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AUTOMATIC HUMAN FACE RECOGNITION USING MULTIVARIATE GAUSSIAN MODEL AND FISHER LINEAR DISCRIMINATIVE ANALYSIS

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Abstract

Face recognition plays an important role in surveillance, biometrics and is a popular application of computer vision. In this paper, color based skin segmentation is proposed to detect faces and is matched with faces from the dataset. The proposed color based segmentation method is tested in different color spaces to identify suitable color space for identification of faces. Based on the sample skin distribution a Multivariate Gaussian Model is fitted to identify skin regions from which face regions are detected using connected components. The detected face is match with a template and verified. The proposed method Multivariate Gaussian Model – Fisher Linear Discriminative Analysis (MGM – FLDA) is compared with machine learning - Viola & Jones algorithm and it gives better results in terms of time.

Keywords:

Face Recognition, Multivariate Gaussian Model, Image Segmentation, Connected Component, Color Spaces

1. INTRODUCTION

Face recognition is a popular area in Computer Vision having a lot of commercial importance such as biometrics, surveillance etc. It has also successfully able to attract a wide range of researchers from Psychology, Cognitive studies etc. Recently this research topic has been mainly focused based on machine learning and neural networks [1-3]. T.K Leung, B. Modhaddam [4-5] survey mention the feature invariant approaches used for feature detection of eyes, mouth, noise, etc, T. Agui, O. Bernier [6-7] surveys mention the Neural network methods and A.J Colmenarez, M.S. Lew [8-9] mention the informal theoretical approach methods for face recognition. The challenges in these methods are the requirement of large training data and high processing power. To overcome these challenges a Multivariate Gaussian Model is proposed to differentiate skin pixels from non-skin pixels for identifying faces. And experimentally YCbCr color space has been chosen over HSV, nRGB, CIE-a*b for more accuracy. The identified connected components of skin are processed to identify facial regions for finding suitable match from the face dataset. The proposed MGM - FLDA model is the compared with a Viola & Jones [10] algorithm to evaluate runtime efficiency.

2. PROPOSED DESIGN

The proposed design is described in four sections. Section 2.1 describes image preprocessing, section 2.2 describes face detection and section 2.3 describes face identification of face. The block diagram of the proposed design is shown in the Fig.1.

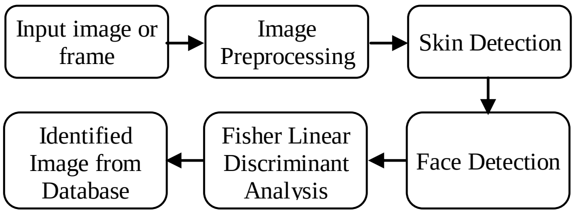

Fig1. Algorithm design block diagram

2.1 IMAGE PREPROCESSING – LOW PASS FILTERING

In this section the smoothing of images is carried out to remove noise [11] caused during the image acquisition. By averaging the spatial data in the image, small impulse noises which might cause disturbances in creating Gaussian model are reduced. A 3 × 3 kernel is used to average the pixel values in the image. The averaging equation is given in the Eq.(1)

$$P(x,y)=\frac{1}{R}\sum_{s=-a}^{a}\sum_{t=-b}^{b}P(x+s,y+t) \tag{1}$$

where, $R=\sum_{s=-a}^{a}\sum_{t=-b}^{b}P(s,t)$

$P(s, t)$ represents pixel value of image at (s, t)

a, b represent kernel size

The preprocessing image is used for face recognition.

2.2 FACE DETECTION

2.2.1 Color Spaces:

The RGB color space not only represents colors but also brightness. The skin color may vary across color range due to change in luminance. Thus the color space in the absence of luminance can be effectively used to segment skin pixels from non-skin pixels [12]. To select an appropriate color space for skin detection, 200 human skin samples of RGB images taken from Caltech Color Images dataset [13] are investigated. The 2D Histograms of the skin samples are constructed with a bin resolution of 400 × 400 in HSV, CIE-a*b, nRGB, YCbCr color spaces to study the characteristics by eliminating the luminance layer. A large amount of human skin density observed to look like normal distribution. Fig.2 describes the histogram of sample skin data distribution in YCbCr color space.

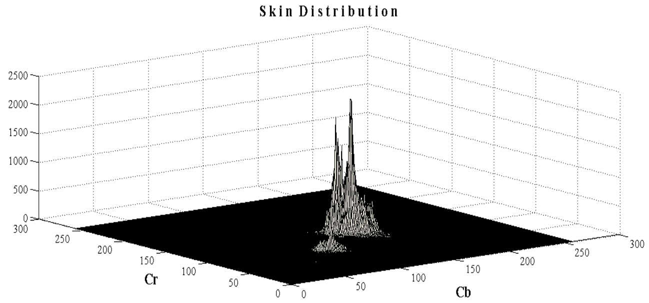

Fig.2. Distribution of skin-color in YCbCr color space

2.2.2 Multivariate Gaussian Model:

The color distribution of 200 sample human skin data randomly selected from Caltech Color Images dataset [13] are used for fitting the Gaussian model. The probability density function of Gaussian model is given in the Eq.(3).

$$P(r,b) = e^{-0.5(x-m)^T C^{-1}(x-m)} \quad (2)$$

where, $m = E\{x\}$

$C = E\{(x\text{-}m)(x\text{-}m)^T\}$

$x = (r,b)^T$

$P(r, b)$ = Probability Density Function

m = Mean of skin samples in r, g layers

C = Covariance of mean values

The experiment is carried out in different color spaces to identify a suitable one. The respective results observed on a sample of 50 images of size 200 × 200 pixels images are given in Table.1.

Table.1. Comparison of skin region detection under various color spaces

Color Space	TP	FP
HSV	73%	80%
CIE-a*b	78%	65%
nRGB	80%	75%
YCbCR	92%	48%

where, TP: True Positives, FP: False Positives

The Fig.3 shows the fitted Gaussian model for YCbCr color space of sample skin data distribution as shown in Fig.2.

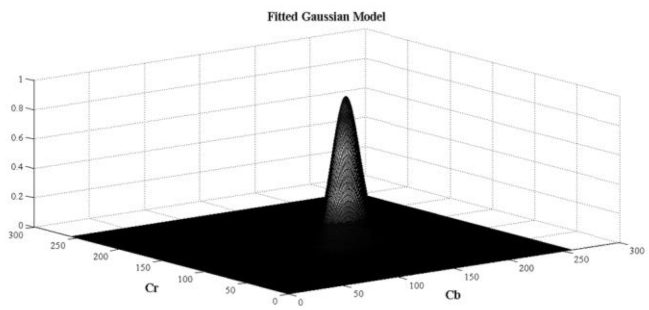

Fig.3. Fitting skin color in Gaussian distribution

With this Multivariate Gaussian Model, a RGB image is converted to a gray scale image. The pixel with maximum value - 1 represents the non-skin region while the pixel with minimum value - 0 represents skin-region. From the Table.1, the True Positives and False Negatives of YCbCr is 92% and 48% respectively. YCbCr performs better in comparison with other.

2.2.3 Adaptive Threshold:

The adaptive threshold is chosen for converting the gray scale image obtained from Gaussian model to get a binary image using a threshold value. The adaptive threshold is automatically chosen based on the observation that the skin region decreases when the threshold value decreases from 1 to 0. In our MGM – FLDA algorithm, a range of 0.05 - 0.55 is taken empirically to choose the threshold value. The optimal threshold is chosen at the point where there is a minimum variation from gray scale image to binary image. Fig.4 shows the converted RGB image to gray scale image by using the fitted Multivariate Gaussian Model.

Fig.4. Gray scale image obtained from Gaussian model

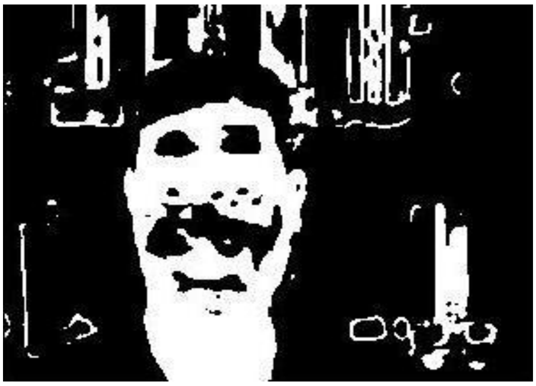

Fig.5. Binary image after applying threshold value

The Fig.5 shows the obtained binary image by using the adaptive threshold value. The obtained binary image is then processed to find connected components for identifying face region.

2.2.4 Connected Components:

As the segmented skin region does not only contain facial region but also other skin regions of human body like hand, legs. So, separating them is required. A connected component is defined as face region in the image, which has 1 or more holes inside it. Its boundary is represented by pixels with value 1, inside with value 0 [14]. The connected components obtained from the binary image are thus filtered to determine whether they belong to face. Eq. 7 describes the threshold equation used to eliminate the connected components.

$$f(x) = \begin{cases} 1, & H \geq 1 \\ 0, & H \leq 0 \end{cases} \tag{3}$$

where, $H = C - E$

H = Number of holes in the region

C = Number of connected components

E = Euler number

2.2.5 Template Face:

A template a chosen by averaging 16 frontal view faces of males and females from the Caltech Color Images Dataset [13], vertically centered at the tip of the nose of the model. Fig.6 shows the sample template face used in this paper.

Fig.6. Template face

The connected component is identified as face if the cross correlation of template face and connected component region has value greater than 0.6 chosen empirically.

2.3 FACE RECOGNITION - FISHER LINEAR DISCRIMINATIVE ANALYSIS

The identified facial connected components are then processed to find similar face from dataset.

A two-dimensional $p \times q$ grayscale image consists an $m = pq$ vector space, so an image with 100 × 100 pixels lies in a 10000 dimensional image space. Zhao W [14] survey mentions dimensionality reduction methods to address such a problem to turn a set of possibly correlated variables into a smaller set of uncorrelated variables.

The Principal Component Analysis (PCA) proposed by Jolliffee [15-16] convert set of correlated variables in smaller set of uncorrelated variables called principal components. However the PCA does not classify any of the information thus results in poor performance during different lighting conditions for identification of faces.

The Linear Discriminative Analysis (LDA) proposed by R. A. Fisher [17-18] groups variables into different classes and perform class specific dimensional reduction. This minimizes the scatter between images of same class and maximizes the scatter between different classes. This method was first successfully used for classifying flowers [19]. Fig.7 show sample fisher faces of the test images from the dataset.

Fisherface #1 Fisherface #2

Fig.7. Sample Fisherfaces of test images

3. RESULTS

In this section we discuss the results of the proposed Face recognition (MGM – FLDA) technique and comparative runtime evaluation between Viola & Jones algorithm [10] are discussed.

MATLAB has been used as the platform to conduct the experiment on Intel Dual Core i5 Processor. The Caltech Color Images Dataset [13] is used to evaluate the proposed algorithm. Fig.8 represents the input image with a rectangular box in it showing the identified facial region. After facial region is detected, a closely matched face from the dataset is shown.

Fig.8. Detected face (Left) and matched face (Right)

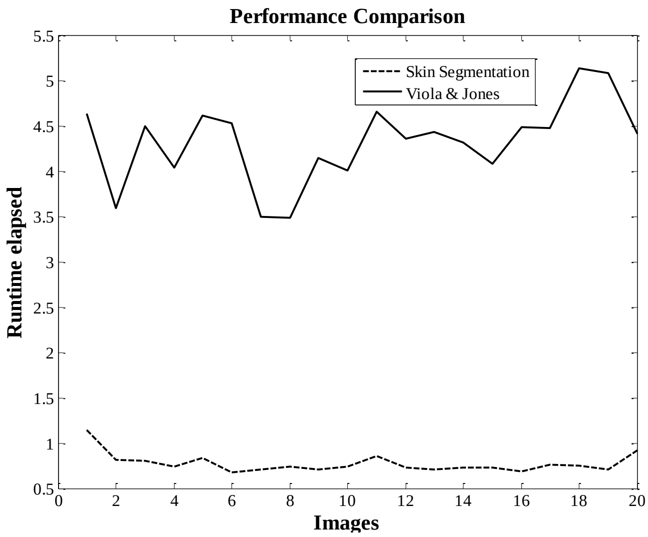

Fig.9. Performance analysis of algorithm

The proposed face detection algorithm vs. Viola and Jones algorithm [10] are compared. A real-time database of 20 images collected of same size having at least one face region is taken to perform this comparison. Here we compare runtime elapsed for identifying each image of the algorithms. The simulation results in the Fig.9 show the performance improvement in terms of time of our proposed face detection over the supervised learning classifier based Viola & Jones algorithm. The average time taken to find face in Viola & Jones algorithm is 4.322ms while that of proposed algorithm is 0.773ms.

4. CONCLUSION

An automatic face recognition algorithm has been proposed which used Multivariate Gaussian Distribution to segment skin from non-skin and identify face regions in image and then Fisher Linear Discriminative Analysis has been used to match faces. The proposed model works well compared to Viola & Jones in terms of time.

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