Bronze Culture Image Recognition System based on Artificial Intelligence and Network Technology

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Abstract. The construction of image recognition system is inseparable from the development of computer network technology and artificial intelligence. Although the previous large-scale integrated circuit technology has made amazing achievements, it still cannot directly perceive the sound, image, text and other information. With artificial intelligence and modern network technology to open up new achievements in this research field, it is particularly important to carry out the research of image recognition system. The bronze culture and art of the Chinese Bronze Age are the crystallization of the wisdom of the ancient Chinese labouring people and a precious heritage our ancestors left us. How to preserve these precious cultural heritages with the means and methods of modern science and technology is a necessary process to further understand the time-honored characteristics of the Chinese nation. This paper will carry out the research from the Angle of modern artificial intelligence network technology integrating art, and strive to depict and preserve the colorful bronze culture systematically and comprehensively. This paper tries to construct a set of bronze cultural image recognition and management system, so that most users can realize the appreciation and management of ancient culture in a modern way through the intervention of artificial intelligence and network technology.

Keywords: Artificial Intelligence, Network Technology, Bronze Culture, Image Recognition System

1. Introduction

Bronze cultural images represent the essence of traditional Chinese art and have been endowed with a special mission of historical and cultural inheritance since the moment they were excavated. The ornamentation of bronze images is closely related to the superb casting technology at that time and even people's aesthetic characteristics [1]. Those colorful patterns are not only the representative of mystery and beauty, but more importantly, they achieve a high degree of unity with the device modeling [2].
Through these works of art, constitute the unique essence of traditional Chinese culture. It is not only a wonderful flower in the treasure house of Chinese culture, but also has a strong color in the history of world art and culture. Bronze culture image recognition and Chinese character recognition is different now, bronze culture image due to various reasons such as history, geography generates a lot of variants, but these were found preserved each variant is regarded as the treasure house of human culture, in the research and use strictly according to the original, such as a little bit untidy, may be considered as specification or incorrect\(^{[3]}\). Therefore, compared with current Chinese characters and image recognition, it is more feasible to identify bronze cultural images from the perspective of features\(^{[4]}\).

Due to the fact that the literati in ancient China tended to depict characters rather than figures, the whole research work of bronze art also presented a weak phenomenon of image research\(^{[5]}\). In history, scholars mostly adopted the attitude of only extending the writing and ignoring the form of these bronze cultures\(^{[6]}\). In addition, due to the long age, there are very few historical materials available for reference, so many aspects of the research are difficult to grasp\(^{[7]}\). Because the bronze ware itself the ornamentation uncertain factor is more, the change is more complex and appears to be relatively difficult. Therefore, for a long time, the depth of the study on the artistic quality of the magnificent and mysterious bronze vessel ornamentation is always not commensurate with the artistic height achieved\(^{[8]}\).

As for the study of bronze decoration, most of them focus on archaeology, aesthetics, anthropology and other aspects, but there are no works that discuss this treasure of human art based on modern artificial intelligence and network technology\(^{[9]}\). This article from the perspective of modern science and technology, strive to achieve with modern artificial intelligence and information network technology as the focus, more systematic and comprehensive analysis, the patterns of the bronze culture image problems, help to get rid of the framework of history, from the broad background of human activities as much as possible to explore and understand the bronze culture of image art taste\(^{[10]}\).

2. Research Method of Bronze Culture Image Recognition System based on Artificial Intelligence and Network Technology

2.1. Image Recognition Method

Image recognition is the most basic and important technology in the field of image research. An image recognition system mainly includes three parts: image information acquisition, information processing and processing, feature extraction, judgment or classification, etc. The specific image recognition process is shown in Figure 1.
In the technical field of image recognition, the method based on image feature extraction is challenged by many technical aspects. There is great blindness in how to represent the extracted feature and how to select the feature value. In order to solve these real-world problems, researchers realized that they had to explore a path through the process of obtaining data. In the process of applying the new technology, people find that the artificial intelligence neural network model can effectively solve this dilemma, and the process from input to output is almost completed in a moment. As a result, the artificial intelligence-based neural network has incomparable advantages in the field of image recognition, and is recognized as the most effective tool to solve the problem of automatic target recognition.

2.2. Image Processing Related Technologies

(1) Image preprocessing

The essence of image preprocessing is to process images to get more useful images for digital recognition. Therefore, the whole preprocessing process is an indispensable process. The pre-processed image can better extract various digital features. The process of image pre-processing is shown in Figure 2.
(2) Image graying

Due to the complexity of the image palette with 256 levels, many common image processing methods cannot be effectively applied to the bitmap, so it must be grayed out first. To reduce to grayscale is to quantify the color order of each pixel in the bitmap in terms of R, G and B components. After image graying, there is no difference in color level, only in brightness. There are various algorithms for image graying. The most direct and effective one is to assign a weighting coefficient to each RGB and then carry out the weighted summation. This method can be expressed as follows:

\[
f(x, y) = 0.3 \times R(x, y) + 0.59 \times G(x, y) + 0.11 \times B(x, y)
\]

Equation (1) is derived from the approximate constructor function of lightness when the RGB tricolor system is converted to the AHMunsell color system. The advantage of the AHMunsell system is that it is very consistent with the color perception of human eyes, and its color space is relatively uniform.

(3) Image binarization

After the image graying is completed, each pixel has a unique value of gray-scale coefficient, which directly determines the brightness of the pixel. In order to further extract image features, it is necessary to carry out binarization processing on the grayscale image. The binarization process is to divide the pixel set into two different color categories according to the segmentation standard and encapsulate the set. Suppose image f(x,y), whose grayscale range is [z1,z2], choose an appropriate grayscale value t, t ∈ [z1,z2] between z1 and z2.

\[
f(x, y) = \begin{cases} 
1 & f(x, y) \geq t \\
0 & f(x, y) < t 
\end{cases} \quad \text{background}
\]

\[
f(x, y) = \begin{cases} 
1 & f(x, y) \geq t \\
0 & f(x, y) < t 
\end{cases} \quad \text{object}
\]
According to the selected threshold, the image is binarized. The object is black and the background is white.

3. Construction of Recognition System

3.1. Image Preprocessing

(1) Image data reading

In order to conduct image analysis and processing, image data should be obtained first, including image width, height and color value of each pixel. Because each file has its own storage format, in order to reduce the amount of computing data, the system is designed to use 256 color BMP bitmap file as input.

(2) Image segmentation

In this study, the image segmentation is divided into two steps. First, the overall inclination of the image is adjusted, and then the image is segmented by the following segmentation algorithm.

(3) Retrenchment rearrangement of images

The normalized images have different character representation positions, so it is very troublesome to extract their features directly. Therefore, it is necessary to compress and rearrange the normalized characters to facilitate the smooth implementation of the feature extraction operation.

3.2 Feature Extraction Module

After the above process of transformation processing, the original set of pixels with different sizes and distribution has become the same size and neatly arranged characters. From these characters, the feature vectors that can best reflect the character features can be segmented, which can be substituted into the BP network model for the training of the network model, and the feature vectors of the samples to be recognized can be extracted, and the image feature extraction can be realized.

4. Effect Test of Bronze Culture Image Recognition System

Image feature extraction is a key problem in bronze culture image recognition. How to extract features of bronze culture image with high precision directly affects the effect of image recognition. In order to verify the optimization effect of BP network and the effectiveness of feature extraction, two groups of experiments were conducted, namely the experiment of feature extraction method by pixel and the experiment of feature fusion. The features in the bronze culture images were segmented. In the training set, there were 10 images in each bronze culture image and 100 training samples. The segmented Numbers in the remaining images were used as test images, and a total of 256 test samples were collected.

4.1. Pixel by Pixel Feature Extraction Method

Firstly, the pixel value of the segmentation character image is extracted as the feature. Since the segmented image is 8x16 dimensional, the number of feature vectors in each image is 128. The size of BP network is: the number of input layer units is 128; The number of hidden layer junctions is determined by the experiment, and the number of output layer units is 10. The permutation and combination of their outputs represent the categories of 10 different Numbers.
According to the calculation formula of BP model, 10 output values are obtained. Here, the output greater than 0.5 is regarded as 1, and the output less than 0.5 is regarded as 0. Then, it is compared with the ideal output of 10 types of output features, namely, the category of graphic features is known. The excitation function used in the experiment is Sigmoid function, and the initial weight interval is [-1,1]. During training, the convergence error is set to 0.001. At the same time in the training process, often vector upon eta and momentum factor a. All experimental data are trained five times the average, the experimental sample of 100, when the input is 128, vector eta is 0.015, the momentum factor is 0.9, a number of hidden layer nodes affect training is shown in Figure 3.

![Influence of the number of hidden layer nodes on network training](image)

**Figure 3.** Influence of different number of hidden layer nodes on network training

As can be seen from Figure 3, as the number of hidden nodes increases, the number of iterations decreases, and the recognition rate is relatively high. When the sample is 100, the input is 128, the momentum factor is 0.9, a number of hidden layer nodes is 20, vector is eta for the influence of network training, as shown in Table 1.

**Table 1.** Influence of different learning rates on network training

| Learning rate | Number of iterations | Training time | Feature recognition rate |
|---------------|----------------------|---------------|-------------------------|
| 0.01          | 1163                 | 16538         | 92.16%                  |
| 0.015         | 578                  | 8014          | 92.37%                  |
| 0.02          | 569                  | 7678          | 93.02%                  |
| 0.04          | 242                  | 3739          | 93.25%                  |
| 0.06          | 208                  | 3477          | 92.87%                  |
As can be seen from Table 1, with the increase of the learning rate, the number of iterations decreases, the convergence speed is fast, and the recognition rate also increases.

4.2. Feature Fusion Method

We extracted 12 coarse grid features from the segmented bronze cultural images, 28 horizontal and vertical projections, 2 pixel percentage features, and a total of 42 original features, so the number of feature vectors of each image is 42. The size of BP network is: the number of input layer units is 42; the number of hidden layer nodes is determined by the experiment, and the number of output layer units is 10. The permutation and combination of their outputs represent the categories of 10 different Numbers. According to the calculation formula of BP model, 10 output values are obtained. Here, the output greater than 0.5 is regarded as 1, and the output less than 0.5 is regarded as 0, and then compared with the ideal output of 10 types of features, namely, the feature category of the image is known. During training, the convergence error is set to 0.001. At the same time in the training process, often vector upon eta and momentum factor a. All experimental data were the average of 5 training sessions. When the number of experimental samples was 100, the input was 42, the learning rate was 0.015, and the momentum factor was 0.9. The influence of the number of hidden layer nodes on the training was shown in Figure 4 below.

| Learning rate | Number of iterations | Training time | Feature recognition rate |
|---------------|----------------------|--------------|--------------------------|
| 0.09          | 155                  | 2502         | 93.22%                   |
| 0.13          | 131                  | 2463         | 93.14%                   |

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Figure 4. Influence of the number of hidden layer nodes on network training

When the sample number is 100, the momentum factor is 0.9 and the number of hidden nodes is 20. The influence of learning rate on network training is shown in Table 2 below.

Table 2. Influence of different learning rates on network training
| 0.01 | 12583 | 60725 | 93.02% |
|------|-------|-------|--------|
| 0.015 | 8624 | 42074 | 92.71% |
| 0.02 | 6097 | 30627 | 92.56% |
| 0.04 | 3472 | 17169 | 92.15% |
| 0.06 | 1692 | 8525 | 92.22% |
| 0.09 | 1161 | 5838 | 92.94% |
| 0.13 | 1077 | 6178 | 92.73% |

As can be seen from the results of the above diagram, with the increase of the number of hidden nodes and the decrease of the number of iterations, the convergence will be faster.

4.3. Results Analysis and Discussion

From the above two experiments, it can be seen that the recognition rate of pixel by pixel feature extraction method is equivalent to that of feature fusion method, and the highest one-time recognition rate is 93.25% in pixel by pixel feature extraction method, which indicates the effectiveness of pixel by pixel feature extraction method. Of course, it can be seen from the number of iterations and training time that the feature fusion method has too few feature dimensions, that is, the number of input nodes of the neural network is too small, the convergence rate is slow, the training time is long, and the convergence does not occur even after 16,000 iterations. The increase of momentum term in the neural network significantly reduces the number of iterations, the network soon reaches the expected error, and reduces the probability of entering the local minimum. The learning rate is closely related to the network training time.

The experiment shows that the image recognition system is very effective, and it can solve the design and training problems of BP network, especially when the network structure is suitable, it can completely avoid the BP algorithm from getting into the problem of local minimum, and speed up the convergence of errors. The experimental results show that when the momentum factor is set to 0.9, not only the convergence speed of the network is greatly improved, but also the correct recognition rate is better.

5. Conclusion

The bronze culture and art of the Bronze Age is not only a precious heritage left to us by the Chinese ancestors, but also a crystallization of the wisdom of the industrious ancient working people. In the process of bronze culture spreading, the extension of bronze visual culture has been constructed. As a special symbol to communicate with human beings in different ages, bronze cultural images have unique visual aesthetic interest and function. This paper analyzes and realizes the construction of bronze culture image recognition system based on artificial intelligence and network technology, and introduces the image feature recognition algorithm based on neural network, in order to improve the network efficiency and recognition accuracy and enhance the stability. By selecting different initial weights several times,
adding momentum factors and adopting the method of changing the learning rate adaptively, the performance of the network is improved, the convergence process is accelerated and the complexity and training time are reduced. To analyze and study this precious bronze cultural heritage with a scientific attitude and method will help us to further understand the traditional culture of the Chinese nation with a long history and make the artistic treasures of China more dazzling.

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