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Research Article

Color Enhancement Algorithm for Visual Communication Posters Based on Homomorphic Filtering

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In order to increase the image quality of visual communication posters and to solve the problems of uneven pixel distribution, distortion, and poor visual effect caused by the lighting environment, an image filtering method, with features based on wavelet and block homomorphic, is proposed on the basis of homomorphic filtering. According to the component change defect of red, green, and blue (RGB) color space, the image color space that needs to be processed is converted into HSV form and then processed in blocks. At that moment, the wavelet transform method is applied to replace the traditional Fourier transform in the block homomorphic filtering to decompose the luminance component. Furthermore, subimages that are decomposed by the wavelet are divided into blocks and then subjected to high-pass filtering so as to obtain a clear image. The investigational outcomes express that the proposed algorithm has an obvious enhancement effect on the visual communication poster image under the variable illumination situation. Furthermore, the suggested technique effectively rectifies the overall brightness of the image and significantly advances the detail contrast of the visual communication poster image. The signal-to-noise (SNR) ratio of our algorithm at different bit rates is higher than that of the LICE and CIE methods. Similarly, the enhancement impact demonstrates that the image statistical parameters of our algorithm are substantially better than those of the LICIE and CIE methods.

1. Introduction

It is possible for natural environmental variables or human causes to cause a lack of illumination, poor visual effects, and low image quality during the process of capturing photos [1–3]. This can happen for a number of reasons one of the challenges that we face. The resolution of the aforementioned issues not only has significant theoretical significance but it also has significant application prospects in practical applications such as aerial images, images obtained through remote sensing, and dark cloud images obtained through video surveillance. Those are just a few examples. Image enhancement technology that makes judicious use of homomorphic filtering [4–6] can fundamentally solve the quality problem of the image, make the visual impression of the image clearer, and better reflect the intricacies of the image.

In recent years, a great number of picture enhancement methods based on a variety of digital image processing applications through various techniques have been created [7–11]. The spatial domain or, more specifically, the spatial frequency domain is the viable option for their development. The enhanced photos offer information that can be helpful and useful for postprocessing, particularly in the segmentation phase of the process. Numerous academics have contributed to a wide range of review documents on various image normalization and segmentation approaches, and those articles have been published in the relevant academic literature. In recent years, a number of researchers have presented a strategy to reduce uneven illumination based on filtering. One of these methods is known as homomorphic filtering. Homomorphic filtering's primary purpose is to level off uneven illumination, reduce dynamic range, and boost contrast. In doing so, it boosts high frequencies and reduces low frequencies by isolating components that reflect light. The wavelet transform is a method of time-frequency analysis that was created on the basis of the short-time Fourier transform [12–14]. Decomposing images with fluctuating illumination into low-frequency images and high-frequency detail subimages is accomplished with the help of the wavelet transform. Image feature improvement is applied to the subimage through processing, which, if done correctly, can meritoriously increase the image quality, and in particular, the quality of variable illumination images can be significantly improved.

This study provides a new method that can not only correct the color of the image; nevertheless, it enhances the edge and other characteristics and details of the images by combining homomorphic filtering and wavelet transform. Its goal is to address the poster artifact and the blurred edge of features. After the single-scale Retinex algorithm grounded on the concept of bilateral filtering has been used to estimate the reflection component of the image, the color of the R channel has been corrected, and then, in order to obtain the corrected image, the color correction of the G channel and the B channel has been obtained according to the ratio of the color attenuation coefficient. In order to increase the visibility and quality of the image that has been corrected, the homomorphic filtering approach along with a Butterworth notch filter is used. In fact, this filter enhances the details and edges of the high-frequency lines in a particular image while suppressing the low-frequency portion of the image. Furthermore, the Laplacian pyramid method is then used to fuse the two images together: images that have had their colors restored and that have been boosted. The key contributions of the research presented in this paper include the following:

(1) An image feature based on wavelet and block homomorphic filtering is proposed on the basis of homomorphic filtering;

(2) The wavelet transform is used to replace the traditional Fourier transform in the block homomorphic filtering to decompose the luminance component;

(3) The homomorphic filtering approach along with a Butterworth notch filter is used to enhance the edges of the high-frequency lines in a particular image while suppressing the low-frequency portion of the image; and

(4) The subimages decomposed by the wavelet are divided into blocks and then subjected to high-pass filtering so as to obtain a clear image.

The leftover part of the manuscript is structured in the following way. Related work and state-of-the-art image segmentation approaches are elaborated in Section 2. The research methodology and design is offered in Section 3. Moreover, filter theory and the proposed model along with the algorithm are also illustrated. Experimental results are obtained through simulations in Section 4. Section 5 summarizes the paper and put forward some interesting directions and planning for our future research.

2. Related Work

When applied to a particular image, the homomorphic filtering can significantly improve the contrast through amending the vividness of the image while instantaneously normalizing it. The method is simple to use and has the potential to generate satisfactory results, in particular when applied to an image that has lighting problems due to its initial capture. The discrete Fourier transform (DFT), logarithmic transform, exponential transform, and inverse discrete Fourier transform (IDFT) are all examples of homomorphic filtering methods. Note that $H(u, v)$ specifies the filtering category. In recent years, an expanding body of research literature has studied a variety of approaches that make use of homomorphic filtering in order to deal with lighting effects. The enhancement of an image's characteristics can be greatly improved, according to the findings of a number of researchers, by employing homomorphic filters that are based on morphology in conjunction with differential evolution algorithms. The method consists of first dividing the image into sub-band elements and then processing each sub-band independently in order to locate the elements with the optimal gain and structure. In the end, each sub-band is blended to produce an image that has been rectified.

Utilizing wavelet transforms for the purpose of picture segmentation has been proposed by a variety of writers [15–20] as the basis for novel strategies for wavelet-based image segmentation. Some researchers at Oleg Air have suggested a homomorphic method, which operates under the presumption that the noise in the log-transformed domain has the same characteristics as white Gaussian noise. A wavelet lifting of hole elimination strategy has been proposed by several academics. Wavelet transform and cross-validation thresholding are two of the strategies utilized by the methodology. Various researchers contributed a homomorphic approach to the investigation of denoising that was accomplished by employing a Bayesian estimator for this particular image. Denoising was accomplished by employing a Bayesian estimator for this particular image. The Gaussian distribution is utilized by some academics for the purpose of signal coefficient modeling, and they advocate for compression and the elimination of speckle noise. For the purpose of approximating the behavior of Gaussian white noise speckle noise, a number of researchers have recommended the use of an adaptive preprocessing filter. A method for removing speckles has been proposed by other researchers. This method employs the M-band wavelet transform and the Wiener filter, and it employs an adaptive threshold method that is based on weighted variance in order to diminish speckle noise. In current ages, researchers have carried out a wide variety of additional investigations on photographs.

Smoothing filtering and sharpening filtering are two distinct types of spatial filtering. The smoothing filtering comprises the mean filtering [21], median filtering [22], and Gaussian filtering [23]. Sharpening filtering is the opposite of smoothing filtering. The Sobel operator, the Roberts operator, and the Prewitt operator filter are all included in the sharpening filter. The goal of smoothing filtering, which in fact is a kind of low-frequency enhancement spatial domain filtering technology that is essentially a low-pass filtering method, is to either blur the image or minimize noise. Smoothing filtering is essentially a low-pass filtering approach. The sharpening filter's primary function is to bring attention to the portion of the grayscale gradient that corresponds to the missing contour, improve the clarity of the image by bringing out the image's edges and that portion of the grayscale gradient, and compensate for the absence of the contour. The sharpening filter is distinct from the smoothing filter in that it employs the differential of the neighborhood as an operator. This increases the degree to which the pixels in the neighborhood differ from one another, hence drawing attention to any rapid changes in the image. Both of these have opposing impacts, which helps them complement one another. It is possible to achieve the effect of the sharpening filter by subtracting the result of the smoothing filter from the original image, and similarly, it is possible to achieve the effect of the smoothing filter by subtracting the result of the sharpening filter from the original image. At this point in time, there is a significant body of research literature that is connected to both smoothing filtering and sharpening filtering.

Some researchers begin by removing edge masks with the help of the Sobel operator and then move on to smoothing filtering in order to isolate details. When used together, these two techniques can provide photos with improved edge detail augmentation. There is, however, a phenomenon in which the edge information of the image is brightened to an extreme degree. Some researchers have proposed an adaptive unsharp mask depth image enhancement algorithm as a solution to the blurring of details that occurs during the smoothing process. This algorithm only extracts the high-frequency share of a particular image without any noise and overcomes the inability of the traditional unsharp mask algorithm to amplify the high frequency. The disadvantages of noise are as follows. However, in the process of fixing significant flaws, this method takes a lot of time, and the size of the filtering window does not satisfy the real-time requirements. Some researchers have proposed remote sensing image enhancement algorithms that are based on filtering and sharpening, and others have established image sharpening and enhancement operators that are based on Sobel and Laplacian in order to enhance image contrast. These solutions were developed in order to address the issue of low image brightness and contrast. However, the fact that some information can be readily lost in the two sharpening processes is not taken into consideration, which may result in the final enhanced image having insufficient information.

Homomorphic filtering [4–6], sometimes known as the HF algorithm due to its shorter form, is a specific technique for increasing the contrast of an image and compressing the brightness range of an image in the frequency domain. It does this by decreasing the low frequencies and increasing the high frequencies, which in turn decreases the changes in lighting and increases the edge detail. Homomorphic filtering can be recognized by the fact that it reduces the range of grayscale values while simultaneously raising the contrast. An underwater picture enhancement method that was offered by certain researchers and is based on the color line model and homomorphic filtering was developed with the goal of providing a more effective solution to the issues of low contrast and color deviation. This method is superior to the methods that are considered to be state of the art at the moment in four different respects: quantitative analysis, qualitative analysis, color accuracy analysis, and the restoration of synthetic underwater images [24]. However, this results in a significant rise in the amount of computing complexity. If you cannot satisfy its requirements, you should consider using parallel computing [25].

An adaptive weighted repeated value filtering technique is something that a few researchers have offered as a solution to the issues of low contrast and salt-and-pepper noise that are present in magnetic resonance MR images. MR images have been enhanced. Nevertheless, the effectiveness of this method is not particularly high, and the configurations of the homomorphic filtering parameters require additional testing and tweaking [26, 27]. An image color enhancement method has been offered by several researchers as a solution to the problem of photographs with low illumination. This method aims to improve the image's brightness as well as its overall quality. The local spatial homomorphic filter is used to improve the brightness while the gradient domain variance is used to suppress the noise and lastly to produce the effect of enhancing the image. In fact, both of these filters are applied simultaneously. However, the issues of contrast and information loss are not taken into consideration, which may result in the visual effect of the image being ambiguous [28, 29].

3. Research Design

3.1. The Filter Theory

3.1.1. Wavelet Transform. A low-frequency fairly accurate subimage and three other high-frequency detail subimages are generated for each layer of the decomposition of the digital picture by the fast decomposition algorithm of the Mallat wavelet. These results are obtained from the digital image. Let's say the initial image is $f(x, y)$. Then, the Mallat wavelet transform will be used to break it down into its component parts.

$$f(x, y) = \sum_{k,l} C_{J+1,k,l}\varphi_{J+1,k,l} + \sum_{k,l} V_{J,k,l}\Psi^{1}_{J,k,l} + \sum_{k,l} H_{J,k,l}\Psi^{2}_{J,k,l} + \sum_{k,l} D_{J,k,l}\Psi^{3}_{J,k,l}. \tag{1}$$

The low-frequency approximation subimage is the first item on the right side of the above equation (1), and the vertical high-frequency detail subimage is the second item. Similarly, the horizontal high-frequency detail subimage is the third item, and the diagonal high-frequency detail subimage is the fourth item. Note that C characterizes the low-frequency approximation coefficient of the image. This should be noted that high-frequency detail coefficients are denoted by the letters V, H, and D. Furthermore, J is the number of different layers of breakdown. The rows and columns of the approximation component coefficient matrix $C_{J+1,k,l}$ are denoted by the notations k and $l \in z$, respectively. The rows and columns are denoted by the notation m and n $\in$ z, respectively. Furthermore, the standard orthogonal scaling function $\varphi(x, y)$ and the wavelet function $\psi(x, y)$ are examples of functions that have dimensions of size equal to x and y, respectively.

The following, in equation (2), is an examination of the multiresolution data consisting of the approximate low-frequency components $C_{J,k,l}$ and the detailed high-frequency components $V_{J+1,k,l}$, $H_{J+1,k,l}$, and $D_{J+1,k,l}$.

$$\begin{cases} C_{J+1,k,l} = \sum_{m,n} h_{2m-k} h_{2n-l} C_{J,m,n} \\ V_{J+1,k,l} = \sum_{m,n} h_{2m-k} g_{2n-l} C_{J,m,n} \\ H_{J+1,k,l} = \sum_{m,n} g_{2m-k} h_{2n-l} C_{J,m,n} \\ D_{J+1,k,l} = \sum_{m,n} g_{2m-k} g_{2n-l} C_{J,m,n} \end{cases}, \quad (2)$$

where $\{h\}$ and $\{g\}$ are the coefficients of the dual-scale equation which describe the scaling function and the wavelet function, respectively. We can execute first-level wavelet decomposition on the image by using formula (1) and then continue to do two-dimensional wavelet decomposition on the approximation components by using formula (2) and so on for following levels or to produce multilevel decomposition levels. Figure 1 presents a diagrammatic representation of the decomposition of the problem.

In the wavelet decomposition procedure described above, the orthonormality criterion was satisfied by both the scale function and the wavelet function. As a result, the following equation (3) is what the wavelet reconstruction of the two-dimensional picture signal looks like.

$$\begin{aligned} C_{J,k,l} = {} & \sum_{m,n} C_{J+1,m,n} h_{k-2m} h_{l-2n} + \sum_{m,n} C_{J+1,m,n} h_{k-2m} g_{l-2n} \\ & \sum_{m,n} C_{J+1,m,n} g_{k-2m} h_{l-2n} \sum_{m,n} C_{J+1,m,n} g_{k-2m} g_{l-2n}. \end{aligned} \quad (3)$$

The image is broken up into its component parts using the wavelet transform so that information about the image's contours and details can be obtained at a variety of different scales. The image can be rebuilt by using the inverse wavelet transform once the deconstructed signal has been processed and analyzed.

3.1.2. Build a Homomorphic Filter Model. In light of the issues that are present in the methods that are currently in use, in accordance with the optical properties of the image, it is known that the image is composed of the natural illumination component $i(x, y)$ and the reflection component $r(x, y)$ of the primary target that can be seen in the image. This is known based on the optical characteristics of the image. It is possible to express the model as given by the following equation.

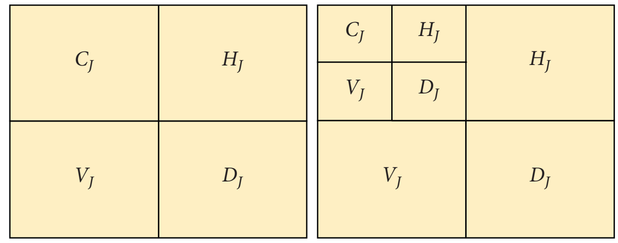

Figure 1: J and $J+1$ scale wavelet decomposition.

$$f(x, y) = i(x, y) r(x, y). \quad (4)$$

In a broad sense, the illuminance component $i(x, y)$ is able to completely reflect whether the lighting circumstances are favorable or unfavorable. If the illuminance component changes gradually, the spectrum will be located in the low-frequency region. Nevertheless, the reflection component $r(x, y)$ will be in the high-frequency zone. In the mapping image, the primary focus is on the particulars of the target object's content, and the component images' spectral regions are characterized by their high-frequency components. According to the previous distribution, all that needs to be done to improve the high frequency of the image is to separate the illuminance component $i(x, y)$ from the reflection component $r(x, y)$ in the frequency component $f(x, y)$ and then compress the low frequency of the image based on this information. The approach has the capability of lowering the brightness component of the image, which results in a visual effect that is more distinct, as explained in later sections.

The calculation is used to select a representative logarithm for both the left and right sides of formula (4). This allows the multiplication operation to be turned into a combination of addition and subtraction operations. Furthermore, this also ensures that there is one less variable than there was before.

$$\ln f(x, y) = \ln i(x, y) + \ln r(x, y). \quad (5)$$

The calculation result of the above formula indicates that the DCT transform should be used in place of the Fourier transform in the conventional homomorphic filter, and the following formula can be produced after the transformation:

$$F(u, t) = I(u, t) + R(u, t), \quad (6)$$

where

$$\begin{aligned} F(u, t) &= DCT[\ln f(x, y)], \\ I(u, t) &= DCT[\ln i f(x, y)], \\ R(u, t) &= DCT[\ln r f(x, y)]. \end{aligned} \quad (7)$$

The result of applying the homomorphic filter function $H(u, t)$ to the input function $F(u, t)$ in the preceding formula is illustrated as given in the following equation:

$$S(u, t) = H(u, t) F(u, t) = H(u, t) I(u, t) + H(u, t) R(u, t). \quad (8)$$

We get this result after filtering, and then putting it through the inverse DCT transform (IDCT), we get the following equation:

$$\begin{aligned} s(x,y) &= IDCT[H(u,t)F(u,t)] \\ &= IDCT[H(u,t)I(u,t)] + IDCT[H(u,t)R(u,t)]. \end{aligned} \tag{9}$$

Following the calculation of the DCT transform, the exponential transform is carried out so that the filtered image can be obtained. The exponential transform is computed using the following equation:

$$g(x,y) = e^{s(x,y)}. \tag{10}$$

The logarithm of the image expansion is chosen using the uniform filtering procedure of the DCT transform operation. The logarithmic result is then achieved, and the DCT transform is carried out after that. We use transform homomorphism to transform the filter.

3.2. Proposed Algorithm

3.2.1. Block Effect Visibility Function Based on HVS. In order to successfully apply the idea of removing obstacles, it is important to integrate the qualities of the visual system. Some research that are linked have demonstrated that certain spatial activities and picture brightness can mask and eradicate the block effect. Nonetheless, the visibility of the block effect is slightly decreased in the texture part. As a consequence of this, the visibility of blockiness is significantly reduced in locations that have a high local background brightness. A local area of the block border is generally understood to refer to the block boundary that exists between a block and an adjacent block.

The vertical and local spatial activities have the ability to disguise the impacts of blocking, and horizontal and vertical functions are established based on the findings of homomorphic filtering calculations. This is denoted by the following equations:

$$A_h = \sum_{u=1}^{7}\sum_{v=0}^{7} R(u,v), \tag{11}$$

$$A_v = \sum_{u=1}^{7}\sum_{v=0}^{7} R(u,v). \tag{12}$$

In the above equations, A_h and A_v are described as the feature activity of block c in the horizontal or vertical directions, respectively. As a result, $R(u,v)$ can be made to represent the remaining blocks in the model of block c which reflect the local activity in the DCT domain value according to its characteristics. This allows $R(u,v)$ to be used to represent the remaining blocks in the model of block c.

In general, the activity in the vertical direction is the primary reason for the hiding of the block effect when there are block effects present in the horizontal direction. This is the case for any existence of block effects in any direction. As a result, each and every one of the actions associated with the vertical or horizontal block impacts can be calculated using the following formulas:

$$A_{\text{total}}^{h} = A_t + aA_h, \tag{13}$$

$$A_{\text{total}}^{v} = A_h + aA_v. \tag{14}$$

As a result, the following equation (15) is how the masking function M_h for the horizontal blocking effect of spatial frequency activity should be defined.

$$M_h = \left(1 + A_{\text{total}}^{h}\right)^{-1}. \tag{15}$$

The calculation formula for the average brightness can be put down if the results of the calculation using the preceding formula are taken into account. The average brightness of the image can be estimated using the following equation:

$$M_1 = 1 + \left(\frac{b}{b_0}\right)^{r-1}. \tag{16}$$

According to the results of the calculations that were done earlier, if the frequency of the spatial activity of the image is unable to reach the normal value range of the masking function, then the visibility of the block effect that is present in the image will also change in a manner that is proportional to this fact. Note that this relationship is given by equation (17). Figure 2 displays the algorithm flow chart that was developed for this article.

$$\eta_h = \beta \cdot M_h \cdot M_1 = \frac{\beta}{\left(1 + A_{\text{total}}^{h}\right) + \left(1 + \left(\dfrac{b}{b_0}\right)^{r}\right)}. \tag{17}$$

3.3. Experimental Data. For the purpose of determining whether or not the algorithm proposed and described in this paper is effective, a variety of poster images are retrieved from the Internet. Then, four distinct types of representative images that exhibit clear variations in light intensity are chosen to serve as the experimental test images. Besides these, several images were combined into another set that is used for the validation purposes. Figure 2 displays the algorithm flow chart that was developed for this article.

4. Results and Discussion

4.1. Results. This section primarily evaluates the prediction accuracy of the visual communication poster color enhancement algorithm (referred here and various graphs as OUR), which is based on homomorphic filtering. Additionally, this section compares and analyzes the following two algorithms: (i) the Low Illumination Color Image Enhancement (LICIE) algorithm and (ii) the Color Image Enhancement (CIE) algorithm.

As can be seen in Figure 3, the signal-to-noise ratio of the OUR algorithm at different bit rates is higher than that of the LICE method and the CIE method, which is an indication

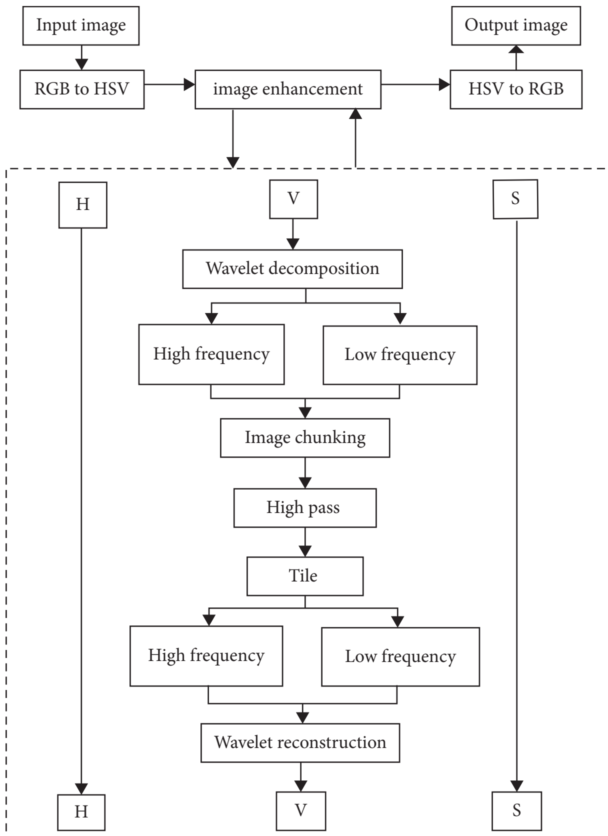

Figure 2: The proposed algorithm flow chart.

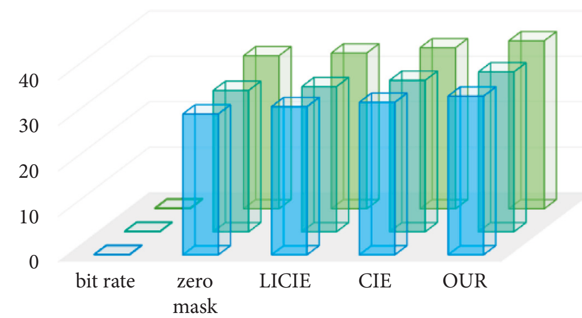

Figure 3: Signal-to-noise ratio at different bit rates.

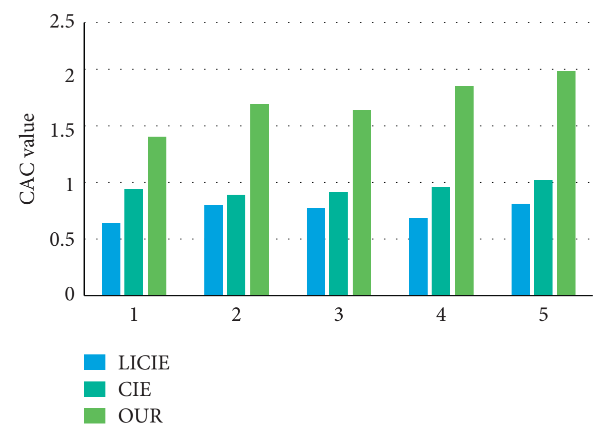

Figure 4: CAC values of four types of images.

that the proposed algorithm is able to effectively eliminate the block effect of the image, protect the edge information of the image, and enhance the image. This is because the lighting conditions make the photos produce different hues when shooting.

A comprehensive evaluation criterion of image objective quality is established in order to further verify the image color enhancement effect of the proposed method. This criterion is then used to evaluate various methods, and the comprehensive evaluation criterion is defined as CAC (Comprehensive Assessment Criteria Index). In order to further verify the image color enhancement effect of the proposed method, a comprehensive evaluation criterion of image objective quality is established. This should be noted that the evaluation criterion is defined as CAC and is given by the following equation.

$$CAC = E^m N^n C^p. \tag{18}$$

In the above equation (18), the E^m metric is the one that measures the similarity of picture structure. The normalized grayscale difference is denoted by the letter N^n. The color-weighted restoration degree is denoted by the letter C^p. The value of the CAC parameter determines how effective the image's color enhancement effect will be. Figure 4 presents the findings of a comparison of the CAC values obtained through the use of various methodologies. An examination of Figure 4 reveals that when the proposed method has been applied to improve the colors of various images, the CAC values that have been obtained are all greater than 1. The fact that this technique's CAC value is noticeably greater than that of the LICE method and the CIE method indicates that the image enhancement effect produced by the suggested approach is superior, which further substantiates this method's status as the superior option.

The results presented in Figure 5 show that the average grayscale value of the image after enhancement processing is greater than the value of the original image. This is due to the fact that each approach has the impact of increasing the brightness of the image to a certain degree. The information entropy values of the processed image are higher than the values of the original image, which indicates that the processed image contains a greater amount of information. Additionally, the average gradient is improved when compared with the value of the original image, which indicates that the image clarity has improved and that the details, such as edges, are more prominent. Contrast the three different kinds of algorithm. The enhancement impact of the algorithm demonstrates that the image statistical parameters of the OUR method are substantially better than those of CIE and LICIE. This indicates that the algorithm presented in this work has the best performance when it comes to the enhancement of images.

4.2. Discussion. During the process of imaging, image distortion or color darkening brought on by environmental or human factors will have an effect on the final visual product.

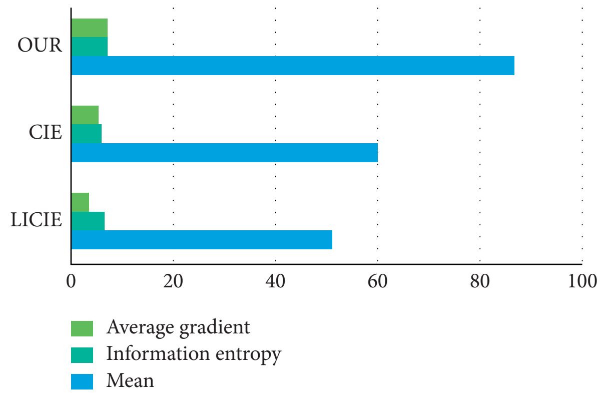

Figure 5: Comparison of the results of different algorithms.

This issue has rapidly risen to the status of one of the most pressing concerns that must be addressed in this area of research. In light of this, a planar vision image that utilizes homomorphic filtering has been proposed. The algorithm is for color enhancement. In order to get the best possible result while processing images, the RGB color space is transformed into the HSV color space according to the features of the color space, and then, a Butterworth-type homomorphic filter is built through the process of homomorphic filtering computation. In order to achieve a color-enhanced image, the block effect must first be removed. Because the threshold of the visibility function result needs to be accurate and effective in the calculation of removing the block effect, the result of the threshold needs to be repeated, and the next step will be to optimize the calculation process. Despite the fact that the algorithm in this paper can finally accomplish the purpose of image color enhancement, this is due to the fact that the threshold of the visibility function result needs to be accurate and effective. The detailed analysis of the proposed algorithm denotes its superiority.

The signal-to-noise ratio of the OUR algorithm at different bit rates is higher than that of the LICE method and the CIE method, which is an indication that the proposed algorithm is able to effectively eliminate the block effect of the image, protect the edge information of the image, and enhance the image. The CAC value of this algorithm is obviously larger than that of the lice method and the CIE method. This fact shows that the image enhancement effect produced by the method proposed in this paper is superior. Furthermore, the enhancement impact of the algorithm demonstrates that the image statistical parameters of the OUR method are substantially better than those of CIE and LICIE. This indicates that the algorithm presented in this work has the best performance when it comes to the enhancement of images.

5. Conclusions and Future Work

In this paper, we propose a variable illumination image feature enhancement algorithm that is based on wavelet and block homomorphic filtering. The goal of this algorithm is to improve the characteristics of some images that are affected by variable illumination, specifically their uneven brightness and low contrast. First, the image is converted from its original color space to the HSV space, and the image brightness component V is used as the enhancement object. Next, a wavelet transform is used in place of the conventional Fourier transform in the block homomorphic filtering in order to decompose the luminance component. Finally, the subimages that were decomposed by the wavelet are divided into blocks, and high-pass filtering processing is performed before the filtered images are reconstructed. This is done so that it is clear, based on the results of the evaluation and analysis of the visual effects and quantitative indicators, that the color enhancement algorithm for visual communication is successful.

When compared with more traditional algorithms, the posters that are based on homomorphic filtering that are suggested in this research have the ability to effectively correct the image brightness that is produced by variations in illumination. It is possible for it to considerably improve the contrast of the image's details, and it can also make the image with changeable illumination have improved global visibility. The fact that our algorithm is so excellent is demonstrated by the fact that it is able to improve the color of the poster extremely effectively. In the future, we will work towards proposing an updated version of the proposed algorithm, where machine learning methods should be used to enhance the accuracy and picture quality. Using big data and the graph convolutional network model will definitely improve the performance of the proposed technique. The filtering task is compute intensive, and the matching time could be significantly reduced using big data analytics.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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