Feature Similarity Image Classification Algorithm Based on Deep Learning

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Abstract: Based on the traditional fuzzy BP classification method, the image with high degree of feature phase was classified with higher misclassification rate. Considering the problems of the traditional methods, in this paper, a classification feature similarity image classification algorithm based on deep learning and support vector machine was proposed. Firstly, the local average noise reduction method was used to denoise the similarity image, and the wavelet image was decomposed by wavelet multi-scale decomposition algorithm. Then, the local information smoothing processing of the image was performed by the RGB color component recombination method, and the rough set feature quantity of the image was extracted. Finally, the extracted feature quantities were input into a support vector machine learner for image classification. In the hidden layer of the classifier, adaptive learning of weighting parameters was performed by the deep learning algorithm to achieve image enhancement processing and classification optimization of batch feature similarity images. The simulation results showed that the accuracy of feature similarity image classification was better, the ability to resist inter-class attribute perturbation was stronger, and the retrieval efficiency of large-scale images was improved.

1. Introduction

With the rapid development of image processing technology and big data analysis technology, it is necessary to optimize the classification design of large-scale images to improve the retrieval ability of images in multimedia databases. In multimedia databases, a large number of images have certain similarity characteristics. The classification of images with strong similarity characteristics is interfered by the inter-class attributes, resulting in poor accuracy of image classification, which seriously affects the retrieval and accessibility of multimedia databases and reduces the efficiency of image retrieval. Therefore, combined with the adaptive learning method of image feature extraction, the optimized classification method of large-scale feature similarity image is studied to improve the image classification ability, which has good application value in the field of related image classification technology research in multimedia database construction and image target recognition [1].

The classification of images is based on the feature extraction and similarity analysis of images of different attribute categories [2]. Combined with big data information processing and classifier design, pattern recognition and artificial intelligence technology are used to realize image classification and retrieval [3]. In the traditional method, the image classification methods mainly include image classification algorithm based on fuzzy C-means clustering [4], support vector machine classification algorithm, wavelet analysis method and image classification algorithm based on Harris corner detection, based on support vector machine learner, image Classification is achieved. In reference [5], an image classification method based on autocorrelation matching detection is proposed. Harris point detection algorithm is used to extract feature points of images; support vector machine classifier is used for image analysis; Large, the real-time image classification is not good. In reference [6], an image classification technique based on SIFT (Scale-Invariant Feature Transform) corner detection is proposed. The similarity feature extraction method is used to extract the statistical feature quantity of the image; the feature quantity is input into the wavelet classifier to achieve image classification; When the image is interfered by the self-similarity feature of the image, the accuracy of the image classification result obtained by the method is not good. In reference [7], in the image classification process using the support vector machine learner, the adaptive learning performance of the implicit layer of the classifier is not good, resulting in low classification accuracy; Especially in the classification of large-scale images, the misclassification rate is higher. In view of the above problems, in this paper, an image classification algorithm based on deep learning and support vector machine classification feature similarity was proposed. Firstly, the local average noise reduction method was used to denoise the similarity image. The wavelet image was decomposed by wavelet multi-scale decomposition algorithm. The rough set feature of the image was extracted. Then the extracted feature quantity was input into the support vector machine learner, and the depth learning algorithm was used in the hidden layer of the classifier to perform adaptive learning of weighted parameters to avoid cluster center disturbance and realize classification optimization of batch feature similarity image. Finally, the simulation experiment was carried out. The results showed that the proposed method had superior performance in improving the accuracy of image classification.

2. Image noise reduction and vector quantization decomposition

2.1. Image local mean noise reduction

In order to achieve effective classification of fuzzy feature similarity images, image denoising processing is first performed to improve the feature resolving power of the image. In this paper, the local mean noise reduction method is used for image filtering to improve the image recognizability. Assume that $f(x,y)$ represents the fuzzy feature similarity image to be classified, and $g(x,y)$ represents the background component of the image.

Using the multi-scale wavelet decomposition method, the template matching processing of $g(x,y)$ is performed; using the template registration method, the image to be classified is divided into 3×3 topologies; four image classification retrieval channels are set; the noise interference term of the image is $\eta(x,y)$; The grayscale pixels $\hat{f}(x,y)$ in the connected region of the image can be expressed as:

$$\hat{f}(x,y)=\begin{cases} g(x,y)-1, & if \quad g(x,y)-\hat{f}_{Lee}(x,y)\geq t \\ g(x,y)+1, & if \quad g(x,y)-\hat{f}_{Lee}(x,y)<t \\ g(x,y), & else \end{cases} \tag{1}$$

At the central pixel point of the feature similarity image, the affine invariant domain of the feature matching is constructed; according to the spatial distribution property of the image, the wavelet scale information entropy is obtained, denoted as H and η. When there are more H and η information, the similarity intensity in the image is higher; at this time, $\hat{f}(x,y)$ is close to $f(x,y)$.

Each sub-band image is binarized in the wavelet domain, and the following results are obtained, expressed as:

$$g(x,y)=h(x,y)*f(x,y)+\eta(x,y) \tag{2}$$

where, $h(x,y)*f(x,y)$ represents the color and texture joint distribution coefficients of the image, the symbol * represents a convolution.

According to the content similarity of the two images, the correlation feature fusion method is used to extract the region features of the image, and the rotation invariant moment is obtained, which is expressed as:

$$g(x,y)=f(x,y)+\eta(x,y) \tag{3}$$

where, $\eta(x,y)$ represents the additive noise term for each subband image.

In the case of additive noise only, the image of the noise reduction output is supported by the support vector machine learner. The depth learning algorithm is used to adaptively weight the classifier, and the statistical feature quantity is extracted to realize the high-resolution recognition of the image [8]. The overall structure of the image classification algorithm is shown in Figure 1.

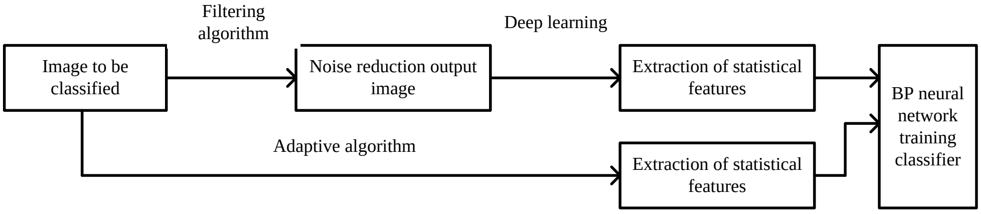


Figure 1.Feature similarity image classification implementation process

2.2. Wavelet multi-scale decomposition

The wavelet-scale multi-scale decomposition algorithm is used to decompose the image after color reduction. First, the vector quantized value of the batch feature similarity image is given, which is expressed as $\hat{f}(x,y)=\beta F(x,y)+(1-\beta)m_l$. Where, $F(x,y)$ represents the statistical feature quantity of the image pixel sequence of the sample with high confidence at the (x,y) point, and m_l represents the embedding dimension of the *k* sub-band image. δ_l^2 represents the local variance of the feature similarity image, δ_η^2 represents LGB's quantized residual component, $\beta=\max[\frac{\delta_l^2-\delta_\eta^2}{\delta_l^2},0]$.

After LGB vector quantization decomposition, the binarization processing of each sub-band image is performed to obtain the noise variance δ_η^2. Using the non-uniform quantization method of (16:4:4), the matching value of the color histogram of the image is obtained, which is expressed as:

$$L_0(r)=\frac{L(r/2)}{2},\ H_0(r)=H(\frac{r}{2}) \tag{4}$$

where, *r* and *θ* represent the coordinates in the polar coordinate system of the frequency domain, and the color feature component in the image satisfies the following condition: $\eta_m(x,y)\in\{-1,0,1\}$.

Using the vector intersection method, the similarity feature components of the image are obtained in the Markov chain model, which is expressed as:

$$p(\eta_m(x,y))=\begin{cases}\frac{r}{4}, & \eta_m(x,y)=-1\\ 1-\frac{r}{2}, & \eta_m(x,y)=0\\ \frac{r}{4}, & \eta_m(x,y)=1\end{cases} \tag{5}$$

where, r represents the matching of texture features, $0\le r\le 1$.

From the statistical distribution of the optical image noise reduction filter output, the mathematical expectation of the additive noise of the image is 0, variance is $\frac{r}{2}$.

The contour edge detection is performed on the image; the Atanassov extension method is used to match the texture features, in the frequency domain corresponding to the Fourier transform, the gradient direction histogram of the kth subband binary image I_{swk} is obtained, which is expressed as:

$$P_{rk}=(\frac{\sum_{j=1}^{c}I_{swk}(1,j)}{c},\frac{\sum_{j=1}^{c}I_{swk}(2,j)}{c},\ldots,\frac{\sum_{j=1}^{c}I_{swk}(i,j)}{c},\ldots,\frac{\sum_{j=1}^{c}I_{swk}(r,j)}{c}) \tag{6}$$

$$P_{ck}=(\frac{\sum_{i=1}^{r}I_{swk}(i,1)}{r},\frac{\sum_{i=1}^{r}I_{swk}(i,2)}{r},\ldots,\frac{\sum_{i=1}^{r}I_{swk}(i,j)}{r},\ldots,\frac{\sum_{j=1}^{c}I_{swk}(i,c)}{r}) \tag{7}$$

where, *c* represents the number of columns of the wavelet multi-scale decomposition matrix of the image, *r* represents the number of lines [9].

3. Image classification algorithm optimization

3.1. Image feature extraction

In this part, the optimization design of the feature similarity image classification algorithm is carried out. In this paper, a feature similarity image classification algorithm based on deep learning support vector machine classification is proposed. The local information smoothing processing of the image is performed by the RGB color component recombination method [10].

The set of intuition ambiguities of the feature similarity image is given as $u=\{u_{ik}\}$ The texture feature matching method is used to reconstruct the edge pixel set of the image; the feature analysis model of the image to be classified is constructed; the invariant moment description method is used to enhance the image information; finally. The information enhancement output is obtained and can be expressed as:

$$I_{GSM}=I(C^N;D^N\mid s^N)=\sum_{i=1}^{N}I(C_i;D_i\mid s_i)=\sum_{i=1}^{N}(h(D_i\mid s_i)-h(D_i\mid C_i,s_i))=\sum_{i=1}^{N}(h(g_iC_i+V_i\mid s_i)-h(V_i)) \tag{8}$$

Considering the variation of the affine invariant region in the image, according to the internal geometry of the feature similarity image and the pixel values of each point, the edge scale of the image classification fusion is obtained by using the neighborhood phase point information reconstruction method in the color space, which is expressed as:

$$p(x,t)=\lim_{\Delta x\to 0}[\sigma\frac{u-(u+\Delta u)}{\Delta x}]=-\sigma\frac{\partial u(x,t)}{\partial x} \tag{9}$$

Where, σ represents the diversity factor of the image, Δx represents the visual difference of image edge information.

Deep learning of feature similarity images is performed using autocorrelation feature matching method. $t(x)=e^{-\beta d(x)}$, where, $0<t(x)<1$, $t(x)$ represents image classification pixel difference characteristics.

Using the RGB color component recombination method, the local information smoothing processing of the image is performed, and the rough set feature quantity of the image is extracted, which is expressed as:

$$L(a,b_m)=\sum_{V_m\in P^{res}}\sum_{V_n\in P^{true}}\frac{|V_m\cap V_n|}{|V|}\log\left(\frac{|V||V_m\cap V_n|}{|V_m||V_n|}\right) \tag{10}$$

According to the contour point of the maximum gray value, in the process of deep learning, the information entropy is calculated, expressed as:

$$L(a,b_m)=\sum_{V_m\in P^{res}}\frac{|V_m|}{|V|}\log\left(\frac{|V_m|}{|V|}\right)+\sum_{V_n\in P^{true}}\frac{|V_n|}{|V|}\log\left(\frac{|V_n|}{|V|}\right) \tag{11}$$

Using the Harris corner detection algorithm, the features of the feature similarity image are extracted; the gray-scale invariant moment of the image feature extraction is obtained, which is expressed as:

$$L(a,b_m)=\frac{1}{\sqrt{a}}\left(\frac{a+1}{2}-\frac{(a-1)f_0}{B}\right) \tag{12}$$

where, *(x, y)* represents a test sample set of images in the gradient direction. Thereby, feature extraction of the image to be classified is achieved.

3.2. Deep learning algorithm for image classification

On the basis of extracting the rough set feature quantity of the image, the extracted feature quantity is input into the support vector machine learner. The support vector machine learner is shown in Figure 2.

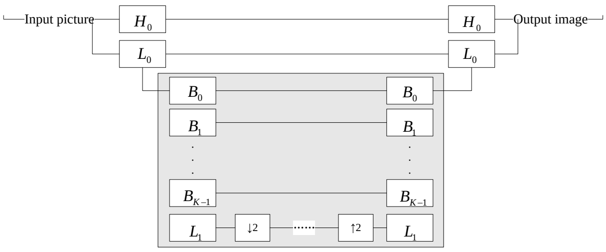


Figure 2. Support Vector Machine Classifier

The support vector machine learner transfer function in Figure 2 is described as:

$$H(r)=\begin{cases}1 & r\geq\dfrac{\pi}{2}\\ \cos(\dfrac{\pi}{2}\log_2(\dfrac{2r}{\pi})) & \dfrac{\pi}{4}<r<\dfrac{\pi}{2}\\ 0 & r\leq\dfrac{\pi}{4}\end{cases}\tag{13}$$

In the hidden layer of the classifier, is the depth learning algorithm used, and adaptive learning of weighted parameters is implemented; the iterative expression of the deep learning algorithm can be expressed as:

$$L(a,b_m)=\frac{1}{\sqrt{a}}\left(\frac{a+1}{2}-\frac{|a-1|}{B/f_0}\right)\tag{14}$$

After the support vector machine is classified, it is further decomposed into a series of band-pass sub-band images in K directions to realize the related information fusion; the image output after the information fusion is obtained, which is expressed as:

$$GD=\left(\frac{1}{|PS|}\sum_{i=1}^{|PS|}d_i^2\right)^{\frac{1}{2}}\tag{15}$$

The above process is repeated until the required level is reached; at this time, the limited range of the cluster center of the image classification is expressed as:

$$SP=\sqrt{\frac{1}{|PS|-1}\sum_{i=1}^{|PS|}(\bar{d}-d_i)^2}\tag{16}$$

Through the above processing, the spatial position information calibration is performed; the adaptive learning of the weighted parameters is implemented to avoid the cluster center disturbance, and the classification optimization of the batch feature similarity image is realized.

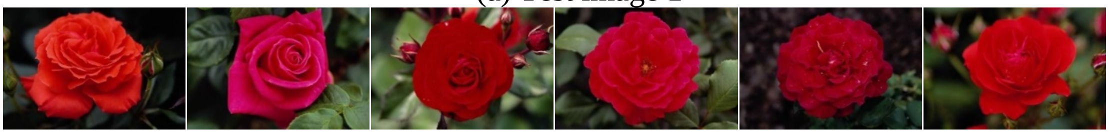
4. Simulation experiments and results analysis

The application performance of the method in the feature similarity image classification is tested. The experiment was designed using MATLAB 7; The experimental data set of image classification is 2000 sets of images in the Corel standard image library; two sets of attribute categories of where are selected for classification, namely elephant and rose; the test sample set size is 200, and the training sample set is 50. The number of input layer nodes in the support vector machine classification is 3, the number of nodes in the output layer is 2, the number of iterations in depth learning is 1000, and the matching coefficients of color, texture and shape features are 0.21, 0.16 and 0.32, respectively.

According to the above simulation environment and parameter setting, the image classification simulation test is performed, and the test images and classification results of the two test samples are obtained, as shown in Figure 3 and Figure 4.

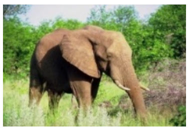
The simulation results of Fig. 4 show that, using this method, the classification performance of the feature similarity image is better, the perturbation ability of anti-class property is stronger, and the classification error rate is lower under the whole sample.

(a) Test image 1

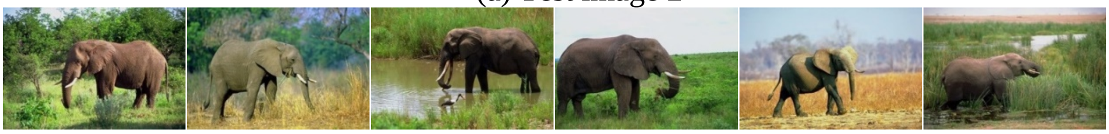


(b) Classification images of some images

Figure 3. Rose image classification results



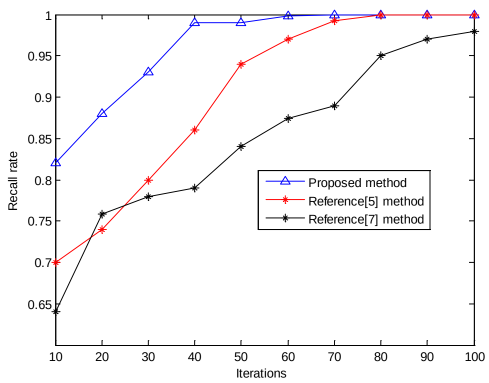
(a) Test image 2



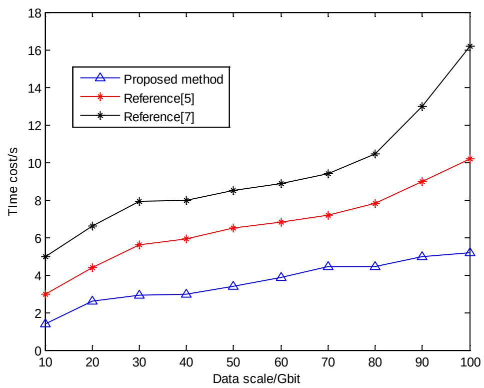
(b) Classification results of some images

Figure 4. Classification results of elephant images

The recall and accuracy of the images under different methods were tested, and the comparison results were obtained, as shown in Fig. 5.



(a) Recall rate



(b) Time cost

Figure 5. Classification performance comparison

Analysis of Figure 5 showed that, by the method in this paper, the deep learning and associated information fusion processing was performed, the accuracy and recall of image classification were higher, the time overhead was smaller, and the performance was better than the traditional algorithm.

5. Conclusion

In this paper, the optimized classification method for large-scale feature similarity images was studied. Combining the adaptive learning method of image feature extraction, a feature similarity image classification algorithm based on deep learning neural network and related information fusion was proposed to improve the image classification ability. Firstly, the local average noise reduction method was used to denoise the similarity image, and the wavelet image was decomposed by wavelet multi-scale decomposition algorithm; Secondly, using the RGB color component recombination method, the local information smoothing processing of the image was implemented, and the rough set feature quantity of the image was extracted; Finally, the extracted feature quantities were input into the support vector machine learner, and adaptive learning of weighted parameters was implemented using a deep learning algorithm to avoid cluster center disturbances at the hidden layer of the classifier, and classification optimization of batch feature similarity images was obtained. The research showed that the accuracy and recall of image classification were higher by the method in this paper.

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