Automatic Color Control Method of Low Contrast Image Based on Big Data Analysis

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Abstract. In order to improve the imaging quality of 3D image with visual feature reconstruction, it is necessary to control the color of low contrast image automatically. A color automatic control technology of low contrast image based on 3D color space packet template feature detection is proposed, the automatic color control model of image based on big data analysis is constructed. RGB decomposition technology is used to extract the color components of low contrast images, and color space gray feature fusion algorithm is used to segment fusion of low contrast images to improve the feature pairing performance of color peak points of low contrast images. Combined with the color space block fusion information of low contrast image, the edge features of high oscillatory region are detected, and the color automatic control of low contrast image is realized. The simulation results show that the color automatic control of low contrast image can improve the peak signal-to-noise ratio (PSNR) of image output, improve the automatic color control ability and imaging quality of low contrast image.

Keywords: Big data analysis · Low contrast image · Fusion · Color automatic control

1 Introduction

With the continuous improvement of 3D visual feature reconstruction technology, computer image processing technology is used for 3D image processing of color image 3D model, combined with high quality information fusion processing of low contrast image. Improving the imaging quality of 3D color image 3D model and studying the dynamic information fusion technology of low contrast image have good application value in 3D digital image design and other fields [1]. The core of color automatic control of low contrast image is 3D image imaging and feature matching. Combined with block information fusion technology, color automatic control of low contrast image is carried out to improve the quality of information fusion, so as to improve the making level of three-dimensional model of color image [2].

Traditionally, the imaging techniques of low contrast image mainly include edge detection imaging algorithm based on gradient operator, 3D imaging algorithm based on wavelet transform. The important structural properties of the image are retained, and the optimal imaging design of the low contrast image is realized. According to the

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above design principle, the related literature is studied [3]. In reference [4], a dynamic fusion method of low contrast image based on multiple texture fusion is proposed. Fuzzy correlation feature detection method is used to extract gray features of multiple texture images and improve the performance of image fusion. However, the resolution of dynamic fusion of low contrast images is low. In reference [5], an image dynamic fusion method based on edge fuzzy feature extraction is proposed, which is inefficient in dealing with large-scale images. In order to solve the above problems, a color automatic control technology of low contrast image based on 3D color space packet template feature detection is proposed in this paper. Firstly, virtual scene reconstruction technology is used for low contrast image acquisition and feature projection processing. The gray eigenvalue reconstruction and edge profile detection of low contrast image is carried out, the color component of low contrast image is extracted by RGB decomposition technology, and the low contrast image is segmented fusion with color space gray feature fusion algorithm. Then the edge features of the high oscillatory region are detected by combining the color space block fusion information of the low contrast image, and the control feature quantity of the visual region of the image is calculated to realize the automatic color control of the low contrast image. Finally, the simulation results show that the proposed method has excellent performance in improving the quality of dynamic information fusion of low contrast images.

2 Low Contrast Image Imaging and Preprocessing

2.1 Vector Model of Low Contrast Image

In this paper, the first step of color automatic control of low contrast image is to construct the vector model of low contrast image. Firstly, the virtual scene reconstruction technology is used for low contrast image acquisition and feature projection processing. The feature distribution model of low contrast image is constructed by Cartesian space reconstruction method [6]. In this paper, the edge profile of low contrast image is detected by multivariate linear fusion method, and the multi-linear fusion model of low contrast image is constructed. In the process of feature decomposition of low contrast image, the feature decomposition value of low contrast image vector composed of scalars $A = \{a_i\}_{i=1}^{N}$ is set up, and the edge pixel decomposition is carried out by using multi-feature fusion technology. The vector model of low contrast image satisfies the following constraints:

$$s \leq t \Rightarrow \kappa^s(A) \leq \kappa^t(A) \tag{1}$$

$$\lim_{P \to +\infty} \kappa^P(A) = \max_i a_i \tag{2}$$

$$\lim_{P \to -\infty} \kappa^P(A) = \min_i a_i \tag{3}$$

Considering the gray pixel level f of the low contrast image, the gray invariant moment feature decomposition method is used to obtain that any gray pixel point of the image is (x, y), and the low contrast image of different attribute categories is projected into the elliptical feature distribution space. The description is shown in Fig. 1.

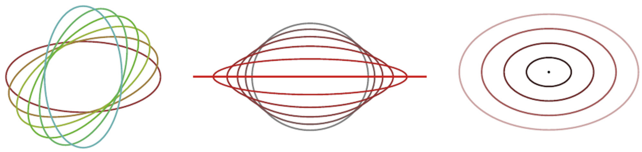


Fig. 1. Edge detection vector model of low contrast image

In Fig. 1, the Harris corner distribution information for low and medium contrast images is expressed as follows:

$$h = \theta/\pi,\ s = 1 - \frac{\lambda_2}{\lambda_1},\ v = \lambda_1 + \lambda_2 \tag{5}$$

Where, θ is the elliptical principal square angle of low contrast image in feature reconstruction space, and λ_1, λ_2 are long and short half axis length, respectively. Through the above design, the vector model of the surface contour feature distribution of low contrast image is obtained. In order to combine the gray pixel information fusion technology to reconstruct the feature, the adaptive information fusion and feature extraction ability of low contrast image is improved.

2.2 Noise Reduction Filtering and Smoothing Processing of Low Contrast Image

Based on the above dynamic information reconstruction and feature extraction of low-contrast images, the image noise reduction filtering process is carried out by using the similarity feature extraction method [7]. In this paper, the information enhancement processing of low-contrast images is realized by using the multiscale Retinex algorithm, and the pixel distribution sequence of the low-contrast images is:

$$Dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E} w((v_i, v_j)) \tag{6}$$

In the above formula, $n = 1, 2, \ldots, T$, represents the number of iterative steps, and the weight coefficient of the feature pixel distribution sequence of low contrast image is $w(e)$. The feature is input into the wavelet filter, and the sub-set of gray pixel $C \subseteq V$,F is formed in the main direction of the imaging. The color and texture joint detection method is used to reconstruct the feature points of the low contrast image by means of the method of joint detection of the color and texture of the image. In the connected region of the image, the gray pixel decomposition method is used to obtain the gray pixel value $I(i,j)$ of the image, which can be represented by $I_{(k)}(i,j)$ as follows:

$$I(i,j) = \sum_{k=1}^{P} I_{(k)}(i,j) \times 2^{k-1} \tag{7}$$

According to the spatial distribution attribute of low contrast color image, the low contrast color image acquisition and feature projection processing are carried out by using virtual scene reconstruction technology, and the gray eigenvalue reconstruction and edge outline detection of low contrast color image are carried out. The low contrast color image is divided into M × N sub-blocks $G_{m,n}$, using the second-order two-dimensional vector constraint control method, and the low contrast color image feature enhancement output is obtained as follows:

$$G_{m,n} = \begin{pmatrix} g_{(m,n)}(1,1) & g_{(m,n)}(1,2) \\ g_{(m,n)}(2,1) & g_{(m,n)}(2,2) \end{pmatrix} \quad m = 1, 2, \ldots, M; n = 1, 2, \ldots, N; \tag{8}$$

Where in

$$g_{(m,n)}(u,v) = I_{(k)g}[2(m-1)+u, 2(n-1)+v] \quad u \in \{1,2\}; v \in \{1,2\}; \tag{9}$$

Where, u is the gray pixel value of low contrast color image $p(i,j)$ in texture joint distribution, and (i,j) is the coordinate value of the corresponding pixel. Through the above algorithm design, the noise reduction filtering and smoothing processing of low contrast color image are realized [8].

3 Optimization of Color Automatic Control for Low Contrast Color Image

The spatial information feature extraction method is used to combine and analyze the low contrast color image. By smoothing, the parallax analysis of low contrast color image is realized. The mathematical expression for designing the function of low contrast color image is expressed as follows:

$$g_i^* = \begin{cases} Rs_j \ , & z \leq i \leq x - y \\ g_i \ , & otherwise \end{cases} \tag{10}$$

Where, R is a specification constant, and a low contrast color image information fusion method based on gray histogram 3D reconstruction is used to construct the dynamic information fusion feature quantity of low contrast color image. Set the gray pixel level of the pixel component at the first bit, and calculate the two-dimensional gray eigenvalues of the low contrast color image, where the maximum gray value of the low contrast color image is:

$$n_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\gamma}} \tag{11}$$

The color space gray feature fusion algorithm is used to segment the low contrast color image, and the partial derivative of the center v_i in the outline wave domain is obtained. according to the correlation feature distribution of the dynamic information fusion of the low contrast color image, when (x_{i+1}, y_{i+1}) is on the right side of the midpoint $(x_i + \frac{1}{2}, y_{i+1})$, take the pixel PE1. The Euler-Lagrangian equation of low contrast color image in phase space (x_{i+1}, y_{i+1}) is obtained by using gray histogram reconstruction method.

$$F_d - \frac{d}{dx}F_{d_x} - \frac{d}{dy}F_{d_y} = 0 \tag{12}$$

According to the reconstruction results, the pixel gray value at the (x, y) frame m of the low contrast color image $F_m(x, y)$ is obtained. The joint feature output of the block fusion of the low contrast color image is as follows:

$$\hat{x}(k/k) = \sum_{j}^{m} \hat{x}^i(k/k)u_j(k) \tag{13}$$

$$P(k/k) = \sum_{j}^{m} u_j(k/k)\{P^j(k/k) + [\hat{x}^j(k/k) - \hat{x}(k/k)][\hat{x}^j(k/k) - \hat{x}(k/k)]^T\} \tag{14}$$

The low contrast color image is interfered by zero mean additive white noise. the maximum gray value outline point marking information of low contrast color image is obtained as follows:

$$g(x, y) = f(x, y) + \varepsilon(x, y) \tag{15}$$

In the process of reconstruction of low contrast color image, the correlation detection template matching function $f(g_i)$ of constructing low contrast color image is as follows:

$$f(g_i) = c_1\tilde{\lambda}_i \sum_{j=0}^{N_{np}} \frac{\rho_j \vec{v}_{ij}}{\left|\vec{v}_{ij}\right|^{\sigma_1} + \varepsilon} \Bigg/ \sum_{j=0}^{N_{np}} \frac{\rho_j}{\left|\vec{v}_{ij}\right|^{\sigma_1} + \varepsilon} \tag{16}$$

Combined with the active contours detection method [9], the gray histogram output eigenvalues of low contrast color image information fusion are obtained to meet $\min_{c\in\{r,g,b\}} (\min_{y\in\Omega(x)} (\frac{I^c(y)}{A})) \to 1$, at this time $\tilde{t}(x) \to 0$. Because of $A > 0$, the distribution field of low contrast color images is obtained as follows:

$$df_{t+1}(i, j, k) = \rho df_t(i, j, k) + (1 - \rho)df_{t-1}(i, j, k) \tag{17}$$

In the formula, ρ represents the correlation coefficient of the pixel matching window of the low contrast color image, realizes the edge detection of the low contrast color image, and completes the color automatic control of the low contrast color image [10].

4 Analysis of Simulation Experiment

In order to test the performance of this method in the dynamic information fusion of low contrast color image, the simulation experiment is carried out, and the experiment is designed by Matlab 7. In this experiment, the color image of a multimedia album product is selected. The test data set of low-contrast color images is Corel standard low-contrast color images, the sample set of low-contrast color images is 2000, and the distribution of edge contour pixels of low-contrast color images is 120 * 200. The color texture matching coefficients of low contrast color image are 0.16, 0.24 respectively. According to the above simulation parameters, the test sample object of low contrast color image is shown in Fig. 2.

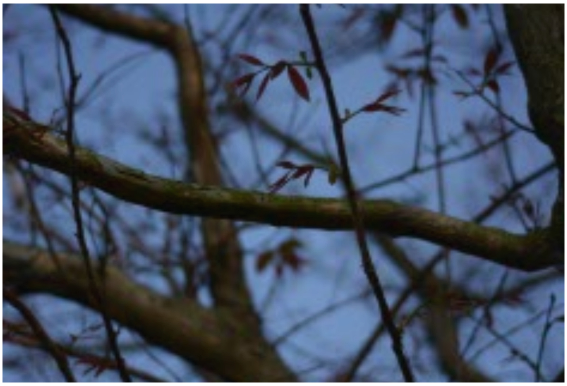


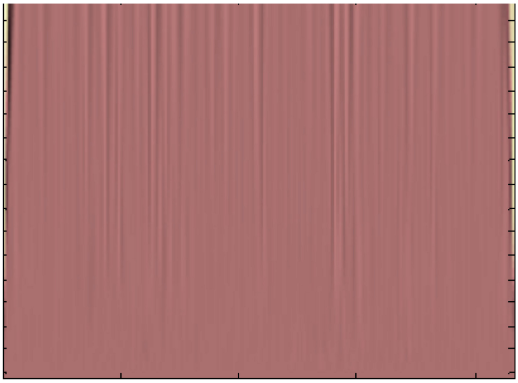
Fig. 2. Low contrast color image test object (Color figure online)

Taking the low contrast color image of Fig. 2 as the test sample, the information fusion is carried out, and the RGB decomposition results of the information fusion are shown in Fig. 3.

As can be seen from Fig. 3, the three colors of RGB can be clearly decomposed by using the method in this paper, and the colors after decomposition are uniform, with good effect. It fully shows that the information fusion effect of this method is ideal. Finally, the optimized low contrast color image is shown in Fig. 4.

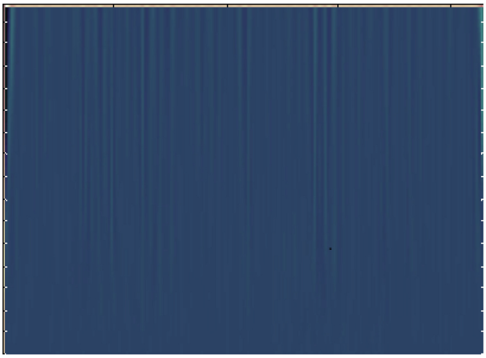
The output signal-to-noise ratio (SNR) of low contrast color image fusion is tested by different methods, and the comparison results are shown in Table 1.

According to the data in Table 1, with the increase of pixel value, the signal-to-noise ratio (SNR) of the SVM method increases slightly. When the pixel value reaches 800, the SNR is 42.3 dB. With the increase of pixel value, the signal-to-noise ratio of PCA is slightly larger than that of SVM. When the pixel value reaches 800, the signal-to-noise ratio is 54.3 dB. The signal-to-noise ratio of the method in this paper changes greatly. When the pixel value reaches 800, the signal-to-noise ratio is 72.3 dB. The experimental results show that the color automatic control of low contrast color image can improve the PSNR of low contrast color image and improve the dynamic imaging quality.



(a)R component product

(b)G component product



(c)B component product

Fig. 3. Dynamic information fusion output of low contrast color image (Color figure online)

Fig. 4. Optimized low contrast color image (Color figure online)

Table 1. Output SNR comparison (dB).

Pixel value	Proposed method	SVM	PCA
200	34.6	21.2	26.5
400	56.8	26.5	32.7
600	69.5	37.6	42.4
800	72.3	42.3	54.3

5 Conclusions

In this paper, a color automatic control technology of low contrast image based on 3D color space packet template feature detection is proposed, the automatic color control model of image based on big data analysis is constructed. RGB decomposition technology is used to extract the color components of low contrast images, and color space gray feature fusion algorithm is used to segment fusion of low contrast images to improve the feature pairing performance of color peak points of low contrast images. Combined with the color space block fusion information of low contrast image, the edge features of high oscillatory region are detected, and the color automatic control of low contrast image is realized. The simulation results show that the color automatic control of low contrast image can improve the SNR of image output, improve the automatic color control ability and imaging quality of low contrast image. This method has good application value in color automatic control of low contrast image. This method can effectively improve the level of 3d model making of color image. However, the control stability of this method has not been tested in this experiment. In the future, the control stability of this method will be further studied in the case of interference.

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