Gender Classification Based on Boosting Local Binary Pattern

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Abstract. This paper presents a novel approach for gender classification by boosting local binary pattern-based classifiers. The face area is scanned with scalable small windows from which Local Binary Pattern (LBP) histograms are obtained to effectively express the local feature of a face image. The Chi square distance between corresponding Local Binary Pattern histograms of sample image and template is used to construct weak classifiers pool. Adaboost algorithm is applied to build the final strong classifiers by selecting and combining the most useful weak classifiers. In addition, two experiments are made for classifying gender based on local binary pattern. The male and female images set are collected from FERET databases. In the first experiment, the features are extracted by LBP histograms from fixed sub windows. The second experiment is tested on our boosting LBP based method. Finally, the results of two experiments show that the features extracted by LBP operator are discriminative for gender classification and our proposed approach achieves better performance of classification than several others methods.

1 Introduction

Face is one of the most important biometric features of human. We can acquire much information of people naturally from observing their faces, such as identity, sexy, age or expression and so on. As a result, many researches achieved greatly remarkable success in the field of biometric person authentication such as face detection, face recognition, gesture recognition, in which the classification of gender is perhaps the most fundamental estimation problem. The earliest attempt to use computer vision techniques for gender classification was based on neural networks. Gollomb et al[1] trained a fully connected two-layer neural network, named SEXNET, to identify gender from 30×30 face images. Brunelli et al [2] used HyperBF networks to recognize male and female, in which two competing RBF networks are trained using several geometric features as inputs. Moghaddam et al [3] investigated to apply the Support Vector Machine (SVM) to classify gender with low-resolution “thumbnail” faces. And Wu et al [4] introduced an automatic real-time gender classification system based on Adaboost, in which the LUT–type weak classifiers are trained by the Simple Direct Appearance Model (SDAM) method.

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Local Binary Pattern is a powerful operator for texture description, proposed by Ojala[5] originally, which is defined as a grayscale invariant texture measure, derived from a general definition of texture in a local neighborhood. The LBP method has already been used in a large number of applications, including texture classification, image retrieval, face image analysis, and so on. Timo et al[6] presented a novel approach for face recognition, which takes advantage of the LBP histogram. In their method, the face area is equally divided into several sub windows from which the LBP features are extracted and concatenated to represent the local texture and global shape of face images. Recently, Li et al [7] proposed a systematic framework for fusing 2D and 3D information at both feature and decision levels. They used LBP as the representation of faces in 2D and 3D images, and applied the AdaBoost to selecting effective feature from a 2D+3D feature pool. In addition, the LBP operator is also used in the application of facial expression recognition [8, 9].

In this work, we present a novel approach for gender classification by boosting local binary pattern-based classifiers. Firstly, the training sample is scanned with the scalable sub windows, which is moved horizontally and vertically around the images. The histograms of Local Binary Pattern are extracted from the small windows to describe the local features. And the LBP histograms of each small window are averaged to generate a histogram template for the class of male or female. The Chi Square distance between histogram of samples and templates is computed as the features for discrimination. By mean of the Adaboost algorithm, the most useful features are selected, and the strong classifier is obtained in the form of linear combination of LBP feature based weak classifiers.

The rest of this paper is organized as follow: In Section 2, the LBP representation is introduced briefly. Section 3 describes AdaBoost algorithm for feature selection and strong classifier construction in detail. And two experiment results of gender classification based on LBP operator are given in the Section 4. At last, we make the conclusion in section 5.

2 Local Binary Pattern

The original version of the LBP operator labels the pixels of an image by thresholding the 3×3−neighbourhood of each pixel with the center value and considers the result as a binary number. Then the histogram of the labels is used as a texture descriptor. Just as described in Fig.1(a).

The major limitation of the original LBP operator is that it can not obtain dominant features with large scale structures. Thereby the primary LBP operator is extended to

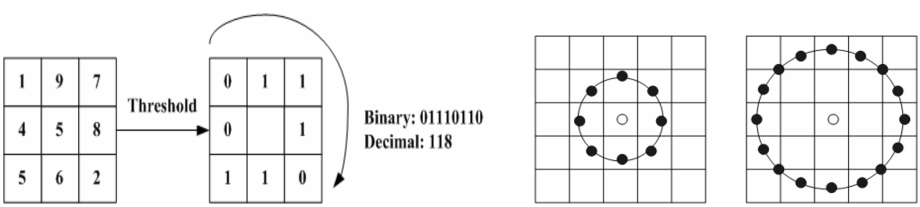

Fig. 1. (a) The basic LBP operator. (b) Two examples of the extended LBP: The circular (8, 1) neighborhood, and the circular (16, 2) neighborhood.

use neighborhoods of different size[10]. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. There are two samples of extended LBP in the Fig.1(b), where (*P,R*) means *P* sampling points on a circle of radius of *R*. As a result of the first extension, the size of feature vectors extracted by LBP operator with different number of neighborhoods is quite large, and the contribution of most feature vectors for texture description is limited. Hence, another extension of LBP is to use so called uniform patterns. A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. According to the texture image, the experiment in the paper [10] shows that the uniform patterns contribute 87.2% of the total pattern data when using the (8, 1) neighborhood and 70.7% in (16, 2) neighborhood. So, it is proved that uniform patterns appear to be fundamental properties of local image texture.

We use the notation $LBP_{P,R}^{u2}$ for operators, where the subscript shows that the operator is in a (P, R) neighborhood, and the superscript u2 stands for using uniform patterns and labeling all remaining patterns with a single label. A histogram of the labeled image $f_l(x, y)$ is defined as following:

$$H_i = \sum_{x,y} T\{f_l(x, y) = i\}, \qquad i = 0, \cdots, n-1 \tag{1}$$

where n is the number of different labels produced by the LBP operator and

$$T(A) = \begin{cases} 1 & A \;\; is \;\; ture \\ 0 & A \;\; is \;\; false \end{cases} \tag{2}$$

This histogram contains information about the distribution of the local micro patterns, such as edges, spots and flat areas, over the whole image.

In former LBP based method for face analysis, the image is divided into several sub windows $W_0, W_1 \cdots W_{m-1}$ to achieve the goal of retaining the spatial information. The spatially enhanced histogram is defined as

$$H_{i,j} = \sum_{x,y} T\{f_l(x, y) = i\} T\{(x, y) \in W_j\} \qquad i = 0, \cdots, n-1, \, j = 0, \cdots, m-1 \tag{3}$$

There are several possible dissimilarity measures proposed for histogram, such as histogram intersection, Log-likelihood statistic. In our work, Chi square statistic (x^2) is adopted:

$$x^2(S, M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i} \tag{4}$$

where S and M respectively denote sample and template distributions.

3 Adaboost Learning

Boosting[11] is a general algorithm of constructing accurate strong classifier by combining several weak classifiers. The combined strong classifier could achieve very high accuracy when the accuracy of each weak classifier is slightly better than random guess. In the last decade, Boosting has been widely applied to many practical pattern recognition problems, for example, Schapire and Singer[12] presented a boosting-based system for Text Categorization, and Yang et al[13] proposed a face recognition method using AdaBoosted Gabor features. Furthermore, most important application of boosting algorithm is face detection. Viola et al[14] developed a face detection system based on cascaded Adaboost that is capable of detecting face very rapidly and accurately.

- Given example images (x_1, y_1), …, (x_n, y_n) where $y_i = 0,1$ for negative and positive examples respectively.
- Initialize weights $\omega_{1,j} = 1/2m, 1/2l$ for $y_i = 0,1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1,...,T$:
  1. Normalize the weights, $\omega_{t,i} \leftarrow \frac{\omega_{t,i}}{\sum_{j=1}^{n} \omega_{t,j}}$ so that ω_t is a probability distribution.
  2. For each feature j , train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to $\varepsilon_j = \sum_i \omega_i \left| h_j(x_i) - y_i \right|$
  3. Choose the classifier, h_t , with the lowest error ε_t .
  4. Update the weights: $\omega_{t+1,i} = \omega_{t,i} \beta_t^{1-e_i}$, where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$.
- The final strong classifier is: $H(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq 0.5 \sum_{t=1}^{T} \alpha_t \\ 0 & otherwise \end{cases}$

  where $\alpha_t = \log(1/\beta_t)$

Fig. 2. The binary-classified Adaboost algorithm [11]

In the procedure of Boosting algorithm, the effective features are learned from a large feature set firstly, and weak classifiers are constructed based on one of the selected features. Finally, these weak classifiers are boosted into a strong classifier. In general, the training error of the strong classifier approaches zero exponentially in the number of rounds, if the accuracy of combined weak classifiers are slight better than 50%. In Adaboost learning, we are given a sequence of training samples $s = (x_1, y_1),...,(x_m, y_m)$ along with a distribution $\omega_{t,i} = (\omega_{t,1} ... \omega_{t,m})$. The $\omega_{t,i}$ is reweighed after each learning round t , and the distribution of incorrectly classified examples is increased so that the weak learner is forced to focus on the hard examples in the training set. The binary classified version of Adaboost is shown in Fig. 2.

4 Experiment and Discussion

We design two experiments for gender classification based on Local Binary Pattern operator. Two experiments are all made on the image sets collected from FERET database. The training set consists of 2000 images with 256 gray levels, 1200 of male subjects and 800 of female subjects, and the test set comprises others 400 images selected from FERET database, in which the subject of men and women are all 200. In preprocessing, we crop the face area from original image based on the two eyes location. The cropped images are scaled to 144 pixels high by 120 pixels wide and processed by illumination compensation and histogram equalization. There are several samples of the training set shown in the Fig.3.

Fig. 3. Some samples of training set collected form FERET database

Experiment A – This experiment is performed to test the effectiveness of LBP feature for gender classification. Here a face image is equally divided into small sub windows from which LBP features are obtained and concatenated into a single, spatially enhanced feature histogram. We divide 144×120 pixels facial image into 24×20 pixels so that 36 (6×6) sub windows are given in total, see Fig.4. The 59-bin $LBP_{8,2}^{u2}$ operator is used for each sub window, and the length of the extracted histogram is 2124 (59×36).

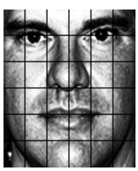

Fig. 4. An example of face image divided into 6×6 sub windows

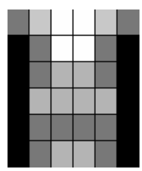

Fig. 5. The weights set corresponding to Chi Square distance

We apply the Self Organizing Maps (SOM) method to separate the training set into 10 classes, 5 for male images and 5 for female images. After the SOM training, the final weight vector for each node is the centroid of the class, i.e., the template vector, which corresponds to the template of each class. Investigating the male and female images from training set, we find out that the area of eyebrow, bridge of a nose, and chin contribute the most effective features to distinguish between men and women. As a result, a weights set corresponding to the divided face images is designed to improve the performance of the gender classification. The weights set is shown in Fig.5, where black squares mean weight is 0, dark grey is 1, light grey is 2 and white is 4.

In the classification, the weighted Chi Square distance is adopted to be as the measurement:

$$x_{\omega}^{2}(S,M)=\sum_{i,j}\omega_{j}\frac{\left(S_{i,j}-M_{i,j}\right)^{2}}{S_{i,j}+M_{i,j}} \tag{5}$$

where ω_j is the weight of sub windows j. Then, the histogram of the input image is matched with the closest template, and the input images are considered to be as male if their histograms are matched 1 to 5 classes, otherwise they are female.

Experiment B – This is an experiment of classifying gender based on boosting LBP. There are obviously two aspects that can be improved in experiment A: (1). The equal division to face image limits the variety of the size and position of the extracted features. By scaling and shifting the sub windows can capture much more features, which maintain the more abundant and detailed information of face images. (2). The weights set of Chi Square distance is predefined, which may be rough and subjective. It will be more rational that the weights of sub windows are computed by statistical learning such as Adaboost algorithm.

In experiment B, the scaling and shifting sub windows are used to obtain the features and Adaboost are applied to select the useful features and computed the weights set, which can overcome the above two drawbacks effectively. There are 12221 LBP features in total extracted by scanning the each face image with scalable windows. The LBP histograms in a given class are averaged to generate a histogram template for this class. The Chi square distance is applied to construct the weak classifier set by computing the dissimilarity measure of histogram between sample and template. Finally, Adaboost algorithm is used to combine the strong classifier for gender classification by learning features from the weak classifier set. The first three sub windows selected by Adaboost are shown in Fig.6.

Fig. 6. The first three sub windows selected by Adaboost.

Result and Discussion – The performance of experiment A and experiment B is 82.75% and 95.75% respectively, and the experiment result compared with several gender classification methods also tested on the images set collected from FERET database are list in Table.1. The correct rate of experiment A and experiment B with other methods shows that the features extracted by LBP operator are discriminative for gender classification. And our simple template matching using LBP can achieve better result than the sixth method listed in the Table 1 also using nearest neighbor for discrimination. According to the experiment B, its accuracy is higher than ICA+LDA, ICA+SVM, only a bit lower than SVM+RBF kernel method. It is denoted that the boosting LBP approach can construct effective nonlinear classifier for gender classification. Furthermore, the comparison between our boosting LBP method and LUT-based Adaboost method indicates that the features obtained by LBP operator are more powerful to describe local texture than Haar like features for gender classification. Additionally, the accuracy of the two experiments in this section demonstrates that the LBP histograms of scalable and movable sub windows yield more complete and agile description of face images than the fixed one, and the weights set chosen by Adaboost algorithm is more reasonable than the predefined one.

Table 1. Comparisons of different methods for gender classification

Method	Accuracy
Experiment A	82.75%
Experiment B	95.75%
ICA+LDA in [3]	93.33%
ICA+SVM in [3]	95.67%
SVM+RBF kernel in [3]	96.62%
Nearest neighbor in [3]	72.84%
LUT-based Adaboost in [4]	85.46%

5 Conclusion

In this paper, we have proposed a novel method for gender classification by boosting statistical Local Binary Patterns based classifiers. LBP features extracted by scanning face images with scalable sub windows are introduced to be as a powerful texture description for classifying male and female. The Chi square distance between corresponding Local Binary Pattern histograms of sample image and template is used to construct weak classifiers pool. Adaboost algorithm is applied to build the final strong classifiers by selecting and combining the most useful weak classifiers. Two experiments illustrate that LBP features are effective for gender analysis, and the boosting LBP method can achieve better performance than several other methods.

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