Research on Visual Display Method of Virtual Experimental Elements Based on Big Data Technology

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Abstract. In order to solve the problem that the visual simulation image of virtual experimental element is missing in the reconstruction module of virtual experimental element, and the reconstruction accuracy of virtual experimental element is not good. A visual display method of virtual experimental element visual simulation image based on big data technology and virtual visual reconstruction is proposed. Firstly, the information transmission model of virtual experimental element visual simulation image is constructed. Then the 5-level wavelet decomposition method is used to decompose and fuse the visual simulation images of virtual experimental elements, and big data fusion technology is used to reconstruct the visual information of virtual experimental elements. The visual simulation image visualization of virtual experimental elements is realized. The simulation results show that this method has good visual display performance and high feature fusion degree in the reconstruction and modeling of virtual experimental element visual simulation image, and has high value in the application of virtual experimental element visual display and digital reconstruction.

Keywords: Big data technology · Virtual experimental elements · Visual display

1 Introduction

With the development of image processing technology, the visual display of virtual experimental elements by using big data technology can improve the visual reconstruction and recognition ability of virtual experimental elements. The application of virtual visual simulation imaging has a broad application prospect in the scientific and technological fields such as visual display and display of virtual experimental elements [1]. The virtual experimental element visual simulation image is used to reconstruct and model the virtual experimental element, and the digital reproduction and visual display of the virtual experimental element are realized. The research on visual display method of virtual experimental elements based on big data technology and virtual scene reconstruction has been paid more and more attention [3].

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The visual display of the virtual experiment element by using the virtual scene simulation method is mainly to carry out three-dimensional scattered point recombination and visual display through the three-dimensional organization model, and the template matching is carried out in combination with the statistical shape model (SSM) method, the visual display and reconstruction of the pixel information points of the visual simulation image of the virtual experimental element are realized, a point distribution model (PDM), The LWT wavelet decomposition reconstruction method and the irregular triangular network modeling method and the like, the method uses the laser beam to scan the object to carry out three-dimensional characteristic reconstruction and information modeling of the image, improves the texture information and the pixel point characterization ability of the image, in which, the reference [3] proposes an image modeling method based on a transmission space and a color texture correlation image segmentation, the reconstruction precision of the image is improved, the signal-to-noise ratio of the digital image output is high, but the calculation cost of the virtual experimental element visual simulation image processing algorithm is large, and the modeling real-time of the laser imaging is not good [4]. A three-dimensional reconstruction and modeling method of an ultrasonic image based on a multi-scale Retinx image denoising and enhancement processing is adopted to realize the visual display of the three-dimensional ultrasound image [5], by denoising and enhancing the ultrasonic image, the feature point tracking and calibration capability of the three-dimensional scanning image is highlighted, but the method is easy to be interfered by the external disturbance information in the modeling of the three-dimensional image, and the modeling effect of the output image is not good when the interference intensity is large, The accuracy is not high.

In view of the above problems, a visual simulation image display method based on large data technology and virtual scene reconstruction is presented in this paper. Firstly, the information conduction model of the virtual experiment element visual simulation image is constructed, and the priority judgment of the sub-space structure block matching and the visual display of the virtual experimental element information missing area is carried out. Then the feature decomposition and information fusion of the visual simulation image of the virtual experimental element are carried out by adopting the wavelet decomposition method, and the visual information reconstruction of the virtual experimental element is carried out to realize the visual display of the visual simulation image of the virtual experimental element. Finally, the performance test is carried out by the simulation experiment, and the superiority of the algorithm in the information reconstruction and modeling of the visual simulation image of the virtual experimental element is shown.

2 Information Conduction Model and Image Preprocessing

2.1 Visual Simulation Image Information Transmission Model of Virtual Experimental Elements

By constructing the information transmission model of the visual simulation image of the virtual experimental element, the information acquisition and feature extraction of the visual simulation image of the virtual experimental element are carried out. in the acquisition of the visual simulation image of the virtual experimental element, the reflected beam is reflected to the laser output port by using the virtual experimental element of laser beam scanning [6]. The pixel feature arrangement sequence is different and the three-dimensional laser imaging is obtained. In the information reconstruction of the visual simulation image of the virtual experimental element, the size of the sub-block of the modeling feature area is selected. The visual simulation image of each M < N virtual experimental element is divided into rectangular blocks of ((M/16) + 1) * ((N/16) + 1), as shown in Fig. 1.

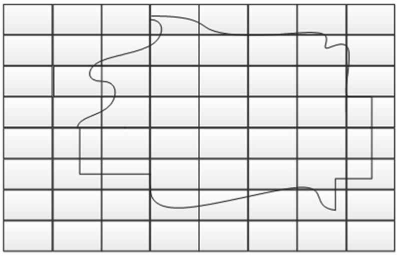


Fig. 1. Visual simulation image rectangular block of virtual experimental element

Selecting the most similar matching block to perform three-dimensional feature reconstruction on the image to be visualized display area to obtain the information conducting pixel set of the internal points of each sub-block, the point on the boundary is determined by the similarity degree of the dark primary color current block in the visual simulation image of the virtual experimental element and the display block to be visualized, the information conducting priority characteristic matching is carried out, and when the information conduction iteration is carried out, The related elements of the adjacent blocks of the visual simulation image of the virtual experimental element need to be gradient-smoothed [7]. The affine invariant moment feature extraction is carried out with the affine invariant kernel function of 3 * 3, and the affine invariant moment has the invariance of the rotation translation and the scale, so that the feature mining can be carried out through the template matching of the image, and the template size m * n determines the image processing template. The visual simulation image texture information of the virtual experimental element in the unit time is $G(x, y; t)$, and the intuitionistic fuzzy set of the visual simulation image texture sub-space of the virtual experimental element is defined as the conduction function as follows:

$$p(x, t) = \lim_{\Delta x \to 0} [\sigma \frac{u - (u + \Delta u)}{\Delta x}] = -\sigma \frac{\partial u(x, t)}{\partial x} \tag{1}$$

The ergodic characteristics of the image features in the scene are obtained, and the information flow density vector of the virtual experimental element visual simulation image texture structure is obtained as follows:

$$p(x, y; t) = -\sigma \nabla u(x, y; t) = -\sigma G(x, y; t) = -\sigma [G_x(x, y; t)i + G_y(x, y; t)j] \tag{2}$$

In which, i, j is a unit direction vector, and based on the visual significance of the target in the visual display process of the virtual experimental element, the visual simulation image structure texture information conduction model of the virtual experimental element is constructed, and the rare degree in the whole scene is obtained, And the global rare degree of the visual simulation image of the virtual experimental element is obtained by adopting the zero-uniform traversal [8]. On the basis of the analysis, the state equation of the texture information conduction model of the visual simulation image of the virtual experimental element is described as:

$$\begin{cases} f(x_1, x_2) = r_1 x_1 (1 - \frac{x_1}{N_1} - \sigma_1 \frac{x_2}{N_2}) = 0 \\ g(x_1, x_2) = r_2 x_2 (1 - \sigma_2 \frac{x_1}{N_1} - \frac{x_2}{N_2}) = 0 \end{cases} \tag{3}$$

In the above formula, r_1 and r_2 represent the local and global salient feature sets of the virtual experimental element visual simulation image, σ_1 represents the mean value of the image feature, and N_1, N_2 are the noise component.

On the basis of constructing the information transmission model of the virtual experimental element visual simulation image, the information collection and feature analysis of the virtual experimental element visual simulation image are realized, which provides an accurate data basis for the virtual experimental element modeling [9].

2.2 Priority Determination of Visual Simulation Image Reconstruction of Virtual Experimental Elements

In the information transmission model, the priority of visual display of the information missing area of the virtual experimental element visual simulation image is determined by using the sub-spatial structure block matching method [10]. The subspatial structure model of visual simulation image of virtual experimental element is designed as shown in Fig. 2.

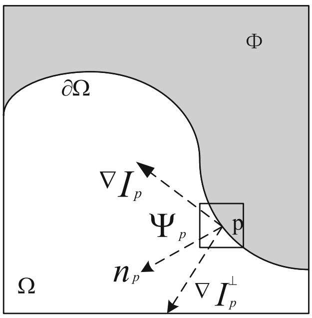


Fig. 2. Subspatial structure model of image

In Fig. 2, Ω represents the absence of information from the visual simulation image of the virtual experimental element (the white area), ϕ represents the information intact area (gray area) of the virtual experimental element graph, $\partial\Omega$ represents the edge line of the information intact area and the information missing area, p represents the pixel point of the virtual visual simulation of the virtual experimental element on $\partial\Omega$, and Ψ_p represents the fuzzy membership degree set of the visual pixel point of the virtual experimental element visual simulation image centered on the SF point. The priority of 3D image reconstruction in the subspatial structure of the image [11].

Firstly, the priority coefficient of the block to be rebuilt is calculated, the edge pixel points of the virtual experimental element visual simulation image are updated, and the multi-dimensional search method of subspace feature information is adopted. The information points of the virtual experimental element visual simulation image are searched by gray level until there are no edge pixels. The mean value of the features is used as the pheromone in the sub-spatial structure block, and the global rarity feature decomposition of the virtual visual simulation imaging is carried out. The iterative equation of feature decomposition is described as follows:

$$u^{(n+1)}(x,y) = u^{(n)}(x,y) + \delta u_1^{(n)}(x,y) \tag{4}$$

$$u_1^{(n)}(x,y) = M\Delta_s u^{(n)}(x,y) + N\Delta_t u^{(n)}(x,y;d) \tag{5}$$

It is assumed that the size of the visual simulation image of the virtual experimental element to be rebuilt is that the size of the $m \times n$, feature scale block Ψ_p is $s \times s$. Through the matching of the sub-spatial structure blocks, the priority determination of the unknown pixel points of the virtual experimental element visual simulation image is realized. The priority ranking of pixel points satisfies:

$$P(|\overline{x_T} - K| < \frac{\lambda_\chi \sigma}{\sqrt{N}}) \approx \frac{2}{\sqrt{2\pi}} \int_0^{\lambda_\chi} e^{-\frac{1}{2}t^2} dt = 1 - \chi \tag{6}$$

Wherein, $\overline{x_T}$ is the mean value of local contrast window of virtual experimental element visual simulation image, χ is significance weight, K is global rarity coefficient, σ is threshold.

3 Improved Implementation of Image Processing Algorithm

3.1 Image Feature Decomposition and Information Fusion of Visual Simulation of Experimental Elements

On the basis of the above information transmission model construction and the priority determination of virtual experimental element visual simulation image reconstruction, the visual display design of virtual experimental element is carried out. In this paper, a visual display method of virtual experimental element visual simulation image based on big data technology and virtual visual reconstruction is proposed [12]. The 5-level wavelet decomposition method is used to decompose and fuse the visual simulation images of virtual experimental elements. For the visual simulation images X and Y of two virtual experimental elements in the information transmission model, The SSIM value of the similarity between the visual simulation images of the two virtual experimental elements is defined as follows:

$$SSIM = [l(X,Y)]^{\alpha}[c(X,Y)]^{\beta}[s(X,Y)]^{\gamma} \tag{7}$$

The 5-level wavelet decomposition is used, the whole frequency band of the virtual experimental element visual simulation image can be divided into six. According to the wavelet decomposition CSF characteristic curve, the grid vertexes of the virtual experimental element visual simulation image reconstruction are determined. Six weights are taken for the scattered three-dimensional sampling points. Through the 5-level wavelet decomposition of the visual simulation image of the virtual experimental element, the structure similarity characteristics of the wavelet of the visual display image of the virtual experimental element are obtained as follows:

$$ws(X,Y) = \frac{2\left|\sum_{i=1}^{N} c_{x,i}c_{y,i}\right| + K}{\sum_{i=1}^{N} |c_{x,i}|^2 + \sum_{i=1}^{N} |c_{y,i}|^2 + K} \tag{8}$$

The gray information contrast of $l(X,Y)$, virtual experimental elements visually displayed by virtual experimental elements is characterized by the feature structure of $c(X,Y)$, virtual experimental elements. The results of feature decomposition and information fusion of images obtained by wavelet decomposition of $s(X,Y)$, are as follows:

$$l(X,Y) = (2u_x u_y + C_1)/(u_x^2 + u_y^2 + C_1) \tag{9}$$

$$c(X,Y) = (2\sigma_x\sigma_y + C_2)/(\sigma_x^2 + \sigma_y^2 + C_2) \tag{10}$$

$$s(X,Y) = (\sigma_{xy} + C_3)/(\sigma_x\sigma_y + C_3) \tag{11}$$

Wherein, u_x, u_y are the pixel intensity mean of image X, Y, σ_x, σ_y are the standard deviation of local contrast window of X, Y, σ_{xy} is edge information covariance, and C_1, C_2, C_3 are global rarity constants.

3.2 Realization of 3D Reconstruction of Visual Simulation Image of Virtual Experimental Element

On the basis of the above five-level wavelet decomposition method for the feature decomposition and information fusion of the visual simulation image of the virtual experimental element, the visual information reconstruction of the virtual experimental element is carried out. The visual simulation image visualization of virtual experimental elements is realized, and the parameters of wavelet structure similarity WSSIM of visual simulation images of two virtual experimental elements are calculated.

$$WSSIM = [l(X,Y)]^{\alpha}[c(X,Y)]^{\beta}[ws(X,Y)]^{\gamma} \tag{12}$$

and through the multi-scale decomposition of the global rare degree, the energy of the two direction sub-bands in the information conduction model of the visual display imaging of the virtual experimental element is respectively:

$$E_{HL_i} = \sum_j (c_j^{HL_i})^2, E_{LH_i} = \sum_j (c_j^{LH_i})^2 \tag{13}$$

The weight of the global and local operations is updated by the fusion of the similarity of the SSIM, and the image is subjected to convolution with a Gaussian kernel function of different scales, so that the reconstruction output of the visual simulation image of the virtual experimental element is obtained as follows:

$$\omega_{HL_i} = \frac{E_{HL_i}}{E_{HL_i} + E_{LH_i} + E_{HH_i}} \tag{14}$$

$$\omega_{LH_i} = \frac{E_{LH_i}}{E_{HL_i} + E_{LH_i} + E_{HH_i}} \tag{15}$$

$$\omega_{HH_i} = \frac{E_{HH_i}}{E_{HL_i} + E_{LH_i} + E_{HH_i}} \tag{16}$$

The probability of each pixel variance in the whole diagram is calculated, the significance of the characteristic points of virtual experimental elements is measured, and the structural similarity characteristics of the images in the high-frequency subband of the wavelet is calculated as:

$$WSSIM_{H_i} = \omega_{HL_i} \cdot WSSIM_{HL_i} + \omega_{LH_i} \cdot WSSIM_{LH_i} + \omega_{HH_i} \cdot WSSIM_{HH_i} \tag{17}$$

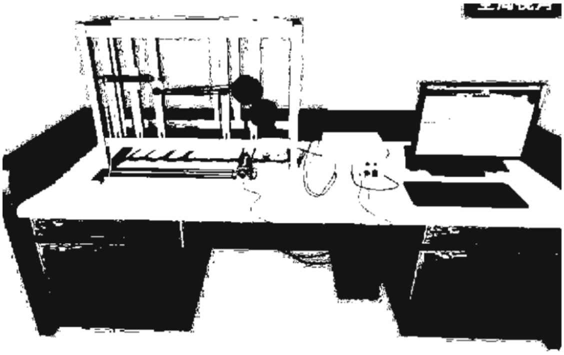
Thus, the wavelet structure similarity of the visual simulation image of the virtual experimental element is calculated, which is recorded as FWSSIM:.

$$FWSSIM(X,Y) = \frac{\omega_{LL} \cdot WSSIM_{LL} + \sum_{i=1}^{5} (\omega_{H_i} \cdot WSSIM_{H_i})}{\omega_{LL} + \sum_{i=1}^{5} \omega_{H_i}} \tag{18}$$

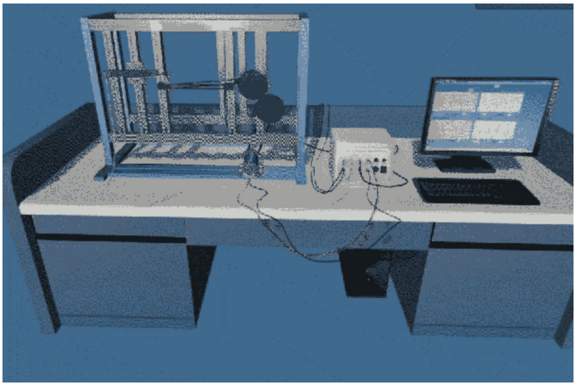
Based on the above processing, the visual display of virtual experimental elements is realized.

3.3 Simulation Experiment and Result Analysis

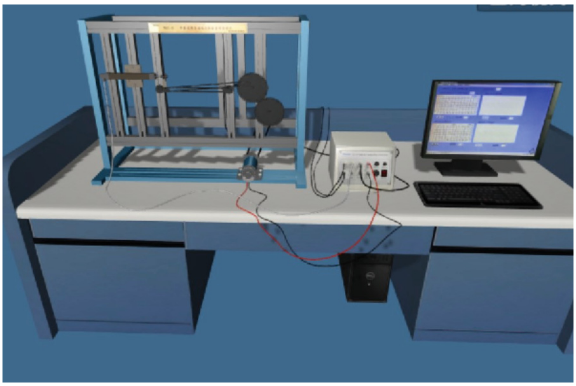
In order to verify the effectiveness of the algorithm, the visual simulation images of different types of virtual experimental elements are used for reconstruction simulation. The test platform is, Pentium (R) 4 CPU 3.00 GHz and 1 G memory of windows 10



(a) Original experimental element image



(b) Reconstruction with traditional method



(c) Reconstruction with proposed method

Fig. 3. Virtual scene simulation modeling and simulation of virtual experimental elements

system. Using Matlab simulation software, the algorithm is programmed and designed. The experimental samples are taken from the visual simulation image database of Criminisi large virtual experimental elements, and the sub-spatial structure block matching and visual display of virtual experimental element information missing area are carried out. The information feature sampling and information fusion of the virtual experimental element visual simulation image are realized, the search step size N = 4 is set, and the sample block matching template of the virtual experimental element image is 9×9. The window sizes are 3 * 3, 5 * 5, 9 * 9, 17 * 17. According to the above simulation environment and parameter setting, the original virtual experimental element image is obtained, and the virtual visual simulation reconstruction results of the virtual experimental element are carried out by using this method and the traditional method, as shown in Fig. 3.

It can be seen from the diagram that the virtual visual scene reconstruction of virtual experimental elements is carried out by using this method, and the visual display and reconstruction quality of the image is better, which improves the imaging quality of the image, in order to describe the performance of the algorithm quantitatively. The root mean square error (RMSE) and execution time of peak signal-to-noise ratio (PSNR), reconstruction are used as test indexes, and the comparative results are shown in Table 1. The results show that the virtual scene simulation modeling of virtual experimental elements is carried out by using this method, and the peak signal-to-noise ratio of the output image is high, which indicates that the imaging quality of the reconstructed image is better and the root mean square error is low. The results show that the feature extraction accuracy of virtual visual simulation imaging is high and the execution time is short, which shows that the real-time performance of this method is better and the performance index is superior to the traditional method.

Table 1. Comparison of the modeling performance of the virtual experimental element of the virtual scene simulation.

Test pattern	PSNR/dB		RMSE		E-time/ms	
	Proposed method	Traditional method	Proposed method	Traditional method	Proposed method	Traditional method
1	55.6	32.1	0.025	0.168	3.1	43.7
2	73.4	44.2	0.046	0.114	3.4	32.5
3	48.6	42.4	0.058	0.254	2.7	12.4
4	66.4	51.6	0.028	0.318	2.3	18.6

4 Conclusions

In this paper, a visual display method of virtual experimental element visual simulation image based on big data technology and virtual visual reconstruction is proposed. Firstly, the information transmission model of virtual experimental element visual simulation image is constructed, and then the feature decomposition and information fusion of virtual experimental element visual simulation image are carried out by using wavelet decomposition method, and the visual information reconstruction of virtual experimental element is carried out. The visual simulation image visualization of virtual experimental elements is realized. The results show that the visual display performance of virtual experimental element scene simulation image reconstruction modeling is better, the PSNR of the output image is improved, the reconstruction error is reduced, and the image quality is improved. The method in this paper has a good application value in the visual display and reconstruction of experimental elements.

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