Image detail enhancement of two-dimensional animation scene based on dual domain decomposition

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Abstract: In order to improve the performance of traditional image detail enhancement methods in distortion, real-time and detail information error, a new two-dimensional animation scene image detail enhancement method based on dual domain decomposition is proposed in this paper. Firstly, the two-dimensional animation scene image is divided into basic image domain and image detail domain by double domain decomposition. Then, the basic image domain is reconstructed and the image detail domain is denoised. Finally, the image detail enhancement is realised by fusing the results of information reconstruction and denoising. The simulation results show that the enhancement process of this method takes at least 11 minutes, and the maximum local standard deviation can reach 0.975, which is closer to 1.000, indicating that this method has the advantages of low distortion, high real-time performance and small detail information error.

Keywords: two dimensional animation scene image; dual domain decomposition; basic image domain; image detail domain; information reconstruction; denoising; Information fusion; detail enhancement.

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1 Introduction

With the rapid update of digital multimedia technology, two-dimensional image technology is becoming more and more mature. At the same time, two-dimensional and three-dimensional image processing has become a research hotspot (Yan et al., 2020). Space is formed by the encirclement between shapes. Compared with the entity form, although the concept of space is difficult to express concretely, as a form, it can be expressed visually (Shen et al., 2019). In animated films, the three-dimensional space must eventually be represented on the two-dimensional plane. The animation image established in the two-dimensional scene is the two-dimensional animation scene image (Lin, 2021). However, in the process of generating two-dimensional animation scene map, due to the influence of the external environment, it is easy to lead to poor quality (Li, 2020; Yan et al., 2021; Jiang et al., 2021). In this case, making the detail information in the image more obvious through enhancement processing has become an important visual processing technology.

Cao and He (2020) propose an image detail enhancement method based on weighted guided filter layering. Based on the layered processing and filtering of the original image, this method separates the basic image and detail information, then adds an edge detection operator to the guided filtering to retain the image edge information as much as possible, and makes the image detail information more obvious by using AHE algorithm and Laplace sharpening filtering. However, this method has high image distortion. In reference (Long and He, 2020), an image enhancement method based on multi-layer fusion and detail recovery is proposed. This method creates Retinex enhancement layer, brightness enhancement layer and detail highlight layer in image space. In the Retinex enhancement layer, the weighted guided filtering is used to weaken the influence caused by the halo phenomenon. In the brightness enhancement layer, the normalisation function is used to improve the image brightness. In the detail highlighting layer, the image details are highlighted on the basis of optimising the artificial bee colony algorithm. In the detail prominent layer, the method also uses gamma correction to weaken the local detail blur. Although this method can effectively enhance the image details, it has the disadvantage of long processing time, resulting in poor real-time performance. In reference (Wei and Ouyang,

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2021), an image enhancement method based on bright pass bilateral filter is proposed. In this method, the illumination component of the image is obtained by bilateral filtering of different scales, and then the reflection component of image details is obtained by Retinex theory. Then the information degree of illumination component and reflection component is improved by multi-layer brightness a priori mapping method, so as to obtain the enhanced image. However, in practical application, it is found that after the enhancement processing of this method, the local detail information of the image has the problem of large error.

Aiming at the shortcomings of traditional methods, this paper designs a two-dimensional animation scene image detail enhancement method based on dual domain decomposition. The design idea of this method is as follows:

Firstly, the Gaussian filter is used for double domain decomposition, the two-dimensional animation scene image is input into the Gaussian filter, the basic image domain is separated after smooth filtering, and the image detail domain is separated according to the difference between the original image and the basic image domain;

Secondly, the information of the basic image domain is reconstructed, and the high-dimensional vectors in the basic image domain are processed by extracting the block features of the basic image domain on the basis of back projection.

Then, wavelet transform is used to denoise the image detail domain, and the specific location of the noise is obtained and cleaned.

Finally, the results of information reconstruction and denoising are fused to realise image detail enhancement.

2 Image detail enhancement of two-dimensional animation scene based on dual domain decomposition

2.1 Two domain decomposition of two-dimensional animation scene image

Based on the dual domain decomposition processing, this research realises the detail enhancement processing of two-dimensional animation scene images.

Dual domain decomposition is to divide the image into two parts, one is the basic image domain, the other is the image detail domain. The basic image domain includes the basic information of the image, and the detail information and noise information of the package image in the image detail domain (Dai et al., 2019). Finally, the enhanced image in the basic image domain and the detail image in the image detail domain are fused to complete the overall detail enhancement processing.

In this study, Gaussian filter is used to complete dual domain decomposition. The two-dimensional animation scene image is input into the Gaussian filter, the basic image domain is separated after smooth filtering, and the image detail domain is divided according to the difference between the original image and the basic image domain.

The pre decomposition process of Gaussian filter is as follows:

$$G = \frac{1}{2\pi\varepsilon^2}\exp\left(-\frac{a^2+b^2}{2\varepsilon^2}\right) \tag{1}$$

In formula (1), G represents two-dimensional Gaussian kernel function (Tian et al., 2020), and its variance is ε. a and b represent the position information in the horizontal and vertical directions respectively.

$$K = p_{bi} + p_{ddi} + p_{oi} * G \tag{2}$$

In formula (2), p_{oi} represents the original image information corresponding to each colour channel, p_{bi} represents the basic image domain information corresponding to each colour channel, p_{ddi} represents the image detail domain information corresponding to each colour channel, $S \in \{R, G, B\}$ represents the three colour channels of the two-dimensional animation scene image, and * represents convolution operation.

Through image double domain decomposition, all the noise in the two-dimensional animation scene image can be retained in the image detail domain, so as to avoid being affected by noise amplification when extracting the information features of the basic image domain.

2.2 Basic image domain information reconstruction

On the basis of dividing the image into two domains, the detail information in the basic image domain is strengthened by means of information reconstruction in the basic image domain. Therefore, based on the construction of the numerical imaging model of the basic image domain of the two-dimensional animation scene image, the difference in the basic image domain is formed by defining the guiding function, so as to complete the information reconstruction (Son et al., 2019). The specific reconstruction process includes: pre-processing, feature learning, model training and model construction.

a Basic image domain pre-processing. Due to the environmental impact such as system errors, if some original basic image domain samples are reconstructed without processing, the data characteristics in the output results of the basic image domain numerical imaging model will be not obvious. Therefore, the process of processing the basic image domain is very important. In this study, the structure parallel to the linear type is selected to deal with the corrosion reflection component, so as to effectively eliminate the influence of difference in the basic image domain.

b Feature learning. The main goal of feature learning is to make the basic image domain numerical imaging model more accurate, improve operation efficiency and master more obvious basic image domain information features (Chen et al., 2020).

c Basic image domain numerical training. Through many training and calculation data, a series of basic image domain values that meet the expectation and target optimisation are finally generated.

d Model building. Using the basic image domain values obtained through the above processing, the numerical imaging model is constructed as follows:

$$M = -\frac{p^2 + q^2}{2\varepsilon\tau^2} \tag{3}$$

where M represents the numerical imaging model in the basic image domain, τ represents the range compression parameter in the non-significant image region, p and q represent pixels in the basic image domain respectively (Ge et al., 2020).

Different from the image detail domain, the pixels in the basic image domain have a compromise processing method of spatial proximity. When reconstructing the information in the basic image domain, the edge information is easy to produce fuzzy artefact information (Fu et al., 2020). Therefore, this study uses guided filtering to establish a linear constraint relationship between pixels, and then uses a local window to guide pixels to generate edge gradient and control the forward rotation process of pixels, so as to control the generation of artefact information in the image detail domain.

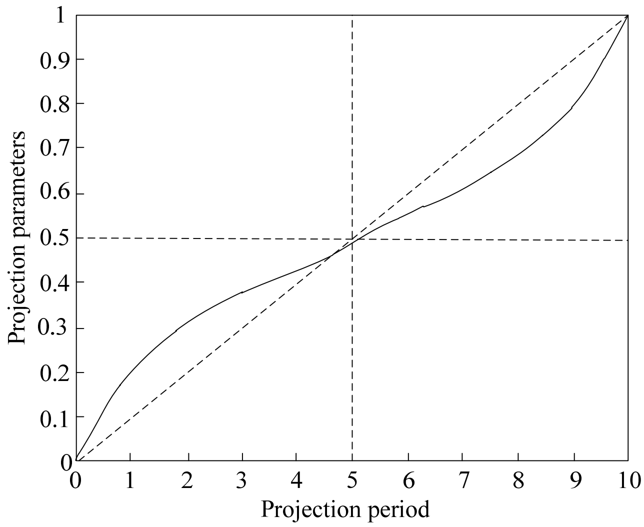
After processing the artefact information, the local window function is used to calculate the image cost caused by forward rotation. When reconstructing the basic image domain information, the LR image reconstruction method is used to set the interpolation function between the image pixels, randomly select a pixel, use the cubic polynomial to construct the correlation function between the adjacent pixels of the pixel, and use the back projection method to project the pixel interpolation into the above constructed numerical imaging model, the change of projection parameters during projection processing is shown in Figure 1.

According to the parameter changes shown in Figure 1, the projection parameters show an increasing change process within the calibrated projection period. In order to ensure the accuracy of image information reconstruction, SRCNN model is used to extract the block features of the basic image domain and process them into corresponding high-dimensional vectors. The obtained basic image domain reconstruction information can be expressed as:

$$X_{oi} = \frac{\exp M \times Y}{\mu} \tag{4}$$

where X_{oi} represents reconstruction information of the basic image domain, Y represents block features of the pre-processed basic image domain, and μ represents pre-processing parameters (Shan et al., 2019).

Figure 1 Projection parameters change during reconstruction of basic image domain



2.3 *Image detail domain denoising*

After the reconstruction of image information, in order to improve the accuracy of image detail processing, the image detail domain is denoised. The information of image detail domain with noise can be described by the following formula:

$$X_{ddi} = E_{ddi} + N_{ddi} \tag{5}$$

where E_{ddi} represents the effective information in the image detail domain, and N_{ddi} represents the noise signal in the image detail domain. Gaussian white noise with variance of φ^2 is described as n_{ddi}, which obeys $n \sim (0, \varphi^2)$ distribution. If the multiplicative noise signal appears in the image detail domain, it needs to be processed by logarithmic transformation. In logarithmic size, multiplicative noise can be converted into Gaussian white noise.

The wavelet transform process in detail domain of image with noise has the following characteristics:

1 The wavelet transform coefficient has a certain spatial orientation characteristic, and the edge data in the horizontal direction, vertical direction and corner line direction can provide strong support for the subsequent image detail domain denoising.

2 White noise sequence can be transformed by wavelet basis coefficient, so that it can be represented by zero-mean white noise.

3 In the wavelet transform domain, the signal energy is mostly near the coefficient with high absolute value, while the noise information is completely opposite. Therefore, a threshold is set, the coefficient that does not exceed the threshold is set as 0, and the wavelet coefficients exceeding the threshold are stored (Fan and Liu, 2021). Based on the wavelet coefficients after processing, it can be known that the partial coefficients are normal signals in the detail domain of the image,

while the remaining coefficients have noise, so the specific location of noise can be obtained and cleaned.

2.4 Detail enhancement of two-dimensional animation image by dual domain fusion

In this study, the two-dimensional animation scene image is divided into two parts: basic image domain and image detail domain through dual domain decomposition processing, and then the basic image domain is reconstructed, the image detail domain is denoised, and then the results of information reconstruction and denoising are fused to realise image detail enhancement processing.

When designing the image detail enhancement process of two-dimensional animation scene, the reconstructed basic image domain information and the denoised image detail domain information are taken as the processing objects. The image domain difference formed by the guiding function can be expressed in the following form:

$$D_i = \min_{i \in k} \frac{\alpha_i + \beta_i}{P_i} \tag{6}$$

where D_i represents the difference value of image domain calculated, α_i and β_i represent the adjustable parameters of the image pixels of the two-dimensional animation scene, P_i represents the pixel function of the output two-dimensional animation scene image.

According to the calculated image domain difference, set the same detail parameters in the guidance area, and the numerical relationship of the set parameters can be expressed as follows:

$$\gamma_k = \frac{\frac{1}{V}\sum_{i=1}^{k}(D_i)^2 \times h}{n_p} \tag{7}$$

where V represents the variance in the image domain, n_p represents the total number of pixels in the two-dimensional animation scene image, h represents the total number of guided filtering times, and the meanings of other parameters remain unchanged.

In order to control the effect of different detail parameters on the two-dimensional animation scene image, the weak energy processing gain is used to process the gain in the image, so as to adjust the energy in the image. The numerical relationship of this process can be expressed as:

$$\lambda = \frac{\gamma_k \times \log \varsigma}{\Delta\phi} \tag{8}$$

where ς represents the preset image parameters, ϕ represents the energy value, and $\Delta\phi$ represents the energy gain.

Under the control of λ, a Gaussian smoothing process is constructed in the two-dimensional animation scene image. By changing the contrast of edge information in the image, the intensity parameters in the image area are continuously adjusted to control the halo formed in the image. Set a dynamic processing process to form a detail highlighting effect within the image range, and build an illuminance value relationship between the basic image domain and the image detail domain. The process is as follows:

$$I(a,b) = \frac{q(a,b)}{\lambda} + L \tag{9}$$

where $I(a, b)$ represents the illuminance relationship between the basic image domain and the image detail domain, $q(a, b)$ represents the background illuminance of the low-illuminance region, L represents the JND parameter, and the meanings of other parameters remain unchanged.

Under the above illuminance numerical relationship, taking the background illuminance parameter as the enhancement object, a numerical enhancement process is constructed by using the image subtraction model. The numerical relationship can be expressed as:

$$Z = \frac{R / I(a,b)}{1 - \frac{I(a,b)}{\varpi}} \tag{10}$$

where Z represents the construction of numerical enhancement function, R represents the reflection component of the two-dimensional animation scene image, ϖ represents the control factor, and the meanings of other parameters remain unchanged.

In order to avoid over enhancement, the reflection image is used to set a numerical region in the control factor to control the over enhancement of two-dimensional animation scene image by the enhancement algorithm. Then, the information of the basic image domain and the image detail domain is fused, and the process is as follows:

$$Q = \frac{Z \times (p_{bi} + p_{ddi} - N_{ddi}) \times \lambda}{G} \tag{11}$$

Based on the above process, the two-dimensional animation scene image is decomposed into two domains to obtain the basic image domain and image detail domain. Secondly, the information of the basic image domain is reconstructed, and the image detail domain is denoised. Finally, the processed basic image domain and image detail domain are fused to complete the detail enhancement of the two-dimensional animation scene image.

3 Experiment and result analysis

In order to verify the practical application performance of the two-dimensional animation scene image detail enhancement method based on dual domain decomposition, the following experimental verification process is designed.

3.1 Experimental data

The sampling iteration number of the two-dimensional animation scene image is 500, the resolution of image feature extraction is 280 kHz, and the interference signal-to-noise ratio is 25 dB–40 dB. The remaining experimental data parameters are shown in Table 1.

3.2 Experimental scheme

In order to improve the persuasiveness of the experimental results, the image detail enhancement method based on weighted guided filter layering in reference (Cao and He, 2020) and the image enhancement method based on multi-layer fusion and detail restoration in reference (Long and He, 2020) are compared to complete the performance verification with the method in this paper.

This experiment compares the distortion, real-time and detail information error of image detail enhancement methods. Among them, the distortion is reflected by the matching number of feature points. The more the matching number of feature points, the smaller the distortion of image detail enhancement method; the real-time performance is reflected by the time-consuming of the enhancement process. The less the time-consuming of the enhancement process, the higher the real-time performance of the image detail enhancement method; the detail information error is reflected by the local standard deviation of the image. The larger the local standard deviation is, the smaller the detail information error is.

Table 1 Statistical table of experimental parameters

Parameter number	*Parameter name*	*Parameters size*
1	Two-dimensional animation scene image pixels	288 * 255
2	Two-dimension animation scene image edge width	0.75
3	Denoising threshold	0.860
4	Two-dimension animation scene image signal-to-noise ratio	75 dB
5	Image edge intensity	120 dB
6	Image information integrity	98.44%

3.3 Results and analysis

Firstly, the distortion of different methods is verified by taking the number of feature point matching as the index. The statistical results of feature point matching quantity of different methods are shown in Table 2.

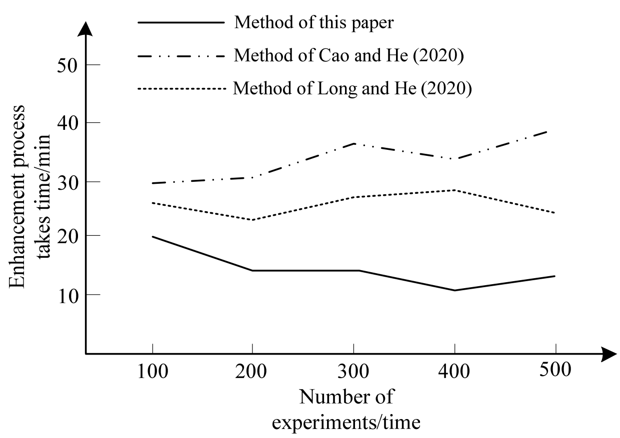
Table 2 Comparison of feature point matching quantity of different methods

Number of experiments/ time	*Method of this paper*	*Method of reference (Cao and He, 2020)*	*Method of reference (Long and He, 2020)*
100	5,217	3,915	4,560
200	5,364	4,287	4,783
300	5,371	4,409	4,607
400	5,289	4,316	4,532
500	5,540	4,242	4,550

It can be seen from the results shown in Table 2 that when the number of experiments is 100, the number of feature points matched by the method in this paper is 5,217, the number of feature points matched by the method in reference (Cao and He, 2020) is 3,915, and the number of feature points matched by the method in reference (Long and He, 2020) is 4,560; when the number of experiments is 300, the number of feature points matched by the method in this paper is 5,371, the number of feature points matched by the method in reference (Cao and He, 2020) is 4,409, and the number of feature points matched by the method in reference (Long and He, 2020) is 4,607; when the number of experiments is 500, the number of feature point matching of this method is 5,540, the number of feature point matching of reference (Cao and He, 2020) method is 4,242, and the number of feature point matching of reference (Long and He, 2020) method is 4,550. In the experimental process, the maximum number of feature points matching of this method can reach 5,540, which shows that compared with the two traditional methods, the image distortion of this method is lower.

On this basis, the timeliness of different methods is verified by taking the time-consuming enhancement of the treatment process as the index. The statistical results of the time-consuming enhancement process of different methods are shown in Figure 2.

Figure 2 Comparison of time-consuming enhancement processes of different methods



It can be seen from the results shown in Figure 2 that when the number of experiments is 100, the enhancement process of the method in this paper takes 20 minutes, the enhancement process of the method in reference (Cao and He, 2020) takes 30 minutes, and the enhancement process of the method in reference (Long and He, 2020) takes 27 minutes; when the number of experiments is 300, the enhancement process of this method takes 13 min, the enhancement process of reference (Cao and He, 2020) method takes 35 min, and the enhancement process of reference (Long and He, 2020) method takes 28 min; when the number of experiments is 500, the enhancement process of this method takes 12 minutes, the enhancement process of reference (Cao and He, 2020) method takes 38 minutes, and the enhancement process of reference (Long and He, 2020) method takes 23 minutes. In the whole experimental process, the enhancement process of this method takes at least 11 minutes, which shows that compared with the two traditional methods, this method has higher timeliness. This is because this method reconstructs and denoises the decomposed basic image domain and image detail domain respectively, and fuses the two images after processing, so the time of image detail enhancement is greatly shortened.

Finally, taking the local standard deviation as the index, the detail information errors of different methods are verified. The statistical results of local standard deviation of different methods are shown in Table 3.

Table 3 Comparison of local standard deviation of different methods

Number of experiments/ time	*Method of this paper*	*Method of reference (Cao and He, 2020)*	*Method of reference (Long and He, 2020)*
100	0.975	0.902	0.884
200	0.970	0.911	0.871
300	0.952	0.917	0.869
400	0.954	0.913	0.870
500	0.966	0.918	0.863

According to the results shown in Table 3, when the number of experiments is 100, the local standard deviation of the method in this paper is 0.975, the local standard deviation of the method in reference (Cao and He, 2020) is 0.902, and the local standard deviation of the method in reference (Long and He, 2020) is 0.884; when the number of experiments is 300, the local standard deviation of the method in this paper is 0.952, the local standard deviation of the method in reference (Cao and He, 2020) is 0.917, and the local standard deviation of the method in reference (Long and He, 2020) is 0.869; when the number of experiments is 500, the local standard deviation of the method in this paper is 0.966, the local standard deviation of the method in reference (Cao and He, 2020) is 0.918, and the local standard deviation of the method in reference (Long and He, 2020) is 0.863. In the experimental process, the maximum local standard deviation of this method can reach 0.975, which shows that compared with the two traditional methods; the local detail information error of the image of this method is smaller. The reason for the above experimental results is that the text method decomposes the two-dimensional animation scene image, then reconstructs the information in the basic image domain and denoises the image detail domain, so the local standard deviation of the image is greatly reduced.

4 Conclusions

In this study, the two-dimensional animation scene image is divided into two parts: basic image domain and image detail domain through dual domain decomposition processing, and then the information in the two image regions is processed through the process of fusion information reconstruction and denoising, so as to complete the image detail enhancement processing. Through the design of simulation experiments, it can be seen that the number of feature points matching of this method can reach 5,540 at most, the enhancement process takes at least 11 minutes, and the maximum local standard deviation can reach 0.975, which shows that this method has the application advantages of low distortion, high real-time performance and small error of detail information.

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