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Dynamic Reconstruction Algorithm of Calligraphy Characters Based on Self-organizing Mapping

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Abstract. Due to the growth of society and the steady progress of economic construction, people are no longer only satisfied with the material needs of life, but more begin to pursue spiritual satisfaction. As a traditional art in China, China calligraphy has renewed its vitality. The rapid growth of artificial intelligence (AI) provides a new storage medium for calligraphy works and brings new ideas for the inheritance and dissemination of calligraphy art. The depth image contains the depth information of the scene. It is precisely because the depth information contained in the depth image represents the surface geometry of the objects in the scene that the depth image can directly use the 3D information of the geometry of these objects to reconstruct the scene in three dimensions. In this article, a dynamic emphasis algorithm of calligraphy characters based on self-organizing mapping (SOM) and CAD is proposed, and the calligraphy skeleton is extracted by SOM algorithm to ensure the continuity and smoothness of the calligraphy skeleton, so as to better reproduce the calligraphy characters in three dimensions. The comprehensive experimental results show that SOM model has a good application effect on the dynamic reproduction of calligraphy characters, and the image feature recognition accuracy is high, and the optimized image effect is obviously better than the comparison algorithm.

Keywords: Artificial Intelligence; Self-Organizing Mapping; CAD Calligraphy Characters; Dynamic Reproduction
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1 INTRODUCTION

The rapid growth of AI provides a new preservation medium for calligraphy works, which enables the historical calligraphy works to be preserved and shared in digital form, thus achieving the purpose of serving users. Amitrano et al. [1] carried out Spatial analysis of Self-organizing map of urban area map. By analyzing the construction of different image materials, it explored the model construction of urban reference data. Object based image analysis is an image processing technique that can segment and classify objects in an image. It can segment different objects in the image through image segmentation algorithms, and classify each object through feature extraction and classification algorithms. By combining self-organizing map clustering with object-based image analysis, objects in the image can be divided into different categories and similarities and differences between different objects can be discovered. Firstly, self-organizing map clustering algorithms can be used to cluster images, dividing the objects in the image into different categories. Then, object-based image analysis algorithms can be used to further process each category, extract the features of each category, and perform classification and recognition. Self-organizing map clustering is a clustering method based on neural networks, which can map high-dimensional data into two-dimensional or three-dimensional space while clustering the data. This method can perform well in processing large-scale data and discover nonlinear structures in the data. However, the results of self-organizing map clustering may exhibit some noise and irregularity, as it is based on the similarity between data points for clustering. Because the content of calligraphy works objectively shows the cultural and artistic features and the mood of the characters at that time, it is helpful for people to learn and study the origin and changes of some historical and cultural phenomena and styles. Gardner et al. [2] conducted topology adaptive mapping highlight analysis under multivariate analysis. It performs spectral overlap supervised analysis on color labeled image datasets. The CCSOM algorithm can reduce the dimensionality of ToF-SIMS hyperspectral imaging data to low dimensional space, and use color labeling to display different features in the data. In the results of Self-organizing map, color markers are used to distinguish different cluster centers. Different colors can be selected based on the content and properties of the cluster center, such as element type or compound type. Visualize the color marked circular Self-organizing map results. Circles can be used to represent different clustering centers and distinguish different elements or compounds based on color. The visualization results can be used to analyze the distribution and content of elements and compounds in the sample. The visualization of ToF SIMS hyperspectral imaging data using color marked circular Self-organizing map can provide more intuitive and in-depth information to help users better understand and analyze the distribution of elements and compounds in samples. At the same time, this method can be further expanded and optimized according to specific needs, such as adjusting clustering algorithms, parameters, and color labeling to adapt to different application scenarios and requirements, which can display data more intuitively, analyze and interpret them. This method can be applied in fields such as chemical composition analysis and materials science, and has broad application prospects. AI provides a new idea for the inheritance and dissemination of calligraphy art. With the help of intelligent equipment, the process of calligraphy creation and famous works are displayed, so that people can appreciate the beauty of calligraphy without leaving home. These digital works not only provide convenience for people to appreciate works of art in different historical periods, different authors and different styles, but also help to compare and study the calligraphy styles and their changes in different periods of a calligrapher's life. Compared with the traditional 2D color image, the depth image contains the depth information of the scene, so the 2D image combined with the depth image can be used for 3D reconstruction, and the reconstructed 3D image can represent the 3D information of the scene more intuitively.

Gardner et al. [3] mapped the image analysis of mass spectrometry imaging for multivariate analysis using machine learning. Combining visualization algorithms, a multi-layer standard depth profile representation similarity analysis was constructed. By constructing a model for three-dimensional visualization of material connections. It analyzed the clustering space model of surface clusters. Convert the original TOF-SIMS depth profile data into matrix form, with each row representing one pixel and each column representing different elements or ions. It includes the size of the input layer of SOM (i.e., the number of rows and columns of the pixel matrix), the size of the output layer (usually a reduction multiple of the size of the input layer), Learning rate, inertia and other factors. Based on the determined SOM parameters, a neural network is randomly initialized, where each neuron represents a pixel in the input layer and has a weight vector corresponding to the pixel in the input layer. Selecting the nearest neuron as the winning neuron.

Then, the weight vector of each neuron is updated according to factors such as Learning rate and inertia. After training, the weight vector of the SOM network can be visualized to display the distribution of different elements or ions in the input data. Based on the visualization results, the distribution patterns of different elements or ions in the input data and their relationships can be further analyzed. Grande and Gómez [4] analyzed and constructed the image standard processing results of Self-organizing map. The basic method of protein tissue segmentation in Topological space is carried out through a fuzzy function. Different tissue types in the image can be separated to aid in disease diagnosis and research. When processing magnetic resonance imaging data, the SOM algorithm can be used to reduce the dimensionality of high-dimensional data to a two-dimensional or three-dimensional plane or surface. This can simplify complex high-dimensional data into a form that is easier to visualize and analyze, while preserving important features and structures of the data. It uses pseudo labels to guide network training and organizational segmentation. Specifically, the PSOM algorithm first uses traditional tissue segmentation methods to generate pseudo labels that indicate the positions and shapes of different tissue types in the image. Then, the PSOM algorithm uses these pseudo labels to train the SOM network and uses the SOM algorithm to reduce the dimensionality and visualize the image data. Through this method, the PSOM algorithm can quickly and accurately segment brain tissue, and improve the visualization and interpretability of the organization. The skeleton extraction of calligraphy characters, that is, thinning, is an important prerequisite for the study of calligraphy digitalization. The main shortcoming of most existing calligraphy skeleton extraction algorithms is that they do not conform to human visual habits, and the main manifestations are artificial small branches and skeleton fracture and bifurcation distortion. Among the massive information data, the image can most intuitively represent the information of the observation scene, and it is the most intuitive way for people to know the world and obtain information. In the shape decomposition algorithm, a target is first decomposed into some simple parts, and then the skeleton of these simple parts is extracted to form the skeleton of the whole target. The depth image is different from the traditional 2D image, and the information it expresses is the 3D depth information of the scene, that is, the depth information of the imaged scene. By combining the depth information in the depth image with the 2D information of the traditional optical image, the 3D space region of the target scene can be reconstructed in a certain range. In this article, a dynamic emphasis algorithm of calligraphy characters based on SOM and CAD is proposed, and the calligraphy skeleton is extracted by SOM algorithm to ensure the continuity and smoothness of the calligraphy skeleton, so as to better reproduce the calligraphy characters dynamically in three dimensions.

Kasetkasem et al. [5] detected the Self-organizing map of the pipeline image. It analyzes the commonly used image pipeline extraction, detection, tracking and positioning in the water environment. Based on the determined SOM parameters, a neural network is randomly initialized, where each neuron represents a pixel in the input layer and has a weight vector corresponding to the pixel in the input layer. Provide input data to the SOM network and calculate the distance between each neuron and the input data, selecting the nearest neuron as the winning neuron. Then, the weight vector of each neuron is updated according to factors such as Learning rate and inertia. After training, the weight vector of the SOM network can be visualized to display the distribution of different pipelines in sonar images. Based on the visualization results, the distribution patterns of different pipelines in sonar images and their relationships can be further analyzed. By using the SOM algorithm, pipeline extraction can be performed on forward-looking sonar images to better understand the position and shape of pipelines, and to discover the relationships between different pipelines. Usually, in the imaging process of images, due to the influence of illumination or other environmental factors, or the quality problem of camera hardware equipment and the limitation of imaging equipment, the generated images will have poor quality, low resolution and carry noise. However, the appearance of these image quality problems will affect other practical applications of images. The challenge of Chinese character stroke segmentation and extraction is mainly reflected in the complex structure of Chinese characters, the overlapping of different strokes, the change of the thickness and length of strokes, and the variety of forms and writing methods of the same stroke in different fonts. Because the depth image is different from the traditional 2D image, it contains the 3D information of the scene, that is, the depth information of the depth image combined with the traditional 2D information can be used to reconstruct the real scene. Combining the depth image with the traditional 2D image, we can reconstruct the 3D space area of the target scene in a certain range to obtain the object information of the scene. Due to the poor quality of depth images obtained by general depth sensors, it will affect the effect of 3D reconstruction and cannot meet people's needs for obtaining 3D information. In this article, the 3D dynamic reproduction algorithm of calligraphy characters based on SOM and CAD is studied, and the following innovations are made:

⊖ In order to solve the problem that there are too many invalid branches in skeleton extraction and the continuity and accuracy of strokes cannot be guaranteed by the current methods, this article improves and optimizes the main curve algorithm based on the structure of calligraphy characters, and carries out skeleton extraction, skeleton tracking and stroke order acquisition on calligraphy images.

⊜ To solve the problem that the magnification can't be selected as needed when the traditional model reconstructs the image by establishing a hierarchical SOM model, and to highlight the edge information of calligraphy characters, so as to obtain a high-performance dynamic reproduction algorithm of calligraphy characters.

On the basis of summarizing the related research in the fields of calligraphy and character recognition, this article puts forward the application of SOM and CAD technology to the image processing of calligraphy characters. The method part of the article specifically introduces the design idea of changing the model; In the model test part, the effectiveness of this method is verified by comparing with the traditional method. Finally, the work and limitations of this article are summarized and the direction of further research is analyzed.

2 RELATED WORKS

Khattab et al. [6] conducted an analysis of remote sensing image schemes using weight schemes. It performs unsupervised classification on the spatial spectral accuracy of pixel schemes. Multi kernel Self-organizing map is an extended method based on Self-organizing map algorithm. It uses multiple kernel functions to cluster data and extract features. Different from the traditional Self-organizing map, multi-core Self-organizing map can use multiple different kernel functions to cluster data at the same time, which can better adapt to different types of data distribution. This method combines multi-core Self-organizing map and unsupervised spectral spatial multi-scale feature learning technology, which can effectively extract features from hyperspectral images and classify them. In the classification of hyperspectral images based on multi-core Self-organizing map, multi-core Self-organizing map algorithm can be used to reduce the dimension of hyperspectral images. This method can extract features from hyperspectral images and classify them by considering both spectral and spatial information. In unsupervised spectral spatial multi-scale feature learning, multiscale technology can be used to decompose hyperspectral images, and Self-organizing map algorithm can be used to extract and classify features at each scale. Konovalenko et al. [7] analyzed the optical character normalization model of image Geometric transformation. The projection analysis of affine normalization proves that the superposition of Quadratic function in unconstrained optimization is correct. Through the Affine transformation, the image is translated, rotated, scaled and other operations, so that the image character posture is correct for subsequent recognition. By using perspective transformation to correct the distortion of the image, the characters in the image are corrected to parallelograms for subsequent recognition. When selecting the best affine image normalization method, it is necessary to evaluate the impact of different normalization methods on character recognition accuracy and select a normalization method that can improve recognition accuracy. Evaluate the calculation time and efficiency of different normalization methods, and select the method with faster calculation speed to facilitate the processing of large-scale image data in practical applications. Evaluate the robustness of different normalization methods to image noise, light changes, and character pose changes, and select a method with strong robustness to handle various complex image situations in practical applications. Hierarchical double stream growth Self-organizing map with instantaneous is a Unsupervised learning algorithm for human activity recognition. It can transform real-time sensor data into Self-organizing map with instantaneous and hierarchical structure for human activity identification. The main idea of this algorithm is to divide the input data stream into two parts: the instantaneous part and the historical part. The instantaneous section includes the current input data, while the historical section includes the previously input data. Then, use these two parts separately for training and testing to achieve better performance. Nawaratne et al. [8] first assigned each data point in the input data stream to different neurons, and then clustered based on the similarity between the data points. In the clustering process, the algorithm divides data points into instantaneous and historical parts, and uses different weights to calculate their similarity. Ouyang et al. [9] conducted an self-organizing mapping clustering algorithm for automatic node classification. It constructs a visual unit area analysis of image pixels for automatic color classification. In the color segmentation of polychromatic images based on node growth Self-organizing map, the Self-organizing map algorithm can be used to reduce the dimension and visualize the polychromatic images. Through this method, different color regions can be mapped to different nodes, thereby achieving color segmentation of the image. Node growth technology is an extension technology for Self-organizing map, which can automatically determine the number and location of nodes through the growth process of Self-organizing map algorithm.

In multi-color image color segmentation based on node growth Self-organizing map, node growth technology can be used to determine the number and location of nodes in each color region, so as to extract the features of each color region more accurately. Multi color image color segmentation based on node growth Self-organizing map can be applied to color analysis and application fields of various multi color images, such as image classification, target detection, color design, etc. Through this method, color information in images can be extracted more accurately and further analyzed and applied. Qi et al. [10] proposed the construction of a geometric neural network graph with edge deepening. It analyzes the high-quality reconstruction of 3D scenes on the surface of depth images. Usually, Recurrent neural network models such as LSTM or GRU are used, which can serialize features and consider spatial information in images. By using the output of CNN as the input of RNN, the network can learn more rich image information. In edge deepening geometric neural networks, some techniques need to be adopted to improve the performance and accuracy of the network. For example, techniques such as residual connections and batch normalization can be used to improve the training effectiveness and generalization ability of the network. In addition, techniques such as skip layer connections and multi-scale feature fusion can also be used to enhance the network's ability to extract image details and texture information. Sen et al. [11] conducted a possibility analysis of self-organizing maps of natural feature environments using artificial intelligence light detection. Unsupervised weight testing through artificial intelligence. It analyzed the ground weight intensity coordinate results of the filtering algorithm. Based on the determined SOM parameters, a neural network is randomly initialized, where each neuron represents a laser point and has a weight vector corresponding to the attribute values of the laser point. Provide input data to the SOM network and calculate the distance between each neuron and the input data, selecting the nearest neuron as the winning neuron. Then, the weight vector of each neuron is updated according to factors such as Learning rate and inertia. Based on the visualization results, it is possible to further analyze the distribution patterns of different urban features in laser point space and their relationships. By using the SOM algorithm, unsupervised urban features can be extracted from airborne LiDAR data, thereby better understanding the spatial structure of cities and discovering the relationships between different features. Complex self-organizing maps are a neural network model used for clustering and classifying data. In adaptive imaging, complex self-organizing maps can be used to cluster and classify image data, thereby extracting the most representative image features and structural information. Adaptive imaging is an imaging method that adjusts in real-time based on environmental changes and target object characteristics. Through adaptive imaging, optimization and adjustment can be achieved based on different scenes and target objects, thereby improving the quality and efficiency of imaging. This technology can adaptively image the underground three-dimensional structure, which can improve the accuracy and efficiency of underground exploration and detection. Shimomura and Hirose [12] continue to improve the scanning information detection of Self-organizing map 3D visualization images. It constructs a coefficient system for retrieving scattering by simulating amplitude and phase information. Extracting important feature information by searching for peak phase in signals or images. In underground 3D imaging, important features of underground structures can be extracted through peak phase retrieval. In underground 3D imaging, complex Self-organizing map algorithm can be used to reduce the dimension and visualize the underground structure features obtained from peak phase retrieval. Through this method, underground structures can be more intuitively displayed and further analyzed and explained.

The text similarity detection method based on n-gram using Self-organizing map and similarity measurement is a Unsupervised learning algorithm for text similarity detection. Stefanovič et al. [13] uses Self-organizing map and similarity measurement to detect the similarity between two texts. And it can be used in different fields, such as Natural language processing, information retrieval, etc. The main idea of the algorithm is to convert the text into a digital vector, and then use Self-organizing map to reduce the dimension of the text vector to a low dimensional space. In low dimensional space, similarity metrics can be used to calculate the similarity between two texts. In low dimensional space, which is used to reduce high-dimensional data to low dimensional space for visualization. Unlike traditional dimensionality reduction methods, the ISOMAP algorithm does not need to know the dimensions of the data in advance, but maps high-dimensional data into low dimensional space through self-organization. Wang et al. [14] analyzed the analysis and construction of complex circuit Matrix unit of Self-organizing map. It determines the intelligent neural computing clustering analysis of image cross arrays. It can be used for data image mining and optimization. In data image mining, Self-organizing map algorithm can be used to reduce the dimension of image data and visualize it, so as to better understand the characteristics of data. In data optimization, Self-organizing map algorithm can be used to sort data for better optimization. Wickramasinghe et al. [15] conducted a systematic modification classification of the system structure. Through different Supervised learning, different resolution features of the hidden layer are optimized. Deep Self-organizing map (DSOM) is a neural network model for unsupervised image classification. It combines Self-organizing map and deep learning technology, and can effectively classify and extract features from images. The DSOM model consists of a deep neural network and a Self-organizing map network. Deep neural network is used to extract advanced features of images and input these features into Self-organizing map network. To map different categories to different nodes through Self-organizing map. This method can be effectively applied to various image classification tasks, and does not need label information. It is a Unsupervised learning method. In a word, depth Self-organizing map is an effective unsupervised image classification method, which can be used for various image classification tasks, and has the ability to automatically learn image features and Self-organizing map.

The traditional 2D color image contains the color information of the imaging scene, and the information expressed is the 2D information of the scene, which cannot accurately express the 3D scene information of the real world. In order to solve the problem that there are many invalid branches in the current method when extracting the skeleton, and the continuity and accuracy of strokes cannot be guaranteed, this article establishes a hierarchical SOM model to solve the problem that the magnification cannot be selected as needed when reconstructing the image with the traditional model, highlights the edge information of calligraphy characters, and ensures the continuity and smoothness of the calligraphy skeleton, so as to better reproduce the calligraphy characters dynamically in three dimensions.

3 METHODOLOGY

3.1 Calligraphic Character Recognition Based on SOM

Chinese characters are an important carrier to inherit Chinese culture, and calligraphy shows the unique writing art of Chinese characters in China, which is a treasure of Chinese traditional culture. The method of feature selection and extraction of calligraphy image and the method of feature selection and extraction of calligraphy image are similar. For calligraphy images, there are usually many irrelevant information such as image background, and the common features such as color and texture of ordinary images are not discriminating. China's calligraphy characters express meaning by form, so the shape characteristics can distinguish China's calligraphy characters well. The generation of calligraphy characters based on image processing mainly takes the existing works as the material, which is used to generate French characters with the same or similar style as the specific works. It mainly extracts the materials such as French radicals or calligraphy strokes from the existing works, transforms them accordingly, and finally synthesizes calligraphy characters. This article presents a dynamic reproduction algorithm of calligraphy characters based on SOM and CAD. The process of calligraphy font feature recognition based on SOM is shown in Figure 1.

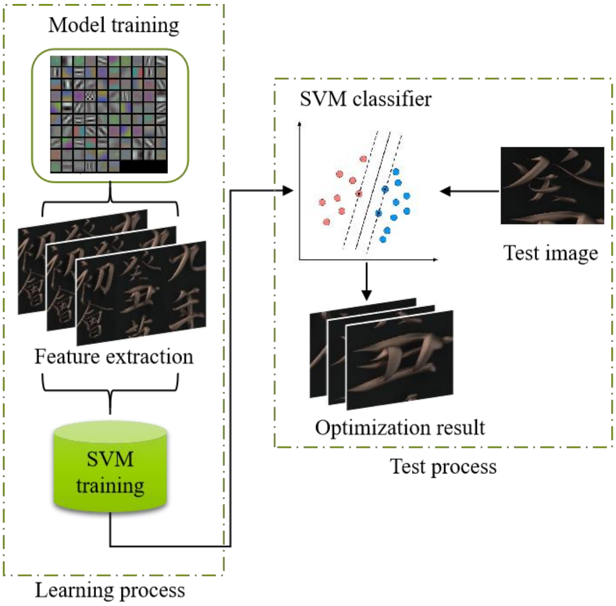

Figure 1: Calligraphy font feature recognition process based on SOM.

Training neural network is a very complicated process, because the change of parameters in the previous layer of the network will lead to the change of input distribution in each layer. The change between input data will lead to the nonlinear distribution change of input internal data, which finally makes the network model difficult to train. Changes in the distribution of parameters between layers of the network will slow down the training process, which requires us to choose the parameters of the network model carefully, and we have to reduce the learning rate and initialize the parameters of the filter carefully.

Since the self-encoder and discriminator share all the weights except the last layer, they can be put together, and the shared network part is represented by H. The Encoder encoder is represented by:

$$\mu = f_1(H(X)) \tag{1}$$

$$\log \sigma^2 = f_2(H(X)) \tag{2}$$

The discriminator D can be expressed as:

$$D = f_3(H(X)) \tag{3}$$

Where f represents different mappings of the last layer of the network.

In order to reduce the problem of fuzzy synthesis of calligraphic images, the fidelity of images is judged by inference network. Inferring that the network tries to assign a "true" label to the real training sample x and a "false" label to the generated sample x_f ; The generating network attempts to generate image samples that can be inferred as "true" by the network prediction. The introspective confrontation losses of the inferred network and the generated network are respectively expressed as:

$$L_{adv}^{(G)} = L_{KL}\left(z_{a,f}\right) \tag{4}$$

Where $z_{a,f}$ represents the authenticity unit of the generated sample.

Some calligraphy works may have document border lines, which will affect the subsequent word segmentation and recognition, so it is needed to remove the document border lines. In this article, the algorithm uses rectangular structured elements to get the horizontal and vertical border lines of the image respectively, and then obtains all the redundant border lines in the image by fusion, and then removes the border lines by frame difference method. Because of the complex shape and style of calligraphy characters, it is difficult for the general public to recognize them. The calligraphy character recognition method proposed in this article uses retrieval-based methods to help users recognize these characters.

Different calligraphers have different writing habits, so the presentation and arrangement of calligraphy handwriting will vary from person to person. Based on annotation information, the sum of the correlation matrices of all images is taken as the correlation matrix of the entire dataset, where N represents the number of training images. The correlation matrix can reflect the correlation relationship between various physiological and anatomical structures in the dataset from a macro perspective. So, the correlation matrix CM is represented as

$$CM = \sum_{i=0}^{N} CM_i \tag{5}$$

In the matrix, the conditional probability between some targets is small, and this kind of data rarely appears, which is easy to form noise, which will not only affect the distribution of the overall data, but also affect the convergence of the model. In order to filter out these noises, this article uses a threshold ε to binarize the matrix CM :

$$CM_{ij} = \begin{cases} 0, P_{ij} \le \varepsilon \\ 1, P_{ij} > \varepsilon \end{cases} \varepsilon \in [0,1] \tag{6}$$

The matrix representing the weighted graph $G = (V, E, w)$ is called the weighted adjacency matrix, and is set as W . Firstly, the Laplacian matrix of graphs is obtained by defining the convolution formula of graphs with the theory of graphs. The traditional Fourier transform, convolution analogy to Fourier transform and convolution on the graph signal get the following graph convolution product definition:

$$y = Ug_\theta(\Lambda)U^T x \tag{7}$$

Where x is the input graph signal and $U^T x$ is the matrix form of Fourier transform of graph signal x, where U is the characteristic vector of graph Laplacian matrix, and $\Lambda = diag([l_0, l_{l_{n-1}}]) \in R^{n \times n}$, $g_\theta(\Lambda) = diag(\theta)$ and $\theta \in R^n$ are a Fourier coefficient vector.

3.2 Dynamic Reproduction and 3D Modeling of Calligraphy Characters

The marking system based on the recognition results of calligraphy characters applies the recognition results of calligraphy characters to the marking platform of calligraphy characters, and the recognition results are recommended to users as reference marking information, which helps users to mark quickly, thus making the recognition method of calligraphy characters based on the image database of calligraphy characters and serving the construction of the image database of calligraphy characters. Collect a dataset of high-resolution color images and corresponding low resolution depth images, which should include various scenes and object types. In order to train the network, it is necessary to define an appropriate Loss function to measure the difference between the high-resolution depth image output by the network and the real high-resolution depth image. Use the prepared data set and the defined Loss function to train the network. The Backpropagation can be used to optimize the network parameters to minimize the Loss function. During the training process, hyperparameters can be adjusted and regularized to improve the generalization ability and stability of the network. After the training is completed, use the test dataset to evaluate the performance of the network. Test data can be input into the network to obtain the prediction results of high-resolution depth images, and evaluation indicators can be used to evaluate the accuracy and quality of the prediction results. The SOM operation process of extracting the representation features of calligraphy font images is shown in Figure 2.

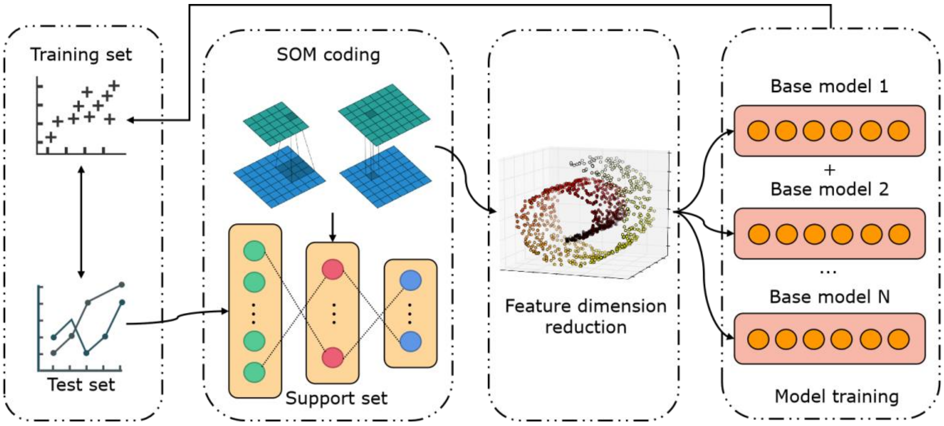

Figure 2: SOM operation process of representation feature extraction of calligraphy font image.

The purpose of binarization of calligraphy works is to remove the color information in the original calligraphy works, turn the pictures into grayscale images, and simplify the subsequent processing. By setting the new threshold to the midpoint of the average above and below the old threshold, the optimal threshold is iteratively obtained, and then the image binarization is realized according to the optimal threshold.

The dynamic replication and 3D modeling of calligraphy text is a challenging task that requires comprehensive consideration of factors such as the form, strokes, dynamic features, and 3D spatial structure of calligraphy text. It should be noted that the dynamic reproduction and 3D modeling of calligraphy characters need to use a variety of technologies and methods, including computer vision, machine learning, computer graphics, physical simulation, etc. At the same time, it is also necessary to have a deep understanding of the basic principles and techniques of calligraphy art in order to achieve high-quality calligraphy text replication and modeling effects.

The SOM operation process for feature extraction of calligraphy font images is as follows: Firstly, preprocessing of calligraphy font images is required, including image normalization, noise removal, grayscale, and other operations, in order to facilitate subsequent feature extraction. Based on the size and number of features of calligraphy font images, determine the structure of the SOM network, including network size, node type, and number of nodes. For each node, initialize a corresponding weight matrix with the same size as the calligraphy font image. Select random samples from calligraphy font images as inputs to the SOM network. For each node, the similarity between the sample and the node weight matrix can be calculated using Euclidean distance, cosine similarity and other methods. Select the node with the highest similarity to the sample as the best matching node. For the best matching node, update the weight matrix of the node based on its weight matrix and input samples. Repeat the above steps until the weight matrix of the SOM network stabilizes or reaches the preset number of training times. Finally, based on the weight matrix of the SOM network, calligraphy font images can be represented as feature vectors. Each node corresponds to a feature vector, which represents the features of the calligraphy font represented by the node. Using the extracted feature vectors for calligraphy font recognition, style conversion, creation, and other applications can be processed according to different needs.

It should be noted that SOM algorithm needs to set appropriate parameters in the training process, such as Learning rate, neighborhood radius, etc. These parameters have a certain impact on the effect of feature extraction. At the same time, the SOM algorithm also has certain limitations, such as being unable to handle high-dimensional data and difficult to determine network structure. Therefore, in practical applications, it is necessary to choose appropriate feature extraction methods based on specific situations.

4 MODEL TEST

In the task of image semantic segmentation, it is usually needed to evaluate from different indicators to analyze whether the expected processing effect has been achieved. This article compares the new method with the conventional method to verify the correctness of the new method, and compares the classical RNN algorithm with CNN algorithm. On this basis, the application of the new method in font CAD is comprehensively analyzed and verified. The algorithm in this article is mainly based on tensor stream platform, and the hardware device adopts NVIDIA-3070GPU graphics card. The use of GPU is helpful to accelerate the training of neural network. The number of rounds of training is set to 300, the number of cycles of generating network in each round is 100, and the batch number is 50. See Table 1 for the requirements of environmental configuration parameters of batch processing system.

Project	*Version*
Operating system	Windows 11
CPU	Intel(R) Core(TM) I7-13700K
Internal storage	16GB
Hard disc	1TB
GPU	RTX 3070
Memory	8G
DL framework	TensorFlow 2.5
Database administration	Navicat for SQLite
Compiler	Python 3.8
Interface development	Qt Designer

Table 1: Requirements for environmental configuration parameters of the system.

In the training and testing stage of the network, the low-resolution depth image is obtained by down sampling the original high-resolution depth image. By intercepting overlapping image blocks from all training images as training samples. The image block size of training sample input and label is 40*40. In each layer of network, the size of input and output is kept consistent by boundary expansion. Each pair of training data contains a low-resolution depth image, a color image of the corresponding scene and a high-resolution depth image as a label. Figure 3 shows the optimization effect of calligraphy image.

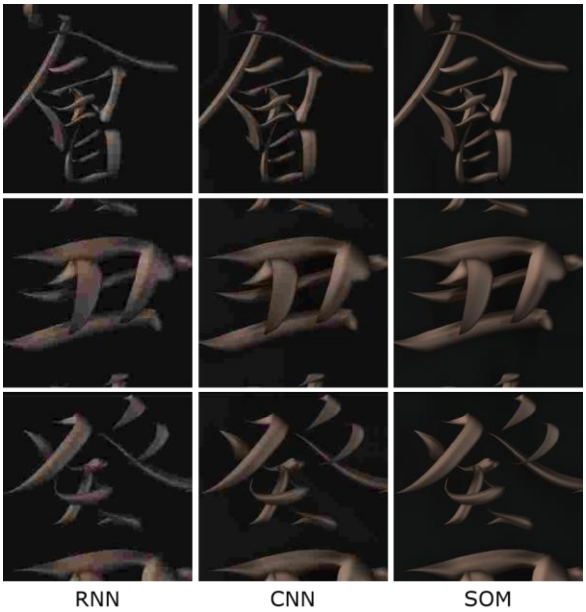

Figure 3: Comparison of optimization effect of calligraphy image.

The dynamic reproduction algorithm of calligraphy characters in this article is compared with the image processing performance of recurrent neural network (RNN) and convolutional neural network (CNN). The feature recognition precision of different algorithms is shown in Figure 4. The recall of different algorithms are shown in Figure 5.

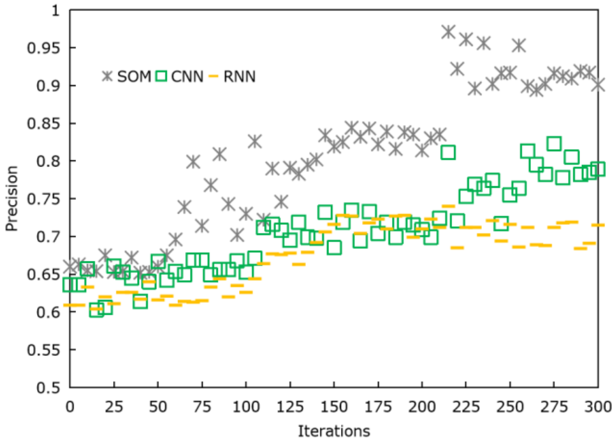

Figure 4: Recognition precision of different algorithms.

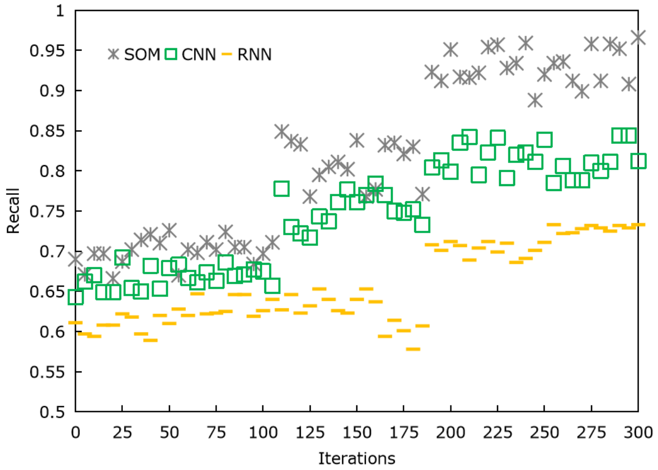

Figure 5: Recall of different algorithms.

It can be seen that the precision and recall of this algorithm are at a high level. The algorithm has excellent performance, which can extract the outline of the object and get the font boundary accurately.

The semantic segmentation method needs to deal with the stroke overlap separately. The visualization results show that the color of the stroke overlap area is different from that of its nearby strokes, because the stroke overlap area corresponds to at least two different types of strokes, and the task of semantic segmentation is to classify each pixel of the image, that is, each pixel corresponds to only one type. In order to make the semantic segmentation completely deal with the task of stroke extraction, it is needed to classify the overlapping strokes into one category separately, and then combine them with the strokes in the nearby areas to form basic strokes after obtaining the result of semantic segmentation. Compare the output results of different algorithms with the actual image features, as shown in Figure 6, Figure 7 and Figure 8.

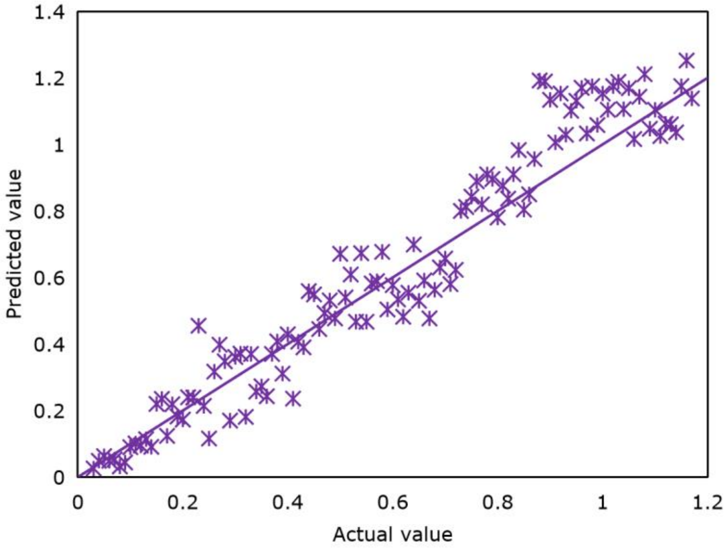

Figure 6: Scatter plot of RNN actual and predicted values.

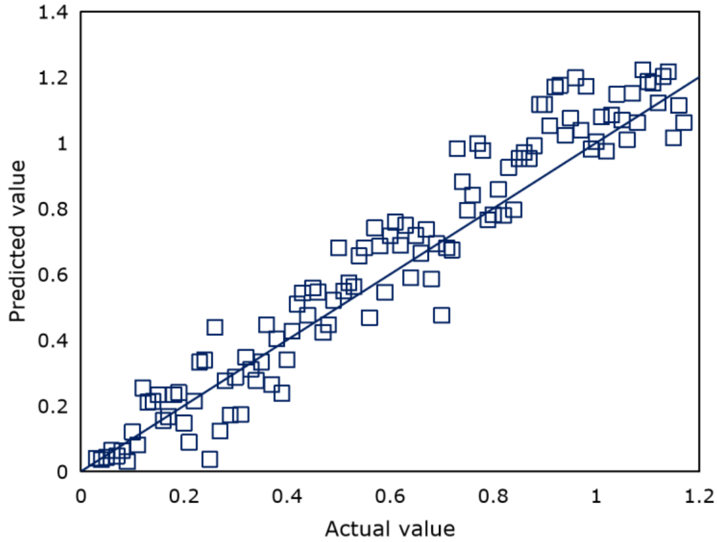

Figure 7: Scatter plot of RNN actual and predicted values.

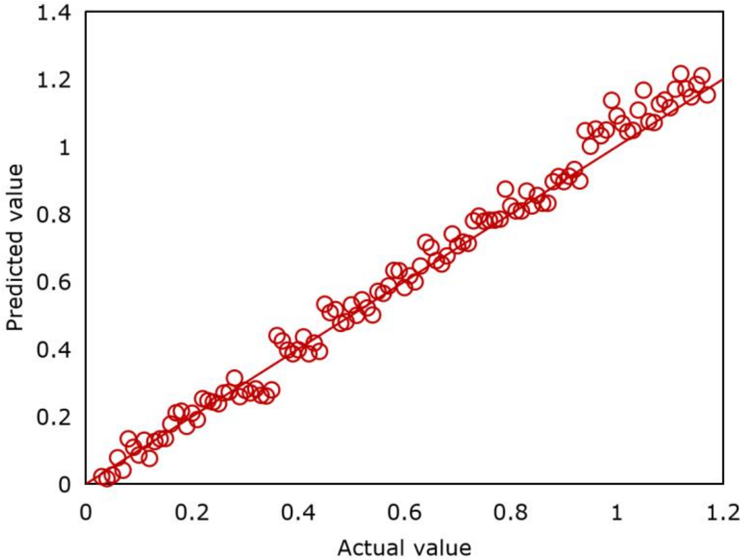

Figure 8: Scatter plot of actual and predicted SOM values.

The comprehensive experimental results show that SOM model has a good application effect on the dynamic reproduction of calligraphy characters, and the image feature recognition accuracy is high, and the optimized image effect is obviously better than the comparison algorithm. After binarization, thinning based on the principal curve and obtaining the stroke order, the original character image is restored to the stroke width on the thinning skeleton and reproduced frame by frame according to the stroke order, and the effect of dynamic reproduction of the original calligraphy characters is obtained. Compared with the original characters, the reproduction effect of calligraphy is accurate and close to the original state of calligraphy characters, and the system execution results are exactly the same for the same character. Calligraphy reproduction has a good consistency for the whole poem, which can better reflect the calligrapher's writing characteristics and better grasp the writing characteristics in detail treatment.

Compared with traditional methods, SOM can not only process calligraphy images with simple background, but also be more suitable for calligraphy images with complex background. By observing the visual results of the image, we can know that the main reason is that there are noises of different sizes in the background. Small noises can be removed through the denoising network, and large noises are difficult to remove, because pixel information such as colors of these noises is similar to that of calligraphy areas, and they will be mistaken for foreground. The SOM model proposed in this article not only learns the pixel information, but also learns the segmentation rules such as the structure of words and the position distribution of foreground and background, and the binarization effect is greatly improved.

5 CONCLUSIONS

The application scenarios of AI have been broadened day by day, and people have made more use of AI in daily life, art and music. Compared with the traditional 2D optical image, the depth image contains the depth information of the scene and can describe the 3D structural characteristics of the object. The quality of depth image is not affected by illumination and the reflection characteristics of objects in the scene, and it can accurately represent the 3D structure information of the surface of the target object in the scene. In order to solve the problem that there are too many invalid branches in the current method for skeleton extraction, which can not guarantee the continuity and accuracy of strokes, this article improves and optimizes the main curve algorithm based on the structure of calligraphy characters, and carries out skeleton extraction, skeleton tracking, stroke order acquisition and other processing on calligraphy images. The results show that SOM model has a good application effect on the dynamic reproduction of calligraphy characters, and the image feature recognition accuracy is high, and the optimized image effect is obviously better than the comparison algorithm. This method shows great advantages in the extraction of calligraphy skeleton, and obtains a good quality skeleton, which provides a new idea for skeleton extraction. Machine learning uses a large number of existing training data samples to train and learn effective feature mapping by constructing deep network models with multiple hidden layers, so as to improve the accuracy of data prediction results.

The next research needs to deeply analyze the internal relationship between different weight parameters and their learning effects, and adopt the optimal solution to further improve the efficiency of selecting the optimal solution and greatly shorten the learning time, which lays the foundation for the application of multi-classifier joint learning algorithm based on weight in DL.

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