Gender Identification Using SVM Based on Human Face Images

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***Abstract*—Gender identification is a new domain in image recognition. Gender identification of human face is to judge one's gender according to his/her face features. The article adopted local binary pattern (LBP) algorithm to build feature subspaces, and processed data using Support Vector Machine (SVM) learning models. Experiments showed that integration of LBP algorithm with linear SVM and integration of LBP algorithm with low-order polynomial SVM are better than Gauss-kernel function.**

Keywords-human face images, gender identification, local binary pattern, support vector machine, kernel functions

I. INTRODUCTION

With the development of image processing techniques, human face recognition techniques have been applied so broadly [1]. Meanwhile, the gender identification technique based on human faces images has become to be one of mode recognition research focuses. Gender identification of human face images means that computers process human face images, extracts the features of images, then identifies the gender by using classification. Gender identification has broad research prospects. It can enhance the interaction capability of some systems. It can identify and control the scenes where there are requirements for gender. Since 90s, numerous domestic and foreign scholars started to study person face identification. The dominant adopted methods include: 1) artificial neural network and support vector machine (SVM). For instance, Cottell and Metcalfe made principal component analysis and BP neural network combination, and applied them in human face recognition; Moghaddam et al. took advantage of SVM classification based on RBF kernels to human face identification [2]. Meanwhile, they make comparison with some neuralnetwork methods and linear classifier method, and concluded that The SVM method has best results. 2) AdaBoost classification method. Shakhnarovich [3] took use of Haar basis features and AdaBoost method to gender identification, and completed automation tracking gender detection. B. Wu et al. [4] at Tsing Hua University proposed LUT AdaBoost method. It is faster and effective than the conventional AdaBoost. PCA method has good applications on human face identification. B. Wu et al. at analyzed a number of schemes composed of SVM based on fixels, PCA+SVM, PCA+AdaBoost, PCA+AdaBoost+SVM methods, and made comparison among them, finally found that there are no large differences on correct rate.

The experiments adopted the combination of LBP feature extraction and multiple SVM classification methods. The FERET face database was taken as the training set and testing set. The experiment results were obtained successfully.

II. PROCESS OF GENDER IDENTIFICATION BASED ON HUMAN FACE IMAGES

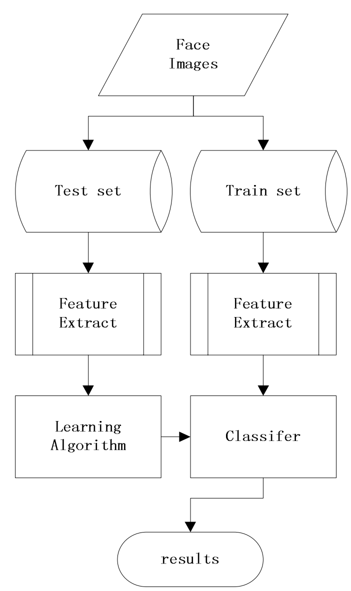

Figure 1. Basic process of gender identification base on human face images

The flowchart of pattern recognition system is shown in Figure 1. The data set is segmented into the training set and testing set. The training set has enough samples so that the machine learning quality can be guaranteed. Further, the positive and negative samples are comparable.

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Otherwise, there would be bias effect for the resulting decision function. We mark the female and male pictures as number 1 and 2, respectively. The data in the test set will be used to test the classifier performance. Any sample in the test set is taken as a input, the classifier can output the male or female result. When the test set is taken as input as a whole, the classifier can tell male or female samples. Additionally, it can identification correct rate. (A premise is that the tag of the test sample is preset). Otherwise, it could not output correct rate.

A. Human Face Feature Extraction

Description and representation of human faces is essentially feature extraction. Extraction methods include ones based on global features and others based on local features. Recently, subspace method based on global features achieved big success. They compose principal component analysis (PCA), linear differentiation analysis (LDA), and independent component analysis (ICA). The PCA method was proposed in 1991 by Kiby and Turk [5]. It aims to find the vector group (orthogonal basis) representing human face images in the sense of the least square by using linear transform, whereby lower the image data dimension, reduces the computation complexity. Belhumeur[6] proposed Fisher LDA in 1997 which takes sample classification capability as the target. The method increase deviation among sample class, and decrease the deviation in sample class. Bartlett et al. [7] proposed ICA method, which is based on correlation in sense of all statistics. Its computation complexity is higher than PCA. Experiments turned out that it has no advantage on correct rate. Human face representation mentioned above based on global features is sensitive to illumination, gesture, expression and other factors. On the contrary, feature representation of human face local features is insensitive to these factors. Ahonen et al. [8] proposed human face representation method based on LBP features in 2004. The article will extract human face image features by the LBP algorithm, and classify images.

B. LBP algorithm

LBP means local binary pattern which was put forward by Ojalai in 1994 [9]. Its basic idea is that the central pixel is taken as a threshold, and surrounding pixels are compared with the central point. If it is larger than the threshold, the bit is set to be unity, if less, it will set to be zero. As a result, a binary code can be obtained to represent local features. The LBP algorithm takes use of P and R to represent it. P denotes pixel number in neighbor domain, while R denotes the radius of neighbor domain. Figure 2 shows the LBP algorithm with different parameters.

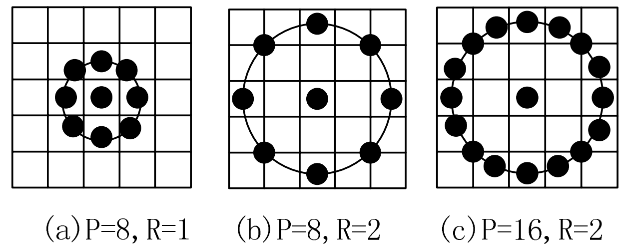


Figure 2. Values of P and R in LBP operator

The circular center denotes the pixel in the central position, and neighbor black points denote neighbor point. R represents the distance between the central point pixel and the neighbor point. The pixel locating at the crossing point can obtain the pixel value by averaging.

$$LBP_{P,R} = \sum_{i=1}^{P} s(g_i - g_c)2^i, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

Equation 1 is the LBP coding formulae, in which g_c represents pixel value in the neighbor domain of the central point. After obtaining central point pixel code, the corresponding dot product will be derived in accordance with distinct binary weights, whereby the LBP algorithm is the dot product of binary codes and corresponding weights, as shown in Figure 3.

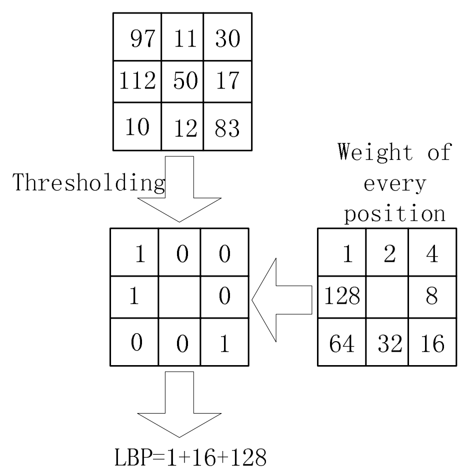


Figure 3. Calculation process of LBP operator

LBP operator is the gray level invariant, but not rotation invariant. Image rotation will get different mode values. Maenpaa et al. improved LBP method and put forward uniform patterns with rotation invariant [10]. The method is continuously rotating circular neighborhood to get a series of initial definition of the LBP value, and the minimum value is supposed as the result value. For example, 00001111 can express eight models as shown in figure 4. The number of models is reduced from 256 to 58 by this method, which means the dimension of feature will be reduced greatly. This LBP called Uniform-LBP were recognized to be a fundamental property of texture as they provide a vast majority of local texture patterns in examined textures, such as edges. In this paper, all the following LBP means Uniform-LBP.

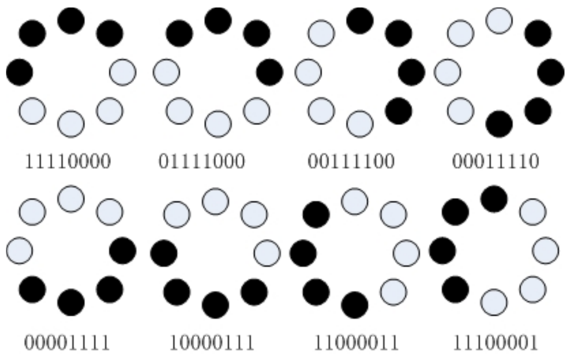
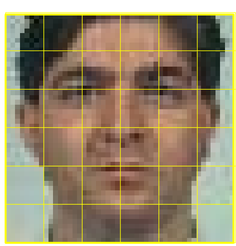
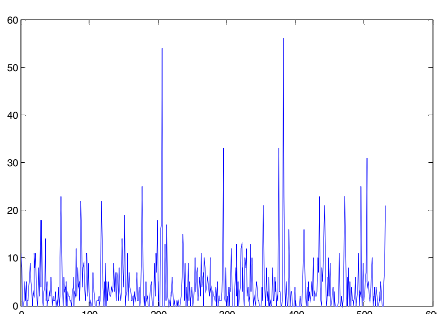


Figure 4. Models represented by 00001111

When the LBP algorithm is used to extract human face characteristics, the human face image is divided into several regions as shown in Figure 5. In each region, the pixel's LBP algorithm will be implemented. Then, the LBP histogram is derived. It is represented by vectors. That is, it is represented by the characteristic vector of the image. Figure 5(a) shows that the human face image is divided into 6×6 regions, and every region contains 8×8 pixels. Finally, the image's histogram is represented by a vector of 531 dimensions.



(a)



(b)

Figure 5. Face image region partition, (b) LBP histogram

LBP algorithm is simple in computation and its computation load is small. From the view of classification, it lowers training cost, and improves training speed. Moreover, the LBP algorithm has better classification capability. It not only represents texture feature of images, but also reflects the characteristic distribution. It has robustness of illumination and rotation. LBP feature extraction is an independent example extraction, not dependent on whole training samples. It does not take use of mutual relationship among samples.

III. SVM Machine Learning Models

Based on feature extraction, designing appropriate classifier can enhance the correct rate of classification results. Until now, there are numerous mature learning algorithms, such as neural network, sensing machine, K neighbor, Bayes algorithm, AdaBoost algorithm, EM algorithm and support vector machine, and so on. The experiment adopted SVM and tested the linear kernel, polynomial and Gauss kernel, and got comparatively objective results.

In 1963, Vapnick proposed SVM [11] method in solving pattern recognition. SVM is a binary mode. The simple case is linear dividable SVM. That is the hard-interval maximum SVM as shown in Figure 6.

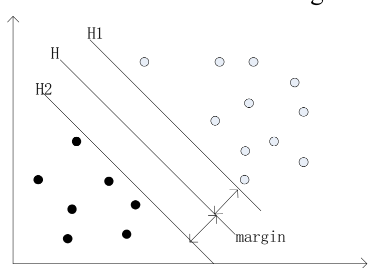


Figure 6. Support vector machine

The conditions of constructing a SVM are that the training data is linear dividable. Its learning strategy is maximum interval method. It can be represented by convex quadratic optimization, and its original optimization is

$$\min_{w,b}\frac{1}{2}\|w\|^2 \qquad (2)$$
$$s.t.\, y_i\left(w\cdot x_i+b\right)-1\geq 0, i=1,2...,N$$

Its solution is w^*, b^*. The resulting linear SVM, detached hyper-plane is $w^*\cdot x+b^*=0$. The classification decision function is

$$f(x) = sign(w^* \cdot x + b) \quad (3)$$

However, in practice, training data are not linearly dividable. It can be solved by approximate linearly dividable. Introducing relaxing variable ξ_i, it can make data “dividable”. Consequently, the problem is written as

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i$$
$$s.t. y_i\left(w \cdot x_i + b\right) - 1 \geq \xi_i, i = 1, 2..., N$$
$$\xi_i \geq 0, i = 1, 2...N \quad (4)$$

For non-linear classification problems in input space, It can be reduced to a linear classification problem in some high-dimension feature space through non-linear transform. Due to the duality，the object function and the classification decision function are involved in inner product of one examples and another example, therefore, it need not to fix the non-linear transform explicitly. Whereas the kernel function replaces the inner product. It is

$$K(x, z) = \phi(x)\phi(z) \quad (5)$$

The solved non-linear SVM is

$$f(x) = sign(\sum_{i=1}^{N} \alpha_i^* y_i k(x, x_i) + b^*) \quad (6)$$

In these experiments six kernel functions were adopt which include linear kernel, high order polynomial kernels and Gaussian kernel. These six results were compared at last.

IV. IMAGES DATA AND EXPERIMENTS

The experiment adopted FERET face database. The set has 200 examples in the training set, among which there are 100 female and 100 male examples. There are 461 examples, among which 124 examples are female, and 227 examples are male. Figure 7 shows some real examples.

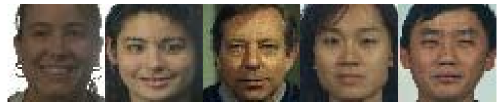


Figure 7. Some image samples

The experiment adopted LIBSVM toolbox, which is a free software package. It is developed by Dr. Zhiren Lin at Taiwan University. It is tractable and powerful. It can solve classification, regression and distribution statistics. Further it supplies linear, polynomial, radial basis and S-shaped functions, self-defined kernel function. It is developed by C++ language, however, the author offers Matlab, Java, Perl interfaces. The LBP method is used to extract features. The linear kernels, polynomial kernels and Gauss kernels are used to conduct classification recognition. The Table 1 lists experiment results. Observing these experiment data, it turned out that the linear kernel is better than other kernels, supports less vectors, has fast speed.

Polynomial kernel function adopts 4 orders to do test, respectively. The results show that the high the order, the less ideal the effect. Theoretically, Gauss kernel should have better results. However, the experiment results are opposite. We divided the training set into 4 equal shares, and adopted cross-validation method to select gammar is 0.1 and 0.005. It has higher cross-validation correct rate compared with other gammar values. When using test set to verify, the resulting correct rate is only 81.75%. It is worse than other kernel functions. The experiments turned out that the Gauss kernel is not better than other kernels in practice of human face gender identification.

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TABLE I. RESULTS OF GENDER IDENTIFICATION

Parameters	**Linear kernel**	**2nd-order polynomial**	**3rd-order polynomial**	**4th-order polynomial**	**5th-order polynomial**	Gauss kernel
Accuracy (%)	90.45	90.24	90.24	89.8	89.37	81.78
Support Vectors	123	141	148	155	163	200
Positive Vectors	62	67	70	69	74	100
Negative Vectors	61	74	78	86	89	100