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Computer-aided Digital Image Inpainting Algorithm and Image Special Effects Processing Based on Deep Learning

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Abstract. When processing the image, the image that is easy to process is not covered and missing. The image will be partially missing or pixels will be lost due to the low accuracy of the transmission equipment or the unstable network. The main purpose of image inpainting is to generate enough real content, so that the restored image has complete structure and details with visual effects. In this article, deep learning (DL) and CAD technology are applied to the process of digital image special effects processing and restoration, trying to reduce the retrieval range through image feature information classification, and removing background interference information through image positioning and cutting. The test results show that the recall of this algorithm for digital image restoration has increased by more than 15%. The method successfully predicted the information of the large missing area in the image, and realized the realism of the photo, which produced clearer and more coherent results than the previous methods. In the work of image special effects processing, we should sum up experience and introduce AI technology according to specific needs to enhance the advanced nature of image special effects processing.

Keywords: Image Restoration; Image Special Effects Processing; Deep Learning; CAD
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1 INTRODUCTION

Computer aided digital Inpainting algorithm and image special effect processing are two important research directions in the field of digital Inpainting. Digital Inpainting refers to the repair of damaged, missing or occluded areas in the image to restore them to the original and complete state. Computer aided digital Inpainting algorithm usually uses neural network model to fill or estimate the missing or occluded data in the image by learning a large number of sample data. Image special effects processing refers to the various processing of images to present different visual effects. The image special effect processing algorithm based on depth learning usually adopts the Convolutional neural network model. Through the convolution operation on the image, the feature information of the image is extracted, and then various special effects are processed on the image through different post-processing methods, such as color transformation, contrast adjustment, fuzzy processing, etc. At present, computer-assisted digital Inpainting algorithm and image special effect processing algorithm based on deep learning have been widely used in many fields, such as digital image inpainting, image enhancement, image denoising, image super-resolution, etc. Image digital restoration technology is a very important restoration technology in the field of image restoration, which infers the lost image information data by analyzing and processing the existing information of the image. Digital Inpainting technology is from the perspective of people's psychology and vision, by properly analyzing and processing the edge information of the covered object, and extending and connecting the edges in a certain direction. Thus, the masked part of the image can be correctly and reasonably filled, achieving visual continuity and achieving similar effects to manual repair. Inpainting can be traced back to the Renaissance, which originated from the restoration of defective artworks by art craftsmen. In order to make the repaired area appear consistent and reasonable with the overall appearance, craftsmen usually use the adjacent information of the damaged area in the artwork as prior information, gradually supplementing it internally. Nowadays, due to the increasing efficiency of information image transmission, people are increasingly inclined to use images to transmit information. There are many reasons that may compromise the integrity of image information during image acquisition, transmission, and storage. This is a technique that utilizes known information to automatically repair missing information in images. Digital restoration technology is the process of obtaining prior knowledge of damaged images through statistical analysis of the information retained in the images, and utilizing relevant algorithms to effectively estimate missing parts. The DL based patching method, as a new patching technique, has attracted the attention of researchers since its inception and has undergone extensive application research. This method not only obtains the color and texture features of the image to be repaired, but also obtains the semantic features of the image.

From the moment digital images are generated, it is necessary to face the problem of damaged image information integrity caused by low accuracy of acquisition and transmission equipment in the process of acquisition, transmission, storage, etc. The purpose of restoration is to remove occlusion in the image, reconstruct missing information from the background information in the image, and fill the designated visual input area with real data. The process of filling the designated area of visual input with real data is highly subjective. In the repair of image special effect processing parts, the generation of anti Sexual network (CAN) learning algorithm can effectively optimize CAD modeling technical parameters, and accurately identify and classify image feature information. This article applies CAD and DL to assist in the digital image special effects processing and restoration process, effectively and accurately denoising and correcting the original image, ensuring accurate pixel level calibration accuracy between images.

DL is a learning method based on familiar machine learning to construct multi-layer neural networks. The constructed network structure extracts the features of the input data and forms an abstract representation of the output layer by combining the features of the hidden layer. In the proposed model, select a center point from the boundary of the area to be repaired, and then select an image block of appropriate size. If blocks with similar textures are found in other areas of the image, they are migrated to the target area and this iteration continues until the entire image is completely repaired. The test results indicate that this method can better repair the curved contours and irregular textures of missing objects using reference images. The traditional image inpainting algorithm can effectively repair some patterns, but the results are smooth and fuzzy in some scenes. When the missing area is too large or the image is complex, the inpainting effect will be poor. Based on this, this article constructs a digital image special effect processing and restoration model based on ML algorithm, and its main innovations and contributions are as follows:

(1) Geometric distortion, gray distortion and color distortion often occur in the process of obtaining or displaying digital images. In this article, the distortion of digital images is analyzed, and the correction method of distorted images based on DL and CAD is proposed.

(2) In order to further improve the image inpainting accuracy and recognition efficiency, this article tries to reduce the retrieval range by classifying image feature information, and remove background interference information by image positioning and cutting.

This article first introduces the importance of image inpainting research and the significance of DL and CAD technology in the field of image inpainting, then constructs a computer-aided digital image inpainting model based on GAN, and tests the performance of the algorithm through image data sets, which proves the application effect of the algorithm in digital image inpainting algorithm and image special effects processing.

2 RELATED WORK

Image digital restoration processing has great applications in different digital fields. Due to the general lack of supplementary functions required for image reconstruction in digital images, Abdulla and Ahmed [1] have developed a patch limited search mechanism for repairing scratches, which is similar to the Palace Museum's determination of image patch priority and improves the quality search of patches in both objective and subjective aspects. Ahmad et al. [2] applied computer-aided MRI image restoration. By collecting and analyzing computer tomography data of soft tissues, its construction describes the problem of image restoration approximation in the sampled dataset. An example of image restoration is provided by analyzing the convergence of the equilibrium equation. Chen et al. [3] performed sparse range spatial difference processing on spectral images. By performing group sparsity regularization on spatial spectral images, an algorithm model based on spatial correlation restoration was analyzed. Compared with other methods, this method has been proven to be effective in model data recovery. Deng and Dragotti [4] proposed a deep learning image processing based on multimodal image restoration. It adopts a deep learning network architecture for the key features of the image reconstruction feature preservation module. Including RGB guided deep image super-resolution and multi noise fusion of flash images. Traditional Inpainting patches are difficult to complete the overall restoration of image micro characteristics. Dhondse [5] introduced the artwork of image heritage to conduct image loss analysis of intuitive Fuzzy set repair. Through the minimum patch and feature matching of missing images, the overall repair of digital images has been meticulously carried out. Hudagi et al. [6] conducted image reconstruction analysis in deep convolutional networks. It uses Bayesian probability fusion to investigate the limitations of mixed images. The hybrid image method is based on deep learning and double functions. By searching for the nearest patch, the shortest patch suitable distance for residual images was found. Li et al. [7] conducted a network adaptive Feature selection detail feature analysis for multi-level images. By fusing spatial information from different contextual information, it introduces a new adaptive module that excels in image supervised link expression. This module achieves spatial fusion of visual defogging effects while achieving information expression. Liu et al. [8] used a neural network algorithm based on a non-local Self-similarity prior to fill in the missing whole rows and columns of the image. By analyzing the problem of missing or incomplete special structures in images, an alternating optimization framework for 3D similarity vectors in images was constructed. The results of quantitative visual evaluation of images indicate that the model for non-local images has good repair performance. Mao et al. [9] proposed a similarity single Inpainting method based on self-attention Generative adversarial network. It introduces global relevant regions of damaged images and uses a network adversarial model generated by learning region models. The results show that the local feature overlap similarity of images with overlapping distributions is high.

Noori et al. [10] analyzed the construction of fuzzy edge structure information regions based on convolutional networks. By reconstructing image blur, it proposes a region filling structure based on the edge ratio of convolutional images with missing information. Mixing the calculated product results with convolutional masks preserves the structural details of the image. Song et al. [11] analyzed the degradation and optical distortion of underwater image models. Through the high-resolution channel design of the model image, it constructs a saturation compensation modification mechanism based on the Scene graph. By analyzing the priority of underwater images, it evaluated the robust statistical performance of image restoration with image channel attenuation. Yang et al. [12] conducted low-frequency recursive multiscale modeling of stripe images using wavelet transform. The proposed network training scale is beneficial for the model effectiveness construction of image synthesis processing. It has a significant effect on removing rain streaks from images that include visibility factors. Zhang et al. [13] used a spatial denoising method using hyperspectral overlapping cubes to improve image quality. It studied the validation of the experimental effect of image cube space alternation based on k-means clustering algorithm. The results show that the optimized efficient alternating image algorithm has a certain recovery effect. Zhang et al. [14] conducted an analysis of the denoising ability of the image restoration module of neural networks. Through the design of image parameters, it constructs an image restoration denoising mode. The superiority of this method in solving various image restoration problems has been demonstrated through prior testing of super-resolution. In order to address the visible light visual impact of outdoor haze and other factors on images, Zheng et al. [15] conducted saturation enhancement analysis of local details in images. By analyzing image sequences with adaptive saturation of images, the effectiveness of image structure experiments for scene deep learning was constructed.

3 COMPUTER AIDED DIGITAL IMAGE RESTORATION ALGORITHM BASED ON GAN

Convolutional neural network (CNN) introduces more effective feature learning part on the basis of multi-layer deep neural network, which makes it have stronger feature learning ability. Specifically, it introduces convolution layer and pooling layer with local displacement connection before the original fully connected layer. When the input image or feature map passes through the convolution layer, in order to ensure that the edge features of the image are not lost and the size of the feature map will not decrease rapidly with the increase of the quantity of convolution layers, the input and output sizes of the convolution layer will be set to be the same. The feature map decreases with the deepening of the network, so as to reduce the parameters and speed up the convergence, a pooling layer is added after the convolution layer. The purpose of pooling is to simplify the information output by convolution layer. The convolution layer reduces the data dimension, and the pooling layer compresses the data and parameters while retaining the main features. Different convolutional network structures and solving strategies need to be designed for different training scenarios.

The quantity of traditional deep neural network nodes is usually too large to be operated in practice. Therefore, people build CNN, and reduce the quantity of nodes in the neural network by sharing weights, which can deepen the learning depth and improve the correct rate. In this article, a digital image special effects processing and restoration model based on CAN is constructed on the basis of traditional CNN. The retrieval range is reduced by image feature information classification, and the background interference information is removed by image positioning and cutting, thus providing technical support for ML algorithm to assist digital image special effects processing.

The idea of adversarial generation of 3D models is to use generators to generate 3D models and use discriminators features are true or false. During the training process, the parameters of the discriminator and generator are constantly updated. When they reach equilibrium, the generator can generate almost real 3D models that cannot be recognized by the discriminator. However, networks are often unstable during the training process, resulting in unsatisfactory results. By extracting the simplest method of three views, the front view, top view, and side view were obtained from the three fixed directions of the model, and the similarity of these two-dimensional contour feature maps was compared. However, this simple view cannot express the spatial information such as the topology structure of the model itself, and the final retrieval performance cannot be satisfied enough. The traditional Inpainting algorithm can effectively repair some patterns, but in some scenes, the results are smooth and fuzzy. When the defect area is too large or the image is complex, the repair effect will be poor. This article constructs a digital image special effects processing and restoration model based on CAN. Narrowing the search scope through image feature information classification, removing background interference information through image localization and cropping, providing technical support for ML algorithm assisted digital image special effects processing. The model of GAN discriminator is shown in Figure 1.

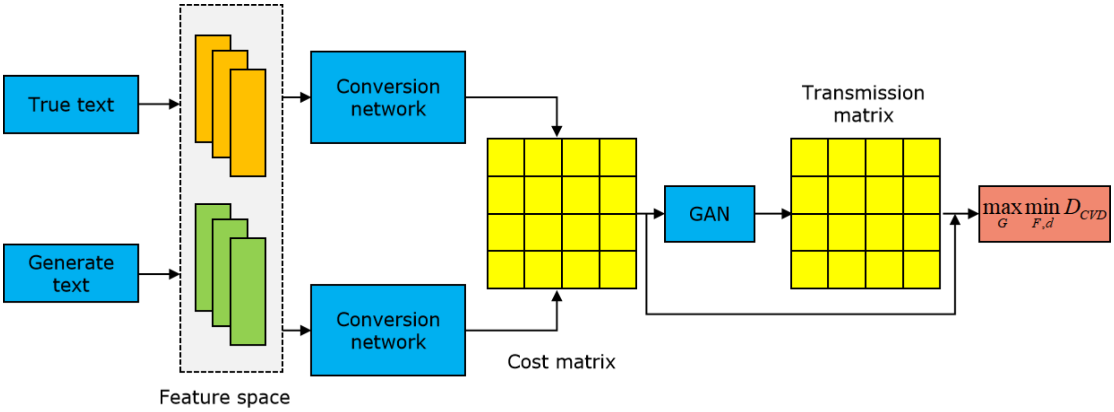

Figure 1: GAN discriminator model.

GAN-based image inpainting method can not only produce similar textures, but also restore semantic information. However, there are still some shortcomings in the restored image, such as the deformed structure inconsistent with the adjacent areas, the low degree of detail reduction, and the inconsistency between the texture and semantics of the restored image. The edge repair model structure is based on deep convolution GAN model, including GAN and discriminant network. Among them, GAN uses the structure of self-encoder, and there is a network composed of 8 continuous residual blocks between the encoder and decoder of self-encoder. The structure of self-encoder tends to output images with blurred edges. If the encoding-decoding process of self-encoder is regarded as lossy, the distance between the output result and the real data is obviously too large. The solution to this problem is to merge the input images at the end of the decoding stage and use them as the input feature map of the next layer, so that most of the compressed information can be obtained.

The traditional GAN consists of a GAN and a discriminant network, in which the discriminant network is responsible for discriminating the authenticity of the whole image generated by GAN and assisting in optimizing GAN. However, this classical coding and decoding structure will pass through a series of down-sampling layers and up-sampling layers, which will cause the loss of image detail information and affect the clarity and detail reduction of the final restoration results. In order to train the network effectively, this algorithm first preprocesses the GAN to make it have a certain repair ability, and then improves the repair effect by training the GAN, the global discriminant network and the local discriminant network.

Let X_i^k represent the sum of inputs of neurons i in k layer, and Y_i^k is the output. The weights of neurons j in layer $k-1$ to i in layer k are W_{ij}, so there is the following functional relationship:

$$Y_i^k = f\left(X_i^k\right) \tag{1}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{2}$$

Generally, f is an asymmetric Sigmoid function:

$$f\left(x_i^k\right) = \frac{1}{1+\exp\left(-X_i^k\right)} \tag{3}$$

If the output layer is the m layer, the actual output of the i neuron in the output layer is Y_i^m. Let the corresponding image signal be Y_i, and define the error function e as:

$$e = \frac{1}{2}\sum_i \left(Y_i^m - Y_i\right)^2 \tag{4}$$

The point cloud semantic segmentation network 3D MiniNet, which combines 2D and 3D learning layers, uses fast nearest neighbor search methods and sliding frames to search for pixels after spherical projection. The advantage of this method is that it directly uses mature two-dimensional neural networks and does not require the construction of complex network architectures, thus achieving good segmentation results for small and simple scenes. Calculate the transformation matrices of two surfaces using the SIFT algorithm, and calculate the transformation matrices between multiple surfaces using the ICP algorithm; By using surface reconstruction methods to combine multiple surfaces into one surface, a three-dimensional model of the object is ultimately obtained. In a layer by layer greedy unsupervised network, the parameters of each layer are only controlled by the input of the current layer. Therefore, the unsupervised network can be pre trained layer by layer, and then the network parameters can be fine-tuned through supervision to form a new training mode of "full iteration update single layer".

Assume that the input size of l layer is $C^l \times H^l \times W^l$ tensor, C^l is the quantity of input channels of l layer, and the size of a single convolution kernel is $C^l \times h^l \times w^l$. Then, corresponding to the convolution layer with C^{l+1} hidden neurons, the output of the corresponding position is as follows:

$$y_{d,i^l,j^l} = \sigma\left(\sum_{c^l=0}^{C^l}\sum_{i=0}^{h^l}\sum_{j=0}^{w^l} p_{d,c^l,i,j} \times x_{c^l,i^l+i,j^l+j} + b_d\right) \tag{5}$$

Where d is that numb of neurons in the l lay; i^l and j^l represent location information. With the constraints of Equation (6) and Equation (7):

$$0 \le i^l \le H^l - h^l + 1 \tag{6}$$

$$0 \le j^l \le W^l - w^l + 1 \tag{7}$$

Where p is the convolution kernel parameter; b is the bias parameter in convolution; $\sigma(\cdot)$ is the activation function.

In the expression of real scenes, traditional two-dimensional images lack depth information to describe three-dimensional real-world scenes, often unable to meet the needs of semantic understanding of these tasks. However, traditional geometric feature extraction methods cannot effectively understand the semantics of 3D data, so there are still many problems that need to be solved urgently. The representative view method based on shape similarity obtains sufficient rendered views from different perspectives. By using the method of view aggregation class analysis, a set of significantly different views were obtained, which were used to represent the previously extracted rendered views. Due to the high complexity of solving single view modeling in 3D space, another idea is to project 3D information into 2D space and select 2D space to supplement missing information. This method predicts depth maps from different perspectives, and then completes the modeling process through depth map fusion.

In the repair work, we not only need to pay attention to material properties, but also actively take texture mapping measures. The texture image in the flat state is mapped to the corresponding 3D model. Firstly, the material of the mapped image is captured using a digital camera, and then processed using 2D static processing digital tools to complete the image stitching and restoration operations. The CAN model for image restoration is shown in Figure 2.

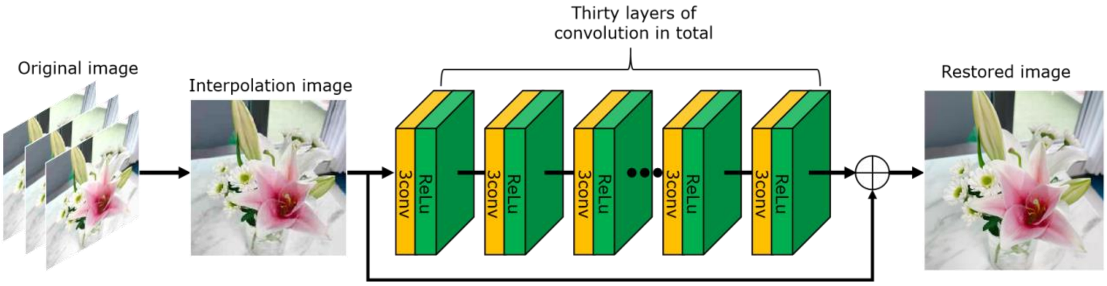

Figure 2: Image restoration CAN model.

GAN uses the structure of self-encoder, and the discriminant network uses the ordinary CNN structure. The specific content filling model diagram is shown in the following figure, which is similar to the network architecture of the edge repair model, except that the content filling model is not optimized. The image inpainting method based on sample block matching chooses the inpainting order of samples through different strategies, which makes the sample blocks with structures get high priority to be painted in advance, so it can effectively maintain the continuity of the structure in the image.

When training the model, DL algorithm iterates every time it traverses the data. The model obtains image features through continuous iteration and then adjusts parameters. Theoretically, the greater the quantity of iterations, the better the result of the model. However, in the limited data, the characteristics obtained by the model are also limited, and finally the model training will usher in a convergence. If we continue to iterate later, it will only waste the computing power of the computer. Using the linear combination of image sampling values at the past p moments to predict the image signal sampling values at the next moment with the minimum prediction error is called p -order linear prediction of image signals. That is, the predicted value of $x(n)$ is:

$$\hat{x}(n)=\sum_{i=1}^{p} a_i x(n-i) \tag{8}$$

Where $\{a_k\}$ is called p -order linear prediction coefficient. The prediction error is:

$$e(n)=x(n)-\hat{x}(n)=x(n)-\sum_{i=1}^{p} a_i x(n-i) \tag{9}$$

The prediction error sequence obtained by z transformation of this equation is the output of a system with the following system transfer function:

$$A(z)=1-\sum_{k=1}^{p} a_k z^{-k} \tag{10}$$

$$E=\sum_{n=p}^{N-1}\left[x(n)-\sum_{i=1}^{p} a_i x_{n-i}\right]^2 \tag{11}$$

The prediction coefficient $\{a_k\}$ when E is the minimum is the same as the parameter $\{a_k\}$ of the system function in the digital model generated by the image signal.

Before CAD modeling, it is need to fully grasp the characteristics of modeling structure, accurately set the size and direction of triangle according to the specific modeling situation, and ensure that it can be consistent with the modeling structure characteristics of objects. Polygon modeling can be used to describe the complex decorations, strengthen the handling of details, and with the help of computer technology and high-profile software, the accuracy of modeling can be guaranteed.

4 TEST RESULTS AND ANALYSIS

The training data of this experiment are Image Net data set and Celeb A data set. A subset of Image Net data set is extracted in this experiment. The test set is used to assess the final results of the model, and also verifies the generalization ability of the model, but it will not affect the adjustment of parameters. The training set is used to fit the model and set the parameters of the model, and then combined with the verification set to adjust the parameters, which is also the largest data set. After each iteration, the feedback accuracy of the test set is used to judge the iteration, and the iteration result with the highest accuracy is saved. In the experiment, the optimization accuracy of each algorithm is fixed, the maximum quantity of iterations is set to 300, the population quantity of all algorithms is set to 15, and all test function dimensions are set to 30, and each experiment is repeated ten times, and the iteration is stopped when the optimization error of the algorithm is less than 0.001.

In order to make the training set picture meet the requirements of this experiment, it is need to preprocess the training set picture to meet the requirements of neural network for input data. In the preprocessing stage, there are mainly operations such as adjusting the image size and using masks to artificially damage the image. In computer operation, the time required for each matching is the same, so reducing the quantity of matching times can reduce the time required for image restoration and make the recognition results display faster. The test results of image restoration processing time under different quantity of nodes are shown in Figure 3.

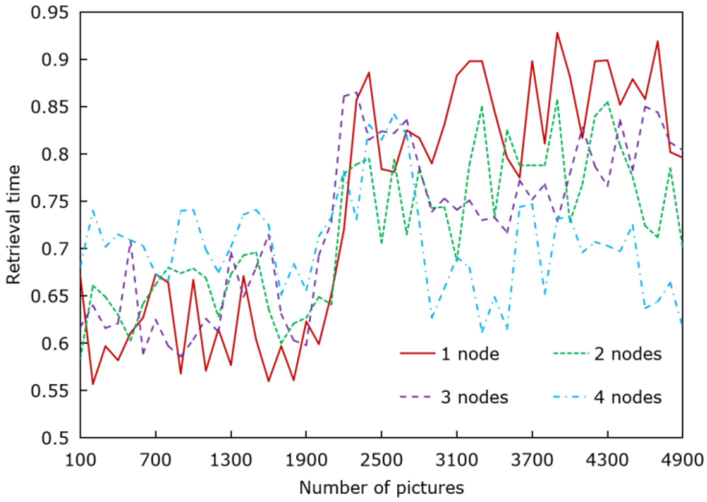

Figure 3: Time-consuming image restoration.

As can be seen from Figure 3, in the case of a large quantity of pictures, the operation efficiency of multi-node image restoration has obvious advantages. The algorithm divides the whole process of repairing the missing area into several sub-stages, and only a part of the missing image is repaired in each stage, so the corresponding loss function is used to guide the image repair in each stage. Using digital image processing technology, the sensory information and experience are quantified and systematized as accurately as possible to obtain clear characteristics and laws, so as to improve the accuracy and reliability of object image restoration.

Global Discriminative Network (GDN) and Local Discriminative Network (LDN) are both deep learning models used for image classification. They all attempt to extract useful features from images in order to distinguish between real and fake images. Global Discriminant Network (GDN) attempts to extract global features from the entire image, which can be used to determine whether the image is real or not. GDN usually uses Convolutional neural network (CNN) to extract image features, and uses discriminators to learn how to distinguish between real images and forged images. Local discriminant network (LDN) attempts to extract features from local regions of the image. Unlike GDN, LDN learns the features of local regions and learns discriminative features within each local region. This method can improve the accuracy of the model without losing the global information of the image. It should be noted that the performance of GDN and LDN depends on the quality and quantity of training data, as well as the parameter settings of the model. Therefore, in practical applications, adjustments and optimizations need to be made according to specific circumstances. In order to pay more attention to the generation quality of missing areas, the algorithm uses both global discriminant network and local discriminant network to judge the probability that the whole image and local image are real data respectively. By combining these two discriminant networks to supervise the training of GAN, the forged image generated by GAN can be made to be similar to the real image in whole and in part. Figure 4 shows the error comparison of different image inpainting. Figure 5 shows the error comparison of different image inpainting algorithms on the test set.

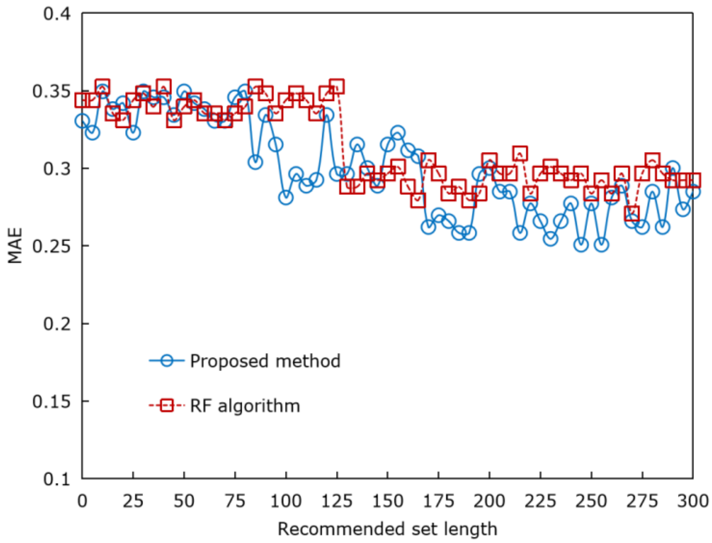

Figure 4: Error of different image inpainting algorithms on training set.

And the overall reduction is about 15%. The fusion invariant features after dimensionality reduction can retain the key information of digital images, which can not only significantly improve the recognition performance, but also improve the recognition efficiency.

In the process of extracting the features of the input image by the encoder, a lot of useful information will be lost due to the continuous down-sampling, resulting in the lack of detailed texture in the forged image generated by the decoder. The function of the discriminant network is to judge whether the input image is the real data in the data set or the forged data generated by

GAN. Using the countermeasure loss provided by the discriminant network to optimize GAN can make the image generated by GAN visually as real as possible and have more details. Figure 6 shows the image inpainting accuracy test of different algorithms.

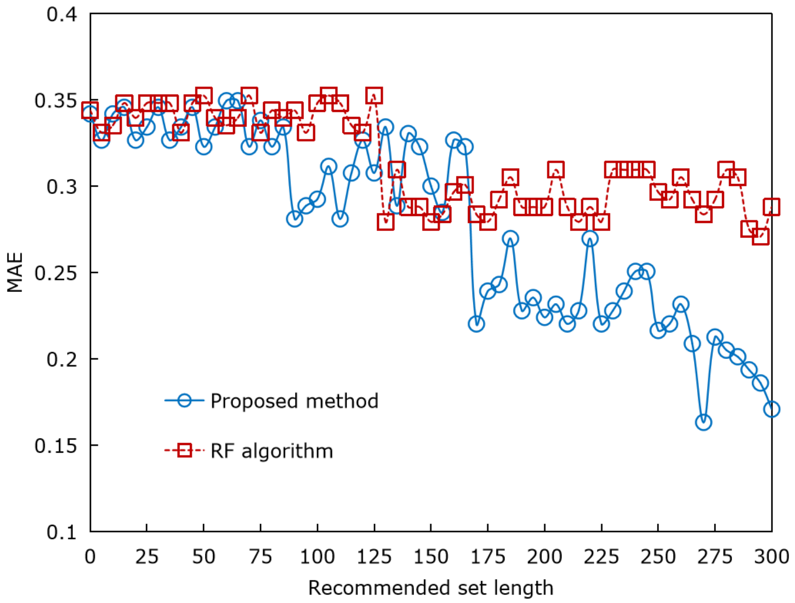

Figure 5: Error of different image inpainting algorithms on test set.

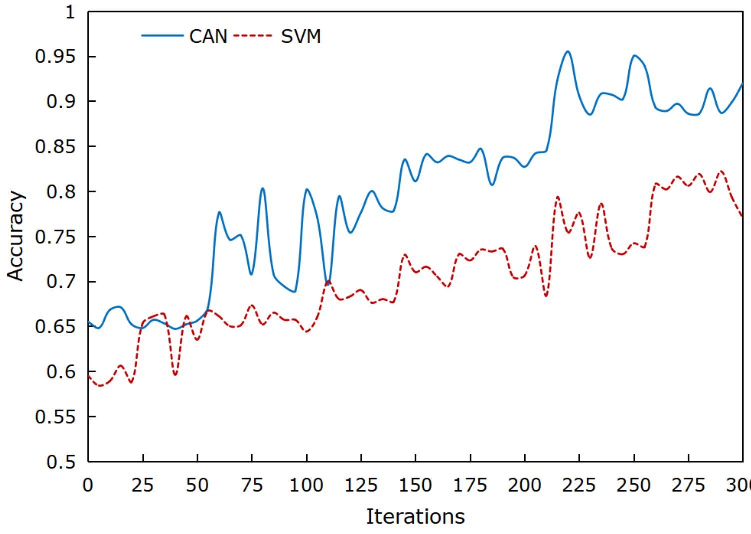

Figure 6: Image inpainting accuracy of different algorithms.

As can be seen from Figure 6, the accuracy of this algorithm is improved by 22.35% compared with the traditional algorithm. In the process of iterative optimization of the network, the design of loss function considers that the single mean square loss design will lead to poor network effect, so regularization is considered to the loss function, but the prior information of the network is extracted from the image, and the process of adding regularization has an impact on the network.

This method obtains ideal digital image feature recognition results, and the recognition accuracy is higher than other digital image feature recognition methods.

The purpose of GAN is to generate a forged image similar according to the input damaged image, and then paste the part of the forged image corresponding to the missing area. In the field of image restoration, the classic GAN is CNN with "encoder-decoder" structure. The hidden layer space between the encoder and the decoder is generally much smaller than the dimension of input and output. The encoder encodes the input image into the hidden layer space, and the decoder generates a forged image according to the representation of the image in the hidden layer space. Compared with high-level statistical features, the classification model of digital image features based on low-level features can get higher accuracy. Compare the recall of the algorithm for digital image restoration, as shown in Figure 7.

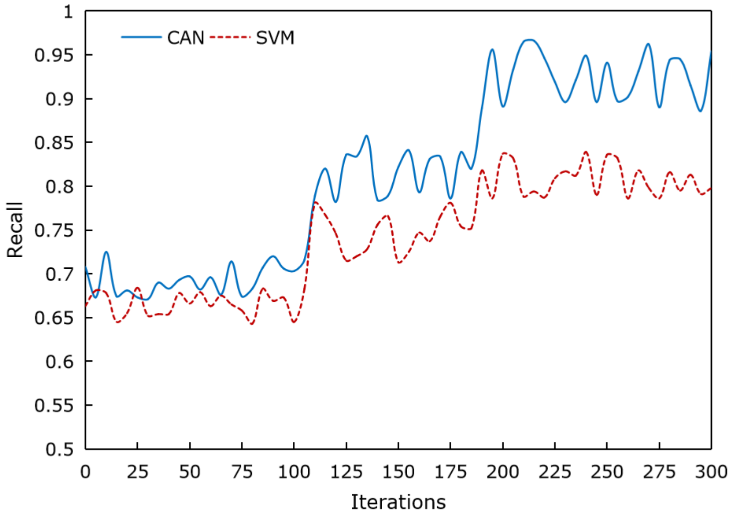

Figure 7: Comparison of recall of digital image restoration.

The test results show that the recall of this algorithm for digital image restoration has increased by more than 15%. In the network is generally composed of the data generated by training and model parameters. In the process of network training, the optimizer is used to improve the network model and parameters, minimize the loss function and get the most suitable and optimal model parameters. Using ML algorithm to repair digital images can greatly preserve the details of complex images and provide guidance for image special effects processing. Through the improvement of this article, the convergence speed of CAN parameters is faster, and the final model classification accuracy is higher.

5 CONCLUSION

Image inpainting mainly uses the known information around the defect area to estimate the defect area and fill in the texture information. In this article, CAD and DL are applied to the process of special effects processing and restoration of auxiliary digital images, and effective and accurate image denoising and image correction are carried out on the original images, so as to ensure that the calibration accuracy between images is accurate to pixel level. The test results show that the recall of this algorithm for digital image restoration has increased by more than 15%. The digital image inpainting method based on CAN can effectively solve the problem that digital images are not clear and stereoscopic, and provide guidance for image special effects processing. In this article, a model design method of multi-level merging input images is proposed, that is, the input images are merged many times at the output end of the generator, and the middle part still adopts the coding-decoding mode, which has achieved good results in dealing with local color cast anomalies. Using the improved encoder not only improves the coding efficiency, but also obtains more detailed features, ensuring the consistency of vision and semantics. In the image restoration of image special effects processing parts, the application of CAN learning algorithm can efficiently optimize the technical parameters of CAD modeling, accurately identify and classify image feature information, and improve the reliability of image special effects processing and data processing efficiency.

In this article, the model does not consider all kinds of damage shapes, but only adopts the large damage in the center, which cannot meet the requirements of the actual situation. Therefore, in the future work, it is need to continue to improve the model to make it suitable for a wider range of damage.

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