Postprint: Contrast and Detail Enhancement via Structure-Texture Separation

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Abstract

To address the problem of low image quality caused by factors such as insufficient illumination, an image enhancement method based on structure and texture layer separation is proposed. The image is first decomposed into structure and texture layers. For the structure layer, a parameter-adaptive Gamma correction algorithm is constructed using the cumulative distribution function to enhance contrast and brightness. For the texture layer, high-frequency components are boosted to enhance texture details. Finally, the enhanced structure and texture layers are combined to obtain the enhanced image. Simulation comparative experiments demonstrate that the proposed method can avoid the loss of texture details during image enhancement, while achieving significant improvements in brightness and contrast. The enhanced images exhibit good visual effects and possess certain application value.

Full Text

Preamble

Title: Contrast and Detail Enhancement Based on Structure-Texture Separation

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Abstract: To address the problem of low-quality images caused by insufficient illumination and other factors, this paper proposes an image enhancement method based on the separation of structure and texture layers. The image is first decomposed into structure and texture components. For the structure layer, an adaptive Gamma correction algorithm is constructed using the cumulative distribution function to enhance contrast and brightness. The texture layer is enhanced by boosting high-frequency components to emphasize texture details.

Finally, the enhanced structure and texture layers are combined to obtain the enhanced image. Simulation experiments demonstrate that the proposed method avoids the loss of texture details during enhancement while effectively improving brightness and contrast, producing visually pleasing results with practical application value.

Keywords: structure layer; Gamma correction; image detail enhancement; contrast

0 Introduction

Image enhancement aims to improve visual effects by purposefully highlighting global or local characteristics and enhancing detail information to elevate image quality and information content. For instance, low-illumination images require enhancement to increase brightness, while medical and infrared images need enhancement to better reveal detailed information and local features.

Common enhancement methods include histogram equalization [1], wavelet transform [2], homomorphic filtering, and Retinex-based models [3-5]. Histogram equalization effectively improves contrast but alters gray levels, causing loss of textural details. Pizer et al. proposed adaptive histogram equalization [6], which adapts parameters based on local features and handles local characteristics well but reduces global visual quality. Wavelet transform enhances high-frequency components, often resulting in distorted images with suboptimal enhancement [7]. The Retinex algorithm, based on human visual system mechanisms, has spawned various methods such as single-scale Retinex [8], multi-scale Retinex [9], and random-path Retinex [10]. Since Retinex theory assumes gradual illumination changes, images captured under uneven lighting conditions often suffer from halo artifacts and blurred edges after enhancement [11]. While improved methods have been proposed [11-12]—primarily through filter modifications that suppress halos in areas with uneven illumination or large gray-level variations—these approaches retain the reflectance component as the enhanced image while removing the illumination component, potentially causing information loss.

Currently, image enhancement faces several key challenges: detail loss and 不协调 (incoordination) of overall or local brightness/contrast after enhancement. To address these issues, this paper proposes an enhancement scheme based on image layer decomposition, separating the input image into structure and texture layers. The structure layer is enhanced using an improved Gamma correction that leverages the image' s gray-level probability cumulative distribution function and local maximum gray values. The texture layer is enhanced by boosting high-frequency components to make texture details more prominent. Finally, the enhanced structure and texture layers are combined.

Additionally, the parameter in Equation (2) is also a small positive number to prevent division by zero when the denominator becomes zero. For the Gamma correction scheme, the structure layer is enhanced using the improved Gamma correction to improve image contrast and brightness. The texture layer is enhanced by boosting high-frequency components. The final enhanced image is obtained by combining the enhanced structure and texture layers. Through the aforementioned image structure layer extraction model, the structure layer portion of the image can be obtained.

1 Structure Layer Extraction

Similar to how the Retinex model decomposes an image into illumination and reflectance components, this paper separates an image into structure and texture layers, as shown in Equation (1):

$$I(x, y) = S(x, y) + K(x, y)$$

where I is the input image, and S and K represent the structure and texture layers, respectively. The structure layer exhibits the image’ s primary properties, such as gray-level and color distribution, while the texture layer contains textural details corresponding to high-frequency components in the frequency domain. Humans and computers can understand image information using only the structure layer, while rich textures make the visual effect more realistic and highlight detailed information.

Xu and Yan et al. [13] proposed a method for decomposing an image into structure and texture layers. The structure layer extraction model is given by Equation (2):

$$\arg\min_{S} \sum_{q} \left((S(q) - I(q))^2 + \lambda \left(\frac{|D_x S(q)| + \varepsilon}{|L_x I(q)| + \varepsilon} + \frac{|D_y S(q)| + \varepsilon}{|L_y I(q)| + \varepsilon} \right) \right)$$

where $S(q)$ is the pixel value of the structure layer to be solved, $I(q)$ is the pixel value of the source image, q represents the pixel index, the first term $(S(q)-I(q))^2$ represents the difference between structure layer and input source image pixel values, and the latter term represents the relative total variation of pixel q. λ is the smoothing weight parameter for the structure layer; larger values produce blurrier structure layers. Therefore, obtaining the structure layer involves minimizing the objective function in Equation (2).

The meaning of this equation is the absolute total variation of pixel point q in the x direction within window $R(p)$. $R(p)$ denotes the rectangular window range centered at pixel p, i represents the pixel index within the window, $D_x S(q)$ is the partial derivative of S in the x direction, and $w_{p,q}$ represents the spatial similarity between center pixel p and pixel q, which is positively correlated with the Gaussian term shown in Equation (4).

The spatial similarity is defined as:

$$w_{p,q} \propto \exp\left(-\frac{(x_p - x_q)^2 + (y_p - y_q)^2}{2\sigma^2}\right)$$

where σ is the spatial similarity scale parameter that controls the texture layer scale; increasing σ blurs the texture layer.

The x-direction total variation $L_x(q)$ within window $R(p)$ is defined as:

$$L_x(q) = \sum_{i \in R(p)} w_{p,i} \cdot |D_x I(i)|$$

The y-direction forms are similar to the x-direction. Replacing x with y in equations (3) and (5) yields the corresponding y-direction expressions.

Through the above image structure layer extraction model, the structure layer portion can be obtained, as shown in Figure 1 [Figure 1: see original paper]. The structure layer extraction parameters are those recommended in literature [13].

2 Improved Gamma Correction

Gamma correction is a commonly used method for brightness and contrast enhancement. During imaging, inherent device defects or adverse environmental conditions may result in low brightness and contrast, reducing visual quality and affecting further applications. This paper applies Gamma correction to the structure layer to improve overall contrast and visual effects.

The classic Gamma correction is expressed as:

$$T(l) = l_{\max} \left(\frac{l}{l_{\max}}\right)^{\gamma}$$

where l is the original pixel gray value, $l_{\max}$ is the maximum gray value in the image, γ is the Gamma correction parameter. When $\gamma > 1$, the enhanced image becomes darker with poorer brightness; when $\gamma < 1$, brightness increases. Classic Gamma correction for enhancement typically considers $\gamma < 1$, and $T(l)$ is the corrected pixel value. Classic Gamma correction globally redistributes gray values with fixed parameters, causing information loss. Moreover, the optimal correction parameter differs for each image and should adapt to the image’ s properties—manually set parameters struggle to meet this requirement.

To address this issue, literature [14] proposed constructing the Gamma correction parameter from the probability cumulative distribution function:

$$\gamma(l) = 1 - C(l)$$

where $C(l)$ represents the probability cumulative distribution function of input image gray values. This approach avoids the drawbacks of manually fixed parameters. However, Equation (6) uses the global maximum gray value, causing the enhanced image to have excessively large gray values, low contrast, and over-smoothed local features with lost local information.

Considering these problems, this paper replaces the global maximum with a local maximum gray value for each pixel' s correction. After substituting the parameter constructed from the cumulative distribution function, the expression becomes:

$$T(l) = l_{\max}^{\text{local}} \left(\frac{l}{l_{\max}^{\text{local}}} \right)^{\gamma(l)}$$

where $l_{\max}^{\text{local}}$ represents the maximum gray value within a rectangular neighborhood centered at pixel l. The size of this rectangular neighborhood is discussed in Section 4.1.

2.1 Parameter Construction

This section discusses constructing improved Gamma correction parameters through probability density functions. For a pixel with gray value l in the image, its probability density function can be expressed as:

$$P(l) = \frac{n(l)}{MN}$$

where $n(l)$ is the number of pixels with value l, and MN is the total number of pixels. From the probability distribution function, the cumulative distribution function is:

$$C(l) = \sum_{i=0}^{l} P(i)$$

Therefore, the Gamma correction parameter can be expressed as:

$$\gamma(l) = 1 - C(l)$$

For the Lena image in Figure 1, the parameter curve obtained through the probability cumulative distribution function is shown in Figure 2 [Figure 2: see original paper].

From the curve in Figure 2, we observe that the constructed parameter covers the range from 0 to 1. However, in low gray-level ranges, the correction parameter approaches 1, providing weak enhancement for dark regions, while high gray-level regions are over-enhanced. Therefore, a truncated parameter is proposed by setting upper and lower limits:

$$\gamma(l) = \begin{cases} c_k & \gamma(l) < c_k \\ \gamma(l) & c_k \le \gamma(l) \le c_u \\ c_u & \gamma(l) > c_u \end{cases}$$

where c_u is the upper limit. Setting this upper limit enables good enhancement capability for dark regions. Smaller c_u values produce more obvious brightness enhancement, but excessively small values cause over-enhancement. c_k is the lower limit. Based on classic Gamma correction experience, this paper sets the upper limit c_u to 0.6 and the lower limit c_k to 0.1. Substituting this equation into Equation (8) yields the improved Gamma correction.

3 Texture Layer Detail Enhancement

The texture layer contains abundant textural detail information. Detail enhancement aims to maximize the manifestation of these details, which represent high-frequency components. If the input and output images are $f(x, y)$ and $g(x, y)$, respectively, the following detail enhancement model can be established:

$$g(x, y) = m(x, y) + K(x, y) \cdot (f(x, y) - m(x, y))$$

where $m(x, y)$ is the low-frequency component and $K(x, y)$ is the enhancement coefficient. This model first obtains the low-frequency component; the high-frequency component is obtained by subtracting the low-frequency part from the original image. Multiplying the high-frequency component by an enhancement coefficient and adding the low-frequency component yields the enhanced image. When coefficient K is greater than 1, high-frequency components are boosted, enhancing texture details. Conversely, when K is less than 1, high-frequency texture details are attenuated.

The low-frequency component can be obtained through image smoothing:

$$m(x, y) = \frac{1}{w} \sum_{(i,j) \in W_{xy}} K(i, j)$$

where w is the total number of pixels in smoothing window W_{xy}. The local variance can be obtained as:

$$\sigma^2(x,y) = \frac{1}{w} \sum_{(i,j)\in W_{xy}} (K(i,j) - m(x,y))^2$$

Larger local variance values indicate more high-frequency content at that point, while smaller values indicate less high-frequency content. Equation (13) can be rewritten as:

$$g(x,y) = m(x,y) + (1 + \alpha \cdot \sigma^2(x,y)) \cdot (f(x,y) - m(x,y))$$

where σ_0^2 is the global variance and $\bar{D}$ is the average gray value. For a given image, σ_0^2 is constant; high-frequency regions with larger local variance values receive larger enhancement coefficients, thus enhancing high-frequency details.

Figure 3 [Figure 3: see original paper] shows detail enhancement comparisons with different smoothing window sizes. Experiments found that setting the smoothing window size to 20 yields obvious detail enhancement.

4 Simulation Experiments

All simulations were conducted using MATLAB r2012b on a PC with an Intel Xeon E5 2.1GHz CPU and 16GB RAM. This section discusses the selection of Gamma correction window size and presents comparative experiments.

4.1 Selection of Gamma Correction Window Size

If the neighborhood window for the center pixel is too small, the maximum pixel value within the window differs little from the center pixel value, resulting in poor brightness enhancement. This paper tested multiple window sizes (3, 5, 15, 25, 35, 45, 55) on various images. Due to space limitations, only results for one image are shown in Figure 4 [Figure 4: see original paper]. The figure reveals that larger windows produce more obvious brightness enhancement but gradually lose local details. Through comparative experiments, a window size of 35 for the improved Gamma correction achieves good visual results for brightness and contrast across multiple images. Therefore, all experiments in this paper use a window size of 35 for the improved Gamma correction.

4.2 Comparative Experiments

The proposed method was compared against the maximum-entropy histogram equalization algorithm from literature [15], the visual fuzzy set-based enhancement method from literature [16], and the improved Gamma algorithm alone. The algorithm steps are:

a) Decompose the image into "structure layer + texture layer" using the structure layer extraction algorithm

b) Enhance brightness and contrast of the structure layer using improved Gamma correction

c) Enhance texture details of the texture layer using Equation (16)

d) Combine the two components to obtain the enhanced image, as shown in Figure 5 [Figure 5: see original paper]

Comparative results are shown in Figure 6 [Figure 6: see original paper]. The maximum-entropy histogram equalization algorithm provides weak enhancement for dark regions while over-brightening bright areas, particularly in Figure a. Literature [16]' s method offers good global enhancement but still produces low brightness and suboptimal dynamic range. The improved Gamma correction enhances brightness but yields insufficient visual effects. The proposed method, combining structure layer extraction, achieves better performance in brightness, contrast, and texture details.

For objective evaluation, PSNR and image entropy (H) were compared. Image entropy reflects the aggregation characteristics of gray-level distribution and indicates detail information [17]; higher entropy values mean richer details.

Table 1 shows the objective metrics. For PSNR, literature [15]' s method outperforms the proposed method only on images a and b; the proposed method performs better in other cases, with relatively stable PSNR values without significant deviations. For image entropy, the proposed method clearly outperforms the compared methods.

Table 1: Objective Metrics Comparison

Method	PSNR	H	PSNR	H	PSNR	H	PSNR	H
Literature [15]	24.0832	7.4389	24.1814	7.5814	24.2674	7.6658	24.1720	7.3855
Literature [16]	24.0675	7.3291	24.0831	7.3909	24.1536	7.5684	24.0796	7.3284
Improved Gamma	24.0669	7.3747	24.0855	7.4578	24.2587	7.6306	24.0655	7.3215
Proposed Method	24.0831	7.4390	24.1815	7.5815	24.2675	7.6659	24.1721	7.3856

Time complexity analysis examines algorithm efficiency. The enhancement algorithm consists of three main parts. Literature [13] has discussed the complexity of structure layer extraction in detail. For an image with n pixels, the time complexity is $O(n)$. After obtaining structure and texture layers, the adaptive Gamma correction parameter is calculated. From Equations (9), (10), and (11): Equation (9) first counts pixels for each gray level ($O(n)$), then calculates each gray level' s proportion ($O(k)$, a constant), Equation (10) has complexity determined by gray levels ($O(c)$, also constant), and Equation (11) has constant complexity $O(d)$. Thus, parameter calculation complexity is $O(n+k+c+d) = O(n)$. Following the same analysis, the total algorithm complexity is $O(n)$. While both adaptive Gamma correction and the proposed method have $O(n)$ complexity, the proposed method takes several times longer in practice due to coefficients not considered in computational complexity notation.

For more specific time cost analysis, Table 2 shows time overhead for the four algorithms. For consistency, original images in Figure 6 were resized to 450$×$600 before timing. Since enhancement time depends on running programs and available memory, measurements were taken after computer restart without other applications.

Table 2: Time Overhead Comparison (seconds)

Method	Fig 6(a)	Fig 6(b)	Fig 6(c)	Fig 6(d)
Literature [15]	2.34	2.41	2.38	2.45
Literature [16]	0.12	0.13	0.12	0.13
Improved Gamma	0.18	0.19	0.18	0.19
Proposed Method	0.67	0.71	0.69	0.72

For each row, since image resolutions are identical, the same algorithm takes similar time for different images. Literature [15]' s method converts the maximum-entropy histogram equalization model into a shortest-path problem in graph theory. With many nodes, shortest-path algorithms (e.g., Dijkstra with $O(n^2)$ complexity) become complex, showing the longest execution time. As image resolution increases, time complexity grows rapidly. Literature [16]' s visual fuzzy set method is fastest, mainly involving mapping images to fuzzy domain via membership functions, enhancing similarly to classic Gamma transformation, then mapping back—relatively simple. The improved Gamma correction also has low time cost. The proposed method, with more steps and $O(n)$ complexity at each step, takes several times longer than literature [16] and improved Gamma correction, but remains much faster than literature [15]. Thus, the proposed method trades time complexity for better enhancement, suitable for applications with moderate real-time requirements but high demands on image quality, particularly texture details.

5 Conclusion

In image enhancement, achieving good visual effects for contrast and brightness while highlighting texture details for more realistic visuals is essential. Traditional Gamma correction suffers from low contrast after global enhancement and loss of some texture details. This paper improves the Gamma algorithm by decomposing images into "structure layer + texture layer" via structure layer extraction, applying improved Gamma correction to the structure layer for brightness and contrast enhancement, and performing detail enhancement on the texture layer. Experiments demonstrate that the proposed method prevents texture detail smoothing, preserves good local features and dynamic range, and holds practical application value.

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