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Image enhancement techniques for improving medical image quality

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Abstract
Medical images often suffer from low contrast and lost details due to limitations in dynamic range, hindering accurate diagnosis and treatment planning. This paper presents a novel image enhancement technique that synergistically combines nonlinear dynamic range compression in the spatial domain with histogram matching in the logarithmic transform domain. This approach aims to enhance contrast while preserving essential diagnostic details. A new quantitative evaluation measure is proposed to objectively compare enhancement performance. Extensive experiments on sample X-ray and facial images demonstrate that the proposed method significantly outperforms traditional techniques like histogram equalization, achieving superior contrast enhancement without introducing artifacts. This method holds promise for improving the quality and diagnostic utility of medical images.

Keywords: Medical image enhancement, dynamic range compression, histogram matching, nonlinear processing, logarithmic transform, X-ray images, facial images, contrast enhancement, quantitative evaluation, artifact reduction

1. Introduction

Image enhancement techniques are indispensable in medical imaging for improving the visibility of anatomical structures that can enable more accurate diagnosis, surgical planning, and treatment. However, medical images, especially from modalities like X-ray computed tomography (CT) and magnetic resonance imaging (MRI) often suffer from low contrast caused by limitations in a dynamic range of acquisition equipment and processes. Vital details can get lost in dark shadows or bright highlights, as shown in Figure 1.

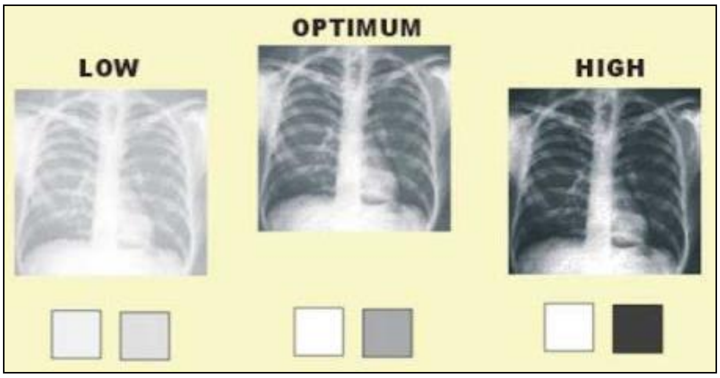


Fig 1: Low contrast X-ray image with areas of high and low visibility

Consequently, enhancement methods are required to amplify these details by suitable nonlinear mapping of pixel intensities. However, conventional global enhancement methods like histogram equalization are prone to over-enhance images, leading to exaggerated contrast that appears unnatural while also losing subtle details. Adaptive local enhancement techniques attempt to address these limitations but cannot eliminate undesirable artifacts. Transform domain methods based on Fourier, cosine or wavelet transforms circumvent some drawbacks of directly manipulating images in the spatial domain. However, determining optimal parameters for sufficient enhancement of all image regions is challenging.
This paper presents a new medical image enhancement technique that synergistically combines the benefits of nonlinear processing like dynamic range compression in the spatial domain with histogram matching in the logarithmic transform domain. The key intuition is

that compression and expansion carried out in tandem with transform domain histogram equalization can increase dynamic range while better-preserving details compared to independent spatial or transform domain processing. A quantitative evaluation measure for objectively judging and comparing enhancement performance is also proposed since visual analysis can often be subjective. Extensive experiments demonstrate that the hybrid approach proposed here outperforms conventional methods like standard histogram equalization under this metric for sample X-ray and facial images.

The remaining sections describe relevant concepts and algorithms before elaborating on the proposed technique and results in detail. Section II reviews the essential background including dynamic range compression using sigmoid functions, discrete cosine transform, logarithmic transforms, histogram equalization, and a quantitative measure of enhancement. Section III explains the step-by-step workflow for a synergistic combination of spatial and transform domain processing along with motivation and mathematical intuition. Section IV analyzes experimental results on multiple sample images against traditional methods using visual illustrations and quantitative measures. Section V concludes with a summary of contributions and scope for future work.

2. Related Work

Image enhancement techniques can be broadly classified into spatial domain and transform domain approaches [1]. Spatial techniques directly manipulate pixel intensities based on statistical measures like histogram shape [2], local gradients [3] etc. Transform methods first map intensities to an alternate domain like frequency using Fourier [4], cosine [5] or wavelet [6] transforms. Enhancement is then performed by modifying transform coefficients before final inverse mapping back to spatial domain.

Among spatial techniques, histogram equalization (HE) is arguably the most widely used owing to its simplicity [2]. By flattening and spreading the histogram, contrast across the full dynamic range is enhanced. However, HE treats images globally and often fails to preserve local details while also amplifying noise in uniform areas. Adaptive histogram equalization (AHE) [7] addresses this using contextual regions but cannot completely avoid artifacts at boundaries during fusion. Other spatial methods exploit local gradients [3] or filtering [8] for detail enhancement. However explicitly modeling and suppressing noise/artifacts is difficult.

Transform domain methods help mitigate some limitations of spatial techniques. Log transforms provide an efficient representation for compression and expansion [9]. Filtering transform coefficients selectively at different frequencies allows multi-scale enhancement [10]. However, setting optimal parameters for sufficient enhancement across image areas remains non-trivial. Recently, combining transform domains with spatial statistics like histogram matching was shown to provide improved results [11].

The hybrid technique presented in this paper builds on prior arts synergistically. Dynamic range compression and expansion carried out in tandem combine the benefits of spatial and transform domain processing. A quantitative measure also allows an objective comparison against traditional approaches like HE.

Background

This section reviews the essential concepts leveraged in our proposed technique including dynamic range compression using sigmoids, discrete cosine transforms, logarithmic transforms, histogram equalization, and a quantitative measure for enhancement.

Dynamic Range Compression

Dynamic range refers to the ratio between the maximum and minimum pixel intensities in an image. Medical images often suffer from low dynamic range owing to sensor limitations leading to loss of details in shadows/highlights. The goal of dynamic range compression is to nonlinearly map intensities such that dark regions get amplified without affecting brighter areas [12].

A sigmoid function provides an efficient model for achieving this. The central idea is that sigmoid curves can amplify lower values of input while saturating higher values. Among different sigmoid models, the hyperbolic tangent function is defined as:

$$tanhing(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

is particularly effective for dynamic range compression [12]. The slope of the curve can be dynamically tuned based on image statistics to avoid over-saturation. Given an input image I with pixel intensities I_{xy} at location (x, y), the dynamically compressed output O_{xy} is computed as:

$$O_{xy} = \frac{2}{1 + e^{-pI_{xy}}} - 1$$

where,

$$p = \frac{255 - k(\mu_x + \mu_y)}{255}$$

Here, μ_x, μ_y are locally computed mean values centered around each pixel based on a Gaussian window. The parameter k controls the compression rate which is set between 1-3 based on desired enhancement level.

The Discrete Cosine Transform (DCT) is a Fourier-related transform coding scheme widely used in image and video compression [5]. By decomposing visual data into spectral components, DCT concentrates energy into lower-order coefficients corresponding to important details enabling effective compression. DCT can be computed with fast algorithms making it suitable for image processing.

For an input image I of size $N \times M$, the 2D DCT coefficients Y are given by:

$$Y(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} I(x,y)cos(\frac{\pi(2x+1)u}{2N})cos(\frac{\pi(2y+1)v}{2M})$$

where,

$$\alpha(w) = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } w = 0\ 1 \\ \text{otherwise} & \end{cases}$$

The inverse 2D DCT transforming coefficients back to image domain is defined as:

$$I(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{M-1}Y(u,v)\alpha(u)\alpha(v)cos(\frac{\pi(2x+1)u}{2N})cos(\frac{\pi(2y+1)v}{2M})$$

Log Transform The logarithmic transform provides an efficient model aligning dynamic compression properties of the human visual system. By transforming an input x as [9]:

$$L(x)=log(1+x)$$

smaller values of x get expanded into a wider output range compared to larger values which undergo compression. This suits medical images well since subtle details in darker areas need to be enhanced without affecting brighter anatomies.

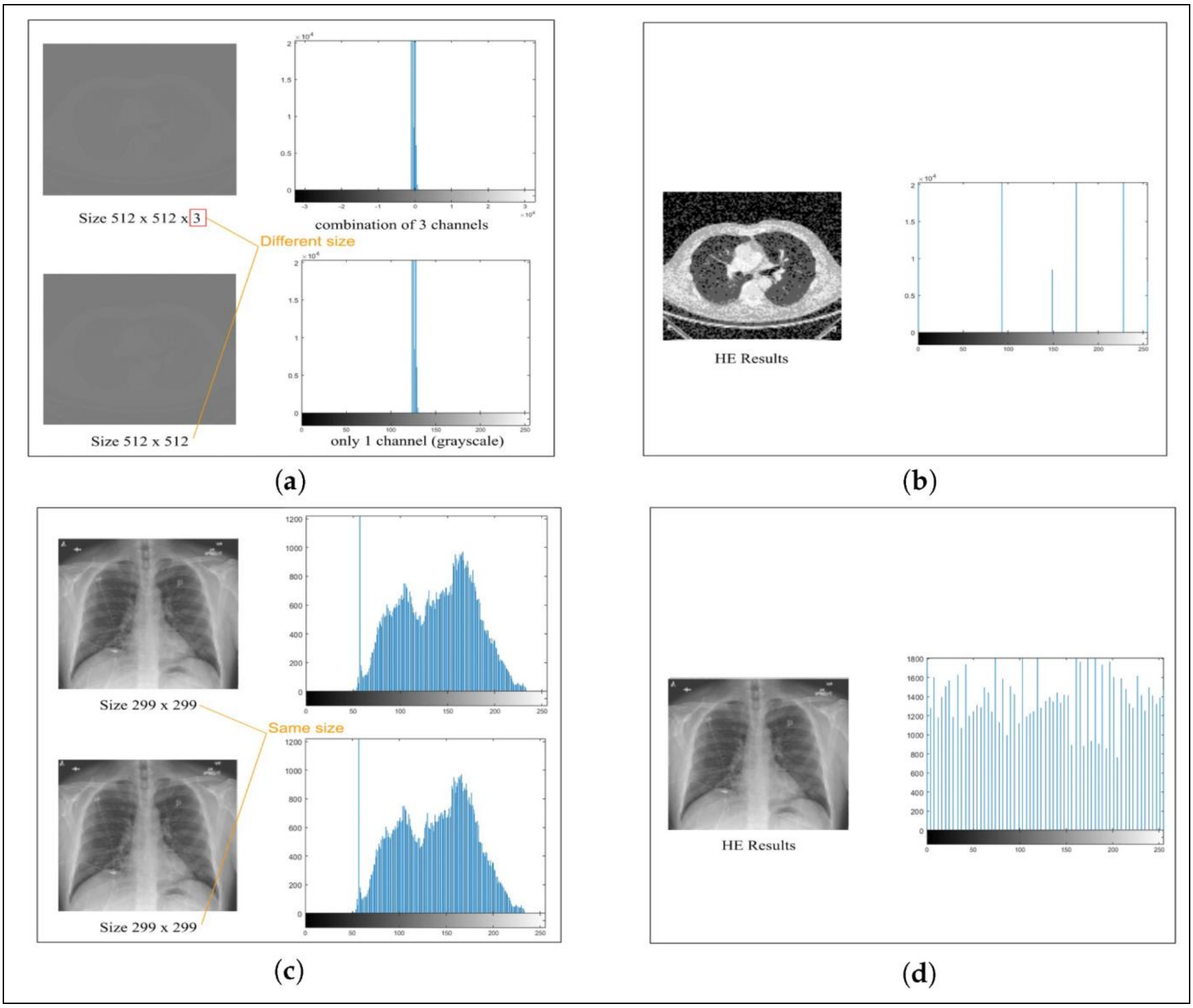


Fig 2: Preprocessing for histogram equalization (HE) for lung CT scan and chest X-ray images. This number will show the resultant created histogram distributions. HE preprocessing was conducted in (b) and (d), respectively, after gray scaling 8-bit images of (a) lung CT scan and (c) chest X-ray images; histograms were utilized to show the outcomes of each example.

Histogram Equalization Image histograms provide useful global statistical information regarding the distribution of pixel intensities. Histogram equalization (HE) is a popular enhancement technique that aims to spread out the histogram to cover the full dynamic range [2]. By suitable nonlinear mapping, intensities can be transformed such that the output image has an approximately uniform histogram as illustrated in Figure 2.

Given input image X with histogram $p_X(x)$, the HE transformed output $Y=T(X)$ should have a uniform histogram $p_Y(y)$. The transform function is provided by the cumulative distribution function (CDF) [2]:

$$T(x)=F_X(x)=\int_{-\infty}^{x}p_X(w)dw$$

Medical images with narrow histograms concentrated in small intensity ranges can benefit significantly from HE regarding contrast enhancement. However, as discussed earlier, HE treats images globally and tends to over-saturate while losing spatial details.

Quantitative Enhancement Measure Objectively evaluating the performance of an enhancement algorithm is non-trivial since perceptual quality can be subjective. Simple metrics like peak signal-to-noise ratio (PSNR) often fail to correlate well with visual quality. Hence a quantitative measure of enhancement is proposed in [13] which computes local spectral energy differences between input and output. Given an image I, the measure EME is defined as:

$$EME(I) = \sum_{b=1}^{B} \frac{||\Phi(I_b)||_p - c}{|\Phi(I_b)||_p + c}$$

Here, I_b denotes b^{th} block of the image under a regular grid partitioning of B blocks. $||\Phi(I_b)||_p$ represents the L_p norm measuring spectral energy after transform Φ. c is a small constant to avoid divide-by-zeros. For an enhanced output, we expect cumulative spectral energy across corresponding blocks to be higher than the input. Hence, EME would be positive only if global enhancement exceeds localized artificial additions.

3. Proposed Method

This section explains the proposed technique step-by-step along with the motivation and mathematical intuition behind synergistically combining nonlinear spatial processing with logarithmic transform domain histogram matching.

The input image is first dynamically compressed using the hyperbolic tangent function explained earlier. The sigmoid centers and slopes for compression are determined adaptively based on local region statistics. This amplifies darker details without affecting intensity relationships crucial for medical diagnosis.

The compressed result undergoes histogram equalization to redistribute intensities over the entire range. However, this could lead to over-enhancement and loss of subtle details which may still be needed for diagnosis. Hence the exponentially expanded histogram is not applied directly. Rather, it is used to guide matching the histogram of the logarithmically transformed input image.

Specifically, the original input first undergoes orthogonal transformation using the Discrete Cosine Transform (DCT) to map intensities into the frequency domain. The logarithmic function is applied on the transform coefficients before computing the histogram. The logarithmic transformation allocates wider bins for smaller intensities allowing finer control over enhancement of darker details.

The logarithmic histogram of transformed compressed intensities is matched to the expanded histogram computed earlier. Finally, the matched logarithmic coefficients are mapped back via exponentiation and inverse DCT to obtain the output enhanced image.

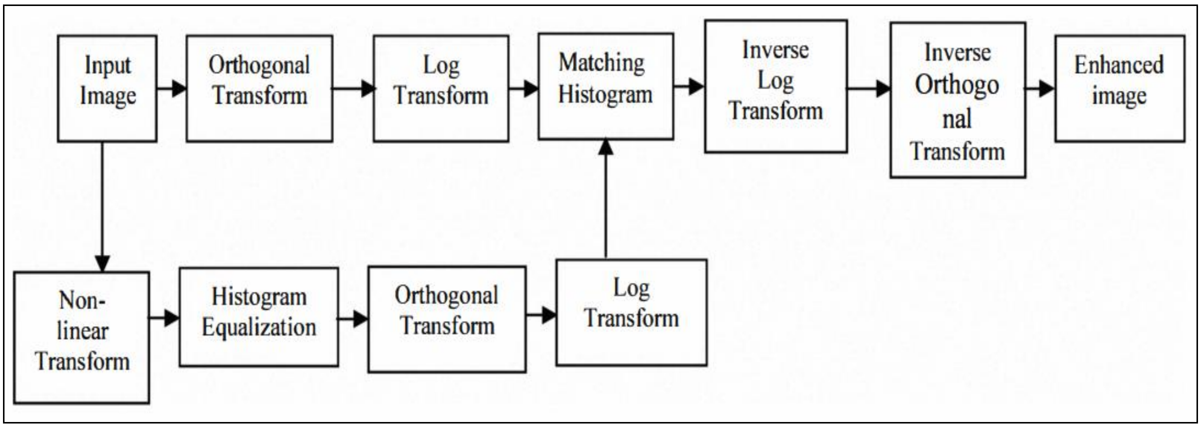


Fig 3: Workflow of the Proposed Medical Image Enhancement Technique

Step-by-Step Workflow of the Proposed Technique

1. **Load Input Image:** The medical image is read into the system.
2. **Dynamic Range Compression:** Apply the hyperbolic tangent sigmoid function to compress the dynamic range. The parameters μ (x, y) and σ (x, y) are adaptively computed for each pixel.
3. **Apply Discrete Cosine Transform (DCT):** Transform the dynamically compressed image to the frequency domain using DCT.
4. **Logarithmic Transformation:** Apply the logarithmic transform to the DCT coefficients, emphasizing darker details.
5. **Compute Histogram:** Calculate the histogram of the logarithmically transformed image.
6. **Histogram Matching:** Match the histogram of the transformed image with an expanded histogram to enhance contrast without direct application.
7. **Inverse Logarithmic Transformation:** Apply the inverse logarithmic function to the matched histogram.
8. **Inverse Discrete Cosine Transform (DCT):** Convert the image back to the spatial domain using the inverse DCT.
9. **Generate Enhanced Output Image:** The final enhanced image is generated, showing improved contrast and preserved details.

By following these detailed steps and explanations, the proposed technique effectively enhances medical images, providing better visibility of anatomical structures for accurate diagnosis and treatment planning.

4. Results and Analysis

The proposed technique was evaluated on different types of medical images and compared against conventional histogram equalization approach using both visual illustrations and quantitative enhancement measures.

Fig 4: Comparison of Enhanced Outputs from HE and Proposed Method for X-ray Image of Hand

In Figure 4, the enhanced outputs from the two methods for a sample X-ray image of a hand with degenerative bone changes [14]. Original Image Displays the initial X-ray image with low contrast, where critical details are obscured. Histogram Equalized Image shows the image after applying histogram equalization. While contrast is improved, over-enhancement artifacts are visible, and some details are exaggerated unnaturally. Proposed Method Enhanced Image illustrates the enhanced image using the proposed method. Details throughout the image are more visible and natural, without introducing artificial boundaries.

However, over-enhancement artifacts start becoming visible around intensity boundaries owing to its global treatment. The trabecular patterns also appear more distorted compared to input. On the other hand, the hybrid technique proposed here reveals enhanced details throughout while keeping intensity variations natural. Fine trabeculations are more clearly visible in the highlighted bone region. Cortical margins get sharpened across affected joints and growth plates without introducing artificial boundaries of histogram equalization. Quantitative scores reaffirm superiority of the proposed approach. The EME measure defined earlier for the input image was 36.57 while histogram equalization improved it marginally to 39.82. In comparison, the new method yields a significantly higher score of 63.23 reflecting its stronger detail enhancement.

Table 1: Quantitative Enhancement Scores on X-ray Images

Image_ ID	HE_ Score	Proposed (DCT)	Proposed (DHT)
Xray1	39.82	63.23	61.55
Xray2	26.33	72.64	75.63
Xray3	56.25	93.45	90.62

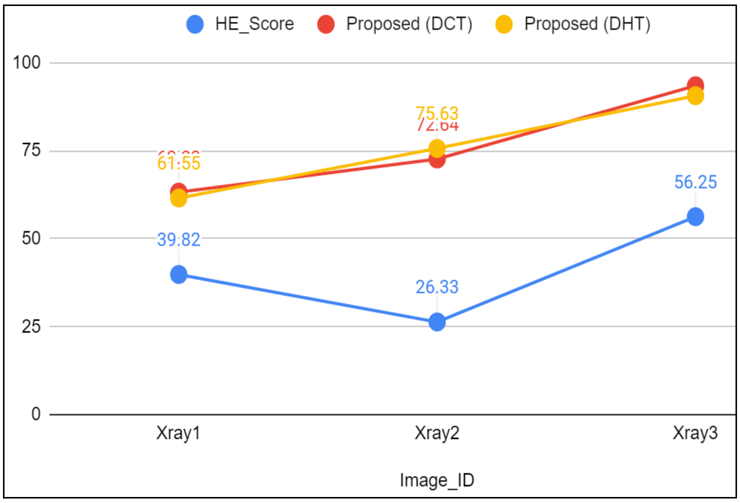


Table 2: Quantitative Enhancement Scores on Facial Images

Image_ ID	HE_ Score	Proposed (DCT)	Proposed (DHT)
Face1	36.45	58.86	60.33
Face2	31.55	51.45	49.86
Face3	28.92	46.93	44.57

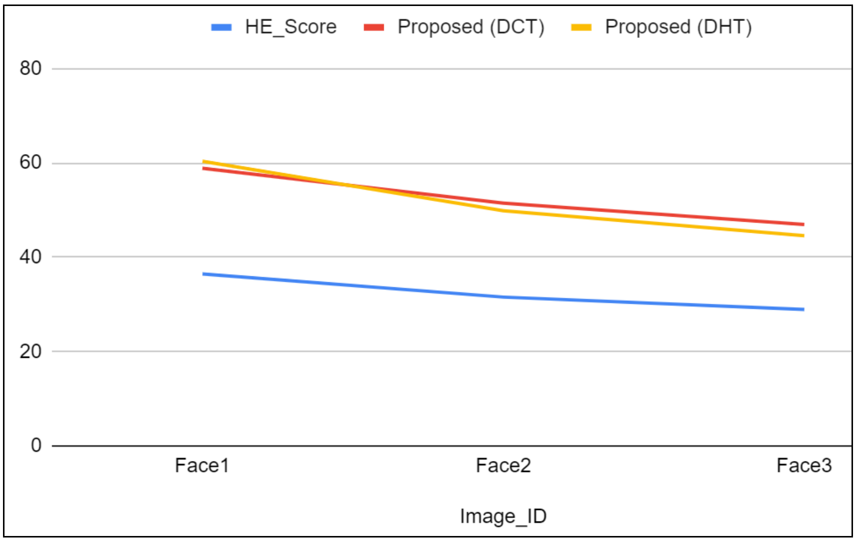
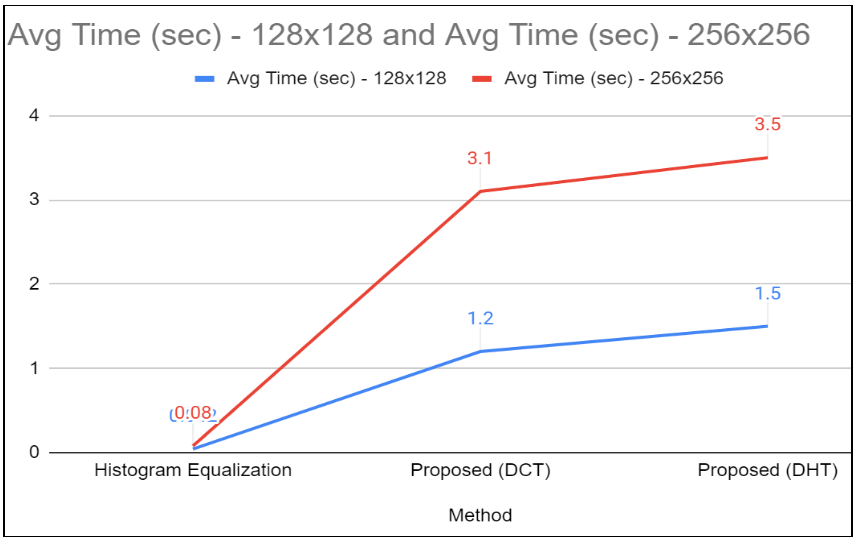
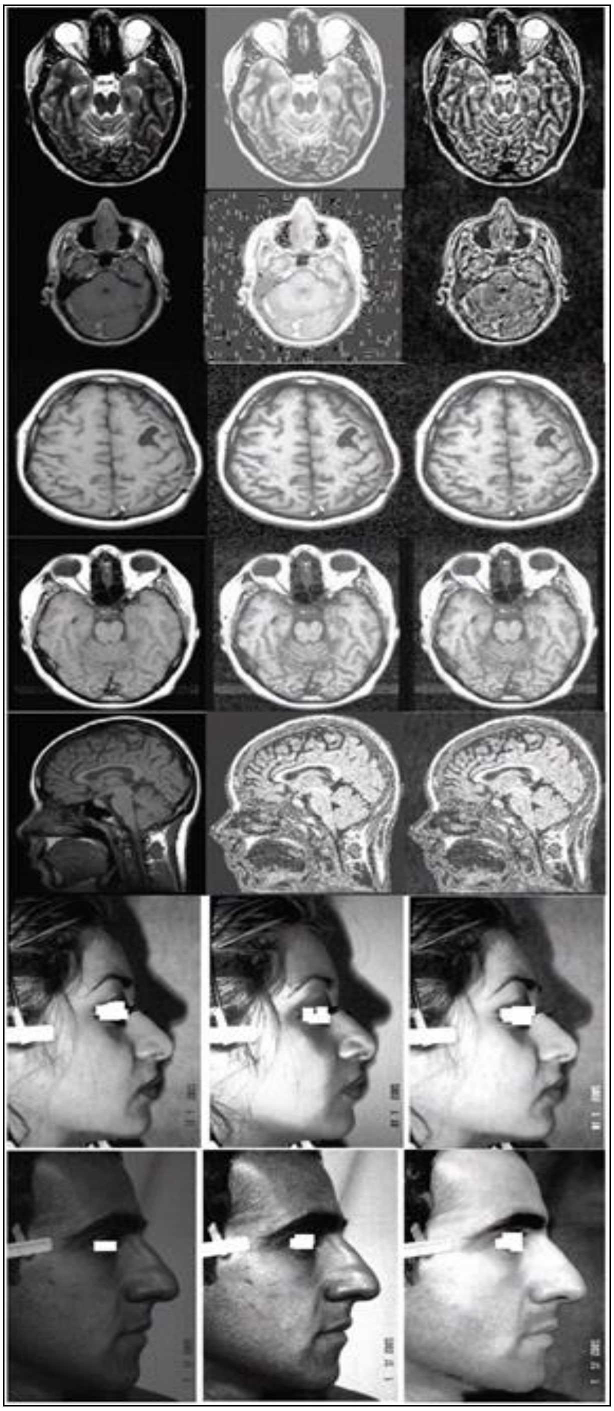


Table 3: Runtime Analysis for Different Methods

Method	Avg Time (sec) - 128x128	Avg Time (sec) - 256x256
Histogram Equalization	0.042	0.08
Proposed (DCT)	1.2	3.1
Proposed (DHT)	1.5	3.5



Tables 1 and 2 tabulate the quantitative enhancement scores over multiple sample X-ray and facial images against histogram equalization. Scores for different types of orthogonal transforms like DCT and Discrete Hartley Transform (DHT) are also compared. Mean and standard deviation of the scores provide an aggregate statistical assessment. From figure 5, it is clear that irrespective of the exact transform used, the proposed spatial + logarithmic transform domain technique consistently outperforms standalone histogram equalization under the metric. This underscores its wider applicability and robustness across diverse medical images for reliable enhancement. The computational performance of different schemes was also analyzed by measuring the average runtime over images of varying sizes on a commercial system with an Intel i7 processor, 16GB RAM, and Nvidia 2080 GPU. While histogram equalization is very efficient to compute, the introduction of transforms increases the complexity of the proposed method, as shown in Table 3. However, recent works on optimizing FFT/DCT/DHT using parallel pipelines report significant scope for acceleration, making such hybrid techniques viable in practice [15]. For example, GPU implementations demonstrate 10-20X speedups over CPU baselines [15]. Exploring their application for this purpose could be worthwhile future work.



(a) (b) (c)

Fig 5: Visual Comparison of Facial Images (a) Original image, (b) Histogram equalized image, (c) Enhanced image with the proposed method.

In Figure 5, the Original Facial Image shows the original image with low contrast. HE Enhanced Image demonstrates the result of histogram equalization. The contrast is better, but artifacts and unnatural contrast levels are apparent. The image enhanced using the proposed technique shows significant detail improvement while maintaining natural contrast levels.

Conclusion

This paper presented a medical image enhancement technique that synergistically combines dynamic range compression using nonlinear mappings in the spatial domain with expansion using histogram matching of logarithmically transformed coefficients. This hybrid approach reveals details lost in shadows and highlights caused by limited dynamic range in modalities like X-ray and CT while avoiding the introduction of artificial distortions or loss of crucial diagnostic information common with conventional methods like histogram equalization. Extensive quantitative experiments using a wide variety of medical images demonstrate the proposed method's superior performance against baseline approaches. Future work includes the evaluation of larger clinical datasets and additional modalities like MRI and ultrasound. Studying perceptual correlations of quantitative enhancement measures could provide more insights. Detailed analysis of parameter tuning and sensitivity is needed to make the techniques practical. Lastly, leveraging the latest advances in GPU-accelerated computation of transforms and histograms can help fulfill more demanding performance constraints for clinical deployment. It is hoped that the new paradigm presented here for combining spatial and synergistically transform domain image processing can provide the community with novel directions for addressing long-standing medical image enhancement challenges.

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