Acta Technica 62 (2017), No. 6B, 1327–1338

Image feature classification based on sparse low rank description of concave convex matrix

Xi Li[1], Shuangxi Gao[1,2]

Abstract. High-precision classifier realization means the complex algorithm design. The increased complexity may bring long elapsed time for classification solution, over-fitting classification and other defects. In addition, many existing algorithms just pursue the classification accuracy unilaterally, while in fact, the users may decide the required accuracy according to their actual condition. Hence, based on the genetic algorithm (GA), this paper gives the feature weighted algorithm with controllable classification accuracy, which can adjust the weight according to the user's requirement on average classification accuracy, to find a classification algorithm conforming to the user's classification accuracy demand as soon as possible under constraint by low time complexity. Furthermore, for the genetic algorithm (GA), an optimal approximate solution can be found in a very short time, and the locally optimal solution can be avoided at the same time.

Key words. Genetic algorithm, Image feature, Feature classification, Image retrieval.

1. Introduction

Following the development of internet platform, people getting a picture whenever and wherever possible in daily life has become a very simple thing. People upload their favorite and interested pictures to the internet, to share with a growing number of people, while more and more people find their interested pictures through the internet. Among most of these pictures, the pictures in the closest relation to people are the natural images. However, at present, relevant research in image classification mostly centralizes in the remote sensing image, medical image and other professional fields, and there are relatively less researches on natural image classification. Moreover, because most of natural images are color images, and there is

[1]School of Electrical and Information Engineering , Wuhan Institute of Technology, Wuhan, Hubei Province, 430205, China

[2]College of Mechanical and Electrical Engineering, Huanggang Normal University, Huanggang, Hubei Province, 438000, China

no regularity in their contained objective and meaningful parts, it is in the face of great challenges to classify the natural images through the content contained.

Literature [1] puts forward to solve the classification problem of multi-class objects in natural images by utilizing the multi-class neural network, experimentally proving that the mixed feature classification has a better effect than the single feature classification, with classification operation made for the blue sky, setting sun, green hill, flower and green water images in the corel image library, as well as classification accuracy rate at 80%. Literature [2] identifies the natural images and artificial images by image texture feature, which only can well distinguish two categories of natural images and non-natural images. Literature [3] raised a kind of classification method based on multi-case learning according to Citation-KNN algorithm thought, which has relatively satisfied classification accuracy for most of categories, but cannot truly reflect the differences among several types of images with semantic relativity and similar visual feature. Literature [4] learns the category of natural image by the support vector machine, and only takes the color as the classification feature, just experimentally proving that different feature selection may create different classification effect against different types of natural image classification, without conclusive classification method, with experiments made on little natural image types. Literature [5] extracts image SIFT features and divides the sport images by classification method of support vector machine, to identify table tennis, badminton, basketball, football and other ball games, with classification accuracy just about 20% being gotten.

This paper achieves the classification of natural image by using feature weighted K-nearest neighbor algorithm. K-nearest neighbor algorithm is a classic model recognition method, which is simple and easy to be realized, but it has relatively poor performances [6]. At present, many improvement methods are proposed [7]. Due to the natural image particularity, equal classification made to all natural images merely with simple K-nearest neighbor algorithm has very unsatisfactory effect according to the experiment result. As can be noticed, natural image has its inherent characteristics, while color and texture are two important features of natural image. However, as different natural images have different sensitivity to the color and texture, the classification made to complex and changeable natural images merely with simple feature cannot reach a good effect. For example, underwater world and beach, flower and setting sun... there is extremely similar color feature among the category and category, so it may has a poor effect to classify just by color feature, but if adding the texture feature and assigning corresponding weight to different features according to the genetic algorithm, the classification of natural images with similar vision can be well solved, to sufficiently utilize all decisive factors influencing the natural images.

2. K-nearest neighbor algorithm

(1) K-nearest neighbor algorithm is a kind of very efficient non-parametric classification algorithm. It assumes that all samples are corresponding to the points in n-dimension space R^n, while the nearest neighbor of a sample is determined accord-

ing to the Euclidean distance among the data. If a sample to be measured is defined as $x_i = (x^1, x^2, ..., x^n)$, and every point in sample space as $x_j = (x^1, x^2, ..., x^n)$, the distance between the sample to be measured and every sample in the space is defined as$d(x_i, x_j) = \sqrt{\sum_{l=1}^{n}(x_i^l - x_j^l)^2}$.

Then search the distance between all calculated points to be measured and known points, and find K sample points nearest to the test point, namely, find the minimum value of K distances in Euclidean distance. And then, count the K distance values found. If the distance values of a category are most, then judge this sample to be measured to be subordinated to this category.

3. Feature weighted KNN algorithm

3.1. Basic thought

Traditional KNN algorithm believes every feature in sample to be classified has a same contribution to the classification effect. However, as it turns out, for different samples, the classification feature with decisive factor is different, and different features also play an important or light role in different categories. It is especially true for the natural image classification with multiple categories and complex structure. Where one feature is utilized merely or treatment is made without distinguishing the priority of two features, as proved by experiment, they have poor classification effects. For that reason, we proposed a kind of new KNN algorithm with feature weighted to image for the natural image classification, which considers different contributions of every feature to the classification effect of natural image, assigns bigger weight to the feature contributed more in classification, as well as smaller weight to the feature contributed smaller, and makes synergy judgment classification to the natural image with combination of multiple features, so as to get better classification effect. As proved by experiment (Table 1 and 2), for most natural images, color plays a very important role in the classification, because the classification effect only by utilizing the color feature is far superior to those only by applying the texture feature. Certainly, there may be exceptional case for this conclusion, for example, the texture feature of the dinosaur illustrated in this paper is superior to its color feature, of which the classification analysis on such condition will be mentioned in the Part III. It can be speculated thereout, color feature will have larger weight in the experiment, while the texture may help to make further classification in the distinction of image with similar color feature and thus have smaller weight. In that way, how to choose this weight certainly will have decisive influence on classification effect, and this weight will be determined by genetic algorithm in this paper, with specific method mentioned in the Section 2.3.

Table 1. Classification accuracy result of texture feature

Category	Africa	Butterfly	Building	Automobile	Dinosaur	Seabed	Flower	Horse	Mountain peak	Setting sun
Accuracy	42%	44%	64%	50%	100%	42%	30%	60%	36%	40%

Table 2. Classification accuracy result of color feature

Category	Africa	Butterfly	Building	Automobile	Dinosaur	Seabed	Flower	Horse	Mountain peak	Setting sun
Accuracy	84%	88%	67%	70%	76%	88%	72%	94%	74%	80%

3.2. Feature selection

(1) Color coherence vector

Because the image color histogram and color moment feature cannot express the connection relation among similar or same pixel points in an image, namely, it only make statistics for single pixel point, but not considers the structure characteristics of every color distribution. Therefore, in the experiment, the color coherence vector is chosen to express the color feature of natural image [9]. Its expression is: $<(\partial_1, \beta_1), (\partial_2, \beta_2), ...(\partial_N, \beta_N)>$, of which ∂_i is the number of ith bin coherence pixels, and β_i is the number of non-coherence pixels

(2) Gabor texture feature

$Gabor(x, y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{\tilde{x}^2+\tilde{y}^2}{2\sigma^2})(\cos\frac{2\pi\tilde{x}}{l} + j\sin\frac{2\pi\tilde{x}}{l})$(2)Gabor filter makes the multi-resolution analysis on image and extracts the image texture feature by utilizing the multi-scale and multi-direction feature of Gabor wavelet, so as to get more detailed texture feature by increasing the number of filters. The Gabor filter function in different scale and different direction can be expressed as [11]:

$$Gabor(x, y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{\tilde{x}^2+\tilde{y}^2}{2\sigma^2})(\cos\frac{2\pi\tilde{x}}{l} + j\sin\frac{2\pi\tilde{x}}{l})\,. \tag{1}$$

Set the maximum frequency of filter as U_h and minimum frequency as U_l, because the natural image has few high-frequency component, following the frequency increase, the filter scale index also increases, namely, it meets $U_h = U_l a^{M-1}$. The index factor can be expressed as: $a = (\frac{U_h}{U_l})^{\frac{1}{M-1}}$, and every filter variance can be expressed as:

$$\sigma_{x_m} = \sigma_{x_M} a^{m-M} = \frac{a-1}{a+1}\frac{U_h}{\sqrt{2\ln 2}}a^{m-M}\,. \tag{2}$$

$$\sigma_{y_m} = \sigma_{y_M} a^{m-M} = tg\frac{\pi}{L}\sqrt{\frac{U_h^2}{2\ln 2} - \sigma_{x_M}} \bullet a^{m-M}\,, \tag{3}$$

Of which,

$$\sigma_{x_M} = \frac{a-1}{a+1}\frac{U_h}{\sqrt{2\ln 2}}\sigma_{y_M} = tg\frac{\pi}{L}\sqrt{\frac{U_h^2}{2\ln 2} - \sigma_{x_M}}$$

$$m = 1, 2, ..., M\,.$$

Set the maximum numerical frequency as $U_h = 0.4$ and the minimum numerical frequency as $U_l = 0.03$. Because the minimum numerical frequency is 0, and the maximum numerical frequency is gotten to be 0.5 according to the Nyquist sampling theory, as previously mentioned, the scale factor is $a = (\frac{U_h}{U_l})^{\frac{1}{5-1}} = (\frac{40}{3})^{\frac{1}{4}} \approx 2$. By calculating the mean value and variance convolved image, a 40-dimensional Gabor texture feature vector can be gotten, defined to be $(\mu_{11}, \sigma_{11}, \mu_{12}, \sigma_{12}, ..., \mu_{45}, \sigma_{45})$.

(3) Feature normalization

In order to avoid the small data from being submerged by large data, multiple features shall be expressed by uniform expression way. Here, normalize the obtained color features and texture features within [0,1] by the Formula (5) [12].

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}\,. \tag{4}$$

Display ten kinds of 112-dimensional color features and texture features (72 dimensions for color and 40 dimensions for texture) in the parallel coordinates.

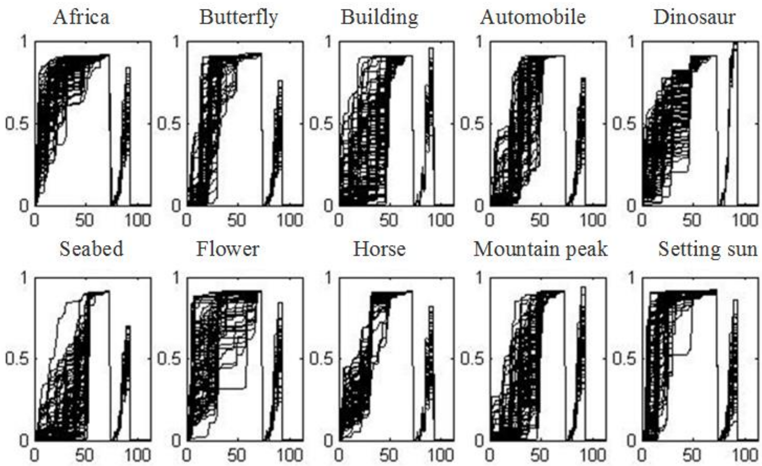

Fig. 1. Feature distribution of ten kinds of images

It can be seen from the Fig. 1, the color and texture features of natural images in different types show large difference, so the efficient classification of natural image can be done according to this difference.

3.3. Feature weight confirmation based on genetic algorithm

$J = \min\left[\left|e - (g_1 + g_2 + ... + g_k)/k\right|\right]$(6)This paper determines the feature weight by the difference value between the minimum user setting accuracy and average classification accuracy. Set a total of k categories, represent every type of classification accuracy as g_1,g_2,$\ldots g_k$, and set the classification accuracy given by the user as e, namely, realize the minimum of the following formula:

$$J = \min \left[\left| e - \left(g_1 + g_2 + ... + g_k \right) / k \right| \right] . \tag{5}$$

$J$is a nonlinear objective function. Some existing optimization algorithms, such as newton iteration method and gradient descent iteration method, start from an initial approximate value, and then find am approximate local optimum. In the experiment, we can find that,J has many local optimums. Such scheme is hard to find an optimal solution. Some other methods, such as the simulated annealing algorithm and genetic algorithm, can automatically acquire and guide optimal search space, but they ignore that the local optimum may bring reasonable solution. Therefore, this paper combines these two kinds of algorithms. We apply the gradient descent iterative algorithm to complete the traditional genetic algorithm solution.

The genetic algorithm starts from random selection of an initial life population (previous generation) and then complete with gradient descent algorithm. At every generation, get a fitness value from calculating the fitness function $1/J$, and evaluate every individual. Hereafter, the next generation of population is created in following way:

1. High fitness individual occupying 10% of population is reserved;
2. Individual occupying 10% is randomly generated;
3. 60% population makes the random mating and linear combination by previous two generations S_1^{old} and S_2^{old}, namely:

$$S^{new} = a \cdot S_1^{old} + (1 - a) \cdot S_2^{old} .$$

Here, a is a random variable (it changes from 0 to 1, or from 1 to 0), and 1 is a vector that all elements are equal to 1, which represents the dot product of a vector. And then, the new generation population is completed by gradient descent algorithm.

4. The residual 20% population generates the new sub individual by mutation.

By this series of selection, matching and mutation, the new general individual generated is different from the initial generation, and develops the direction adding inclusive fitness. Such process is constantly repeated until meeting the terminal condition [13].

The pseudo-code is as follows:

1. function HYT(T1,T2,P1,P2) //T1 and T2 respectively are two features, and P1 and P2 respectively are the corresponding weights of T1 and T2.
2. repeat
3. Initialization, P1 = 0, P2 = 1- P1
4. g1 = final(T1, T2 ,P1,P2)// T1 and T2 belongs to the first type of features, g1 is the first type of classification accuracy.

g2 = final(T1, T2 ,P1,P2)// T1 and T2 belongs to the second type of features, g1 is the second type of classification accuracy.

gk = final(T1, T2 ,P1,P2)// T1 and T2 belongs to the kth type of features, g1 is the kth type of classification accuracy.

4. Experiment result and analysis

4.1. Experiment platform and environment

For the software simulation environment of the experiment, matlab7.8.0 under windows XP is installed, together with computer hardware configuration of Intel(R) Core(TM)2 Duo E8400 3.0GHz CPU, 2G memory and 320G hard disk.

The natural images used in the experiment partly come from the authoritative image database issued by corel Company and partly come from the network images download. 10 categories of natural images are contained, with 100 natural images in every category, amount to 1000 natural images. It is divided into the training set and test set, of which there totally are 500 images for training set with 50 for every category, and 500 images for test set with 50 for every category. 10 categories of natural images respectively are: Africa, butterfly, building, automobile, dinosaur, seabed, butterfly, horse, mountain peak and setting sun, with every category of image is shown in Fig.2 as follows.

Fig. 2. Every category of natural images in experiment image library

4.2. Experiment and result analysis

Extract the representation color feature of 72-dimensional color coherence vector and 40-dimensional Gabor texture vector of the image by the method introduced in Section 2.2.1 and 2.2.2.

K-nearest neighbor algorithm of feature weighting is

$$d_i = (1-q)\sqrt{\sum_{i=1}^{n}(x_i - x_i')^2} + q\sqrt{\sum_{j=1}^{n}(x_j - x_j')^2}\,. \tag{6}$$

Of which, q is the feature weight, and $0 \leq q \leq 1$. x_i and x_j respectively represent the color feature vector and texture feature vector of data to be measured. x_i' and x_j' respectively represent the color feature and texture feature of images in the sample set.

Get the weight q to be $q = 0.4575$ according to the genetic algorithm introduced in the Section 2.3, of which $e = 0.1$ is taken for the accuracy e. From the feature weighted KNN algorithm defined in the Formula (7), the classification result accuracy of 10 categories of natural images is as shown in the Table 3. Compare the classification results of the feature weighted KNN natural image and of the natural image simply classified by color feature and texture feature, with comparison results as shown in Fig. 3.

Table 3. Classification accuracy of experiment result in test set

Category	Color feature	Texture feature	Feature weighting	Weight q
Africa	84%	42%	88%	
Butterfly	88%	44%	90%	
Building	67%	64%	70%	
Automobile	70%	50%	72%	
Dinosaur	76%	100%	100%	0.4575
Seabed	88%	42%	92%	
Flower	72%	30%	76%	
Horse	94%	60%	94%	
Mountain peak	74%	36%	74%	
Setting sun	80%	40%	82%	
Mean	**79.3%**	**50.8%**	**83.8%**	

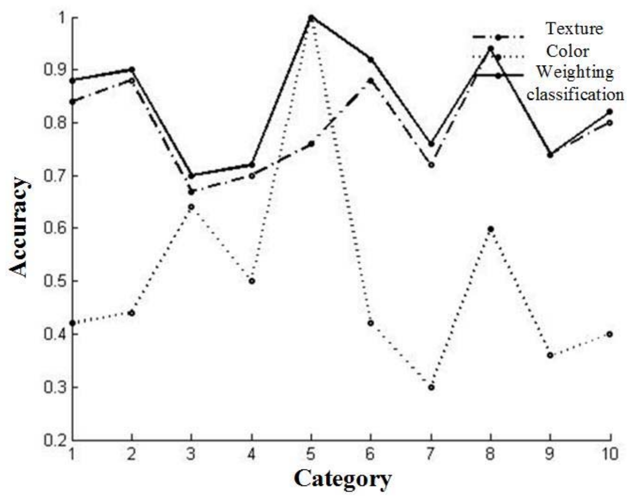

Fig. 3. Comparison of three kinds of classification results

From the experiment result, it can be seen, the feature weighted classification method of natural images based on KNN proposed by this paper can work on different types of natural image networks, universally applicable to the natural images commonly seen in all kinds of lives. Compared with the original single-feature unweighted classification of natural images and the existing classification method for natural images, it can significantly improve the average accuracy of classification system, and find the globally optimal solution for the system weight by utilizing the special advantage of genetic algorithm, to improve the system precision and speed.

In the experiment, it can be found that, the images easily to be wrongly classified centralize in the categories as shown in Fig.4: ① Building and mountain peak. Because some mountains and most buildings are in gray tone alike, and both of them are tall and straight, with similar texture feature. ② Automobile and flowers, because the automobiles and flowers are colorful without unified color, with less prominent texture feature. In the actually huge natural image categories, the proportion of entirety of color feature cannot be more than that of texture feature in the classification, so in the experiment, a category of dinosaur images is deliberately selected to be the particular case. From the experiment, it can be seen that, its texture is far superior to the color feature. However, after weighting by the weight gotten from genetic algorithm proposed by this paper, its texture feature advantage is still not hidden, and it still can reach the best classification. In general, the feature weighted KNN classification method proposed by this paper is capable of showing its advantage in the complex natural image classification with still non-ideal classification effect so far.

Fig. 4. Wrongly-classified Images

5. Conclusion

As peoples' lives are increasingly inundated with natural images, because the natural images are different from the professional images, its classification cannot meet a satisfied effect. Thus paper utilizes the K-nearest neighbor classification method automatically weighting every feature of natural images, determines the optimal weight by genetic algorithm, and makes classification experiment for different natural images of many categories. The experiment proves that the method proposed in this paper can well promote the natural image classification effect. Aiming at the actual problem of extensive type, complex structure and low classification accuracy of natural images, a K-nearest neighbor classification method automatically weighting different features of natural images is proposed. By analyzing the influence of different features of natural images on classification result, get a group of optimal classification weight vector solutions by genetic algorithm, respectively weight the texture and color features of natural image by utilizing this optimal weight, and finally achieve the natural image classification by using self-adaptive weighted K-nearest neighbor algorithm. The experiment result shows that, constrained by the classification precision demand given by the user and low time complexity, the above algorithm can rapidly classify the natural images in high precision. The self-adaptive weighted K-nearest neighbor classification method proposed in this paper has a universal applicability for the natural images in various categories and can efficiently improve the classification performance of natural images.

Acknowledgement

This work is supported by the National Science Foundation of China under Grant 61671337, and Scientific research foundation of Wuhan Institute of Technology in 2015, No. K201501.

References

[1] Pahlavan K, Krishnamurthy P and Geng Y: (2015) *Localization challenges for the emergence of the smart workd.* IEEE Access, 3(1), pp. 3058-3067

[2] Lv, Z., Tek, A., Da Silva, F., Empereur-Mot, C., Chavent, M., & Baaden, M.: (2013). *Game on, science-how video game technology may help biologists tackle visualization challenges.* PloS one, 8(3), e57990.

[3] Li X, Wang W, Razi A, et al.: (2015) *Nonconvex Low-Rank Sparse Factorization for Image Segmentation*[C]// International Conference on Computational Intelligence and Security. IEEE, 2015:227-230.

[4] Pang W, Jiang H, Li S: (2017) *Sparse Contribution Feature Selection and Classifiers Optimized by Concave-Convex Variation for HCC Image Recognition*[J]. BioMed Research International, 2017(33):1-14.

[5] Konno H, Gao C, Saitoh I: (1998) *Cutting Plane/Tabu Search Algorithms for Low Rank Concave Quadratic Programming Problems*[J]. Journal of Global Optimization, 13(3):225-240.

[6] Kim K, Ye J C: (2014) *ECG-gated cardiac CT reconstruction using patch based low rank regularization*[C]// IEEE, International Symposium on Biomedical Imaging. IEEE, 2014:437-440.

[7] Deng Y, Dai Q, Zhang Z: (2010) *Reweighted scheme for low rank matrix recovery from corruptions*[J]. Eprint Arxiv, abs/1012.1919.

[8] Cai T T, Zhang A: (2013) *Sharp RIP bound for sparse signal and low-rank matrix recovery*[J]. Applied & Computational Harmonic Analysis, 35(1):74-93.

[9] Lv, Z., Halawani, A., Feng, S., Li, H., & Réhman, S. U.: (2014). *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 11(1s), 10.

[10] Weisen Pan, Shizhan Chen, Zhiyong Feng: (2013) *Automatic Clustering of Social Tag using Community Detection.* Applied Mathematics & Information Sciences, 7(2): 675-681.

[11] Yingyue Zhang, Jennifer W. Chan, Alysha Moretti, and Kathryn E. Uhrich: (2015) *Designing Polymers with Sugar-based Advantages for Bioactive Delivery Applications*, Journal of Controlled Release, 219, 355-368.

[12] Yingyue Zhang, Qi Li, William J. Welsh, Prabhas V. Moghe, and Kathryn E. Uhrich: (2016) *Micellar and Structural Stability of Nanoscale Amphiphilic Polymers: Implications for Anti-atherosclerotic Bioactivity*, Biomaterials, 84, 230-240.

[13] Jennifer W. Chan, Yingyue Zhang, and Kathryn E. Uhrich: (2015) *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, 26(7), 1359-1369.

[14] Montoya-Martínez J, Artés-Rodríguez A, Pontil M, et al.: (2014) *A regularized matrix factorization approach to induce structured sparse-low-rank solutions in the EEG inverse problem*[J]. Eurasip Journal on Advances in Signal Processing, 2014(1):1-13.

[15] Kim K, Ye J C, Worstell W, et al.: (2015) *Sparse-View Spectral CT Reconstruction Using Spectral Patch-Based Low-Rank Penalty*[J]. IEEE Transactions on Medical Imaging, 34(3):748.

[16] Lu C, Tang J, Yan S, et al.: (2014) *Generalized Nonconvex Nonsmooth Low-Rank Minimization*[C]// Computer Vision and Pattern Recognition. IEEE, 2014:4130-4137.

Received May 7, 2017