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Optimizing Visual Communication in Online Classrooms Using Image Processing Technology

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ABSTRACT

With the rapid development of online education, the effectiveness of online classrooms has become a key indicator of educational quality. Particularly in terms of visual communication, the application of image processing technology is considered a crucial factor in enhancing the online learning experience. However, existing research has primarily focused on improving basic image clarity and color adjustments in classroom visuals, lacking in-depth exploration of adaptive optimization of classroom visuals in complex environments and the integration of visual effects with teaching content. In response to this gap, this paper proposes an online classroom visual optimization solution based on image processing technology, focusing on two main areas: first, adaptive color correction of online classroom visuals to address color distortion caused by display devices and lighting conditions; and second, visual enhancement techniques for emphasizing key content, aimed at improving students' attention and learning efficiency. Through these technological approaches, this paper not only discusses how to improve the visual quality of online classrooms, but also examines the potential of image processing in conveying teaching content, such as traditional culture, with the aim of achieving a deep integration of visuals and educational objectives to enhance the effectiveness of online education.

1. INTRODUCTION

With the rapid development of information technology, online education has become an important component of the modern education system [1-3]. Especially during the pandemic, the widespread adoption of online classrooms has enabled more students to conveniently access high-quality educational resources [4]. Unlike traditional face-to-face teaching, the teaching format of online classrooms is influenced by various factors such as hardware devices and network environments. In particular, the presentation of the visuals has a direct impact on students' learning experience and learning outcomes [5-7]. To improve the quality of online classroom teaching, the application of image processing technology has increasingly become a key approach to enhancing visual communication effects.

In the teaching content of online classrooms, integrating excellent traditional culture has become an important direction for enhancing the cultural value and teaching depth of the class. Elements of traditional culture often contain rich historical connotations and artistic expressions. However, in online classrooms, how to effectively present these cultural connotations through visual communication methods relies on the support of image processing technology [8-11]. Through adaptive image adjustments and visual enhancement techniques, the quality of the classroom visuals can be improved, enabling students to focus more during the viewing process while deepening their understanding and memory of the teaching content, especially the traditional cultural elements [12-15]. Therefore, exploring how to optimize the visual effects of online classrooms through image processing technology has profound educational significance and cultural value.

Although some studies have already explored the issue of image optimization in online classrooms, most of them are limited to basic aspects such as image clarity and color adjustments, lacking adaptive adjustments of classroom visuals in diverse environments [16, 17]. Moreover, existing visual enhancement techniques mainly focus on improving video fluency and clarity, while research on how visual effects can align with teaching content, especially the precise optimization of cultural transmission, is still insufficient [18-20]. Therefore, how to enhance the visual communication effect of online classrooms through more refined and personalized technical means remains an urgent issue to be addressed.

The main research content of this paper includes two parts. On the one hand, through adaptive color correction technology, the color distortion problems caused by factors such as lighting and display devices in online classrooms are improved, making the colors of the visuals more vivid and natural, thereby enhancing the learners' visual experience. On the other hand, through visual enhancement technology, key content in the classroom is emphasized and reinforced, making it easier for students to grasp the main points and improving the interactivity and appeal of the classroom. Through these technical means, this paper aims to explore how to create more vivid and intuitive visual communication effects in the online classroom environment, thereby improving students' learning efficiency and teaching effectiveness.

2. ADAPTIVE COLOR CORRECTION OF ONLINE CLASSROOM VISUALS

In online classrooms, the types of display devices used by teachers and students vary widely, including computers, mobile phones, tablets, and other devices from different brands. These devices have significant differences in color performance and screen brightness, which can easily lead to inconsistencies or distortions in color. For example, some devices may have deviations in displaying blue or green, thus affecting the clarity and readability of classroom content, especially images or text. In addition, the ambient lighting of the online classroom also has a significant impact on color presentation. Images taken in strong or low light environments may cause color shifts, affecting students' visual perception. These issues not only affect students' learning experience but may also increase the difficulty of transmitting classroom information visually, especially when it involves images and multimedia content, as the accuracy of color is directly related to students' understanding of the teaching content.

Therefore, this paper proposes an adaptive color correction method for online classroom visuals, based on color channel compensation and attenuation techniques, aiming to solve color imbalance problems caused by device differences, lighting changes, and other factors. Unlike traditional algorithms, the method proposed in this paper focuses not only on overall color correction but also on dynamically adjusting the contribution values of each color channel, optimizing the distribution of R, G, and B channels in the visuals to achieve a more natural and accurate visual effect. The basic idea of the method is to analyze the color distribution of the R, G, and B channels in the online classroom visuals and make adaptive adjustments based on different shooting conditions. In practical applications, the red channel is usually more affected by color deviations in different devices, while changes in the green and blue channels are relatively smaller. To address this, this paper compensates for the red channel to ensure that its color performance in the visuals is more accurate, avoiding color distortion or over-saturation. Meanwhile, the blue and green channels are fine-tuned based on actual conditions to avoid over-compensation or excessive attenuation, maintaining the natural transition of colors in the visuals.

In practical implementation, this paper analyzes the color distribution of the three channels (R, G, B) in the online classroom visuals, calculates the average value of each channel, and dynamically adjusts the intensity of each channel based on the differences between these values. For the compensation of the red channel, the difference between the average values of the green and red channels is calculated, and compensation is applied based on this difference to ensure that the red channel appears fuller and more natural visually. For the blue and green channels, adjustments are made based on the average value differences between these two channels, applying compensation or attenuation to ensure a natural transition of colors in the visuals and the overall harmony of the visual effect. For example, if the brightness of the blue channel is lower than that of the green channel, moderate compensation may be applied to the blue channel, while the green channel is fine-tuned based on its performance. Through this adaptive adjustment, the color stability of the online classroom visuals is ensured across different devices and shooting environments, ensuring that students can receive a consistent and accurate visual experience regardless of the device used. Assuming the position of each pixel in the online classroom visual is denoted by (a), the compensated R, G, and B channel values are represented by U_{ez}, U_{hz}, and U_{yz}, the original R, G, and B values by U_e, U_h, and U_y, the average values of the R, G, and B channels by $\overline{U_e}$, $\overline{U_h}$, and $\overline{U_y}$, and the constant by β, the formulas for color compensation and attenuation are defined as follows:

$$U_{ez}(a)=U_e(a)+\beta*\left(\overline{U_h}-\overline{U_e}\right)*\left(1-U_e(a)\right)*U_h(a) \tag{1}$$

$$U_{hz}(a)=U_h(a)+\beta*\left(\overline{U_y}-\overline{U_h}\right)*\left(1-U_h(a)\right)*U_y(a) \tag{2}$$

$$U_{yz}(a)=U_y(a)+\beta*\left(\overline{U_h}-\overline{U_y}\right)*\left(1-U_y(a)\right)*U_h(a) \tag{3}$$

Figure 1 shows the histograms of the online classroom visuals before and after channel compensation.

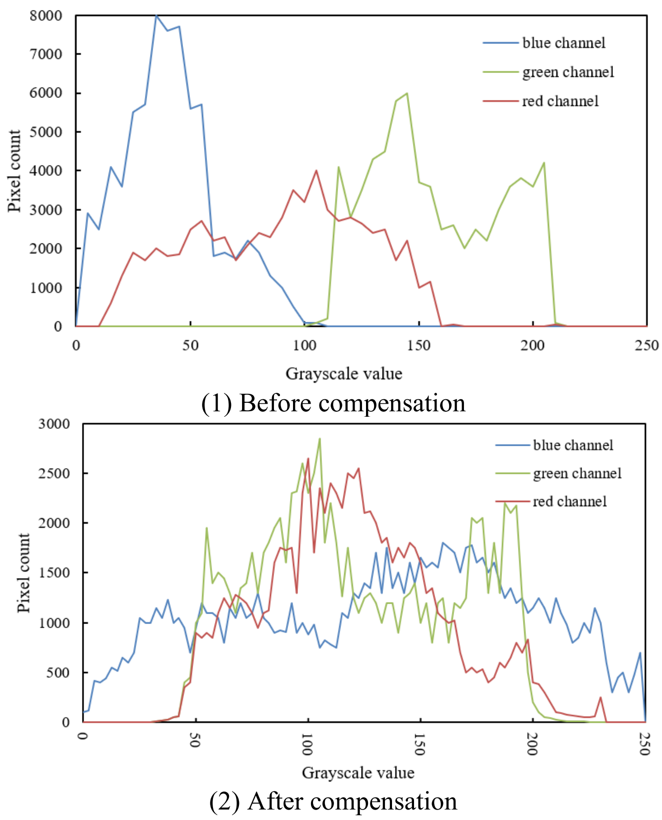

Figure 1. Histograms of the online classroom visuals before and after channel compensation

The traditional grayscale world algorithm, when used to adjust the white balance of online classroom visuals, may introduce red artifacts or cause the overall image to darken due to an over-calculated compensation value, thereby affecting the clarity and readability of the classroom content. For online classrooms, the visual effect of the classroom visuals must remain natural and balanced. Excessive color correction not only reduces the quality of the online classroom visuals but also blurs the details in the image, affecting the students' learning experience. Therefore, after channel compensation, this paper further introduces a white balance algorithm based on gain coefficients to more finely control color adjustments, ensuring naturalness and visual comfort of the visuals. Assuming that the corrected online classroom visual and the uncorrected online classroom visual are represented by d_z and d_z', the estimated maximum value of the channel is denoted by z_{MAX}, the average values of the R, G, and B channels by i_e, i_h, and i_y, and the constant by x, the corrected online classroom visual d_z is as follows:

$$d_z = \sum_{z \in e,h,y} \frac{d_z'}{z_{MAX} \cdot \left(i_z / \sqrt{i_e^2 + i_h^2 + i_y^2} \right) + x} \tag{4}$$

From the above formula, it can be seen that the brightness of the corrected online classroom visual decreases as x increases.

3. VISUAL ENHANCEMENT OF ONLINE CLASSROOM VISUALS

The color deviation problem of online classroom images has been largely addressed through the compensation of color channels and white balance algorithm adjustments mentioned earlier. However, to further enhance the visual effect of the image and ensure that the details and layers of the visuals are clearer, this paper introduces a histogram stretching method based on Gaussian modeling. This method analyzes and adjusts the distribution of the image's histogram, effectively solving the issue of concentration in the histogram distribution, significantly optimizing the contrast and brightness of the image, and thus improving the visual communication effect of the online classroom visuals.

3.1 Gaussian modeling

By modeling the R, G, B channels of the online classroom image with a Gaussian model, finer color and brightness adjustments can be achieved, enhancing the visual layering and contrast of the image, making the content clearer and brighter, thereby improving the student's learning experience and the effectiveness of teaching content delivery.

As a common probability distribution, the mathematical properties of the Gaussian distribution make it well-suited for describing the color distribution in an image. For online classroom images, the histograms of the R, G, B color channels are often not perfectly uniform and may exhibit color biases or excessive concentration in certain areas. To adjust these uneven distributions, this paper uses a single Gaussian model to model the color distribution of each color channel. In this model, the expectation value ω of the Gaussian distribution is used to describe the central position of the color distribution, while the standard deviation δ controls the extent of the distribution's spread. Specifically, ω represents the average color position of each color channel in the image, i.e., the overall color tone center for red, green, and blue; δ determines the concentration of the color distribution. A smaller σ leads to a more concentrated color distribution, reducing the image's color deviation, while a larger δ results in a more dispersed color distribution, making the image's color performance more diverse. The Gaussian distribution can be expressed as $A \sim V(\omega, \delta^2)$. If the random variable A follows a Gaussian distribution, its probability density function is:

$$d(a) = \frac{1}{\sqrt{2\tau}\delta} \exp\left(-\frac{(a-\omega)^2}{2\delta^2} \right) \tag{5}$$

Through this modeling, this paper can independently analyze and optimize each color channel in the online classroom visuals. In practical application, the first step is to use the Maximum Likelihood Estimation (MLE) method to solve for the mean ω and standard deviation δ of each channel, and then adjust the image based on these parameters. MLE is a commonly used statistical method that estimates the optimal parameter values by maximizing the likelihood function of the observed data. In this method, the ω and δ obtained by MLE accurately reflect the distribution characteristics of each color channel in the online classroom image, thus providing a precise basis for subsequent histogram stretching adjustments. Assuming that the estimated value of ω is represented by $\hat{\omega}$, the estimated value of δ is represented by $\hat{\delta}$, the sample values and each pixel value are represented by A_1, and the average pixel value by $\bar{A}$, with the number of samples represented by v, the specific solving formula is:

$$\hat{\omega} = \bar{A} = \frac{1}{v} \sum_{u=1}^{v} A_u \tag{6}$$

$$\hat{\delta}^2 = \frac{1}{v} \sum_{u=1}^{v} \left(A_u - \bar{A} \right)^2 \tag{7}$$

3.2 Histogram stretching

In the visual enhancement of online classrooms, the clarity of images and the natural presentation of colors are crucial for improving teaching effectiveness and student learning experience. For online classroom images, this paper proposes a histogram stretching method based on Gaussian model modeling, aiming to improve the visual performance of the image through precise adjustments and optimization of color distribution, making the image more vivid and layered, thereby enhancing the transmission effect of the teaching content.

Firstly, the first step of histogram stretching is to perform histogram analysis on the compensated online classroom image and normalize the pixel values of the image, mapping the pixel values from the original range of [0, 255] to the standardized range of [0, 1]. The purpose of normalization is to eliminate brightness differences that may exist between different image sources and devices, so that the color range of each image is unified, thus providing a consistent basis for subsequent image adjustments. Further, this paper uses a Gaussian model-based modeling method to analyze each color channel in detail, estimating the expected values ω_e, ω_h, ω_y and standard deviations δ_e, δ_h, δ_y for each channel. Then, based on the maximum and minimum values of each color channel, the color extension coefficient βz is calculated. The purpose of this coefficient is to adjust the contrast and brightness of each color channel, making the color range of the image richer and more balanced. Let the maximum and minimum pixel values of the three channels be represented by U_{zMAX} and U_{zMIN}, and the calculation formula is:

$$\beta_z = \frac{1}{U_{zMAX} - U_{zMIN}} \tag{8}$$

After completing the above steps, for the R, G, and B color channels of the online classroom image, this paper makes the final adjustment through histogram stretching. In this process, each channel of the histogram is independently extended, allowing each color channel of the image to better cover the color space, thereby enhancing the color depth and layering of the image. Let the stretched R, G, and B channel values be represented by U_{ez}', U_{hz}', and U_{yz}', and the compensated R, G, and B channel values be represented by U_{ez}, U_{hz}, and U_{yz}, respectively. The expected values and standard deviations of the three-channel histograms are represented by ω_e, ω_h, ω_y and δ_e, δ_h, δ_y, and the extension coefficient is represented by x_z. The specific process expression is:

$$\begin{cases} U_{ez}' = X - \beta_e \times \frac{\delta_h}{\delta_e} \times \left(\omega_e - U_{ez}\right), U_{ez} \le \omega_e \\ U_{ez}' = X + \beta_e \times \frac{\delta_h}{\delta_e} \times \left(U_{ez} - \omega_e\right), U_{ez} > \omega_e \end{cases} \tag{9}$$

$$\begin{cases} U_{hz}' = X - \beta_h \times \frac{\delta_y}{\delta_h} \times \left(\omega_h - U_{hz}\right), U_{hz} \le \omega_h \\ U_{hz}' = X + \beta_h \times \frac{\delta_y}{\delta_h} \times \left(U_{hz} - \omega_h\right), U_{hz} > \omega_h \end{cases} \tag{10}$$

$$\begin{cases} U_{yz}' = X - \beta_y \times \frac{\delta_h}{\delta_y} \times \left(\omega_y - U_{yz}\right), U_{yz} \le \omega_y \\ U_{yz}' = X + \beta_y \times \frac{\delta_h}{\delta_y} \times \left(U_{yz} - \omega_y\right), U_{yz} > \omega_y \end{cases} \tag{11}$$

In the visual enhancement of online classroom images, improving the contrast and detail representation of the image is crucial, especially when viewed on different devices and in various environments. The contrast of the image often affects the student's viewing experience and information retrieval effectiveness. To address the low contrast problem in online classroom images, this paper further introduces a dual enhancement strategy combining Contrast Limited Adaptive Histogram Equalization (CLAHE) and L-channel enhancement to ensure the clarity and contrast of the image's details and colors.

In online classroom scenarios, the readability of handouts, text, and charts is crucial, and these contents are often hard to distinguish in low-contrast environments. The CLAHE algorithm divides the image into several sub-blocks and applies adaptive histogram equalization on each sub-block for local enhancement, thereby effectively improving the contrast in local regions of the image. Enhancing the L-channel is another key step. The L-channel represents the luminance information of the image, which is the main factor affecting the perceived contrast and brightness levels of the image. In online classrooms, the visibility of the teacher's facial expressions and the teaching content is directly related to the luminance distribution. By enhancing the L-channel, the brightness contrast of the image can be effectively improved, especially in the areas of the teacher's face or charts, ensuring that students can clearly see the image even under different lighting conditions. Let the compensated channel value be represented by $U_{ez}(X)$, the pre-compensated channel value be represented by $U_e(X)$, the green channel value be represented by $U_h(X)$, the average value of the green channel and compensated channel be represented by $\overline{U_h}$, $\overline{U_e}$, and the gain coefficient be represented by x. The formula is as follows:

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 0.412 & 0.358 & 0.180 \\ 0.213 & 0.715 & 0.072 \\ 0.019 & 0.119 & 0.950 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{12}$$

The spatial reference values of the ABC space are represented by A_v, B_v, C_v, and the equation is:

$$\begin{cases} M = 116d\left(B / B_v\right) - 16 \\ x = 500\left[d\left(A / A_v\right) - d\left(B / B_v\right)\right] \\ y = 200\left[d\left(B / B_v\right) - d\left(C / C_v\right)\right] \end{cases} \tag{13}$$

For online classroom images, enhancing the L-channel is especially helpful for improving the visibility of details such as the teacher's facial expressions, blackboard writing, and charts, thereby enhancing the clarity and depth of the teaching content. By converting the RGB image to the Lab color space and applying histogram stretching to the L-channel, with a range set between 0.01% and 99.9%, and setting the luminance values outside the range to 100 and 0, the luminance dynamic range of the image can be effectively expanded. This stretching operation not only enhances the image contrast but also avoids the grayscale unevenness caused by color deviation. Let the modified luminance value be represented by $M'_{[u][k]}$, the pre-modified luminance value be represented by $M_{[u][k]}$, and the maximum and minimum luminance values within the stretching range be represented by U_{MAX} and U_{MIN}, the equation is as follows:

$$M'_{[u][k]} = \left(M_{[u][k]} - U_{MIN}\right) \cdot \left[100 / \left(U_{MAX} - U_{MIN}\right)\right] \tag{14}$$

It should be noted that although both CLAHE and L-channel enhancement effectively improve the contrast and clarity of the image, the low luminance areas may become darker during the enhancement process, especially in noise reduction, where the overall details of the image may be lost due to noise suppression algorithms. This means that while the contrast of the image is improved, there may be issues of detail loss or unclear shadow areas, especially when the image contains a significant amount of noise. Therefore, in practical applications, in addition to using CLAHE and L-channel enhancement, further noise suppression and detail restoration strategies may be needed to ensure that the high contrast does not lead to unnecessary visual discomfort or detail loss.

3.3 Homomorphic filtering

In visual enhancement of online classroom images, ensuring image detail clarity and brightness balance is crucial to improving the student learning experience. In particular, under different lighting conditions, online classroom images may experience loss of detail in darker areas, which impacts the readability of teaching content. This is especially true when the viewer is in a relatively dark environment or when the display quality of the device is suboptimal. In such cases, the teacher's handwriting, diagrams, and screen-shared content may be hard to see clearly if the dark areas of the image lack detail. To address this issue, this paper proposes the use of homomorphic filtering to reduce surface reflections in the image, thereby minimizing detail loss.

Homomorphic filtering begins by applying a logarithmic transformation to the image, which converts the image's brightness information into an additive form. This allows the image's luminance component to be divided into low-frequency and high-frequency parts. In the frequency domain, Fourier transformation is applied to decompose the image, and then a suitable frequency-domain filter is used for processing, as shown in the following equation. This method suppresses the low-frequency illumination component, reducing image brightness inconsistencies caused by environmental lighting changes, while enhancing the high-frequency reflection component to improve the image's detail and contrast. Let the filter used to suppress low-frequency components and enhance high-frequency components be represented by the transfer function $G(i,n)$. The expression is given by:

$$\begin{aligned} &G(i,n)DDS\left(LN\left(d\left(a,b\right)\right)\right) \\ &=G(i,n)DDS\left(LN\left(u\left(a,b\right)\right)\right) \\ &+G(i,n)DDS\left(LN\left(e\left(a,b\right)\right)\right) \end{aligned} \tag{15}$$

where, e_g and e_m are the amplification factors for high-frequency and attenuation factors for low-frequency components, respectively; z is the sharpening coefficient; and i and n represent the horizontal and vertical distances from the filter point to the filter center. The cutoff frequency is denoted as F_0. The expression of $G(i,n)$ can be written as:

$$G(i,n)=\left(e_g-e_m\right)\cdot\left(1-\exp\left\{-z\left[i^2+n^2/F_p^2\right]\right\}\right)+e_m \tag{16}$$

Homomorphic filtering effectively enhances the overall brightness balance of the online classroom image and improves detail visibility in darker regions. In environments with poor lighting or insufficient contrast, the teacher's facial expressions, teaching materials, and text and charts on the screen often appear blurred due to uneven reflections of light. Homomorphic filtering can eliminate the impact of environmental lighting on the image, making the reflective components more prominent and thereby improving the visibility of details in the image.

4. EXPERIMENT RESULTS AND ANALYSIS

This study aims to enhance the visual communication effect in online classrooms through the application of adaptive color correction and visual enhancement techniques. In the experiments, the proposed adaptive color correction technique was first applied to address color distortion issues caused by factors such as environmental lighting and display devices in online classroom settings. The results show that the color correction technique can dynamically adjust the color balance of classroom images, improving the visual quality and enhancing the overall learning experience. Figure 2 visually demonstrates the enhancement in the visual communication effect achieved by the method proposed in this paper. Experimental results indicate that under varying lighting conditions, the color correction technique effectively improves color distortion, making the colors in the image appear more vivid and natural, thus enhancing the visual experience for learners.

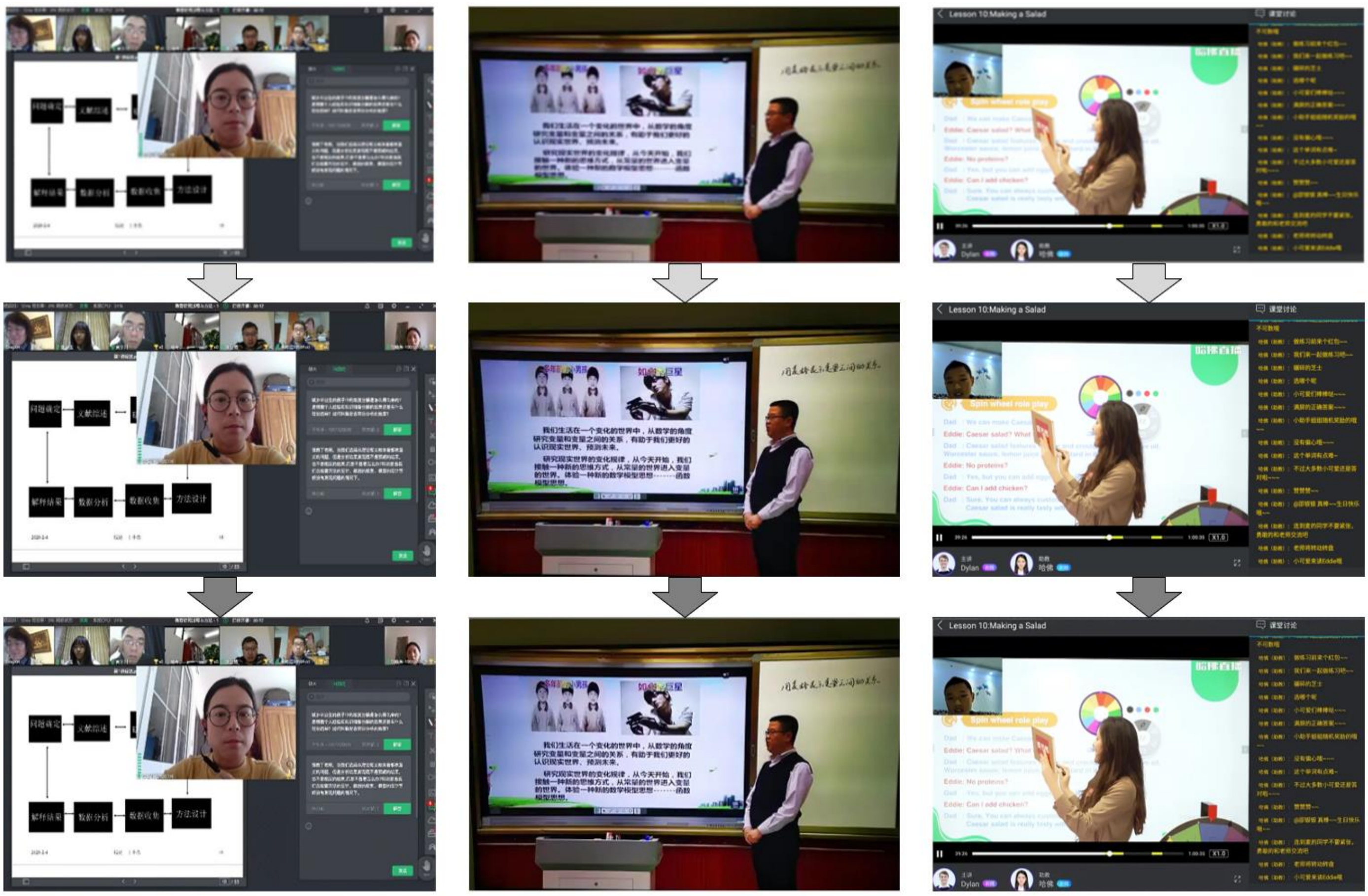

Figure 2. Enhancement of visual communication effect in online classrooms using the proposed method

Table 1. Comparison of evaluation metrics for processing the first group of online classroom images (dark images) using different methods

Image Name	Algorithm	Average Gradient	Information Entropy	*UCIQE*	*UIQM*
	CLAHE	3.854	6.745	0.385	2.825
	MSRCR	7.423	6.889	0.524	2.214
Image (1)	*SRGAN*	6.789	7.521	0.562	2.745
	Contourlet	3.625	6.745	0.388	2.856
	Proposed Algorithm	8.124	7.652	0.574	2.885
	CLAHE	12.235	7.102	0.432	3.120
	MSRCR	21.241	7.456	0.612	2.652
Image (2)	*SRGAN*	18.956	7.526	0.615	2.315
	Contourlet	11.231	7.231	0.435	3.415
	Proposed Algorithm	25.201	7.652	0.668	3.556
	CLAHE	1.652	7.114	0.441	1.325
	MSRCR	4.258	7.203	0.578	2.351
Image (3)	*SRGAN*	2.698	7.325	0.612	1.658
	Contourlet	1.326	7.114	0.446	1.599
	Proposed Algorithm	3.105	7.485	0.642	2.607

Table 2. Comparison of evaluation metrics for processing the second group of online classroom images (bright images) using different algorithms

Image Name	Algorithm	Average Gradient	Information Entropy	*UCIQE*	*UIQM*
	CLAHE	1.125	6.895	0.421	1.785
	MSRCR	2.325	7.236	0.548	2.125
Image (4)	*SRGAN*	2.152	7.321	0.523	1.895
	Contourlet	1.236	6.658	0.421	1.652
	Proposed Algorithm	2.385	7.356	0.556	1.995
	CLAHE	1.798	6.235	0.389	1.678
	MSRCR	2.265	7.245	0.562	2.526
Image (5)	*SRGAN*	3.526	6.895	0.512	2.315
	Contourlet	1.658	6.512	0.432	2.125
	Proposed Algorithm	3.615	7.458	0.618	2.566
	CLAHE	2.898	6.548	0.478	2.248
	MSRCR	7.528	6.325	0.532	2.365
Image (6)	*SRGAN*	6.125	7.145	0.619	2.325
	Contourlet	2.458	6.359	0.456	2.245
	Proposed Algorithm	7.125	7.589	0.625	2.369

Table 3. Comparison of evaluation metrics for processing online classroom images (overexposed) using different algorithms

Image Name	Algorithm	Average Gradient	Information Entropy	*UCIQE*	*UIQM*
	CLAHE	3.325	6.524	0.425	2.458
	MSRCR	6.541	7.235	0.532	3.125
Image (7)	*SRGAN*	5.236	7.215	0.448	2.889
	Contourlet	3.125	6.458	0.389	2.652
	Proposed Algorithm	6.624	7.326	0.562	3.129
	CLAHE	2.895	7.215	0.478	2.654
	MSRCR	4.856	7.526	0.562	2.785
Image (8)	*SRGAN*	4.235	7.235	0.578	2.562
	Contourlet	2.562	7.425	0.445	2.547
	Proposed Algorithm	5.125	7.666	0.632	2.789
	CLAHE	11.235	7.589	0.489	3.625
	MSRCR	13.256	7.215	0.578	3.125
Image (9)	*SRGAN*	14.285	7.325	0.562	3.458
	Contourlet	9.856	7.452	0.446	3.526
	Proposed Algorithm	15.255	7.723	0.623	3.825

According to the data in Table 1, it can be seen that the adaptive color correction and visual enhancement technology proposed in this paper performs better than other algorithms when processing online classroom images. Specifically, in Image (1), the proposed algorithm achieves a "mean gradient" of 8.124, significantly higher than other methods (such as the CLAHE algorithm with 3.854 and the Contourlet transform algorithm with 3.625), indicating that the image details have been better restored and enhanced. In the "information entropy" metric, the proposed algorithm's value of 7.652 also exceeds that of other algorithms, indicating that the image contains more information and the visual content details are clearer. On the other hand, in the UCIQE and UIQM evaluation metrics, the proposed algorithm scores 0.574 and 2.885, respectively, both of which are higher than other algorithms, indicating significant improvement in color quality and overall image quality. In Image (2) and Image (3), the proposed algorithm continues to perform excellently across various metrics, especially in "mean gradient" and "information entropy," both of which are significantly better than other traditional algorithms, further proving the effectiveness of its color correction and visual enhancement effects.

From the data in Table 2, it can be seen that the algorithm proposed in this paper also outperforms other traditional methods when processing bright online classroom images. Taking Image (4) as an example, the proposed algorithm achieves an "Average Gradient" value of 2.385, which is significantly higher than the CLAHE algorithm (1.125) and Contourlet transform algorithm (1.236), indicating that the proposed algorithm can better restore image details and make the image sharper. In addition, the proposed algorithm also performs better in terms of "Information Entropy" (7.356), indicating its advantage in enhancing the information content of the image and enriching the details of the scene. Similarly, in the UCIQE and UIQM metrics, the proposed algorithm achieves relatively high scores of 0.556 and 1.995, showing a strong ability to improve image quality. For Image (5) and Image (6), the proposed algorithm continues to show excellent performance across all metrics, especially in "Average Gradient" and "Information Entropy" (with values of 3.615, 7.458 and 7.125, 7.589), which are significantly higher than those of other algorithms, further validating its superiority in bright scenes.

From the data in Table 3, it can be seen that the proposed algorithm performs excellently when processing overexposed online classroom images, especially in terms of detail recovery and information enhancement. For Image (7), the "Average Gradient" value of 6.624 achieved by the proposed algorithm is superior to other methods (e.g., CLAHE algorithm: 3.325, Contourlet transform algorithm: 3.125), indicating that the proposed algorithm can effectively enhance image details and make the image sharper. In addition, the "Information Entropy" value of 7.326 is also significantly higher than other algorithms, showing its advantage in increasing the amount of information in the image. In the UCIQE and UIQM metrics, the proposed algorithm achieves 0.562 and 3.129, both of which are better than other methods, reflecting the improvement in color quality and overall image quality. Similarly, the data from Image (8) and Image (9) show the advantages of the proposed algorithm, particularly in the improvement of "Information Entropy" and "UIQM", with values of 7.666 and 3.825, further proving the superiority of the proposed algorithm in overexposed environments.

According to the average metrics of UCIOE and UIOM shown in Figure 3, the proposed algorithm significantly outperforms other traditional methods in improving the quality of online classroom images. In terms of UCIOE (color quality index), the proposed algorithm has an average value of 0.606, which is significantly higher than the CLAHE algorithm (0.442) and Contourlet transform algorithm (0.439), indicating that the proposed algorithm can effectively improve the naturalness and color balance of the image, and address the color distortion caused by factors such as lighting and display devices. In terms of UIOM (image quality evaluation index), the proposed algorithm has an average value of 2.817, which is better than the CLAHE algorithm (2.493), MSRCR algorithm (2.613), and SRGAN algorithm (2.547), demonstrating its improvement in overall image quality and detail performance, especially in terms of sharpness, contrast, and color saturation.

By combining the results of UCIOE and UIOM, it can be concluded that the proposed adaptive color correction and visual enhancement techniques have significant effects in improving the quality of online classroom images. The improvement in UCIOE indicates that the algorithm effectively solves the color distortion caused by device and environmental factors, making the image colors more natural and vivid, which is crucial for enhancing learners' visual experience and classroom engagement. Moreover, the improvement in UIOM reflects the enhancement in detail recovery and overall image quality, helping students to see the classroom content more clearly, which in turn boosts interaction and information delivery. Overall, the proposed method not only optimizes the naturalness of the image colors but also enhances image quality through visual enhancement technology, further improving the visual experience and learning effectiveness of online education.

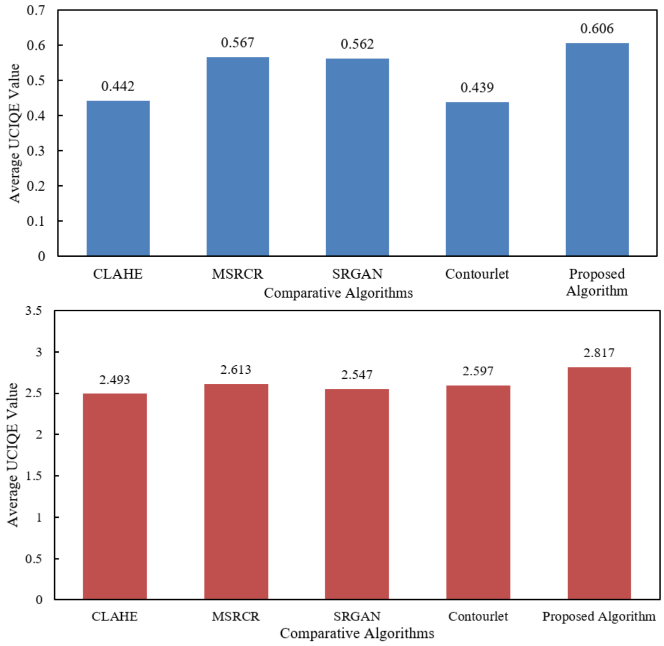

Figure 3. Average statistics of UCIOE and UIOM after processing online classroom images with different algorithms

5. CONCLUSION

This research mainly focuses on improving image quality in online classrooms and proposes an integrated solution based on adaptive color correction and visual enhancement technologies. First, through adaptive color correction, the issue of color distortion caused by lighting changes and differences in display devices is successfully addressed, making the image colors more natural and vivid, effectively improving the visual experience in online learning. Second, through visual enhancement technology, the proposed algorithm highlights and strengthens the key content of the classroom, increasing interaction and engagement, helping students capture the focus of their learning more clearly, and promoting enhanced learning efficiency. The experimental results show that the proposed method significantly outperforms traditional algorithms across multiple evaluation metrics, validating its superiority in color restoration, detail enhancement, and image quality.

This research provides an effective solution for improving online classroom image quality, especially in environments with common issues such as uneven lighting and differing display devices, demonstrating good adaptability and effectiveness. By combining color correction with visual enhancement technology, the proposed method can significantly improve students' visual experience, enhance classroom interaction, and engagement, making it highly significant for improving the quality of online education. However, there are certain limitations in this research. First, the experiments mainly focus on specific image processing scenarios, and future research can verify the algorithm's generalizability and robustness in a wider range of online classroom scenarios. Second, although the proposed algorithm has achieved good results in improving image quality, further exploration is needed regarding its applicability in real-time processing and in different network environments, particularly its efficiency and stability in large-scale online education applications.

Future research can further expand the algorithm proposed in this paper, especially in terms of optimization for different devices and environmental conditions, to improve its versatility and real-time performance. Specifically, studies can explore how to further enhance color correction and visual enhancement effects using deep learning techniques, particularly in complex lighting and variable scenarios. Additionally, by integrating virtual reality and augmented reality technologies, future research can explore more immersive online classroom experiences, further enhancing student learning outcomes and classroom interaction. Lastly, optimizing the algorithm to balance computational efficiency and image quality while reducing resource consumption will be another important direction for future research.

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