Classification Method of Ethnic Minority Patterns Based on Faster R-CNN

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Abstract. The pattern on the costumes and brocades of ethnic minorities are of profound significance, but they are various and often composed of many kinds of patterns. It is not accurate and time-consuming to classify them only by artificial methods. Taking Yao's pattern symbols as an example, this paper collects and arranges the pattern pictures on clothing and brocade, preprocesses the pictures and labels the patterns on the processed pictures according to the preliminary classification. After the data set is made, the data set is trained and tested by Faster R-CNN algorithm. The results show that this method can effectively identify and classify the patterns of Yao nationality while reducing the time-consuming, and the average accuracy can reach 88.71%. It provides a useful exploration to help more ethnic minorities realize the intelligent classification of patterns.

1. Introduction

Chinese people of all ethnic groups record their own history, culture, customs and religious beliefs through clothing, crafts, buildings, songs and other carriers. In particular, the costumes of ethnic minorities are part of the cultural treasures of the Chinese nation due to their exquisite workmanship, diverse patterns and rich folk connotations. Yao nationality is the most widely distributed ethnic minority in South China. There are many branches, and the costume and brocade of each branch are different in color and style. The pattern symbols on them are rich and colorful, which are deeply influenced by national ideology. They are important subjects for the study of Yao folk culture. For example, the dragon dog pattern embodies the totem worship of Panhu by the Yao people [1]. Crimson fingerprint seal, Yaowang seal and so on embody the memory of Baiku Yao and other branches to their ancestors [2]-[3]. Snake patterns and other patterns reflect the worship of the ancestors of the Yao people for the animals and plants with strong reproductive capacity, and express the eternal hope of the nation [4].

Due to the variety of patterns, the traditional classification process is tedious and heavy. Moreover, with the advancement of technology and the increase of信息化, the way of spreading folk pattern symbols has changed from the past. Especially due to the intervention of new media, on the one hand, it provides a new way for the dissemination and protection of folk symbols, and a large number of pattern symbols are preserved and spread in digital form, breaking through the limitations
of traditional communication methods. On the other hand, it also makes the communication subject of folklore symbols change from the original local craftsmen to the media people, and even the information transmitted is greatly influenced by the subjective choice of the media people [5]. Compared with the traditional classification methods, the intelligent classification method based on image recognition and target detection technology, which can realize the fast and accurate classification of large samples. It can also provide convenient pattern recognition services to help users quickly understand the types and meanings of pattern symbols by interfacing with new media such as applications and applets. To a certain extent, it can avoid the misunderstanding of the receiving subject caused by the unequal information in the dissemination of ethnic minority pattern symbols, break the limitation of space and time in the dissemination of pattern symbols, and expand the dissemination range of pattern symbols [6]. This is not just related to the spread of symbols themselves, but also closely related to the spread of folk culture.

In recent years, the application of deep learning technology in the field of image classification has achieved more and more results [7]. In particular, the Convolutional Neural Networks (CNN) model commonly used in deep learning has strong generalization ability and can reduce the spatial dimension of the network through pooling operation, which is superior to other neural network models in image classification. In the application research of pattern classification, Shan-na Wang and others proposed a fabric image emotional classification method based on CNN, which integrates with manual emotional features, and the classification accuracy is 89.7% [8]. Xiao-jun Jia and others used the improved VGGNet model to classify blue calico, with an average accuracy of 89.73% [9]. Besides, they also proposed a method to extract elements of vein patterns, and then classify the extracted elements based on CNN, with an average accuracy of 98.5% [10]. The pattern composition of Yao costumes and brocades is complex, which is often composed of different kinds of patterns, so it is difficult to classify. Nevertheless, Faster R-CNN [11] algorithm can detect and label the objects in this kind of complex image, and finally achieve the pattern classification. Moreover, compared with R-CNN [12] and Fast R-CNN [13], Faster R-CNN algorithm is superior in speed and accuracy. Thus, on the basis of the above research, this paper applies Faster R-CNN to the pattern classification of ethnic minorities and takes the Yao costume and brocade pattern symbols as examples for experiments, which provides technical support for the recognition and dissemination of pattern symbols in combination with new media.

2. Data Set Making and Processing

The original data of Yao costumes and brocade patterns used in this experiment were collected through field shooting, museum shooting and Internet search. According to statistics, there are 471 pictures, covering 26 patterns 89.3%. Before training, the original data collected need to be processed. Firstly, the format of all pictures is converted to PNG, and the resolution is uniformly processed to 300*300. The sample pictures after preprocessing are shown in Figure 1. Secondly, because some of the pictures contain only one pattern and some contain multiple patterns, it is necessary to refer to the format of Pascal VOC data set before training, and mark the patterns on the processed pictures according to the pre-divided categories. Finally, after annotation, put the pictures and annotation files into the folder corresponding to the Faster R-CNN detection program according to the format of Pascal VOC data set. In order to facilitate the network training, the data is processed in batches.
3. Basic Operation Process of Faster R-CNN Object Detection

Faster R-CNN provides the configuration method of VGG16, ResNet_v1 and other pre-training models. This paper adopts the pre-training model of VGG16 network. Firstly, the feature map is generated by the feature extraction of the images in the data set. Then it is transferred to the Region Proposal Network (RPN) for processing. The main processes are: generate anchors, softmax classification, bbox regression, and generate proposals. On the feature map, each pixel can be regarded as an anchor. RPN generates multiple anchor boxes for each anchor point by adjusting the coefficients. These candidate areas are converted into fully connected features by convolution, and the mapping from features to classification layer and regression layer is realized by using 2*k and 4*k convolution kernels respectively. In the classification layer, softmax classification is used to determine whether the candidate area belongs to the foreground (i.e. target); in the regression layer, bbox regression is used to modify the candidate area, so that it is closer to the preset real area (i.e. the box marked during preprocessing). Then, the proposal layer will adjust the anchor points according to the regression results, and select some candidate areas with high prospect scores as proposals. The principle of RPN is shown in Figure 2.

After that, the ROI pooling layer will collect proposals and feature maps to generate proposal feature maps. The output proposal feature maps are calculated through the full connection layer and softmax classification to determine which category each proposal belongs to, output cls_prob probability vector, and obtain the position offset bbox_pred of each proposal by bbox regression to extract more accurate target detection frame. The output parameters such as cls_prob and bbox_pred will be used to optimize the data model of CNN training output and improve the detection performance of Faster R-CNN. The basic operation process of Faster R-CNN is shown in Figure 3.
4. Model Training and Result Analysis

The specific experimental environment of this experiment is: Linux (Ubuntu 16.04) operating system, TensorFlow deep learning framework, Faster R-CNN detection program, CPU is Inteli7-8700HQ, GPU model is GTX 1080Ti, and memory capacity is 11G. In this experiment, the learning rate of neural network training is 0.0025, the number of iterative training is 7000 rounds, and the data model is saved every 500 rounds. The training set consists of 350 pictures, the verification set consists of 61 pictures, and the test set consists of 60 pictures. The verification set is used to adjust the model parameters, and the test set is used to check the recognition accuracy of the model. During the training, the change of total loss is shown in Figure 4. It is thus clear that the total loss tends to be stable when the number of iterations is 4000, which shows that the output model has well fitted the data in the training set at this time. Subsequently, it can be used for subsequent image recognition test.

Using the data model of 7000 times of training, all pictures in the test set are detected. As there are many types of patterns, the data of batch test results are visualized, as shown in Figure 5. The picture shows that the recognition rate of 7 out of 27 patterns is 100%, and the accuracy of deer pattern, pinecone pattern and Yaowang seal is low. After inspection, it is found that the number of image samples of these three types of patterns is small, and they are often combined with other patterns in the same picture, resulting in these patterns being detected with secondary significant targets. From the point of view of improving the average detection accuracy, we should modify the relevant supervision signals and parameter weights in the training process, so that the detection accuracy of such targets can be improved. In addition, the mean Average Precision (mAP) of 27 patterns is 88.71%, and it only takes about 0.4 seconds to detect a single picture, which is fast. The test results of batch test can be exported through the matplotlib module. Now, the test results of two pictures are selected for analysis, as shown in Figure 6. It can be seen that five prominent patterns are marked in the two pictures respectively, and the pattern name is displayed. Moreover, the confidence degree is above 0.9. This proves that the Faster R-CNN detection program has good classification detection ability.
5. Conclusion
The pattern symbols on Yao costumes and brocades are the product of the integration of Yao people's aesthetic concept and cultural connotation. In the current situation of the prevalence of new media communication, intelligent classification method conforms to the development of the times and has unique value. Based on Faster R-CNN, this paper classifies Yao costumes and brocade patterns intelligently. The experimental results show that the intelligent classification method is convenient and fast, and the speed of recognizing single picture is about 0.4 seconds. In addition, multiple prominent patterns in the picture can be marked. The average recognition accuracy of pattern symbols in the test set can reach 88.71%. Next, we will further improve the recognition accuracy by optimizing the network structure, increasing training samples and other methods. We will also apply this method to the recognition and classification of other ethnic pattern symbols and use this intelligent classification method on applications and applets, so that users can easily and quickly understand the meaning of symbols by scanning ethnic pattern through mobile phones. Finally, we hope to achieve the purpose of disseminating the connotation of pattern symbols and folk culture of ethnic minorities with the help of new media.

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7. References
[1] J. Li, "On the Totem Adorement Pattern Designs of Ruyuan Yao Nationality," Art & Design, pp. 114-115, 2011.
[2] N. Lu, "The Artistic Characteristics and Humanistic Connotation of Guangxi minority ornaments: A Case Study of Yao Nationality," Art Panorama, pp. 82-83, 2018.
[3] S. Liu and Z. Jiang, "On Craftsmanship of Baiku Yao Clothing and Its Cultural Connotations," Journal of Silk, vol. 52, pp. 65-71, 2015.
[4] B. Wang, "The Female Dress Adornment and Procreation Worship of Hua Yao," Art & Design, pp. 102-103, 2007.
[5] F. Sun, "Folk Art Symbol and Its Modern Transmission," Ethnic Art Studies, vol. 24, pp. 92-96, 2011.
[6] X. Peng, "New Media Transmission Path of Folk Art," Media, pp. 76-78, 2015.
[7] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436-444, 2015-01-01 2015.
[8] S. Wang, H. Zhang and F. Kang, "Emotion Classification of Necktie Pattern Based on Convolution Neural Network," Journal of Textile Research, vol. 39, pp. 117-123, 2018.
[9] X. Jia, H. Deng, Z. Liu and L. Ye, "Vein Pattern Classification Based on VGGNet Convolutional Neural Network for Blue Calico," Journal of Optoelectronics · Laser, vol. 30, pp. 867-875, 2019.
[10] X. Jia, L. Ye, H. Deng, Z. Liu and F. Lu, "Elements Classification of Vein Patterns Using Convolutional Neural Networks for Blue Calico," Journal of Textile Research, vol. 41, pp. 110-117, 2020.
[11] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017.
[12] R. Girshick, J. Donahue, T. Darrell and J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, 2014, pp. 580-587.
[13] R. Girshick, "Fast R-CNN," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015, pp. 1440-1448.