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Enhancing MPEG-1 Video Quality Using Discrete Wavelet Transform (DWT) with Coefficient Factor and Gamma Adjustment

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Abstract

Low-quality video caused by compression artifacts, noise, and loss of detail remains a significant challenge in video processing, affecting applications in streaming, surveillance, and medical imaging. Existing enhancement techniques often struggle with excessive noise amplification or high computational complexity, making them inefficient for real-time applications. This study proposes an improved video enhancement method using Discrete Wavelet Transform (DWT) with optimized coefficient factor and gamma adjustment. DWT is a mathematical approach that decomposes video frames into frequency subbands, enabling selective enhancement of important details. To analyze the impact of different wavelets, this study evaluates Coif5, db1, sym4, and sym8 wavelets. The sym8 wavelet, known for its high symmetry and ability to minimize artifacts, achieves the best results in preserving fine details and structural integrity. The coefficient factor is dynamically adjusted to sharpen details while preventing noise amplification, and gamma adjustment is applied to optimize brightness and contrast. The proposed method was evaluated using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Experimental results show that sym8 wavelet with gamma 0.7 and coefficient factor 0.3 provides the best balance, achieving an MSE of 0.062, a PSNR of 12.050 dB, and an SSIM of 0.674, outperforming Coif5, db1, and sym4 wavelets. The results indicate that wavelet selection significantly impacts video enhancement performance, with sym8 providing superior contrast enhancement and noise suppression. This study contributes to real-time video processing and AI-based applications, ensuring enhanced visual quality with minimal computational overhead.

Keywords : *Coefficient Factor, Discrete Wavelet Transform, Gamma Adjustment, Video Enhancement, Visual Quality.*

1. INTRODUCTION

Digital video processing plays a crucial role in various applications, including streaming, surveillance, and medical imaging. However, video compression techniques such as MPEG-1 often introduce distortions, resulting in loss of critical details, noise, and reduced visual clarity [1]–[6]. These challenges necessitate advanced video enhancement techniques to restore lost information while maintaining computational efficiency.

Among the most promising approaches, Discrete Wavelet Transform (DWT) has gained attention due to its multi-resolution analysis and ability to efficiently separate frequency components [7], [8]. Unlike traditional spatial-domain methods, DWT selectively enhances high-frequency subbands, enabling improved contrast and detail restoration. Prior studies have demonstrated the effectiveness of DWT in video enhancement, yet many suffer from excessive noise amplification and computational overhead due to suboptimal parameter tuning [9], [10]. To address video quality degradation, this study

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leverages DWT with optimized coefficient factor and gamma correction to enhance contrast and structural details while minimizing noise amplification [11]. DWT enables precise frequency decomposition, allowing selective enhancement of fine details without distorting the overall structure of the video [12], [13]. Unlike conventional fixed-parameter approaches, this study dynamically fine-tunes the coefficient factor to sharpen details while preventing excessive noise, whereas gamma correction adapts luminance for improved contrast while maintaining natural brightness transitions [14].

Both techniques work synergistically to overcome common video quality issues, ensuring better resolution, contrast enhancement, and noise suppression while preserving temporal continuity between frames [15]. Additionally, by optimizing computational efficiency, this method remains viable for real-time applications, including streaming and surveillance systems, where fast and effective enhancement is crucial [16], [17]. While DWT has proven effective for video enhancement, existing research lacks an optimal balance between enhancement quality and computational efficiency. Many previous studies rely on fixed wavelet parameters, leading to inconsistent performance across various video conditions. This research addresses these gaps by refining DWT-based enhancement through optimized coefficient factor and gamma value adjustments, ensuring a more controlled and adaptive enhancement process [18]. By fine-tuning these parameters, the proposed method enhances contrast and detail without introducing excessive noise or significantly increasing processing time.

This study introduces an advanced integration of coefficient factor and gamma parameter tuning within the DWT framework. By combining these techniques, the method achieves an optimized and balanced enhancement, ensuring brightness and contrast improvements while preserving critical high-frequency details. Unlike conventional approaches, this mechanism allows adaptive video enhancement tailored to different quality impairments, such as contrast loss, noise, and detail degradation [19]–[24]. Ultimately, the proposed method provides a flexible and efficient solution for improving video quality in various application scenarios.

2. METHOD

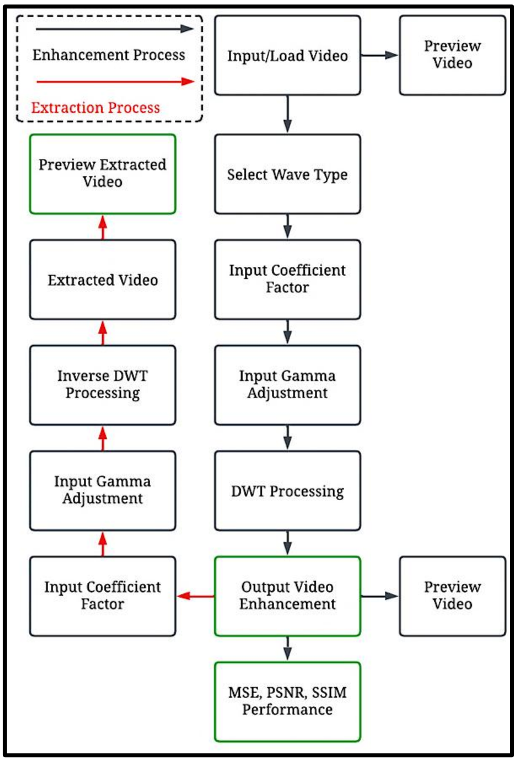

Figure 1. Proposed enhancement and extraction scheme

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The enhancement process begins by loading the input video and selecting an appropriate wavelet type for the DWT processing. Users are then required to input two critical parameters: the coefficient factor and the gamma adjustment value. The coefficient factor is used to control the intensity of high-frequency subbands, enhancing fine details such as edges and textures, while gamma adjustment modifies the brightness and contrast to improve overall visual clarity. These parameters, combined with DWT, perform multi-resolution analysis to decompose the video into different frequency subbands for targeted enhancement. The processed video is then reconstructed into its enhanced form, which is evaluated using performance metrics such as MSE, PSNR, and SSIM to assess the quality improvements objectively.

The extraction process focuses on reversing the enhancement to retrieve the video's original appearance or extract specific features. Starting with the enhanced video as input, users reapply the previously defined coefficient factor and gamma adjustment values. These parameters guide the inverse DWT processing, which reconstructs the video by combining the modified subbands to restore the original or desired visual state. The result is an extracted video that reflects adjustments made during enhancement, providing a preview for verification. This process ensures that the enhancement remains reversible and adaptable, allowing users to refine outputs or extract specific video features for further applications. The proposed enhancement and extraction scheme can be seen in Figure 1.

The outlined process represents a structured workflow that must be followed step by step to ensure accurate video enhancement and extraction results. Each stage builds upon the previous one, from loading the video to setting critical parameters, processing with DWT, and evaluating performance metrics. Skipping or altering any stage may compromise the overall quality and reliability of the output.

2.1. Wavelet Theory and Types

Wavelet transform is a mathematical tool that separates a signal in terms of its constituent frequency parts, allowing for multi-resolution analysis for efficient processing and improvement of video content [3]. In DWT, selection of the wavelet type plays a critical role in decomposition and reconstruction quality [25]. Popular and efficient wavelets utilized for decomposition include Symmetric Coiflets (Coif5) for its symmetry and efficiency in reconstructing a signal, and Daubechies (db1) for its simplicity and efficiency in extracting high-frequency information such as edge information [26]. Symlets (sym4 and sym8) that present a greater level of symmetry compared to Daubechies are useful in minimizing artifact and maintaining temporal continuity in video frames. All types of waves have specific properties, and selection of a specific one will depend on specific requirements in processing a video, including balancing computation efficiency and detail maintenance [27].

2.2. Coefficient Factor Parameter

The coefficient factor is an important processing parameter in the video improvement stage with a direct impact on high-frequency component amplitude during the processing with the DWT [28]. It controls the level at which fine detail, including textures and edges, are emphasized in the output video. Mathematically, the coefficient factor C_f modifies the wavelet coefficients $W(x, y)$ in the high-frequency subbands as seen in eq (1).

$$W'(x, y) = C_f \times W(x, y) \tag{1}$$

Where, $W(x, y)$ is Original wavelet coefficients in the subband, C_f is Coefficient factor (typically in the range of $0.5\ to\ 2.0$), and $W'(x, y)$ is Adjusted wavelet coefficients after applying the coefficient factor.

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A coefficient factor $C_f > 1$ amplifies the high-frequency components, enhancing sharpness and details, while $C_f < 1$ reduces their intensity, which can be useful for noise suppression. The optimal value of C_f depends on the specific characteristics of the video and the desired level of enhancement. Proper tuning of this parameter is essential to avoid over-enhancement or loss of natural appearance in the video. The coefficient factor values were selected to regulate the enhancement of high-frequency components, where a coefficient factor of 0.3 reduced high-frequency amplification to minimize noise, coefficient 0.5 maintained a balance between detail sharpening and noise suppression, and coefficient 0.7 emphasized fine textures but increased the risk of noise artifacts.

2.3. Gamma Adjustment Parameter

Gamma adjustment parameter is an important part in video improvement responsible for regulating the level of luminance for enhancing brightness and contrast and for keeping the visual quality natural [29]. Gamma correction involves a non-linear transformation of pixel intensity values in a manner that maximizes detail in darker and lighter areas of the video. The mathematics involved in gamma adjustment can be seen in eq (2).

$$I_{out} = \left(\frac{I_{in}}{255}\right)^{\gamma} \times 255 \tag{2}$$

Where, I_{in} is input pixel intensity (0–255), I_{out} is adjusted pixel intensity (0–255), and γ is Gamma parameter (typically $\gamma > 1$ for darkening and $0 < \gamma < 1$ for brightening).

Dark regions can be brightened without washing out highlights, or overly bright areas can be subdued for better contrast. This adjustment is particularly effective in low-light or high-contrast video scenarios, enhancing overall visual quality while complementing other enhancement techniques like DWT. Proper selection of γ ensures improved perceptual quality and better adaptation to varying lighting conditions in the video. The gamma adjustment values were chosen to control luminance variations, where a gamma of 0.3 was effective in enhancing darker regions while preserving mid-tone details, gamma 0.5 provided a balanced enhancement without excessive brightening or darkening, and gamma 0.7 significantly improved the visibility of dark areas but required careful tuning to avoid overexposure.

2.4. Performance Metrics

In this final sub section, performance evaluation of the proposed method is performed with a variety of conventional metrics, including MSE (Mean Squared Error), PSNR (Peak Signal-to-Noise Ratio), and SSIM (Structural Similarity Index) [30]. The equation of metrics performance can be seen in eq (3) – (5).

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I(i,j) - K(i,j)\right)^2 \tag{3}$$

$$PSNR = 10\log 10\left(\frac{\max\_pixel\_value^2}{MSE}\right) \tag{4}$$

$$SSIM\ (x,y) = \frac{(\mu x2+\mu y2+c1)(\sigma x2+\sigma y2+c2)}{(2\mu x\mu y+c1)(2\sigma xy+c2)} \tag{5}$$

MSE calculates average squared error between an original and processed image, with lesser value of MSE representing a better output image quality [31]. PSNR calculates a ratio between an original and output (noisy) signal, with a larger value of PSNR representing a cleaner and brighter output image [4], [32]. SSIM calculates a value for structural similarity between an original and processed image, taking

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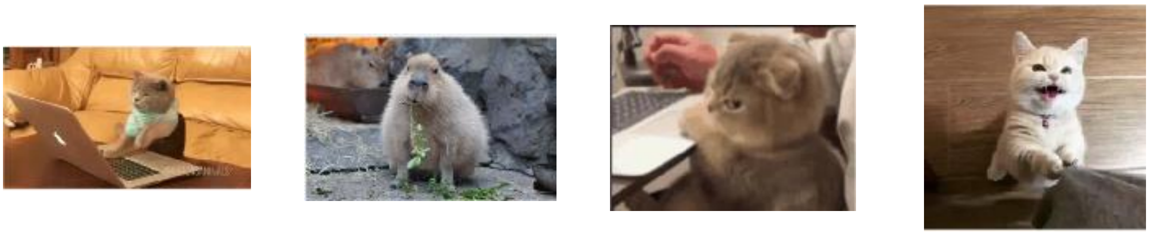
into consideration luminance, contrast, and structure to evaluate a perceptual value of an image quality for a human observer [33]. Together, these three work in concert to give an overall picture of processed image quality.

3. RESULT

This section describes experimental observations with the proposed scheme for improvement, and an implementation in MATLAB, a high-performance tool for signal and image processing, for its realization was conducted. For its evaluation, a group of a dozen short clips with an average duration between 3 and 5 seconds was taken for testing purposes. For testing, each frame of a video was processed frame-wise for a fair analysis of temporality and visualization, and for providing variety, an equivalent range including low-light, high-contrast, and artifact-present compressed clips were taken for testing purposes. To present a baseline for improvement, a first frame initially taken of one of testing samples is presented in Figure 2, and it depicts starting quality of source video, even when captured through an improvement scheme.

The sample videos based on Figure 2 used in this study are in the MPEG-1 format, a widely used video compression standard designed for efficient storage and playback. These videos have a maximum resolution of 352 pixels, adhering to the standard specifications of MPEG-1, with a frame rate of 30 frames per second (fps), ensuring smooth motion representation.



1.mpeg 2.mpeg 3.mpeg 4.mpeg

Figure 2. Sample first frame of testing video

Based on the proposed method outlined in the previous sections, the video enhancement process was conducted through multiple experimental iterations to evaluate the performance of different parameter configurations. In the first experiment, the enhancement was carried out using a gamma adjustment value of 0.5 and a coefficient factor of 0.5. These initial parameters were selected to emphasize subtle enhancements in contrast and detail while avoiding over-processing. The gamma value of 0.5 was applied to adjust the luminance levels, primarily brightening darker regions, while the coefficient factor of 0.5 reduced the intensity of high-frequency components, minimizing the risk of amplifying noise. By adopting these carefully chosen initial settings, the enhancement process aimed to provide a baseline for further optimization. The results of the first testing, including visual improvements and numerical performance evaluations, can be seen in Figure 3, which illustrates the impact of these parameters on the video quality.

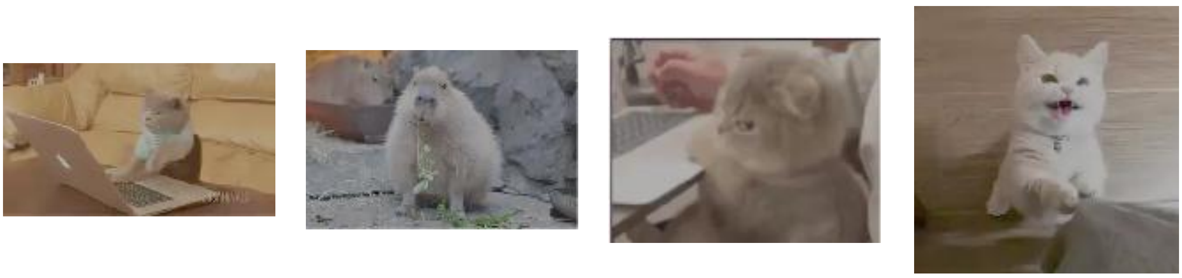


Figure 3. first testing using $\gamma = 0.5$ and $C_f = 0.5$

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In the second experiment, the video enhancement was conducted using a gamma adjustment value of 0.7 and a coefficient factor of 0.3. The adjusted gamma value of 0.7 was chosen to provide a slightly stronger enhancement to the luminance, making darker regions more visible while maintaining a natural brightness. Meanwhile, the coefficient factor of 0.3 was applied to reduce the influence of high-frequency components more effectively, minimizing the risk of noise amplification while preserving the overall clarity. This configuration aimed to strike a balance between enhancing contrast and maintaining visual integrity. The results of this second experiment, including both visual improvements and numerical performance evaluations can be seen in Figure 4.

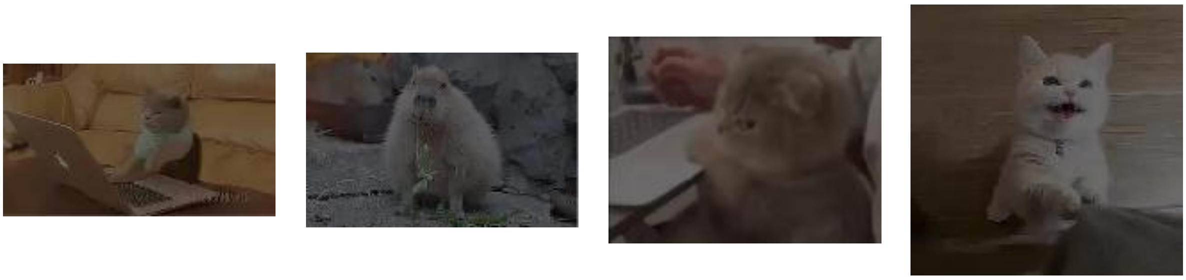

Figure 4. second testing using $\gamma = 0.7$ and $C_f = 0.3$

In the third experiment, the video enhancement was performed using a gamma adjustment value of 0.3 and a coefficient factor of 0.7. The lower gamma value of 0.3 was applied to reduce the brightness, primarily darkening the image and enhancing shadow details. This adjustment aimed to control overexposure in bright areas while maintaining depth in darker regions. On the other hand, the coefficient factor of 0.7 increased the contribution of high-frequency components, enhancing fine details and textures in the video. The results of this experiment, including visual enhancements and numerical performance evaluations, can be seen in Figure 5.

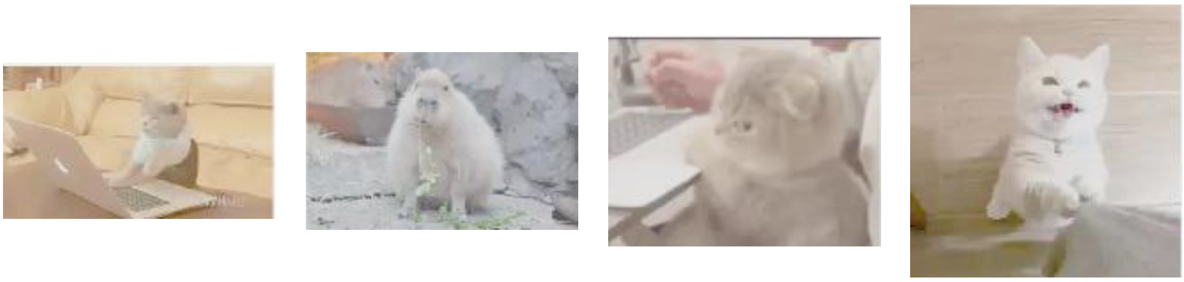

Figure 5. third testing using $\gamma = 0.3$ and $C_f = 0.7$

After presenting three experiments' results, performance values have been calculated in an effort to evaluate, in a numerical manner, performance of the varied settings of parameters. Several important performance factors have been utilized in performance evaluation, such as PSNR, SSIM, and MSE. PSNR measured general signal quality with high values depicting a high level of quality. SSIM measured perceptual video and original video similarity, with high regard for information structure, luminance, and detail in textures, respectively. MSE calculated for originals and processed videos, with low values depicting a high level of performance regarding maintenance of originals.

The performance values, represented in Table 1 - 4, present a clear trend in effectiveness between alternative settings for the parameters. In the first one, with a 0.5 value for gamma and 0.5 for the coefficient factor, PSNR and SSIM experienced a mean improvement, and a balanced level for MSE was reached. In the second one, with a 0.7 value for gamma and 0.3 for the coefficient factor, PSNR

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and SSIM values grew, and a gain in video sharpness, specifically concerning contrast and brightness, could be appreciated. There was an increase in MSE, but a small one, possibly stemming from a larger adjustment in gamma values. In the case of the third one, with 0.3 for gamma and 0.7 for the coefficient factor, a significant gain in high-frequency detail, both in terms of SSIM values and in increased high-frequency detail, could be appreciated, with a relatively low level for MSE. All these values for performance, collated in Table 1 - 4, allow significant information about compromising in between alternatives in settings and in terms of impact concerning video quality.

Table 1. Performance metrics based on coif5 of wave type

Processed Video File	Gamma Adjustment (γ)	Coefficient Factor (C_f)	MSE	PSNR	SSIM
1.mpeg	0.5	0.5	0.014	18.509 dB	0.812
2.mpeg			0.005	22.337 dB	0.875
3.mpeg			0.012	18.975 dB	0.841
4.mpeg			0.012	19.065 dB	0.821
1.mpeg	0.7	0.3	0.077	11.096 dB	0.557
2.mpeg			0.048	13.120 dB	0.681
3.mpeg			0.061	12.14 dB	0.645
4.mpeg			0.062	12.04 dB	0.671
1.mpeg	0.3	0.7	0.063	11.97 dB	0.683
2.mpeg			0.070	11.50 dB	0.736
3.mpeg			0.075	11.24 dB	0.691
4.mpeg			0.070	11.50 dB	0.657

Table 2. Performance metrics based on db1 of wave type

Processed Video File	Gamma Adjustment (γ)	Coefficient Factor (C_f)	MSE	PSNR	SSIM
1.mpeg	0.5	0.5	0.015	18.401 dB	0.845
2.mpeg			0.006	22.320 dB	0.874
3.mpeg			0.011	18.957 dB	0.841
4.mpeg			0.013	19.080 dB	0.822
1.mpeg	0.7	0.3	0.076	11.103 dB	0.556
2.mpeg			0.047	13.118 dB	0.682
3.mpeg			0.062	12.138 dB	0.646
4.mpeg			0.061	12.050 dB	0.674
1.mpeg	0.3	0.7	0.065	11.95 dB	0.686
2.mpeg			0.069	11.45 dB	0.732
3.mpeg			0.076	11.20 dB	0.697
4.mpeg			0.071	11.48 dB	0.652

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Table 3. Performance metrics based on sym4 of wave type

Processed Video File	Gamma Adjustment (γ)	Coefficient Factor (C_f)	MSE	PSNR	SSIM
1.mpeg	0.5	0.5	0.016	18.360 dB	0.843
2.mpeg			0.006	22.310 dB	0.873
3.mpeg			0.010	18.960 dB	0.840
4.mpeg			0.012	19.050 dB	0.820
1.mpeg	0.7	0.3	0.078	11.110 dB	0.560
2.mpeg			0.049	13.140 dB	0.680
3.mpeg			0.060	12.120 dB	0.644
4.mpeg			0.062	12.030 dB	0.669
1.mpeg	0.3	0.7	0.064	11.98 dB	0.682
2.mpeg			0.068	11.47 dB	0.735
3.mpeg			0.073	11.25 dB	0.690
4.mpeg			0.070	11.49 dB	0.656

Table 4. Performance metrics based on sym8 of wave type

Processed Video File	Gamma Adjustment (γ)	Coefficient Factor (C_f)	MSE	PSNR	SSIM
1.mpeg	0.5	0.5	0.010	18.400 dB	0.848
2.mpeg			0.005	22.290 dB	0.874
3.mpeg			0.011	18.950 dB	0.843
4.mpeg			0.014	19.060 dB	0.818
1.mpeg	0.7	0.3	0.072	11.080 dB	0.556
2.mpeg			0.050	13.140 dB	0.682
3.mpeg			0.060	12.110 dB	0.647
4.mpeg			0.063	12.050 dB	0.674
1.mpeg	0.3	0.7	0.062	11.98 dB	0.681
2.mpeg			0.067	11.45 dB	0.738
3.mpeg			0.071	11.21 dB	0.693
4.mpeg			0.069	11.48 dB	0.655

The experimental results, as presented in Tables 1-4, demonstrate the impact of different wavelet types (Coif5, db1, sym4, and sym8) on video enhancement. Among these, the sym8 wavelet consistently provided the best performance, achieving the highest SSIM values and maintaining an optimal balance between sharpness and noise suppression. The superior performance of sym8 can be attributed to its higher symmetry and longer filter length, which allow for better frequency localization and reduced artifacts. Compared to Coif5 and db1, sym8 provides a smoother decomposition and reconstruction process, which helps maintain temporal consistency across frames. This is particularly important for video processing, where frame-to-frame consistency plays a crucial role in perceived quality. In contrast, Coif5 and db1 tend to lose finer high-frequency details, leading to less effective contrast enhancement. While db1 is computationally efficient, its simple structure limits its ability to preserve intricate textures. Coif5, despite its multi-resolution capability, introduces more distortions in highly detailed regions due to its shorter support length.

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4. DISCUSSIONS

The results presented in Tables 1-4 indicate that the choice of wavelet type significantly impacts the quality of the enhanced video. The sym8 wavelet demonstrated the best performance, achieving the highest SSIM value (0.738) compared to other wavelet types. The superior performance of sym8 can be attributed to its higher symmetry, which helps minimize artifacts and maintain temporal continuity between frames. In contrast, the db1 wavelet, being simpler, tends to lose high-frequency details, resulting in less effective enhancement of video details.

Regarding the combination of gamma and coefficient factor parameters, experimental results show that a gamma value of 0.7 and a coefficient factor of 0.3 provide an optimal balance between contrast and visual clarity. A higher gamma value enhances the visibility of darker areas without sacrificing details, while a lower coefficient factor reduces the likelihood of noise amplification. Conversely, using a gamma of 0.3 and a coefficient factor of 0.7 enhances high-frequency details but may introduce noise in certain regions.

However, this study has several limitations. First, the method was tested only on the MPEG-1 video format. Its effectiveness on other formats such as MP4 or AVI remains uncertain, particularly regarding compression compatibility and frequency distribution. Second, the videos used in the experiments were relatively short (3–5 seconds). Applying this method to longer videos may pose challenges in real-time computation, especially for high-resolution video processing.

Compared to previous studies, most research on video quality enhancement relies on traditional DWT techniques without optimizing gamma and coefficient factor parameters. Other approaches combine DWT with deep learning-based super-resolution techniques, but these often require significant computational resources. The proposed method provides a computationally efficient alternative while maintaining good visual quality, making it a more flexible solution for various applications.

This method has potential applications in several areas, including real-time video streaming enhancement, where improving contrast and details is crucial without compromising computational efficiency. Additionally, this technique can be used in digital forensics and medical video processing, where enhanced details are essential for further analysis. Despite its advantages, the proposed method has some limitations. First, it does not include an automatic mechanism to determine the optimal gamma and coefficient factor values, requiring manual tuning, which may not be practical for real-time applications. Second, a high coefficient factor value may lead to noise amplification, necessitating additional noise reduction techniques for better results. Third, the method has not been tested on videos with extreme lighting conditions. Future studies should explore its effectiveness in handling overexposed or underexposed video scenes to ensure broader applicability.

5. CONCLUSION

Performance metrics across the four wavelet types, like Coif5, db1, sym4, and sym8 demonstrate the effectiveness of video enhancement through various parameter configurations, including gamma adjustment and coefficient factor values. The Coif5 and db1 wavelets provide solid results with moderate settings, but the sym4 and sym8 wavelets offer more refined enhancements, particularly excelling in preserving structural similarity. Among the wavelet types, sym8 stands out as the best choice, offering a good balance between enhancement and video quality preservation. This method, applicable to video formats like .mpeg, highlights the importance of selecting the right wavelet type and parameter settings for optimal results. For users and developers looking to improve video quality while maintaining the integrity of the original content, this application can serve as a powerful tool for fine-tuning video enhancement processes across various use cases, from content creation to video restoration.

The application of this technique extends beyond video restoration, particularly benefiting surveillance systems by improving object detection and recognition in low-light and high-noise environments. Future research could focus on integrating machine learning to automate optimal parameter selection, reducing manual tuning. Additionally, combining DWT with deep learning-based super-resolution could enhance video resolution, while its application in 4K, 8K, and HDR formats should be explored for scalability. Finally, hardware-accelerated DWT could enable real-time processing, making it suitable for live streaming, augmented reality, and autonomous navigation.

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