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Research on the algorithm of painting image style feature extraction based on intelligent vision

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ABSTRACT

Because the traditional image feature extraction algorithm does not smooth the image, the success rate of feature extraction is low, the average running time and the false positive rate are increased. In view of the above problems, this paper proposes an algorithm of painting image style feature extraction based on intelligent vision. According to the internal structure of the content image and the painting image, the similarity analysis and the smooth transfer of pixels are carried out, and then the painting image is smoothed with the semi-supervised learning method. On this basis, the similarity rule of painting image style is established, and all the style features are quantified, so as to obtain the self-similarity descriptor of painting image style. Then the similarity coefficient between the painting image and other sample images is calculated, and the similarity matrix is constructed, and the intelligent vision technology is used to complete the extraction of the painting image style features. Experimental results show that this algorithm can effectively reduce the average running time and false positive rate of painting image style feature extraction, and also improve the success rate of feature extraction.

1. Introduction

Painting is a significant form of visual expression in the field of artistic creation. Each type of painting style contains distinctive creative backgrounds and artistic features, and is also the most direct way of featuring each type of painting school. Traditional paintings are created by professionals who spend a lot of time [1]. With the rapid development of computer technology, the creation of images can be better accomplished through image processing technology in the computer field. In the process of image creation by artists, the painting style is an important expression of the features of the painting image [2]. Even if the contents of the paintings are the same, different types of painting styles can present different artistic effects, and the background of the times and cultural meanings contained in them also differ greatly.

In recent years, the rapid development of intelligent vision technology has led to the dramatic progress of image drawing in the field of computer vision, especially the technology in painting image style feature extraction. An image depth hierarchical feature extraction algorithm based on convolutional neural network was proposed in reference [3]. The algorithm firstly abstracts the representation of the painting image to get the important information hidden inside the painting image, constructs the image hierarchical structure combined with the convolutional neural network, then selects the best hierarchical combination according to the matching result, while further uses the upper layer information to describe the lower layer feature map, establishes the features with strong expression ability, and finally completes the feature extraction. An improved ORB-SLAM algorithm for image feature extraction was proposed in reference [4]. The algorithm achieves feature extraction mainly through the modified ORB-SLAM method. Although the above two algorithms achieve a certain degree of application effectiveness, their failure to smooth the painting images leads to a lower success rate of feature extraction and an increase in the average running time as well as the false positive rate.

To address the problems of low success rate of feature extraction, long average running time and high false positive rate in the above traditional algorithms, a new algorithm of painting image style feature extraction is designed in this research based on intelligent vision.

2. Design of painting image style feature extraction algorithm

2.1. Smoothing processing of painting images

In the process of feature data collection, labeled data are often very scarce and require manual processing at the same time. Usually, unlabeled data occupy a larger proportion [5,6]. In the following, the painting images are smoothed mainly by semi-supervised learning. In the process of semi-supervised learning, the target classification function needs to be optimized in time.

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First, the associated relationship of individual data in the dataset X is analyzed, and the incidence matrix w is created. When $i \neq j$, the following definition needs to be set.

$$w_{i,j} = EXP\left(\frac{\left|x_i - y_j\right|^2}{2\sigma^2}\right) \tag{1}$$

Then create a matrix s, which requires the following definition:

$$s = D^{\frac{1}{2}} W D^{-\frac{1}{2}} \tag{2}$$

In Eq. (2), D denotes the diagonal matrix. On this basis, an iterative function is created for solving the optimal label set F. The specific expression is as follows.

$$F\left(t+1\right) = \alpha SF\left(t\right) + \left(1-\alpha\right) Y \tag{3}$$

In which, the regularization framework [7] is shown in Eq. (4) as follows.

$$Q\left(F\right) = \frac{1}{2}\left\{\sum_{i,j=1}^{n} w_{i,j}\left\|\frac{F_i}{\sqrt{D_{ii}}} - \frac{F_i}{\sqrt{D_{jj}}}\right\|^2 + \mu\sum_{i=1}^{n}\left\|F_i - Y_i\right\|^2\right\} \tag{4}$$

In Eq. (4), μ denotes the regularization parameter. The optimized objective function can be expressed as follows.

$$F* = \left(1-\alpha\right)\left(I-\alpha S\right)^{-1} Y \tag{5}$$

In the above process, the label set Y is established in order to complete the transfer of different labels, i.e., the labeled data are transferred to the unlabeled data. In the transfer process, regularization determination is required to be performed under the set constraints [8,9], and at the same time, new labels are given to the data while ensuring that the original data will not be lost to ensure the smooth transfer of labels.

The main reason for smoothing painting images is to remove the noise present in them [10] and to further improve their quality.

For a given content image X and a given painting image Y, both of them are images in RGB color space, which not only contain the same content features, but also have very similar spatial structures. In order to obtain a more desirable feature extraction effect, the painting image needs to be converted into a grayscale map X_{gray}, which is firstly processed by mean filtering algorithm [11,12], and all the pixel values in the grayscale map are converted to obtain X_{result}. The pixel value conversion equation is as follows.

$$X_{result} = \min\left(Int\left(\frac{255 \times X_{gray}}{255 - \beta \times X_{filter}}\right), 255\right) \tag{6}$$

In Eq. (6), X_{result} denotes the grayscale content image smoothed for semi-supervised learning; X_{gray} denotes the grayscale image corresponding to the content image; X_{filter} denotes the image after filtering; β denotes the weight coefficient of X_{filter}.

The incidence matrix and matrix S are created with X_{result} by the semi-supervised learning method. The painting image is smoothed using the semi-supervised learning method and the painting image obtained is as follows.

$$Y_{ragef} = \left(1-\alpha\right)\left(I-\alpha S\right)^{-1} Y \tag{7}$$

In Eq. (7), α denotes the weight coefficient of labeled data smoothing.

2.2. Painting image style feature extraction based on intelligent vision

After smoothing processing of painting images, a research into the painting image style will help reveal the similarities among different painting image styles. In the process of creating painting images, the universally accepted style features in the art field are extracted first and be subject to quantification. The self-similarity descriptor of images is established through computing the similarity of local patches; then a similarity coefficient between the images measured by distance function and other sample images is obtained. A similarity matrix is established via the similarity coefficient as the similarity matrix of image style. The similarity rules of various painting image styles are shown as below.
(1) Rule of consistency: in the same painting images, the painting image style should be consistent; there cannot be two different styles of painting.
(2) Rule of existence: when image I_1 and image I_2 are similar in painting style; then the similarity can be converted into a similarity coefficient [13,14], indicating that the two are of the same type or different types. The value of the similarity coefficient falls in the range of [0,1], in which 0 represents lack of similarity, and 1 complete similarity. Then assuming *similarity* represents similarity between two images, the following can be obtained.
(3) Rule of comparability: the similarity coefficient of painting images of the same type should be higher than that of different types. The following shows measurement by the distance function distance [15,16]. The specific judgment basis is as shown in Eq. (8).

$$\begin{cases} label\left(I_1\right) = label\left(I_2\right) \\ label\left(I_1\right) \neq label\left(I_2\right) \end{cases} \Rightarrow \begin{cases} simlarity\left(I_1, I_2\right) > simlarity\left(I_1, I_3\right) \\ \Updownarrow \\ \text{distance}\left(I_1, I_2\right) < \text{distance}\left(I_1, I_3\right) \end{cases} \tag{8}$$

The similarity between matrix–vectors and between matrix–vector sets can be calculated by computer. It is a quite common concept. In which, distance function is used to measure the similarity between matrix–vectors and meanwhile to analyze the similarity relations among matrix–vectors. The purpose of identifying paining image style is to make use of and compute the distance between vectors and point groups [17,18]. A small distance between them indicates a close similarity between matrix–vectors. By the rules above, assuming the distance between matrix–vectors is smaller than any threshold value, the vector can be included into the nearest point group, i.e. a category.

The common distance measures used in the image processing by the intelligent vision technology are classified as below.
(1) Manhattan distance computing process is as shown in Eq. (9).

$$D\left(P, Q\right) = \begin{cases} \left|P - Q\right| \\ \left|p_1 - q_1\right| + \cdots + \left|p_n - q_n\right| \end{cases} \tag{9}$$

(2) Euclidean distance computing process is as shown in Eq. (10).

$$D\left(P, Q\right) = \sqrt{\left(p_1 - q_1\right)^2 + \cdots \left(p_n - q_n\right)^2} \tag{10}$$

(3) Hamming distance computing process is as shown in Eq. (11).

$$D_h\left(P, Q\right) = \frac{1}{2}\left(n - \sum_{k=1}^{n} p_k \cdot q_k\right) \tag{11}$$

The local feature of painting image includes a vector set, and the Nearest Neighbor classification or voting method is used to conduct image matching and feature extraction [19–21]. Descriptors can be established for the painting image style in the process of painting image style feature extraction. Due to subjectivity of the method, it is hard to describe the style of the entire painting image in a quantitative way via the feature data. It is discovered that global and local patches adopt vector matrix to describe the difference among artistic styles, thus developing the concept of similarity.

Assuming a painting image is $W \times H$(size), and a mesh I is divided into $M \times N$ (number) local patches with equal size, the specification of any local patch i in the painting image is $w_i \times h_i$. Assuming P (number) features are extracted via patches [22,23], the size of matrix quantized is $w_i \times h_i \times P$, as represented by L_i.

As can be seen by the consistency rule, a similarity is involved in the painting image patches as the painting images have the same style. The self-similarity between patch i and patch j can be defined as below.

$$G_{ij} = \frac{\left|L_i - L_j\right|^2}{(w_i \cdot h_i - 1)} \tag{12}$$

Where, L_i denotes the feature matrix corresponding to patch i, and L_j feature matrix corresponding to patch j; w_i denotes the width of patch i, and h_i height of patch i. The coefficient of similarity between patch i and the rest patches can be calculated via Eq. (12), and it is expressed by vector as below.

$$SM_i = \begin{bmatrix} G_{i1}, G_{i2}, \ldots, G_{iM} \\ \vdots \quad \ddots \quad \ddots \quad \vdots \\ \vdots \quad \ddots \quad \ddots \quad \vdots \\ \cdots \quad \cdots \quad \cdots \quad G_{iMN} \end{bmatrix} \tag{13}$$

In Eq. (13), SM_i denotes the matrix of self-similarity between patch i and other patches of painting image styles. For $M \times N$ (number) patches, the self-similarity descriptor of image I style can be obtained by calculating, as expressed below.

$$D_1 = \begin{bmatrix} SM_1 & SM_2, & \cdots & SM_m \\ \vdots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ SM_{MN-M-1}, & SM_{MN-M-2}, & \ldots, & SM_{MN} \end{bmatrix} \tag{14}$$

Assuming Q training samples are involved in the two types of problems, the corresponding similarity coefficient is expressed as below.

$$\alpha_{(i,j)}^{l_m} = e^{\left(\frac{d(x_i,x_j)^2}{\sigma^2}\right)} \tag{15}$$

Sample x_j is set to represent similar samples and the identifier of sample x_j is l_m, then the corresponding similarity coefficient is expressed as below.

$$\beta_{(i,j)}^{l_n} = e^{\left(\frac{d(x_i,x_k)^2}{\sigma^2}\right)} \tag{16}$$

The result of $\alpha_{(i,j)}^{l_m} > \beta_{(i,j)}^{l_n}$ is obtained by the similarity rule (3). The matrix of similarity between final sample x_j and other samples is expressed by Eq. (17).

$$M_{xj} = \begin{bmatrix} \beta_{(i,j)}^{l_1} & \cdots & \beta_{(i,i)}^{l_1} & \cdots & \beta_{(i,Q)}^{l_1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \alpha_{(i,1)}^{l_m} & \cdots & \alpha_{(i,I)}^{l_m} & \cdots & \alpha_{(i,Q)}^{l_m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \beta_{(i,j)}^{L} & \cdots & \beta_{(i,i)}^{L} & \cdots & \beta_{(i,Q)}^{L} \end{bmatrix} \tag{17}$$

Generally, the accuracy of feature extraction is raised by intelligent vision technology in the field of computer image analysis and image processing. The specific operation process is given below.

Step (1): input an initial training set, and meanwhile set positive and negative samples.

Step (2): initialize the weight and set N to represent number of samples in the training set.

Step (3): circulate the training, including weight normalization and weak classifier training. Calculate the corrected error rate and classifier weight. The calculation method is as below.

$$\beta_j = \frac{e_j}{1 - e_j} \tag{18}$$

$$\alpha_j = -\log \beta_j \tag{19}$$

Step (4): extract painting image style by intelligent vision technology. The process is as shown in Eq. (20).

$$h(x) = sign\left[\sum_{j=0}^{N-1} \alpha_j \beta_j (x)\right] \tag{20}$$

3. Simulation experiment and result analysis

An experiment is designed as follows to verify the overall effectiveness of the algorithm of painting image style feature extraction based on intelligent vision described above.

The experiment takes the database of Dunhuang frescoes as the object of study. The database includes a total of 300 images with a resolution of 512 × 512. The experiment conditions: Intel(R)Core(TM)i5-2520M processor +8 GB memory + Linux operating system.

To avoid producing a single experimental result, an image depth hierarchical feature extraction algorithm based on convolutional neutral network proposed in reference [3] and an improved ORB-SLAM algorithm for image feature extraction proposed in reference [4] were used to accomplish performance comparison validation compared with the algorithm presented in this paper.

(1) Success rate of painting image style feature extraction (%)

20 training images chosen were tested in features including line, color and texture feature in all database. The success rate of painting image style feature extraction was set as an evaluation indicator. The results of performance comparison among the algorithms are shown in Fig. 1. It can be seen from the experimental data in Fig. 1 that the algorithm presented in the paper has a remarkably higher success rate of painting image style feature extraction, which stands above 90%, in contrast with the other two traditional algorithms. This is mainly because the algorithm of painting image style feature extraction based on intelligent vision designed in this paper has smoothed the painting image and effectively filtered out the noise in the image, which makes the algorithm of painting image style feature extraction achieve a significantly higher success rate and keep in a stable state.

(2) False positive rate (%)

The comparison results of false positive rate among the three algorithms are shown in Table 1.

Analysis of the experimental data in Table 1 shows that the false positive rate of the algorithms tends to rise with increase in the number of test samples. The maximum false positive rate is 0.12 for the algorithm proposed in reference [3] and 0.19 for the algorithm in reference [4]; whereas the algorithm in the paper has a lower false positive rate (0.02 at most) compared with the two traditional algorithms. This attributes to a series of smoothing processing that the algorithm in this paper conducts aimed at the painting image style feature extraction based on intelligent vision. Smoothing processing will enable region image blocks to become smooth and meanwhile make the boundary of local regions of painting images clearer. It can effectively facilitate

Table 1
Comparison results of false positive rate of different algorithms.

Number of test samples/(piece)	False positive rate		
	Algorithm in this paper	Algorithm in reference [3]	Algorithm in reference [4]
2	0.02	0.05	0.07
4	0.01	0.06	0.09
6	0.02	0.07	0.13
8	0.03	0.09	0.15
10	0.02	0.12	0.19

Table 2
Comparison results of average running time of different painting image style feature extraction algorithms.

Number of test samples/(piece)	Average running time of painting image style feature extraction/(min)		
	Algorithm in this paper	Algorithm in reference [3]	Algorithm in reference [4]
50	0.25	0.30	0.35
100	0.30	0.34	0.41
150	0.34	0.39	0.47
200	0.37	0.42	0.53
250	0.41	0.46	0.57
300	0.45	0.50	0.62

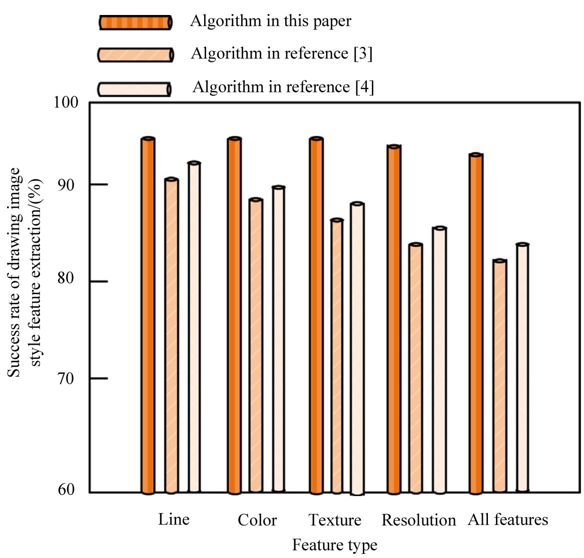

Fig. 1. Comparison results of success rate of different painting image style feature extraction algorithms.

smooth transition between approximate points and help reduce the false positive rate of the algorithm presented in all respect.

(3) Average running time of painting image style feature extraction/(min)

To further validate the superiority of the algorithm presented in the paper, the following experiment is conducted to test and compare the average running time of painting image style feature extraction by the three algorithms. The results are shown in Table 2.

Analysis of the experimental data in Table 2 indicates that the average running time of the algorithms tends to rise with increase in the number of test samples. The maximum running time is 0.50 min for the algorithm in reference [3] and 0.62 min for the algorithm in reference [4]. By contrast, the algorithm designed in this paper has a remarkably shorter average running time, i.e. 0.45 min. It is proved that it is feasible and requisite for the smoothing processing conducted by the algorithm presented in this paper.

4. Conclusion

Targeting problems of traditional feature extraction algorithms in terms of low success rate, long average running time, and high false positive rate, this paper designs a new algorithm of painting image style feature extraction in combination with intelligent vision. Besides, it is proved by the results of simulation experiment that the algorithm can effectively raise success rate of painting image style feature extraction, and lower false positive rate and average running time. In spite of breakthrough to some extent, there are still some imperfections in the algorithm due to limited time, conditions, etc. Follow-up improvements will be made for the algorithm, e.g. improving its capability of directional feature extraction to offer a more effective technical support for the study of image style.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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