% training and 20% testing subjects. Images are normalized to [0,1] per modality. Baselines include: global Histogram Equalization (HE), CLAHE, Gamma Correction, a supervised CNN enhancement (trained on simulated low-contrast/normal pairs), and a zero-reference exposure-only model.

Metric	**Definition**	**Target**
PSNR (dB)	$20\log_{10}(255/\sqrt{\text{MSE}})$	High
SSIM	Structural similarity index (luminance/contrast/structure)	High
Entropy	$-\sum p_i\log p_i$ over intensity histogram	High (contrast)
EPI	$\sum \nabla I_{\rm in}	Low (stable)
BDM	Mean boundary displacement between input/output	Low (stable)

6. Comparative Evaluation

Table 1. Quantitative Comparison

Method	PSNR (dB) ↑	SSIM ↑	Entropy ↑	EPI ↑	BDM ↓
HE	18.42	0.61	6.98	1.42	0.084
CLAHE	20.13	0.68	7.32	1.35	0.072
Gamma	19.57	0.65	7.11	1.28	0.078
SCNN	23.46	0.81	7.89	1.12	0.048
ZR-Exp	22.08	0.76	7.63	1.19	0.056
SFC-ZRNet (Ours)	**25.32**	**0.88**	**8.21**	**1.04**	**0.031**

Quantitative comparison on multi-modality test set ↑ : higher is better ; ↓ : lower is better.

SFC-ZRNet achieves the highest PSNR, SSIM, and entropy, indicating superior contrast enhancement and detail retention. Importantly, it yields the *lowest* BDM (0.031), demonstrating the best structural fidelity – over 30% improvement versus CLAHE. The EPI remains near 1.0 for all learned methods, but note that HE/CLAHE actually inflate EPI (indicating edge exaggeration). The supervised CNN (SCNN) improves PSNR/SSIM over classical methods but still incurs larger boundary shifts (BDM=0.048). The zero-reference exposure-only model (ZR-Exp) improves entropy slightly, but without our spectral terms it introduces artifacts, as seen in its lower SSIM and higher BDM. In summary, SFC-ZRNet attains the best balance: maximal contrast gain with minimal distortion. This is consistent with qualitative findings that lesions and tissue textures appear sharper but anatomically consistent.

- **Modality-wise and Structural Analysis**

Modality	CLAHE SSIM	SCNN SSIM	Ours SSIM	CLAHE BDM	SCNN BDM	Ours BDM
Ultrasound	0.63	0.78	**0.86**	0.081	0.051	**0.029**
MRI	0.71	0.83	**0.90**	0.068	0.044	**0.027**
CT	0.69	0.82	**0.88**	0.072	0.046	**0.032**
X-ray	0.70	0.81	**0.87**	0.067	0.043	**0.030**
Average	0.68	0.81	**0.88**	0.072	0.046	**0.030**

These results suggest:

- **Ultrasound:** Speckle textures are enhanced without structural warping, thanks to tailored high-frequency weighting.
- **MRI:** Tissue boundaries (e.g. gray/white matter, lesions) are better delineated, aided by structural loss.
- **CT:** Bone edges remain sharp but natural, with no artificial halos (our frequency loss prevents ringing).

- **X-ray:** Soft-tissue gradients are enhanced while preserving anatomical proportions (low BDM).

7. Ablation Study

To quantify each component's impact, we conducted ablations, Configurations:

- **A1:** Base network with only exposure and smoothness losses.
- **A2:** A1 + structural losses (EPI+BDM).
- **A3:** A1 + frequency loss.
- **A4:** Full SFC-ZRNet (all losses).

Config	PSNR	SSIM	BDM
A1	21.82	0.74	0.059
A2	23.94	0.84	0.036
A3	23.12	0.80	0.048
A4	**25.32**	**0.88**	**0.031**

Ablation results (same test set). Higher is better for PSNR/SSIM, lower for BDM.

8. Computational Complexity Analysis

Total complexity:

$O(LHWK^2CF+HWlog(HW))$

Parameter count: ~2.9M

Inference time: 31 ms (256×256 GPU)

Clinically feasible.

8.1 Baseline Methods for Comparison

To evaluate the effectiveness of the proposed Structural–Frequency Constrained Zero-Reference Network (SFC-ZRNet), we compare it with representative classical and deep learning-based enhancement methods:

1. **Histogram Equalization (HE)** – Global intensity redistribution.
2. **Contrast Limited Adaptive Histogram Equalization (CLAHE)** – Local adaptive contrast control.
3. **Gamma Correction (GC)** – Non-linear intensity mapping.
4. **Supervised CNN Enhancement (SCNN)** – Paired-learning-based enhancement model.
5. **Zero-Reference Exposure-Based Model (ZR-Exp)** – Exposure-constraint-only zero-reference model.

8.2 Quantitative Comparison

Evaluation was conducted on ultrasound, MRI, CT, and X-ray datasets using:

- PSNR
- SSIM
- Entropy
- Edge Preservation Index (EPI)
- Boundary Displacement Measure (BDM ↓ lower is better)

Quantitative Comparison on Multi-Modality Dataset

Method	**PSNR (dB) ↑**	**SSIM ↑**	**Entropy ↑**	**EPI ↑**	**BDM ↓**
HE	18.42	0.61	6.98	1.42	0.084
CLAHE	20.13	0.68	7.32	1.35	0.072
Gamma Corr.	19.57	0.65	7.11	1.28	0.078
SCNN	23.46	0.81	7.89	1.12	0.048
ZR-Exp	22.08	0.76	7.63	1.19	0.056
SFC-ZRNet (Proposed)	**25.32**	**0.88**	**8.21**	**1.04**	**0.031**

Observations

• HE and CLAHE increase entropy but significantly distort edges (high EPI and BDM).

• Supervised CNN improves PSNR but still introduces boundary displacement.

• Zero-reference exposure-only model fails to preserve frequency balance.

• **SFC-ZRNet achieves the best structural fidelity (lowest BDM) while improving contrast.**

8.3 Modality-Wise Performance Analysis

SSIM and BDM Across Modalities

Modality	**CLAHE SSIM**	**SCNN SSIM**	**Proposed SSIM**	**CLAHE BDM**	**SCNN BDM**	**Proposed BDM**
Ultrasound	0.63	0.78	**0.86**	0.081	0.051	**0.029**
MRI	0.71	0.83	**0.90**	0.068	0.044	**0.027**
CT	0.69	0.82	**0.88**	0.072	0.046	**0.032**
X-ray	0.70	0.81	**0.87**	0.067	0.043	**0.030**

Clinical Insight

- Ultrasound benefits significantly from frequency-aware constraints due to speckle characteristics.

- MRI enhancement shows improved preservation of tissue contrast boundaries.
- CT bone edges remain sharp without artificial halo artifacts.
- X-ray soft tissue gradients are enhanced without structural warping.

9. Statistical Significance Analysis

A paired t-test was conducted between SCNN and SFC-ZRNet results.

- SSIM improvement statistically significant ($p < 0.01$)
- BDM reduction statistically significant ($p < 0.005$)

This confirms the robustness of structural-frequency integration.

10. Computational Complexity Analysis

To evaluate the practical feasibility of the proposed Structural–Frequency Constrained Zero-Reference Network (SFC-ZRNet), we analyze computational complexity in terms of:

- Theoretical time complexity
- Parameter count
- Memory usage
- Inference time

10.1 Network Complexity

Let:

- H×WH \times WH×W = image resolution
- CCC = number of channels
- LLL = number of convolutional layers
- K×KK \times KK×K = kernel size
- FFF = number of feature maps

The computational complexity of a single convolution layer is:

$O(H \times W \times K^2 \times C \times F)$

For the entire network:

$O(L \times H \times W \times K^2 \times C \times F)$

Since SFC-ZRNet uses:

- 8 convolution layers
- 3×3 kernels

- Moderate feature depth

The architecture remains lightweight compared to deep supervised enhancement networks.

10.2 Frequency-Domain Computation Cost

The Fast Fourier Transform (FFT) introduces:

$O(HW \log(HW))$

This is computationally efficient and negligible compared to convolution operations for moderate image sizes (e.g., 256×256).

Because frequency computation is applied once per forward pass, it does not significantly increase training complexity.

10.3 Structural Distortion Computation Cost

Gradient computation (Sobel operator):

$O(HW)$

Boundary detection (Canny-based):
$O(HW)$

These operations are linear in pixel count and introduce minimal overhead.

10.4 Overall Complexity

The total forward-pass complexity becomes:

$O(LHWK^2CF+HW\log(HW))$

Since:

$LHWK^2CF \gg HW\log(HW)$

The dominant cost arises from convolution layers.

10.5 Parameter Comparison

Model	**Approx. Parameters**	**Training Type**
SCNN	~5.8M	Supervised
ZR-Exp	~2.4M	Zero-Reference
SFC-ZRNet (Proposed)	~2.9M	Zero-Reference

The proposed model introduces minimal additional parameters for structural and frequency constraints because they are implemented in the loss function rather than architectural expansion.

10.6 Inference Time Analysis

Measured on a standard GPU (single forward pass, 256×256 image):

Method	Inference Time (ms)
CLAHE	12 ms
SCNN	38 ms
ZR-Exp	27 ms
SFC-ZRNet	31 ms

The slight increase compared to exposure-only zero-reference models is due to FFT and structural computations, but remains suitable for near real-time clinical use.

11. Discussion

The findings confirm that integrating structural and frequency constraints into a zero-reference framework improves contrast while maintaining anatomical integrity. Unlike HE and CLAHE, which increase entropy at the cost of boundary distortion, and supervised CNNs that may still shift structures, SFC-ZRNet explicitly penalizes structural deviation, achieving the lowest BDM with consistently high SSIM. The Boundary Displacement Measure and Edge Preservation Index provide direct control over anatomical fidelity, addressing limitations of conventional metrics such as PSNR and SSIM. The modality-aware frequency constraint further prevents artificial texture amplification, ensuring realistic enhancement across ultrasound, MRI, CT, and X-ray images. With a lightweight architecture (~2.9M parameters) and near real-time inference (~31 ms per slice), the framework remains clinically feasible. Overall, SFC-ZRNet demonstrates that diagnostically safe, zero-reference contrast enhancement is achievable through explicit structural and spectral regularization.

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