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Serial Number Recognition of Ceramic Membrane Based on End-to-end Deep Learning

Yi Wang

School of Cultural Heritage and Art Design, Zhengzhou University of Technology, Zhengzhou, Henan 450044, China, 20151054@zzut.edu.cn

Corresponding author: Yi Wang, 20151054@zzut.edu.cn

Abstract. For manufacturers, serial number (SN) is not only beneficial to the centralized assembly of products, but also brings great convenience to the traceability of production process. For workers in wastewater treatment process, the SN of ceramic membrane is also the basis for them to install ceramic membrane correctly. Image resolution, as a key factor to assess the quality of digital images, is the basis for the subsequent processing of ceramic membrane SN recognition. In this article, an image super-resolution (SR) algorithm based on end-to-end DL and computer aided design (CAD) model is proposed. A deep learning (DL) model suitable for mixed views as input signals is selected, and a hierarchical learning structure is constructed by using deep neural network. Combined with the extracted CAD model views, the SN of ceramic membranes is identified. It's not difficult to seen from the test results that the ceramic membrane SN image recognition model in this article has obvious advantages over the recurrent neural network (RNN), with an accuracy of over 96% and an error of over 25% lower than that of the comparative RNN model. This algorithm improves the reconstruction effect of detailed information in the image, optimize the reconstruction image, improve the automation of Ceramic membrane production and sewage treatment, and promote the development of industrial software.

Keywords: Deep Learning; CAD; Ceramic Membrane; Serial Number; Super Resolution
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1 INTRODUCTION

Membrane separation technology is widely used in sewage treatment process because of its high oil removal rate and low energy consumption. Its working principle is to let only certain substances with specific size pass through the membrane and intercept other particles to achieve separation and purification. Ceramic membrane is the most important part of membrane separation technology, which has attracted wide attention because of its good chemical stability. Due to the carelessness and fatigue of workers, ceramic films may be installed by mistake, which will lead to the failure of sewage treatment process. Therefore, it is of great significance to develop an automatic identification system that can replace manual measurement of ceramic film numbers. As a carrier of information, images make people's life and communication more convenient. It is people's dependence on multimedia and Internet that makes people demand higher image quality. Accordingly, it brings greater challenges to image processing technology. Image resolution is the quantity of pixels contained in the image, which indicates the size that can distinguish the smallest target details. Image resolution, as a key factor to assess the quality of digital images, is the basis for the subsequent processing of ceramic membrane SN recognition.

For manufacturers, SN can perform centralized assembly of products more quickly. More conducive to the centralized construction of products, but also brings great convenience to the traceability of production process. For workers in wastewater treatment process, the SN of ceramic membrane is also the basis for them to install ceramic membrane correctly. The development of image recognition technology benefits from the great improvement of computer calculation speed and accuracy, which provides a feasible scheme for automatic detection of ceramic membrane SN. As a key subsystem, image recognition system often appears in automatic detection systems of many industrial scenes, which has the advantages of automation, high efficiency, overcoming human subjective errors, reducing labor costs, and being free from or less restricted by harsh industrial environment. Usually, the image has the characteristics of color, the style of texture and the difference of shape, which makes it have the ability to go beyond text description. Image resolution is the main measure of image quality. HR images contain clearer structure and richer high-frequency details, which makes people get good visual effects. Image SR reconstruction technology is an important processing method to effectively improve the image resolution at present. It can get HR images and eliminate the blur and noise in the images, especially the SR reconstruction based on a single image, which has attracted more and more attention. Compared with the shallow network, the multi-layer structure of deep network can use more layers to learn the deep feature expression from a more abstract point of view. Therefore, the application of DL technology in ceramic membrane SN recognition can have better results.

DL is a very good way to extract high-level abstract features. However, the existing combination of DL and view, the extracted view cannot fully describe the model information. Therefore, this article studies a new combination of CAD and DL in order to achieve good results. Image SR reconstruction can be used to restore and monitor in the shot image, which makes the content in the picture clearer, and it is easier to lock the target object and provide more accurate clues when abnormal situations occur. The signal processing method is the basic idea of SR reconstruction technology, and the information beyond the cutoff frequency of the imaging system is reconstructed and restored. In other words, it is to restore the high-frequency information lost in the imaging process, so that the resolution of the restored image is higher than that obtained by the imaging system. Image SR reconstruction technology uses image processing method, fully excavates the hidden information in the image without changing the performance of hardware equipment, and then obtains a higher resolution image according to the original image. In this article, an image SR algorithm based on end-to-end convolutional neural network (CNN) and CAD model is proposed, and a hierarchical learning structure is constructed by using deep neural network. In the process of ceramic membrane SN recognition, a DL model suitable for mixed view is selected as input signal, and the parameters of DL model are trained to realize the feature selection of SN image CAD model. Combined with the extracted CAD model view, ceramic membrane SN recognition is carried out.

This article contributes to the innovation of algorithm applications for computer-aided image super-resolution. For ceramic serial number recognition, ultra-high-resolution graphics can provide more accurate content recognition. The following three points are the contributions made in this article.

1. This article proposes a hybrid attempt design model based on deep learning. And using neural networks to use deep learning models as signal inputs brings great convenience to digital image resolution.

2. The SN image recognition model of Ceramic membrane in this paper has obvious advantages over the recurrent neural network (RNN), and its error is lower than that of the comparative RNN model.

3. This study automates and intelligently processes the reconstruction of image details. The production quality level is improved by processing the image of the production management process of Ceramic membrane.

In the first section, it is explained that the development of image recognition technology in Ceramic membrane serial number recognition benefits from the great improvement of computer computing speed and accuracy. Image resolution is the basis and key of digital image quality recognition of Ceramic membrane serial number. Section 2 utilized the research results of numerous scholars for deep learning and hyperspectral analysis mining. A new hybrid convolution module was designed using typical image spatial information mining. In section 3, feature extraction of CNN model and Ceramic membrane SN CAD model is carried out. This section studies and analyzes the SR of SN image of Ceramic membrane and its repair. Image distortion often occurs in the process of image acquisition and transmission. And the obtained image is somewhat different from the original image. Section 4 verifies the effectiveness of the SR model design method and CAD model of Ceramic membrane serial number image based on end-to-end DL proposed in this paper. The test results in section 5 show that the SN image recognition model of Ceramic membrane in this paper has obvious advantages over RNN.

2 RELATED WORK

Due to the fact that deep learning has become a new tool for image reconstruction, its classification task has played an important role in image reconstruction. Antun et al. [1] demonstrated a key phenomenon: deep learning often leads to unstable image reconstruction methods. In the image and sampling domain, some small and almost undetectable disturbances may cause severe artifacts in reconstruction. Ben et al. [2] conducted 3D model CAD matching processing of images. It matches the images obtained from the viewpoint with the information in the 3D CAD model, and initiates automatic processing of the images collected from the viewpoint. Caggiano et al. [3] developed an automatic image machine learning method for online fault recognition to facilitate the identification of material selective defects in metal processing. By constructing the image recognition learning mode based on feature fusion, the defect conditions of the relevant modes were fused to make up for. Chen et al. [4] created three-dimensional techniques for deep learning domain images. The use of DL based SR technology comprehensively achieves the conversion of images from low resolution to high resolution. Chon et al. [5] conducted image training and construction on 3D printed ship models. It analyzed the model group diagram under multi view images. By constructing a CNN model, it obtained hull printing training data from multi view images. Han et al. [6] explored computer graphics using CAD image reconstruction technology based on 3D machine learning. By using network architecture for organizational literature analysis, deep learning techniques were used to conduct comprehensive surveys of individual domains. Analyzed and trained the 3D reconstruction of images using convolutional neural networks (CNN). Knoll et al. [7] conducted a survey on the training data bias and robustness of image reconstruction generalization. It has conducted significant research and analysis on the prospects of deep learning and image reconstruction. Due to the current research hotspots of automatic image processing and machine learning, Lell and Kachelrieß [8] conducted deep learning computer tomography research using the latest CT system to complete various transformations.

Li et al. [9] explored the relationship between two-dimensional and three-dimensional convolutions in networks. By alternately using and collecting elements that currently share spatial information for analysis, it analyzed the results of model construction using 3D hyperspectral images. The method of alternating the learning ability of 2D space achieves the display of structural redundancy results. Li et al. [10] mined three-dimensional convolutional network parameters based on deep learning and hyperspectral analysis. By utilizing typical image spatial information mining, a new hybrid convolutional module was designed. With the rapid development of deep learning, its application scope is becoming increasingly widespread. In the past research on image segmentation in the discipline, there were problems such as low segmentation accuracy and a small number of datasets, which could not effectively meet the actual requirements of segmentation results. Liu et al. [11] conducted research on the reconstruction of medical image segmentation and recognition through deep learning, focusing on addressing these issues. Mastouri et al. [12] conducted imaging analysis of deep learning image models. By developing CAD solutions for CT images, it provides valuable information for model diagnosis. Pan et al. [13] conducted depth capture statistical analysis of advanced color images. An effective method was proposed to conduct adversarial analysis on the capture of nature scale image training networks. Restore missing semantics of various degraded images by providing a convincing result. These methods have a high degree of operational flexibility. Ravishankar et al. [14] conducted a mathematical model reconstruction analysis of the sensor for the quality of graphic imaging systems. By adopting adaptive models of machine learning and domain inspired mathematical design, it constructs a sparsity based machine learning image model construction.

Shen et al. [15] mapped projected radiographs to corresponding 3D anatomical structures using deep learning models. Through computer tomography, it has been proven that volume reconstruction through deep learning can simplify the hardware of tomographic imaging systems in image guided intervention. Shevel et al. [16] conducted an analysis of an image structure parameter combination algorithm based on lifecycle functional description. This algorithm is based on the cycle principle of the created image model and constructs the possibility of product automation design implementation. Practical verification has shown a reduction in product planning time. Thunhofer et al. [17] used image residual peak signal-to-noise ratio for similarity storage index analysis. By analyzing the position sensitivity of existing ultra-high resolution graphic vision, we have completed the inference of image error for ultra-high-resolution images. Solved the problem of non-adaptability of ultra-high-resolution images. Compared with traditional image error calculation methods, it can exhibit more refined details in residual images. Wang et al. [18] performed sub network encoding of input images under existing technology. It exchanges information on convolutional streams through links with high super-resolution. Analyzed object detection and segmentation, including human pose estimation. Zhang and Zhao [19] used convolutional neural networks similar to network image segmentation for cervical image classification and recognition, which greatly improved the efficiency and accuracy of diagnosis. At the same time, better results were obtained than other classification methods, achieving fast classification and prediction of massive image data.

3 METHODOLOGY

3.1 Feature Extraction of CNN Model and Ceramic Membrane SN CAD Model

In the image spatial connection, CNN models are all local connections, not fully connected, that is to say, the perceptual area of each neuron comes from some neurons in the upper layer, and the network structure is locally connected. Then, each neuron only needs to feel the local image area, and does not need to feel the whole situation. Viana et al. proposed a step-by-step processing method to identify alphabetic and numeric characters on industrial containers, and the matching granularity was from coarse to fine, including coarse classification based on character endpoints, character template matching based on special node features and template matching based on external contour features. As a key subsystem, image recognition system often appears in automatic detection systems of many industrial scenes, which has the advantages of automation, high efficiency, overcoming human subjective errors, reducing labor costs, and being free from or less restricted by harsh industrial environment.

Aiming at the detection object such as ceramic membrane SN, which only has the characteristics of three-dimensional depth difference, this article uses CAD to reconstruct the surface of ceramic membrane in order to represent the depth information. By synthesizing multiple neurons responsible for different areas and producing the strongest response, the network produces many nonlinear "filters", which will become more global variables, that is, first create small-scale data and then combine them. The network reduces the quantity of connections in this way, that is, it reduces the quantity of weights that need to be trained. The CNN concept map is shown in Figure 1.

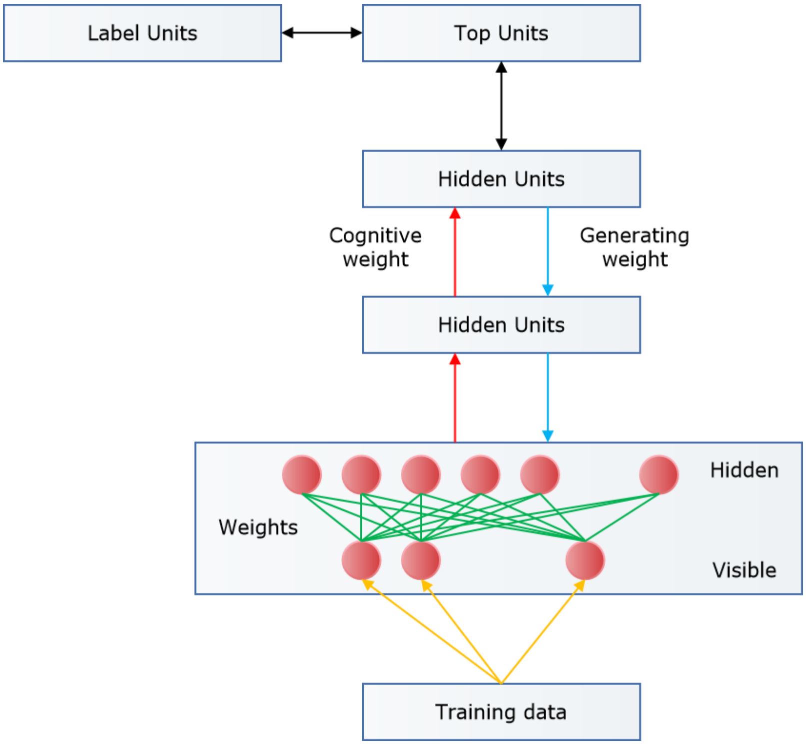

Figure 1: CNN concept map.

The problems that can be solved in the hardware stage should not be left to the algorithm stage as far as possible, so the design of image acquisition system is very important. The lighting effect of light source has a direct impact on the input characteristics of the acquired image, which greatly determines the effect and quality of camera imaging, and then affects the subsequent algorithm processing stage. The dimension of the feature map is reduced in a way similar to down-sampling, and the specific position of the feature is blurred, which reduces the computational complexity and is satisfied with the recognition of many different deformed pictures. CNN uses pooled form for aggregation statistics when spatial sub-sampling. Numajiri et al. proved that for deep networks, increasing width can achieve more effective results than increasing depth. Therefore, the method of joint training of multiple subnets is also an effective solution to improve SR performance. Kim and others put forward the concept and method of SR reconstruction based on single image interpolation, which laid a certain mathematical foundation for the development of reconstruction technology.

In this article, the second-order channel attention module is used in the multi-scale residual attention group, and the second-order statistics focus on the relationship between channel features. The model pays different degrees of attention to different channel features, which stimulates the features that are more important for image SR reconstruction, making feature mapping more expressive and improving the reconstruction performance of the network. The running process of CNN is shown in Figure 2.

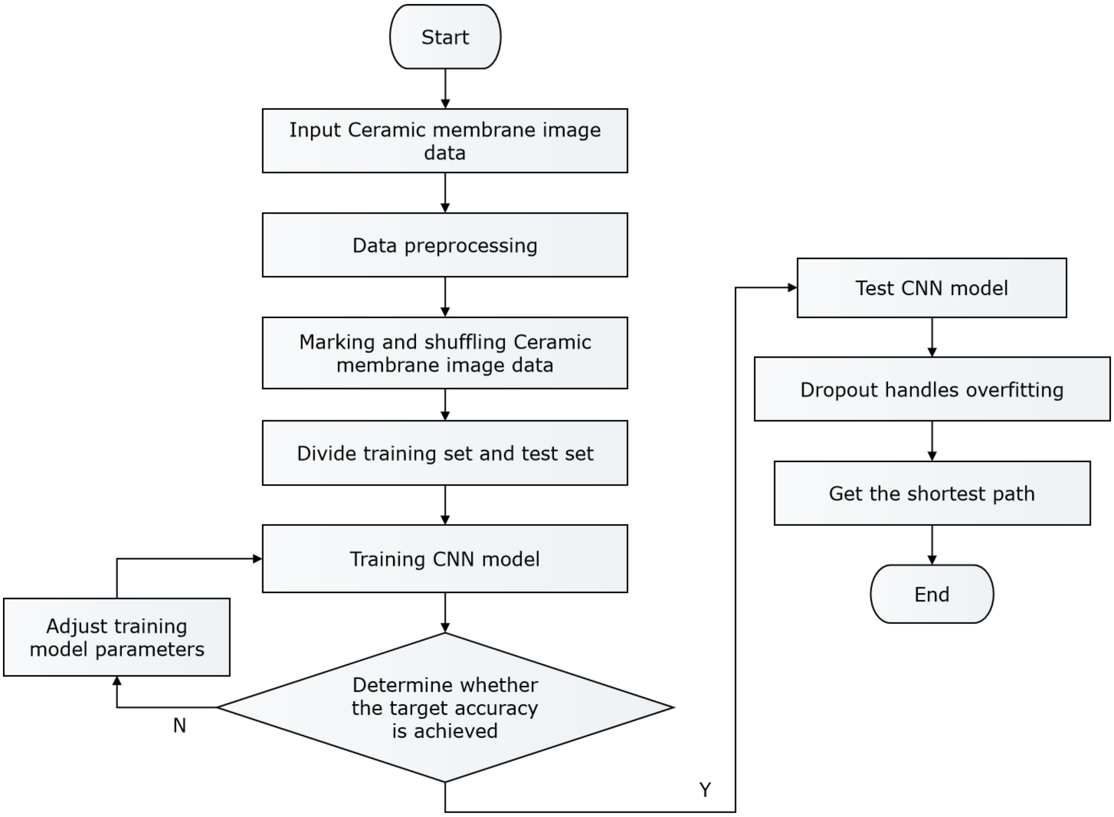

Figure 2: CNN operation process.

The important content of the primary stage of visual computing is to extract the features of different scales, different directions and different moving speeds in the image with the help of various operators. A common method is to convolve images with kernel functions with various shapes, directions, phases and scales. The attractive features of this method are easy to implement, easy to describe and analyze. Whether from the perspective of visual physiology or in practical application, the solution of CAD model matching problem largely depends on the reasonable selection of matching primitives.

CNN is a trainable structure consisting of multiple stages. The input and output of each stage are collections of arrays, which are called feature maps, so CNN is essentially a stack of maps. The CNN function is defined as:

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} \times k_{ij}^l + b_j^l\right) \tag{1}$$

$$F_j^{(n)} = \sum_i w_{ij}^{(n)} * F_i^{(n-1)} + b_j^{(n)} \tag{2}$$

$$F_j^{(n+1)} = f\left(F_j^n\right) \tag{3}$$

$$y_i = \gamma \hat{x}_i + \beta \tag{4}$$

$$\hat{x}_i = \frac{x_i - E_M(x_i)}{\sqrt{Var_M(x_i) + \varepsilon}} \tag{5}$$

Where: $E_M(x_i)$ and $Var_M(x_i)$ are the mean and variance, respectively.

On the basis of smoothing the characteristic information of SN image, firstly, the discrete change degree of gray value in local area of SN image is calculated. Secondly, the fourth moment of brightness distribution of feature information of SN image is calculated. Then, the brightness uniformity of the characteristic region of SN image is calculated and normalized. Finally, the minimum magnification factor of the contrast enhancement of the feature information of the SN image is calculated, and the enhancement of the feature information of the SN image is realized according to the calculation results. In the process of processing visual information by neural computing, the dimension of weight vector is often too high, which reduces the efficiency of learning algorithm. Convolution layer needs forward propagation and backward propagation when training. Forward propagation is to convolve the input image continuously through convolution operation to get the feature map until the output layer is obtained. Backward propagation is to use gradient descent method to adjust the error parameters of the expected result and the output result reversely, so as to get the model closest to the expected result. Four 2D images of a given ceramic film:

$$X = (X_1, X_2, X_3, X_4)^T \tag{6}$$

The directions of the four light sources can be written as the following matrix:

$$L = (L_1^T, L_2^T, L_3^T, L_4^T) = \begin{bmatrix} L_{1x} & L_{1y} & L_{1z} \\ L_{2x} & L_{2y} & L_{2z} \\ L_{3x} & L_{3y} & L_{3z} \\ L_{4x} & L_{4y} & L_{4z} \end{bmatrix} \tag{7}$$

L has been calibrated by the camera as a known quantity. The unit normal vector of the surface of an object is written as:

$$N = (N_x, N_y, N_z)^T \tag{8}$$

Usually, the neighborhood average method is effective to suppress noise, but with the increase of neighborhood, the degree of image blur becomes more and more serious. In order to overcome this shortcoming, the threshold method can be used to reduce the fuzzy effect caused by neighborhood averaging. Image edge detection can effectively reduce the amount of worthless data, that is, the useless part of all the data contained in the original image, thus eliminating a lot of meaningless information and retaining the important structural attributes we need in the image. In ceramic membrane SN image recognition, the image information of HR and low-resolution (LR) images of the same image in low-frequency channel is similar, so it will take extra time to join this part when training the network. Therefore, only learning the high-frequency information between HR and LR images (that is, residual images) can alleviate this training pressure. It is precisely because these hops improve the gradient flow of the network that the training efficiency is accelerated.

3.2 SR of Ceramic Membrane SN Image and Its Repair

Image distortion often occurs in the process of acquiring and transmitting images, and the obtained images are different from the original images to some extent. In order to improve the visual effect and facilitate the understanding and analysis of the image by the machine, the improvement methods or measures to strengthen the characteristics according to the characteristics or existing problems of the image are called image preprocessing. In CAD model, whether the preprocessing measures of the original image are effective or not is related to the quality of feature extraction and stereo matching. Generally speaking, the image resolution is directly proportional to the amount of information. In the process of image acquisition and transmission, it is often affected by factors such as down-sampling, noise and blur, which are mainly caused by image degradation caused by the environment, imaging equipment and transmission introduction. As shown in Figure 3, due to the limitation of lighting conditions and reflection characteristics, the collected SN images have the characteristics of low contrast, low signal-to-noise ratio and uneven illumination.

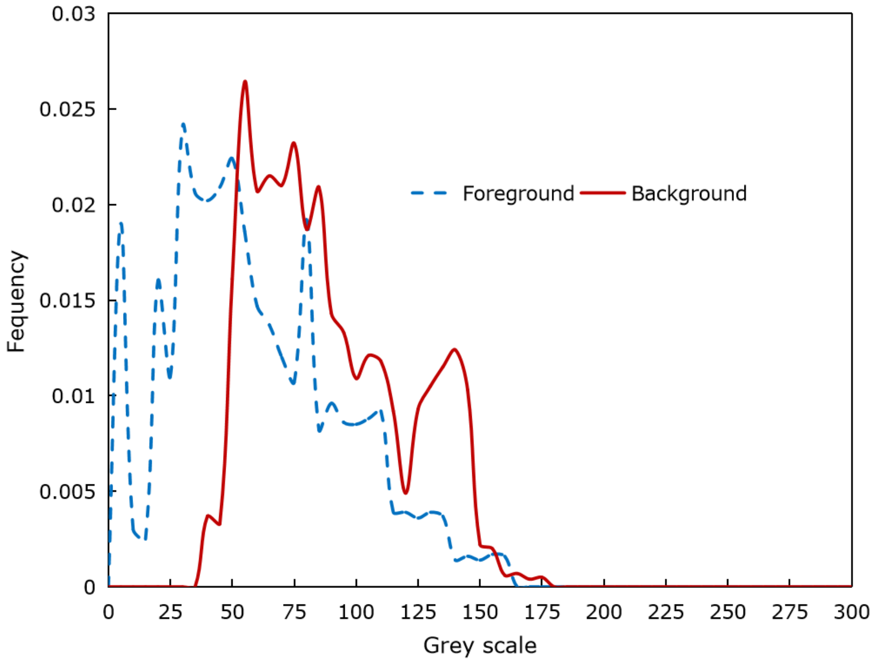

Figure 3: Gray distribution of character area and background area.

The method based on two-dimensional image processing is greatly influenced by image preprocessing or character segmentation. For the template matching method, the recognition accuracy of ceramic membrane SN depends largely on whether the characters and background can be separated accurately. However, for the ceramic membrane SN, it is difficult to design a suitable preprocessing algorithm to distinguish the character area from the background area because the gray distribution of the character area and the background area is very close. Compared with the method based on template matching, the method based on feature selection can suppress redundant information or noise in the image to some extent. However, preprocessing also has a great influence on the quality of feature selection, thus affecting the recognition effect. In addition, feature selection relies too much on prior knowledge, which makes the method based on feature selection unable to solve the problem of ceramic membrane SN identification in complex and diverse scenes, and its robustness and universality are poor.

In this article, an image SR algorithm based on end-to-end DL and CAD model is proposed and applied to the identification of ceramic membrane SN. Aiming at the problem that the correlation of features at all levels in image SR reconstruction network has not been paid enough attention, an image SR reconstruction algorithm of hierarchical attention network is proposed, which uses hierarchical attention module to improve the attention to important features and further enhance the feature selection ability of the network. Figure 4 shows the SN image SR of ceramic membrane and its repair process.

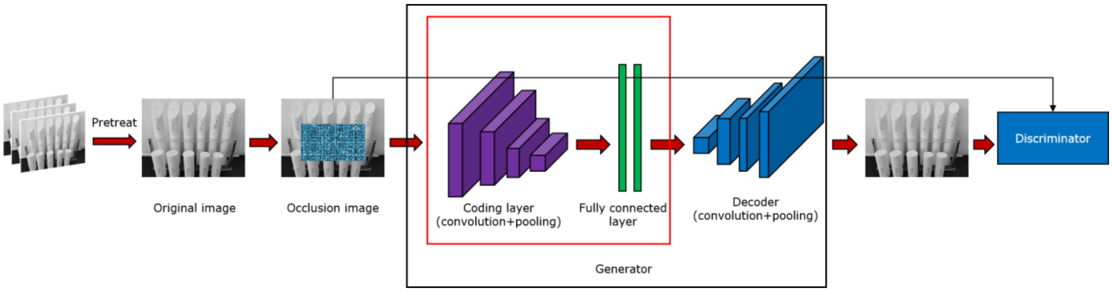

Figure 4: Image SR of ceramic membrane SN and its repair process.

Image features play a vital role in SR reconstruction, and the quality of image reconstruction depends on the ability to extract image characters to some extent. Li et al. proved that a very deep network can be effectively used in image restoration tasks, and this deep network is conducive to learning more effective image information, thus restoring more pixel values of the target area. However, in the process of increasing the depth of the network, it is more difficult to train the model, and it is more prone to gradient explosion or gradient disappearance.

Channel attention can assign more weights to channel features with more information in each layer, which improves the feature selection ability of the network to some extent. So it constructs a hierarchical attention network model. In this model, the hierarchical attention module is added on the basis of channel attention, which can consider the interdependence between different levels and adaptively emphasize hierarchical features, and the feature selection ability of the model has been greatly improved.

$$\bigcup_{i=1}^{N} R_i = R \tag{9}$$

For all i and j, $i \neq j$, there are:

$$R_i \cap R_j = \varnothing \tag{10}$$

For $i = 1,2,\ldots,N$, there are:

$$P(R_i) = TRUE \tag{11}$$

For $i \neq j$, there are:

$$P(R_i \cup R_j) = FALSE \tag{12}$$

In SR reconstruction, attention mechanism can allocate more attention to important areas during network training, thus improving the effect of image reconstruction. In image reconstruction, not all channel features are of the same importance to image reconstruction, but convolution operation pays no difference to different channel features, and does not consider the correlation between channel features. Although channel attention can weight the channel features of each layer, making the channel features with more key information, channel attention can't measure the importance of features in many different layers, especially the shallow features are easily weakened after passing through the deep network. Using hop connection in the network can alleviate this problem to some extent.

The goal of the detection stage is to generate the probability information and position information about the character region of the SN image, so as to extract the candidate text region. Because predicting text and non-text categories requires high-level semantic information and predicting text position requires low-level detailed information, the network model at this stage is relatively more complicated than that at the reconstruction stage. Assuming that the input and output functions of Ceramic SN image character information are expressed as R and R' respectively, the bilateral filtering discrete form expression of SN image character information is as follows:

$$R'=[k,j]=\sum_{m=-p}^{p}\sum_{n=-p}^{p}B[m,n,k,j]R[k-m,j-n] \tag{13}$$

Where p represents a pixel of SN image character information; m represents the variance of SN image character information; n represents the standard deviation of SN image character information; $B[m,n,k,j]$ represents Gaussian kernel function of SN image character information, and its calculation expression is as follows:

$$B[m,n,k,j]=\frac{\exp\left(-\frac{m^2+n^2}{2\sigma_\delta^2}-\frac{R[k-m,j-n]}{2\sigma_\xi^2}\right)}{R(k,j)} \tag{14}$$

Where σ represents the scale parameter of SN image character information.

In SR reconstruction, it is hoped that the characteristics of multi-scale receptive field can be integrated, so that the reconstructed HR image can have more reliable details. However, to extract the multi-scale receptive field features, convolution filters with different sizes need to be combined into the generating network. In this article, the image SR reconstruction algorithm of hierarchical attention network is proposed, which can learn the correlation between different levels of features.

4 RESULT ANALYSIS AND DISCUSSION

In order to verify the effectiveness of the SR model design method of ceramic membrane SN image based on end-to-end DL and CAD model proposed in this article, the traditional SR model of ceramic membrane SN image is compared by comparative simulation experiments. The simulation operating system is Windows 11, the processor is Core i7 13700k, the graphics card is RTX 3060Ti, the memory is 16GB, and the hard disk capacity is 500G. The simulation uses a ceramic membrane SN image with 600*800 pixels randomly selected from Google, which contains 1600 pixels of feature information. Subjectively, several differential operators are assessed. Table 1 compares the noise detection results.

	Original image	*Robert*	*Sobel*	*Prewitt*	*LOG*
Edge points	600	506	455	421	485
Detection ratio	-	84.1%	83.6%	79.7%	84.3%
Misjudgment point	-	None	Basically none	None	None

Table 1: Comparison of detection effects without noise.

In this article, the above experiment is done on the image with noise added. Table 2 analyzes the comparison results of detection effects of Gaussian noise.

	Original image	*Robert*	*Sobel*	*Prewitt*	*LOG*
Edge points	600	481	507	474	492
Detection ratio	-	79.6%	82.3%	78.1%	81.2%
Misjudgment point	-	Basically none	Have	Have	Basically none

Table 2: Comparison of detection effects when Gaussian noise is added.

Image features contain rich information, which can have a very important impact on the performance of SR reconstruction. If the features in the image can be fully utilized, the quality of the reconstructed image will also be improved. And increase the utilization rate of features in the original image, more effective image information can be obtained, thus improving the image reconstruction effect. The SN image data of ceramic membrane with great difference in data distribution interval is discretized in interval, as shown in Figure 5.

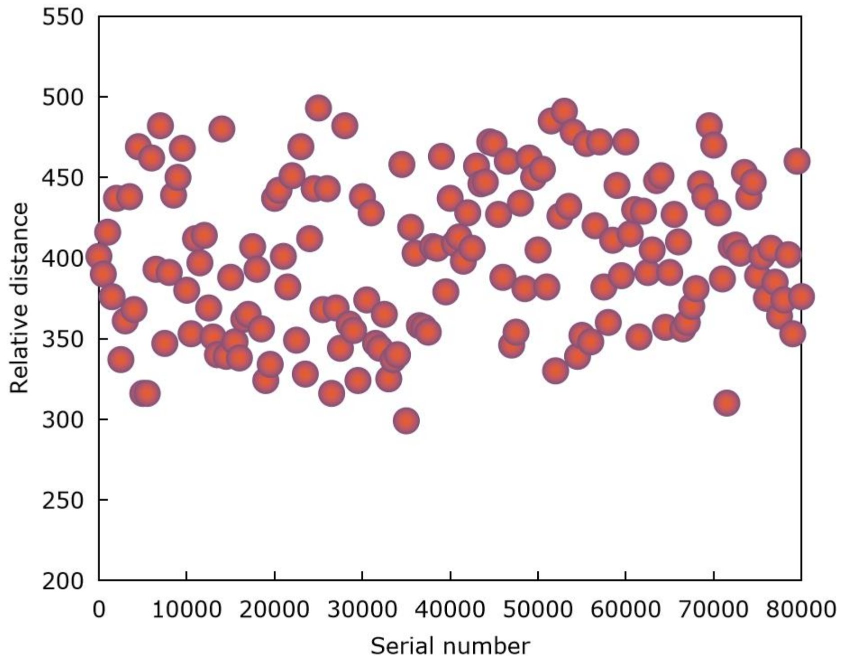

Figure 5: Data outlier removal processing.

Channel attention mechanism can pay more attention to important channel features. Although it has a certain effect on the recovery of high-frequency information, channel attention treats different hierarchical features equally, which leads to the loss of some detailed information in the reconstructed image. There are still difficulties in preserving natural textures and recovering image details. Comparing the recognition error of ceramic membrane SN image between this algorithm and RNN, the result is shown in Figure 6.

It's not difficult to seen that after many iterations, the error of this method has obvious advantages over the contrast algorithm in the SN image of ceramic membrane, and the error is reduced by more than 25% compared with the contrast RNN model.

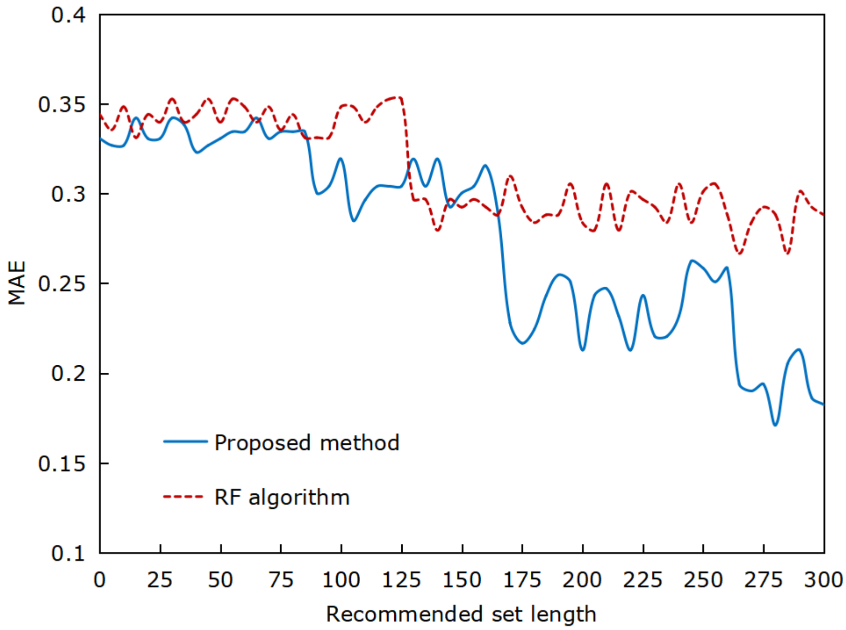

Figure 6: Comparison of identification errors of ceramic membrane SN images.

In the task of image SR reconstruction, attention mechanism is usually used, because attention mechanism can make more important information in the image get more attention during network training, which has a good effect on the reconstruction of high-frequency content and is conducive to the reconstruction of necessary edge structure and texture details in the image. The comparison of image recognition accuracy of ceramic membrane SN is shown in Figure 7.

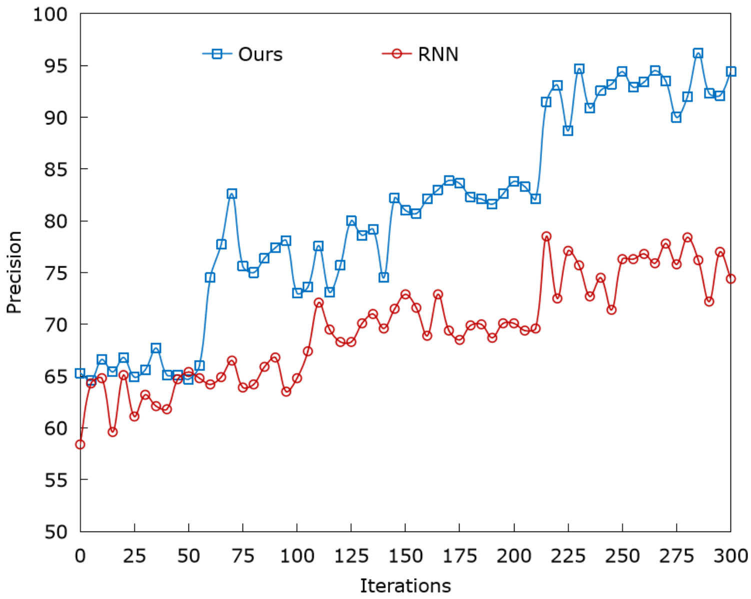

Figure 7: Comparison of accuracy of mine subsidence estimation with different algorithms.

It's not difficult to seen that the image recognition model of ceramic membrane SN in this article has obvious advantages over RNN in both early and late operation, and the accuracy rate is over 96%. The multi-scale residual module uses convolution kernels of different sizes to extract image characters of different scales, so that the features in the image can be more fully utilized; The second-order channel attention module learns the correlation between features through second-order feature statistics, which makes full use of the channel features containing more key information and enhances the expression ability of the whole network.

5 CONCLUSION

Ceramic membrane is an indispensable component in wastewater treatment industry. However, because there is almost no difference in the appearance of ceramic membranes, it is difficult to distinguish them from other ceramic membranes by their appearance characteristics except the SN of laser engraving on their surfaces. In this article, the automatic identification of ceramic membrane SN is studied, which mainly includes the image acquisition system for CAD stereo reconstruction and the detection and identification framework of ceramic membrane based on end-to-end DL. An image SR algorithm based on end-to-end DL and CAD model is proposed. A DL model suitable for mixed views is selected as input signal, and a hierarchical learning structure is constructed by using CNN. The residual dense block is introduced to fully extract the layered features in the image, which is beneficial to the recovery of high-frequency information; Reconstructing image context information at multiple scales by using a multi-scale convolution layer; Using the method of progressive up-sampling to learn the residual, the convergence speed is improved. The test results show that the ceramic membrane SN image recognition model in this article has obvious advantages over RNN, with an accuracy of more than 96% and an error of more than 25% lower than that of the contrast RNN model. At present, there is a lack of research on universality in this article, and the framework should be adapted to all industrial products with three-dimensional embossed characters in the future. If Generative Adversarial Networks (Gan) can be integrated into the end-to-end framework, not only the steps can be reduced, but also the perceived difference information during the framework training may be more abundant.

Yi Wang, https://orcid.org/0009-0002-1218-6132

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