Face Detection and Sex Identification from Color Images using AdaBoost with SVM based Component Classifier

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ABSTRACT

When we talk about a computer based automatic facial feature extraction system which can identify face, gesture etc and estimate sex, age, expirations etc, we always ask for a dependable, fast, reliable classification process. This paper presents an approach to extract effective features for face detection and sex classification system. The proposed algorithm converts the RGB image into the YCbCr color space to detect the skin regions in the color image. Finally Gaussian fitted skin color model is used to obtain the likelihood of skin for any pixel of an image. For facial feature extraction we use Gabor filters at five scales and eight orientations. To solve the classification problem we employ Adaboost_SVM based classifier. Adaboost has been widely used to improve the accuracy of any given learning algorithm. In this paper we focus on combination of Adaboost with Support Vector Machine (SVM) as weak component classifiers to be used in sex classification task. For this classification problem AdaboostSVM based classifier demonstrates better generalization performance than SVM on imbalanced classification problems.

Keywords

Face Detection; Sex Identification; Gabor Filter; AdaBoost-SVM.

1. INTRODUCTION

The most important and impressive biometric feature of human being is the face. It conveys various information including gender, age, ethnicity etc. Face information can be applied in many sectors like biometric authentication and intelligent human-computer interface. Many potential applications such as human identification, smart human computer interface, computer vision approaches for monitoring people, passive demographic data collection, and etc needs a successful and dependable classification method. It is really a very challenging job to detect male or female accurately separating two sets of data. So it is very urgent to have a reliable classifier to improve the classification performance. This paper deals with sex identification based on Adaboost with SVM based component classifier.

Over the last few years there have been attempt to implement machine learning algorithm to classify sex from images. Most of these methods used neural networks for sex classification [1, 2]. Support Vector Machine (SVM) (Vapnik, 1998) is developed from the theory of Structural Risk Minimization. By using a kernel trick to map the training samples from an input space to a high-dimensional feature space, SVM finds an optimal separating hyper plane in the feature space. The use of Support Vector Machines for sex classification application was proposed by Moghaddam et al. in [3]. On the other hand for constructing Ensemble classifiers which is the most developed machine learning system, mostly use two techniques. They are 1.Boosting (Schapire, 2002) and 2.Bagging (Breiman, 1996). The most popular Boosting method, AdaBoost (Freund and Schapire, 1997) creates a collection of component classifiers by maintaining a set of weights over training samples and adaptively adjusting these weights after each Boosting iteration: the weights of the training samples which are misclassified by current component classifier will be increased while the weights of the training samples which are correctly classified will be decreased. Several ways have been proposed to implement the weight update in Adaboost (Kuncheva and Whitaker, 2002). Shakhnarovich, Viola, and Moghaddam [4] applied AdaBoost to the features used by the face detection system created by (Viola and Jones, 2001) on 24×24 pixel images collected by crawling web. They obtained an accuracy of 79%. Baluja and Rowley [5] presented an Adaboost system for gender classification with manually aligned faces. They carried out a thorough experimental comparison between the Adaboost and an SVM classifier by varying face image scaling, translation, and rotation. Castrillon-Santana and Vuong [6] compared the performance of humans and automatic face recognition algorithms for gender classification.

Different techniques have been introduced recently, for example, Matta et al. [7] combined temporal and spatial information such as head motion, mouth motion, and facial appearance to perform gender classification. Lian and Lu [8, 9] used min-max modular SVM with image pixels as input. They also experimented with Local Binary Pattern (LBP) as face features. Xia et al. [10] adopted Local Gabor Binary Papping Pattern to extract face feature. Kim et al. [11] applied Gaussian process method, as it could automatically determine the hyper-parameters.

Most of the methods mentioned above have achieved impressive performance on controlled databases like FERET [16]. But literature shows that there is no unique solution to sex identification problem. So, in this paper we propose a model for automatic face detection and sex identification using AdaBoost with SVM based component classifier. We allow the Gabor filter features to be selected arbitrarily in a large feature pool. In this way, the features selection can be more discriminative, and hence our approach is more accurate for sex identification. Our approach is able to handle a wide range of variations in static color images, based on a lighting compensation technique and a nonlinear color transformation.

This paper is structured as follows. In section 2, related methodology for face detection and sex identification is described, in section 3 experimental results are shown and section 4 contains conclusion.

2. METHODOLOGY

Our proposed face detection and sex classification system is described in Fig. 1.

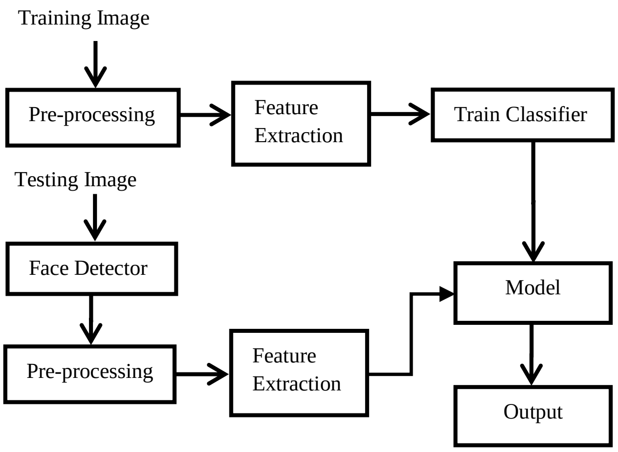


Fig 1: General approach for sex identification system.

2.1 Face Detection

An overview of our face detection system is depicted in Fig. 2, which contains the major module: face localization for finding face candidates.

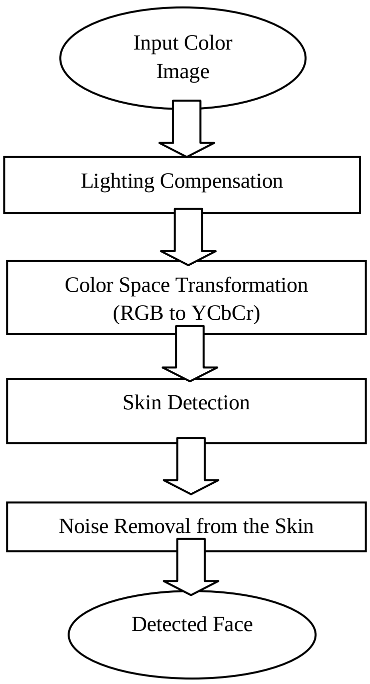


Fig 2: Face detection algorithm for localization of face candidate.

2.1.1 Lighting Compensation

Due to different lighting conditions, the appearance of the skin-tone color can change. We use a lighting compensation technique that uses "reference white" to normalize the color appearance. According to [12], the lighting compensation (LC) algorithm is very efficient in enhancing and restoring the natural colors into the images which are taken in darker and varying lighting conditions. We regard pixels with the top 5% of the luma (nonlinear gamma-corrected luminance) values as the reference white if the number of these pixels is sufficiently large (>100).

The LC algorithm can be defined as followings:

$$S_c = \frac{C_{std}}{C_{avg}} \tag{1}$$

$$C_{avg} = \frac{\sum_{i=1}^{m}(C_i)_{C_i>0}}{\sum_{i=1}^{m}(1)_{C_i>0}} \tag{2}$$

$$C_{std} = \frac{\sum_{i=1}^{m}[max\,(R_i,G_i,B_i)+min\,(R_i,G_i,B_i)]}{2*n} \tag{3}$$

$$n = m = \sum_{i=1}^{m}(1)_{(R_i=G_i=B_i=0)} \tag{4}$$

Where, S_c stands for the scale factor for one specific channel of R, G or B. The C_{std} and C_{avg} separately stand for the standard mean gray value of the specific channel and the mean value non-black pixels in the same channel. Here m stands for the number of pixels in the image, n stands for the number of non-blackpixels in the image.

By calculating the average of the maximum and minimum channel percentage, an adaptive mean gray value of the whole image is gained. Fig. 3 illustrates an example of images and the resultant image after applying the LC algorithm.

Fig 3: Image before and after lighting compensation.

2.1.2 Color Space Transformation

It has been observed that the normalized RGB space is not the best choice for face detection. We adopt the YCbCr space since it is perceptually uniform, is widely used in video compression standards (e.g., MPEG and JPEG), and it is easier in the separation of luminance and chrominance as well as the compactness of the skin cluster.

The RGB to YcbCr color transforation equations are as follows:

$$Y = 0.299R + 0.587G + 0.114B \tag{5}$$

$$Cb = -0.169R - 0.331G + 0.500B + 128 \tag{6}$$

$$Cr = 0.500R - 0.419G - 0.082B + 128 \tag{7}$$

An example of this transformation from RGB to YCbCr is shown in Fig. 4.

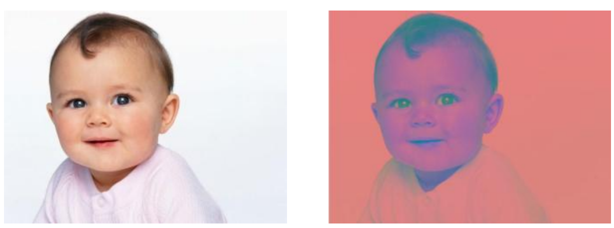


Fig 4: RGB to YCbCr color transformed images.

2.1.3 Skin Color Detection

In the skin color detection process in YCbCr color space, each pixel in the image is classified as skin or non-skin based on its color components. The skin color was determined based on the mean and standard deviation of Cb and Cr component, obtained using 85 training faces. The Cb and Cr components of 85 faces are plotted in the color space shown Fig. 5; their histogram distribution is shown in Fig. 6.

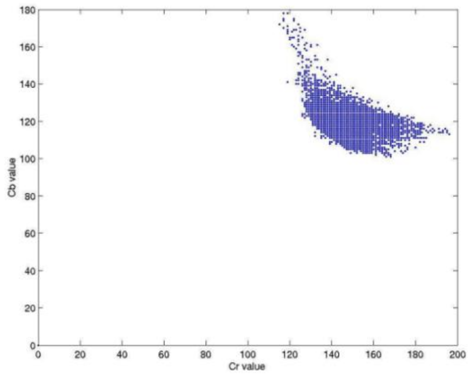
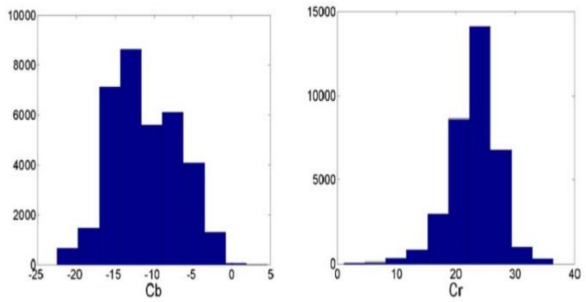


Fig 5: Skin pixel in YCbCr color space.



(a) **(b)**

Fig 6: (a) Histogram distribution of Cb. (b) Histogram distribution of Cr.

The color histogram revealed that the distributions of skin-color of different people are clustered in the chromatic color space and a skin color distribution can be represented by a Gaussian model [19] N(m, C), where:

Mean: $m = E\{x\}$ *where* $x = (r\ b)^T$ (8)

Covariance: $C = E\{(x-m) * (x-m)^T\}$ (9)

Fig. 7 shows the Gaussian Distribution N(m, C) fitted by our data.

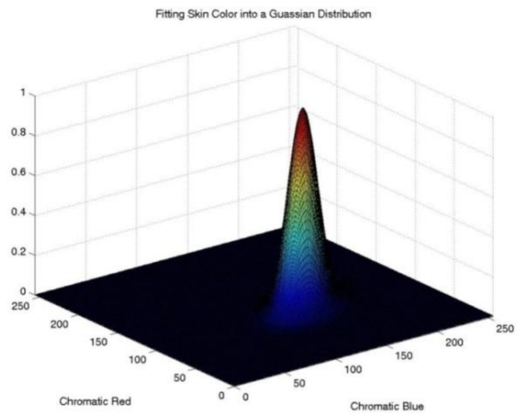


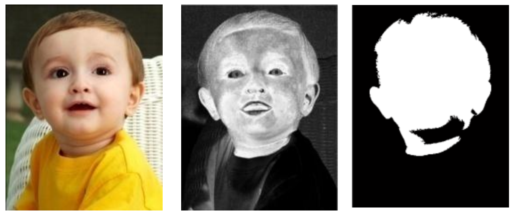
Fig 7: Fitting skin color into a Gaussian distribution.

With this Gaussian fitted skin color model, we can now obtain the likelihood of skin for any pixel of an image. Therefore, if a pixel, having transformed from RGB color space to chromatic color space has a chromatic pair value of (r, b), the likelihood of skin for this pixel can then be computed as follows:

$$Likelihood = P(r,b) = exp[-0.5(x-m)^T C^{-1}\{x-m)] \quad (10)$$

$$where: x = (r,b)^T$$

Hence, this skin color model can transform a color image into a gray scale image such that the gray value at each pixel shows the likelihood of the pixel belonging to the skin. With appropriate thresholding, the gray scale images can then be further transformed to a binary image showing skin regions and non-skin regions. The skin segmented image of previous color image resulting from this technique shown in Fig. 8.



(a) **(b)** **(c)**

Fig 8: Image processing sequences for skin segmentation (a) Original Image (b) Skin-likelihood Image (c) Skin-segmented Image.

After analyzing the connected region for face a rectangular box is introduced to show the location of face. The dimension of the box is calculated from the matrix of the image using the image program tool (Matlab). Some results of detected images are shown in Fig. 9.

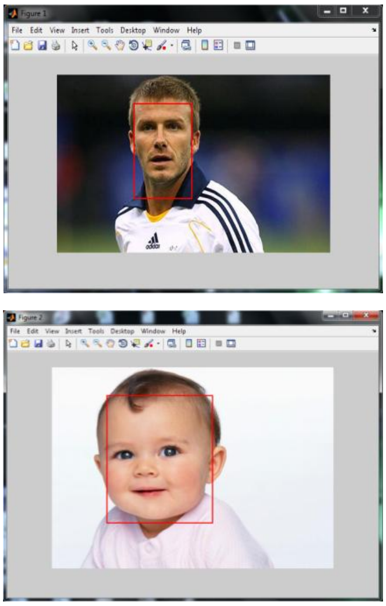


Fig 9: Single face image detection in rectangular bounding box.

2.2 Feature Extraction

In machine learning problem, feature selection also known as variable selection, is the technique of selecting a subset of relevant features for building strong learning models. For the selection of facial features for our sex classification problem, Gabor filters is well suited. A 2D form of Gabor wavelet [18] consists of a planer sinusoid multiplied by a two dimensional Gaussian. 2D Gabor wavelet highlights and extracts local features from an image, and it has the tolerance of changes in location, shape, scale and light.

Here is the formula of Gabor wavelet in space domain:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x^2}{{\sigma_x}^2}+\frac{y^2}{{\sigma_y}^2}\right)+j2\pi\omega x\right] \quad (11)$$

The formula in frequency domain is defined as follows:

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-\omega)^2}{{\sigma_u}^2}+\frac{v^2}{{\sigma_u}^2}\right]\right\} \quad (12)$$

The Gabor wavelet transform adopted in our system is:

$$F(x,y) = a^{scale\ -scaleindex}\ g(x',y') \quad (13)$$

$$x' = (x\ cos\theta + y\ sin\theta) \quad (14)$$

$$y' = (-x\ sin\theta + y\ cos\theta) \quad (15)$$

Where, (x,y)represents a pixel in the image, *scale* is a parameter of spatial frequency, θ is an orientation angle.

$$\theta = \frac{n\pi}{k}, n = (0,1 \dots \dots, k-1) \quad (16)$$

Where, k is the number of orientations. This wavelet can be used at 8 orientations (n=0,… ... 7) and 5 spatial frequencies (scale=1,… …,5).

After applying Gabor filter, an image is converted into 40 images with different scales and orientations. The operation is very complex and slow in spatial domain, so we use FFT in frequency domain and then IFFT to obtain the output in spatial domain. Fig. 10 shows example of Gabor Filter with five scales and eight orientations and Fig. 11 shows how single image is convolved with Gabor Filter of five scales and eight orientations.

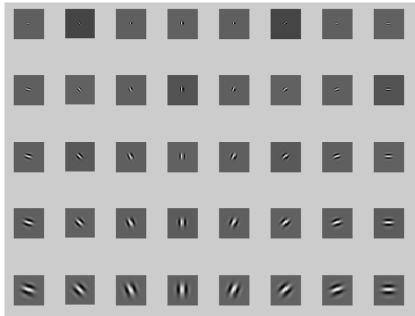


Fig 10: Gabor Filter with five scales and eight orientations.

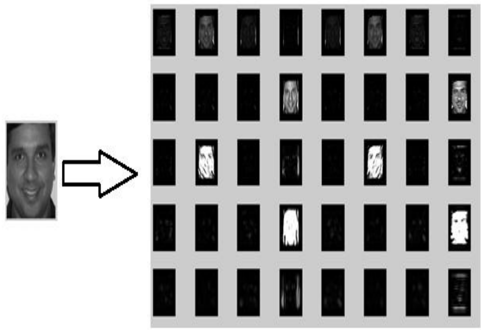


Fig 11: The Gabor features of single face image.

2.3 AdaBoost-SVM

In this paper, we employ RBFSVM as component classifier in AdaBoost [13]. RBF is one of the popular kernels used in SVM classification problem, which has a parameter known as Gaussian width, σ. Here, RBFSVM is used as component classifier in AdaBoost with relatively large value of σ, which corresponds to a RBFSVM with relatively weak learning ability. To update the weights of training samples, re-weighting technique is used.

Consider a set of training samples

$$\{(x_1,y_1),(x_1,y_1) \dots \dots,(x_n,y_n)\}$$

Initial value of σ is set to σ_{ini}, minimal value of σ is set to σ_{min} and each step is set to σ_{stp}.

The weights of training samples are initialized as:

$$w_i^1 = \frac{1}{n}, \text{for all } i = 1, \dots, n \quad (17)$$

Initially, a large value is set to σ. Then we train a RBFSVM component classifier, h_t, on the weighted training set.

Training error of h_t, $\quad \varepsilon_t = \sum_{i=1}^{n} w_i^t, y_i \neq h_t(x_i) \quad (18)$

RBFSVM with this σ is trained as many cycles until error becomes less than 50%. Otherwise decrease the value of σ, by σ_{stp}, to increase the learning ability.

For $t = 1, \ldots\ldots, T$:

Set the weight of component classifier h_t,

$$\alpha_t = \frac{1}{2}\, ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right) \qquad (19)$$

To, update the weights of training samples,

$$w_i^{t+1} = \frac{w_i^t exp\{-\alpha_t y_i h_t(x_i)\}}{C_t} \qquad (20)$$

Where, C_t is normalization constant.

This process continues until σ is decreased to the given minimal value. Final classifier is the linear combination of a series of weak classifiers.

$$f(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x)) \qquad (21)$$

3. EXPERIMENTAL RESULTS

To evaluate the performance of sex identification system, we have prepared a database by combining images from several existing databases with different ethnicity and nationalities and referred as the mixed database. Since the focus of this paper is sex identification, we have selected frontal images with slight expression and illumination variations. It contains a total of consisting of total 2382 faces out of which 1204 are male and 1178 are female each of size 32 x 40 pixels. These are the faces used for training phase. Table 1 provides the composition of the mixed database. It contains images from the CMU PIE [14], AR [15], FERET [16] face databases. The comparison results of different algorithms tested in [17] and our method is shown in Table 2. We have designed GUI using MATLAB-2008a which is shown in Fig. 12. Some sample output results are shown in Fig. 13.

Table 1. Details of Mixed Database

Database	No. of male face images	No. of female face images
CMU PIE	66	56
AR	456	468
Indian Face	250	232
Chinese Face	168	172
www	152	124
FERET	112	126
Total(2382)	**1204**	**1178**

Table 2. Comparison results of different algorithms

Methods	Male Detection Rate (%)	Female Detection Rate (%)
Neural Network	62.31	65.2
Threshold Adaboost	75.26	72.45
LUT Adaboost	75.78	76.71
Mean Adaboost	71.84	73.23
AdaBoostSVM	89.51%	87.80%

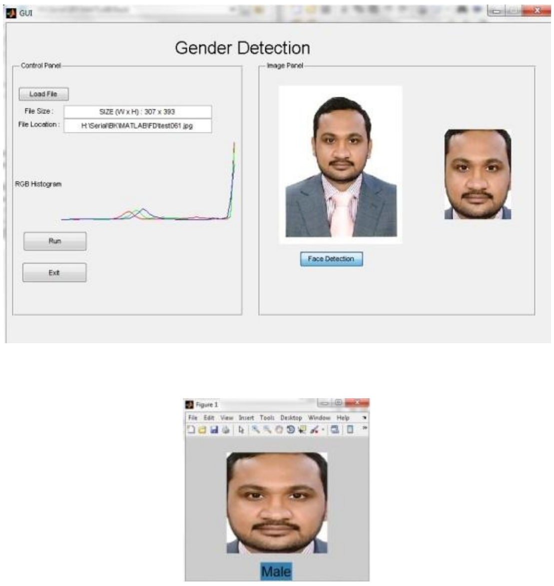


Fig 12: GUI panel for sex identification.

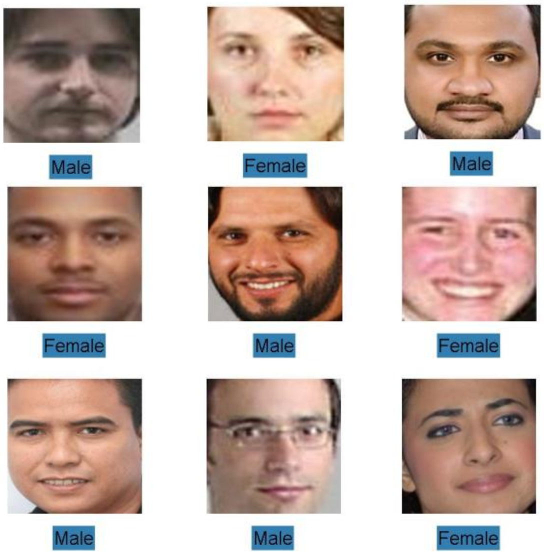


Fig 13: Some output results of the system.

4. CONCLUSION

In this paper, an attempt has been made to identify face and sex from the color image. Experimental results indicate the superiority of this work than other related works in terms of the numbers of face parts, databases and classifiers employed. We have evaluated the relevance of face parts in sex recognition, and considered its potential usefulness in classification under partial occlusions. Detection of human faces is the first step in our proposed system. It is also the initial step in other applications such as video surveillance, design of human computer interface, face recognition, and face database management. We have proposed a face detection method for color images in the presence of various lighting conditions as well as complex backgrounds. We also presented AdaBoost with properly designed SVM-based component classifiers, which is achieved by adaptively adjusting the kernel parameter to get a set of effective RBFSVM component classifiers. Experimental results show that proposed AdaBoostSVM performs better than other approaches of using component classifiers such as Neural Networks. We tested our approach on random images from internet, picture taken by digital camera and achieved great deal of accuracy.

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