Image enhancement for face recognition using color segmentation and Edge detection algorithm

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Abstract

Nowadays Image Processing and Image Enhancement play a vital role in many of numerous applications. This paper introduces the new color face recognition (FR) method that makes effective use of boosting learning as color-component feature selection framework. A facial recognition system is a method of automatically identifying or verifying a person from a digital image or a video frame from a video source. The proposed boosting color-component feature selection framework is designed for finding the best set of color component features from various color spaces (or models), aiming to achieve the best FR performance for a given FR task. Most of the existing color FR methods are restricted to using a fixed color-component configuration comprising of only “two” or “three” color components [5]. This paper addresses and fixes the existing problem and proposes a method by using color segmentation algorithm and edge detection algorithm.

Keywords: Face Recognition (FR), Color-Component, Framework.

1 Introduction

Image processing is the main part in all Face Recognition techniques [1]. Even though we use the latest techniques in face recognition, the result of the FR process depends upon the given input image quality. The accuracy rate of the whole process is much better when we are giving enhanced image from the low quality image by combining one or more color component algorithms [2].

One of the ways to do this is by comparing selected facial features from the image and a facial database application [3]. It is typically used in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems. The overall framework of the proposed color FR method which largely consists of two parts

1) Color component feature selection
2) Color Feature enhancement
2 Related Works

In this paper, to survive with the abovementioned issue, we propose a new color FR method. Our method takes advantage of “boosting” [4, 5] learning as a feature selection mechanism, aiming to find the best set of color-component features for the purpose of achieving the best FR result.

To the best of our knowledge, this work is the first attempt to incorporate feature selection scheme behind boosting learning into FR methods using color information. This is because specific color components effective for a particular FR problem could not work well for other FR problems under other FR operating conditions (e.g., illumination variations) that differ from those considered during the process of determining specific color components.

3 Color Component Feature Selection Method

The proposed algorithm first locates the face region using skin-color. The YCbCr color space is used to detect the skin region on the given input face image. The given input RGB image Fig 1 is converted into the YCbCr color space. Color is a powerful cue of human faces. The distribution of skin clusters is in a small region of the chromatic color space [6]. Processing color is faster than processing other facial features. Therefore, skin color detection is firstly performed on the input color image to reduce the computational complexity.

In order to improve the performance of skin color clustering, YCbCr space is used to build a skin color model. The chrominance components are almost independent of luminance component in the space [7].

There are non-linear relations between chrominance (Cb, Cr) and luminance (Y) of skin color in the high and low luminance region. As stated in, the apparent difference in skin color perceived is mainly due to the darkness or fairness of the skin, characterized by the difference in the brightness of the color, which is governed by Y but not Cb and Cr in YCbCr colour space. Y, luminance component is brightness component, whereas Cb and Cr are chrominance components, which correspond to color components. In the color detection
GammaRGB = (c1 * inputRGBimage) c2 + c3 (1) where c1 = 1.0, c2 = 1.0 and c3 = 0.0

The Y, Cb and Cr components are determined through the following formula using the constant C with the value 128.

\[
Y = (0.299 \times (\text{gammaRGB}[0,i,j] - C)) + (0.114 \times (\text{gammaRGB}[2,i,j] - C)) (1)
\]

\[
C = (0.564 \times (\text{gammaRGB}[2,i,j] - Y)) (2)
\]

\[
Cb = (0.564 \times (\text{gammaRGB}[2,i,j] - Y)) (3)
\]

\[
Cr = (0.713 \times (\text{gammaRGB}[0,i,j] - Y)) (4)
\]

Gamma RGB is the array with 0 represents the Red layer and the 2 represents the Blue layer. The range of Cb is between -50 and 2 while the range of Cr is between 10 and 100 determine the skin region. The given YCbCr image is converted to one-layer gray scale image. This system takes the Green layer. The face boundary is estimated by determining the center point of the gray image face photo.

4 Data for Training and Testing

The training and testing data of this work are mainly from the Corel image data set. The one used in this work has sets A and B. This work is designed to train a classifier to retrieve “person”, so, all the 29 “person” images in set A are used as positive set (there is no “person” images in set B) Fig 2. Because the size of the negative set should not be too much larger than the positive, there are only 72 images for negative set. Most of the negative set images are from set A, some are from set B. Because “Cross Validation” will be used to choose the parameter, the positive and negative sets are divided into two sets. The training set has 16 positive and 41 negative images. The testing set has 13 positive and 31 negative images. Finally, the system is tested on a more
general image set which has 15 “person” images, randomly downloaded and resized from Google, and 204 “non-person” images from set B. Because some of the images in set B has totally different object from those in set A. For example, there are images about trains in set B while there is no one in set A. In order to enrich the training set for better training, some of the representative images are chosen from set B and added to negative training set.

Fig. 2: Training data set

5 Results and Comparison

Most of the existing color FR methods are limited to using a set color-component pattern comprising of only “two” or “three” color components Fig 3. In particular, currently used color-component choices are mostly made through a combination of perception and observed comparison, without any systematic selection strategy [8].

It is critical for any edge detection algorithm that it should determine all edges while o none edge is recognized as edge. Above criteria determines error rate of any edge detection filter. Besides the low error rate, there are two other qualities which an edge detection filter should posses.

1. The distance between actual edge and edge located by filter should be as low as possible
2. Filter should not provide multiple responses for single edge.

Canny edge detector possesses above two qualities and also provides low error rate. Canny edge detector utilizes the convolution operation. A convolution operation is performed by sliding the convolution kernel over the input image or region of image in which we need to detect edges. The kernel is a 3X3 matrix. Output at any pixel location is the sum of the product of values of each cell of the kernel to the values of underlying pixl. Convolution kernel determines gradient in a particular direction depending upon type of kernel used. Value of gradient determines
possibility of any edge passing through that particular point. The two kernels used for detecting horizontal and vertical edges respectively.

As such, existing methods may have a Limitation to attaining the best FR results for given FR task. This is because specific color components effective for a particular FR problem could not work well for other FR problems under other FR operating conditions (e.g., illumination variations) that differ from those considered during the process of determining specific color components.

The existed color FR method which largely consists of two parts:
1) Color-component feature selection
2) Color Feature Enhancement.

Here we propose a new color FR method. Our method takes advantage of “boosting” learning as a feature selection mechanism, aiming to find the optimal set of color-component features for the purpose of achieving the best FR result with the help of DWT, Eigenface and Face congruency Fig 4. To the best of our knowledge, our work is the first attempt to incorporate feature selection scheme underpinning boosting.

The nth statistical moment is

$$\mu_n(\bar{r}) = \frac{1}{M} \sum_{i=0}^{L-1} (\bar{r}_i - m)^n \hat{p}(\bar{r}_i)$$

For image intensities, a sample mean

$$m = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)$$

A fundamental problem in digital signal processing is to find a suitable representation for a signal. Usually different signal representations are based on linear transformations of the signals onto different bases. The transformations help representing the signal in a lower dimensional space. We
use Color Segmentation Algorithm for facial images representation.

Fig 5: Comparison for different datasets

Color Segmentation algorithm has been applied for each partition and final result of the procedure is a matrix which consists of weighting vectors for each partition. First step in application of color segmentation algorithm is to choose population size, i.e. number of individual in the population Table 1.

Using color segmentation algorithm we calculate the color feature panel. And then using the edge detection algorithm we trained the dataset and classify accordingly.

The accuracies for different datasets are found out and results are compared. Here Ada-Boosting gives more result compared to the Edge Detection methods as in Fig 5.

**Conclusion**

In this paper, a novel and effective color FR method is proposed. It is based on the selection of the best color-component features (from various color models) using the proposed variant of boosting learning framework by Ada-Boosting algorithm. The choice of such techniques is a function of the specific task, image content, observers characteristics, and viewing conditions.

This makes the FR method to be effective. For an input represented by a list of $2^n$ numbers, the Haarwavelet transform may be considered to simply pair up input

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Table 1: Feature panel for different datasets.
values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale: finally resulting in \(2n - 1\) difference and gives one final sum.

In the future, research will be directed to the forming of reference image which will provide more information for this algorithm in the training process and add the filtering process.

References


