

Research of batik image classification based on support vector machine

Qing-Ni Yuan*, Jian Lu, Haisong Huang, Weiji Pan

Key Laboratory of Advanced Manufacturing technology (Guizhou University), Ministry of Education, Guiyang 550003, China

Received 1 October 2014, www.cmnt.lv

Abstract

The digital protection and development of batik is applied in the digital design of the arts and crafts by the digital image acquisition of batik to construct a graph database. Its key technology is the automatic classification of image. In this paper, we use image analysis and recognition technology to image classification recognition of five type of batik: Bronze drum lines, Butterfly lines, Bird lines, Fish lines and Flower lines etc. On the basis of the segment image of batik, we extract the shape and texture feature by Histogram of Oriented Gradient (HOG). Then, we respectively use Support Vector Machine (SVM), Minimum Distance Method and BP Neural Network to classify test. The result shows that the classification recognition ability of SVM is better than the Minimum Distance Method and the BP Neural Network. Therefore, the classification recognition method of the Histogram of Oriented Gradient (HOG) and the Support Vector Machine (SVM) is feasible to the automatic classification of batik image.

Keywords: batik image, automatic classification of image, histogram of oriented gradient (HOG), support vector machine (SVM)

1 Introduction

Batik images and symbols have a unique value of art. The folk batik works passed down from ancient times are the carrier of history and culture of a nation. The images and the symbols serve as the testimony of national history, religion, folklores and legends [1]. With the advancement of industrialization and urbanization, the original ecological environment on which batik handicraft depends has witnessed vicissitude. Owing to the effort of protecting world intangible cultural heritage, batik is again full of vitality and creates a wealthy material for the modern printing industry. The digital protection and development of batik goes abreast the advancement of the modern automatic printing and dyeing industry. With creation inspired and mass production realized, the batik art is recalled and integrated it into modern life [2].

As a part of the digital protection and development of batik or other intangible cultural heritages, batik images are classified into 2D images based on their forms. It is able to fill the database with original 2D bitmap or digital image through batik digital image collection. The database is the sources of digital design of crafts. The core of creating the database and the application of image lies in automatic classification which serves to automatic annotation and automatic retrieval of image semantics.

The texture feature of batik of Guizhou Province can be classified to natural texture and geometric texture. Bronze drum lines, butterfly lines, bird lines, fish lines and flower lines are the most important textures [3]. This paper uses image analysis technique to study five textures of batik acquired by photographic remake of digital images,

extract their shapes and texture features and employs support vector machines (SVM) to do quantitative recognition so as to realize automatic classification of batik images.

2 Classification of batik images

Automatic classification of batik image is a kind of recognition classification [4]. It switches 2D grey space to target space and divides images according to their features into categories such as bronze drum lines, butterfly lines, bird lines, fish lines and flower lines. Suppose a batik image contains five image categories expressed by g_i , there is $i=1,2,3,4,5$. Find out five judgment functions

$$\{y_1(x), y_2(x), \dots, y_5(x)\}.$$

Before classification. Then, classify every pixel as the rules prescribe:

$$x \in g_i, \text{ if } y_i(x) > y_j(x), \quad i = 1, 2, \dots, 5; \quad i \neq j. \quad (1)$$

Pre-change the batik image (including de-noising and adjustment); extract features that reflect the eigenvectors of classification targets; subject batik image features to training and produce training models of each image type; classify images according to training types. The core idea is feature extraction and classifier design. This paper uses Histogram of Oriented Gradient (HOG) to extract features and Support Vector Machine (SVM) to design classifiers.

* Corresponding author's email: cme.qnyuan@gzu.edu.cn

3 Feature extractions by HOG

3.1 PRE-CHANGE BATIK IMAGES

Batik images are mainly in blue and white. To make the process easier, we first transform them to grey images. The expression of such transformation is described as:

$$Gray(i, j) = 0.11R(i, j) + 0.59G(i, j) + 0.3B(i, j). \quad (2)$$

In the following step, conduct the binarizing to separate the target object and the background in the batik image, as is shown in Figure 1.



Batik original image Gray transformation image
FIGURE 1 Gray transformation of batik image

3.2 FEATURE EXTRACTION OF BATIK IMAGE

Batik images of Guizhou mainly compose of important textures such as bronze drum lines, butterfly lines, bird lines, fish lines and flower lines. Common shape description methods are region-based expression and contour-based one. The latter of the two has less computation and high accuracy as it only describes the edge points after contour test. HOG is used to do statistics of grey value in the grey image and is a kind of contour-based expression [5].

HOG is derived from Scale Invariant Feature Transform (SIFT). It is good at describing the edge direction. The calculation is as follows:

1) Image normalization.

The original batik images are first subject to image segmentation as shown in Figure 2, and there produce batik target images as training samples. The extracted batik target images are normalized to 64×128.

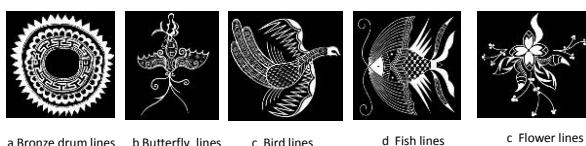


FIGURE 2 Extraction of batik target images

2) Calculation of image gradient.

Use model [-1,0,1] and [-1,0,1] to calculate the horizontal

gradient dx and the vertical gradient by:

$$d_x(x, y) = h(x+1, y) - h(x-1, y), \quad (3)$$

$$d_y(x, y) = h(x, y+1) - h(x, y-1). \quad (4)$$

In the expression, $d_x(x, y)$, $d_y(x, y)$, $h(x, y)$, refers to the gradient and the pixel value of the horizontal level at (x, y) . The gradient value and the gradient direction are expressed as:

$$d(x, y) = \sqrt{d_x(x, y)^2 + d_y(x, y)^2}, \quad (5)$$

$$\theta(x, y) = \arctan\left(\frac{d_y(x, y)}{d_x(x, y)}\right) \in [0, 360^\circ]. \quad (6)$$

Transfer the angle range to $[0, 360^\circ]$ and divide it into 9 sections.

3) Weighed projection based on the direction of gradient value.

Select a 16×16 image block and use the gradient value of each pixel as the weight. Calculate the 8×8 part of the block, or to say, calculate the feature of HOG of each 2×2 cell. We will use 9 bin histograms to collect information of gradient direction of pixel in each cell. Actually, the 360° gradient direction of the cell is divided into 9 direction cells.

4) Normalization of eigenvectors.

The gradient strength changes greatly along with the local background contrast. Therefore, it is necessary to normalize the gradient strength. For a 16×16 histogram, there are $2 \times 2 = 4 \times 9 = 36$ dimensions of features that need normalization.

Suppose the HOG feature of the image block is $w \in M^{36}$, w_i refers to the feature of the i -th dimension. w'_i refers to the value after normalization.

$$w'_i = \frac{w^i}{\sum_i w^i}. \quad (7)$$

5) The ultimate eigenvectors.

Features of each 16×16 histogram are part of the ultimate features of histograms. Input them into the classifier.

4 The design of classifier

Support vector machines (SVM) is based on VC dimension theory and the principle of structural risk minimization. After selecting a kind of non-linear transformation, map the input vector to higher-dimension feature space. Construct an optimal classification hyperplane in the feature space, $w \cdot x + b = 0$. After quadratic optimization of linear and separable hyper-plane, we can get vector W [7]. Use C-SVC to address multiple classifications [8], as is shown below.

The problem solving process is

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i \\ \text{s.t.} \quad & y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, 2, \dots, l. \end{aligned} \quad (8)$$

Then introduce the Lagrange function and it becomes an even planning issue:

$$\begin{aligned} \min \quad & \frac{1}{2} a^T Q a - e^T a \\ \text{s.t.} \quad & y^T a = 0, \quad 0 \leq a_i \leq C, \quad i = 1, 2, \dots, l \end{aligned} \quad (9)$$

Q is the matrix, $Q_{ij} \equiv y_i y_j K(x_i, x_j)$. $K(x_i, x_j)$ is the Kernel function.

The ultimate judgment function is:

$$y = \operatorname{sgn} \left(\sum_{i=1}^l y_i a_i K(x_i, x) + b \right). \quad (10)$$

Kernel function mainly has four types [9]:

1) Linear Kernel

$$K(x, x_i) = (x \cdot x_i). \quad (11)$$

2) Polynomial Kernel, in which s , c and d are parameters

$$K(x, x_i) = (s(x \cdot x_i) + c)^d. \quad (12)$$

3) Radical Basis Function

$$K(x, x_i) = \exp(-\gamma|x - x_i|^2). \quad (13)$$

4) Sigmoid Tanh Function, in which s and c are parameters

$$K(x, x_i) = \tanh(s_i^T x_j + c). \quad (14)$$

Support vector machines (SVM) first switches the input control transformation into a higher-dimension space through non-linear transformation defined by inner product function. It finds the optimal classification surface in this space. Use different kernel function $K(x, x_i)$ to activate different types of learning machine in non-linear decision surface in the input space so that different support vector algorithms are available. Refer to network structure of support vector machines in Figure 3. The network structure is constructed on the basis of Kernel functions and input and output variables.

Every node in the same layer has similar functions. Node in circle shape refers to the support vector node and that in square shape refers to the training of network structure. In the first layer, input SVM training data and test data $x = (x_1, x_2, \dots, x_l)$ are subject to non-linear transformation (inner product); in the second layer, calculate the weight of the data set after non-linear transformation, $w_i = y_i a_i$, w_i refers to the dot product of convolution Kernel; the third layer is the linear combination of intermediate nodes. After decision rule

$$y = \operatorname{sgn} \left(\sum_{i=1}^l y_i a_i K(x_i, x) + b \right),$$

accurate output value y is acquired.

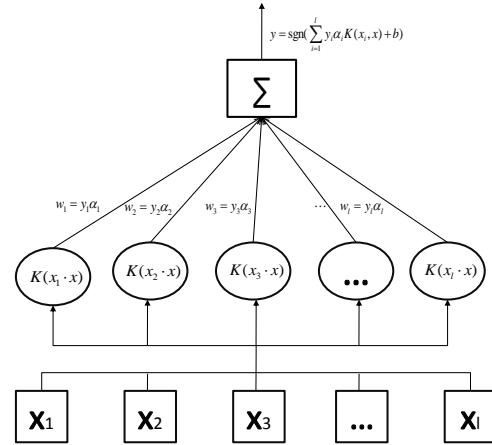


FIGURE 3 Network structure of SVM

5 Test result and analysis

5.1 DATA SET AND EXPERIMENT PARAMETERS

Software platforms in Windows7 and Matlab2010b are used to test the classification algorithm for batik image classification proposed by this paper. Samples are acquired by the photographic remake of batik original images. There are five types: bronze drum lines, butterfly lines, bird lines, fish lines and flower lines. The number of training samples and test samples are shown in Table 1. Normalize all images to 64×128 and extract HOG features. Minimum distance method, BP neutral network classification and support vector machines are used to compare models. Minimum distance method is featured by Euclidean distance. BP neutral network is featured by 6-10-3-layer structure network. The learning speed is set at 0.2. Momentum factor is 1. Stop training when the minimum average error is smaller than 0.002. Use Libsvm classification toolbox to do classification test for four kernel functions with default parameters [8].

TABLE 1 The sample of various type of batik image

Category	Training sample	Test sample
bronze drum lines	60	50
butterfly lines	60	50
bird lines	70	50
fish lines	60	50
flower lines	80	50

5.2 TEST RESULT AND ANALYSIS

Recognition of batik image classifications is shown in Table 2.

TABLE 2 The classification accuracy of various algorithms

Category	Support vector machines (SVM)				Minimum distance method	BP neural network
	Linear	Polynomial	Radical Basis	Sigmoid Tanh		
bronze drum lines	91.3%	82.1%	89.1%	90.2%	80%	81.1%
butterfly lines	80.3%	76.5%	79.4%	80.1%	75.5%	75%
bird lines	79.6%	73.2%	78%	72.1%	74.5%	73%
fish lines	81.2%	76%	79.3%	75.2%	73%	75.1%
flower lines	83.5%	80.2%	81.5%	81.1%	79%	78.5%

From Table 2, it is clear that the recognition of linear kernel function by support vector machines is the most effective one. SVM can classify five textures of batik. Test results show that butterfly lines, bird lines and fish lines are not easy to be recognized. Bird lines are the most difficult type to detect. The reason is that the shape and the direction of the image are deformed to a large extent. But by increasing the number and types of standard samples, the recognition can be realized with a higher accuracy. Besides, image segmentation is also a cause of inefficient recognition. As the line and color of batik are not evenly distributed, there is little difference between background and target object in terms of grey. As a result, the segmentation is not satiable. And the features extracted are not in line with the actual practice.

References

- [1] [Thttp://baike.baidu.com/view/15332.htm?fr=aladdin](http://baike.baidu.com/view/15332.htm?fr=aladdin)
- [2] Huang Y, Tan G 2012 Digital protection and exploration of Chinese intangible cultural heritage *Journal of Huazhong Normal University (Humanities and Social Sciences)* **59**(2) 49-55
- [3] http://baike.baidu.com/link?url=SJzRSwh26QH2yw9E3tSrfDOANfdw47-UMr3yvcS_AXL6wVz5kHOIkN_B_xl1c3G5
- [4] Weng D-y, Yang L 2012 Application of Artificial Intelligence Technology in Remote Sensing Images Classification *Journal of Computer Simulation* **6**(29) 240-3
- [5] Song D, Tang L-b 2013 The Object Recognition Algorithm Based on Affine Histogram of Oriented Gradient *Journal of Electronics & Information Technology* **7**(35) 1428-34
- [6] Niu Jie, Qian Kun 2011 Pedestrian detection based on multi-scale and multi-shape HOG features *ComputerTechnology and Development* **21**(9) 99-106
- [7] Zhang Y, Lin H 2013 Comparison among methods that extract forest information from hyper-spectral remote sensing image *Central South University of Forestry & Technology* **1**(33) 75-9
- [8] Chang C-C, Lin C-J LIBSVM: a Library for Support Vector Machines. <http://www.csie.ntu.edu.tw/~cjlin>.
- [9] Tan K, Du P-J 2008 Hyperspectral Remote Sensing Image Classification Based On Support Vector Machine *Infrared Millim Waves* **4**(27) 123-6

Authors

	Yuan Qing-Ni, 1976, Guizhou Weng'an, China. Current position, grades: associate professor of Key Laboratory of Advanced Manufacturing Technology, Guizhou University, China. University studies: PhD, master instructor. Scientific interest: digital design and manufacturing. Publications: 10 papers.
	Lv Jian, November 1983, China. Current position, grades: professor of Key Laboratory of Advanced Manufacturing Technology, Guizhou University, China. University studies: PhD, master instructor. Scientific interest: creation design, industry design. Publications: 5 papers.
	Huang Haisong, October 1977, Guizhou Dafang, China. Current position, grades: professor of Key Laboratory of Advanced Manufacturing Technology, Guizhou University, China. University studies: PhD, master instructor. Scientific interest: advanced manufacturing technology and artificial intelligence. Publications: 10 papers.
	Pan Weiji, January 1983, China. Current position, grades: associate professor of Key Laboratory of Advanced Manufacturing Technology, Guizhou University, China. University studies: PhD, master instructor, director. Scientific interest: digital protection and development of cultural heritage, CAD/CG technology, digital art and design. Publications: 10 papers, 1 book.