

Race Classification using Craniofacial Features from Colored Face Images

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Abstract:- This paper produces a system for race classification from face images. Two powerful types of local features have been considered: craniofacial features (eyes, mouth, nose) of the faces and color variance of the skin color together to further improve race classification accuracy. For classification, five ratios have been taken which calculated as a mathematical relation between features using four race groups selected from FG-NET, CPIR database and other gathered by us as own database. The system scored a success about 82% in recognition for tested images.

Index Terms— Race recognition; facial features.

I. INTRODUCTION

Face processing and recognition is a key biometric technology with a wide range of potential applications related to security and safety. Major customers of biometric technology can be found in a private sector, particularly among corporations with high security interest and limited access areas like banks, government related departments and services providers to client populations of thousands, often millions of people. Current research efforts in the field involve developing a system to classify faces with respect to race by using information gathered from frontal colored face images. It is well known that people are more accurate at recognizing faces of their own race than faces of other races (i.e., “other race effect”). [1][2] while other researches have proved that humans recognize the gender of adults and children using feature sets derived from the appropriate face age category, rather than applying features derived from another age category or from a combination of age categories. [3]. Obviously, the information of gender, race, and age enhance the search operation when matching unknown faces to a set of known faces by reducing searching space and also optimize face recognition algorithms using face categories. [4]. In our study we designed an algorithm to improve race recognition operation, which has illustrated in Fig. 1.

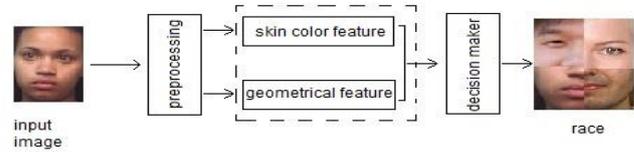


Fig. 1. the main diagram of The Race Recognition System

The face is extracted from an input image then a preprocessing is applied to normalize the input face (e.g., orientation, lighting and posing).

Two kinds of local features have been extracted from local regions of the face, first, geometrical features such as distances and areas between facial features (e.g., eyes, nose, and mouth) second, the color information of skin.

These two feature groups help in determination of the race for input face depending on several conditions and limitations of their values.

Local feature-based methods however, require accurate localization of various facial features which might not be easy in practice [5][6] unless we develop the system to overcome these challenges with ability to detect them correctly. As humans, we are easily able to categorize a person's race from an image of the person's face and are often able to be quite precise in this estimation, to simulate this a new framework for race classification from frontal face images from FG-NET database and CBIR images with natural life albums by:

1. Using the geometrical face features and skin color features, that describe variance of craniofacial morphology and color dependent on using algorithm merge two image processing techniques the geometrical one and **the Color Variance (CV)**.
2. The use of database that is classified as races groups.
3. classify the race category depending on the ratios and color analysis functions.
4. Testing and computing the recognition performance of the system on the above classified database and real people images as well as celebrates.

II. LITERATURE REVIEW OF RACE CLASSIFICATION

Race classification using face images is relatively a new topic in computer vision. Levin (1996, 2000) [10], [11] suggested that racial information is processed as a basic visual feature (cf. Triesman & Gelade, 1980) [12], defined by its presence (as in other-race faces) or absence (as in own-race faces). According to Levin's theory, faces from different races can be thoroughly processed, with the same degree of individuation as own-race faces.

Manuscript published on 30 August 2014.

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Gutta *et al.*[14] achieved 94% accuracy in a four class problem (i.e., Caucasian, Oriental, African, and Asian) using the FERET database which contains gray scale images ,they used an ensemble radial basis functions with inductive decision trees for ethnicity classification.

MacLin and Malpass[7] subjectively found that the race faces are encoded categorically and this categorization drives the perceptual process,also when feature acting as racial marker is changed for identical face can be perceived as faces of another races. Phillips *et al.*[8] analyzed other-race effect on face recognition algorithms using the results of the 2006 Face Recognition Vendor Test (FRVT). They found that Western algorithms (i.e., developed by France, Germany and the United States research groups) recognized Caucasian faces more accurately than East, Asian faces and East Asian algorithms (i.e., developed by China, Japan, and Korea research groups) recognized East Asian faces more accurately than Caucasian faces.

Hosoi *et al.*[9] designed a method based on Gabor wavelets and retinal sampling for ethnicity classification of three types African, Asian, and European. The other-race effect (ORE) in face recognition is typically observed in tasks which require long-term memory. Megan *et al.*[13] found no evidence that the recognition deficit associated with the ORE reflects deficits in immediate encoding with 6 experiments, with over 300 participants.

Manesh *et al.*[15] considered a two class ethnicity classification problem (i.e., Asian and non Asian) using an appearance-based method to determine the confidence of different facial regions using Support Vector Machines (SVM). They reported a 0.0261% error rate with faces normalized using eye and mouth positions. The used face images collected from the FERET and CAS-PEAL databases.

G. Muhammad *et al*[5] investigates and compares the performance of local descriptors for race classification from face images. Two powerful types of local descriptors have been considered Local Binary Patterns (LBP) and Weber Local Descriptors (WLD). First, they investigate the performance of LBP and WLD separately and experiment with different parameter values to optimize race classification. Second, they apply the Kruskal-Wallis feature selection algorithm to select a subset of more “discriminative” bins from the LBP and WLD histograms. For classification, they have considered the minimum distance classifier and experimented with three distance measures: City-block, Euclidean, and Chi-square. using the FERET database. their experimental works on five race groups (classes).

It is obvious that the field of race recognition using face images is newly discovered and less processed against face recognition. Some attempts are made for only two or three class problems, which is relatively easier than many class problems or using many complicated calculation on collected database only. For that we introduce our algorithm which use human knowledge for detecting race depending on geometrical feature and skin color with improving picture technique as well as working on four race groups.

III. THE CRANIOFACIAL FEATURES

It represented mathematically by define the distances between primary face features (eyes,nose,mouth) and the

ratios of these distances. The facial features vary for every person and are affected by several factors such as exposure to sunlight, inherent genetics, and nutrition ,although there is general attributes distinguish among races, as a human, for example ,we take in count the color variance for African and

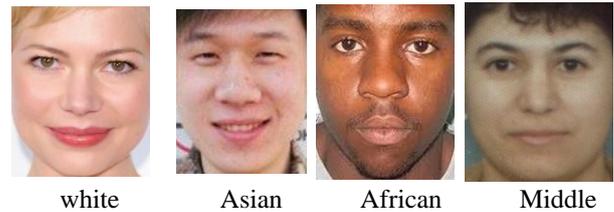


Fig. 2 Four Studied Races

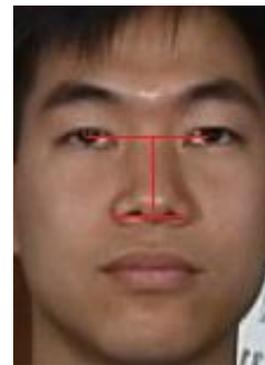


Fig. 3 The craniofacial features

the facial feature for white. Fig. 2 shows the four races recognized by our system :

As we see there :

- a) Color varies from race to other even with presence of different level of lighting.
- b) When color level for different races had intersected, the dispensation of facial feature can be a good tool for showing difference ,Fig. 3

IV. PROPOSED SYSTEM

The system reads image from the database and crops the face to save it in the system database. By using image processing technique we extract the primary and secondary features that are used to determine the race group ,as showed in Fig. 1.

A. Preprocessing

The first step is to prepare the input image for features extracting by cutting face part then we use single scale retinex and multi scale retinex algorithms^[16](single scale retinex SSR and multi scale retinex MSR)to adjust the illumination variation, enhance the light and contrast in the input color images The single scale retinex for a point (x,y) in an image is defined as ^[17](1).

$$R_i(x,y,c) = \log[I_i(x,y)] - \log[F(x,y,c) \otimes I_i(x,y)] \quad (1)$$

Where $R_i(x, y, c)$ is the Retinex output of channel i (i.e R,G,B) at position x,y and $I_i(x, y)$ is the image value for channel i . In (1), the symbol \otimes represents the convolution operator and $F(x,y,c)$ is the Gaussian surround function shown in (2):



$$F(x,y,c)=(k) \exp \left(\frac{-(x^2 - y^2)}{c^2} \right) \quad (2)$$

k is determined by:

$$k = \frac{1}{\sum x \sum y F(x,y)} \quad (3)$$

The constant c is the Gaussian surround constant (analogous to the σ) generally used to represent standard deviation. The Gaussian surround constant c is referred to as the scale of the Retinex.

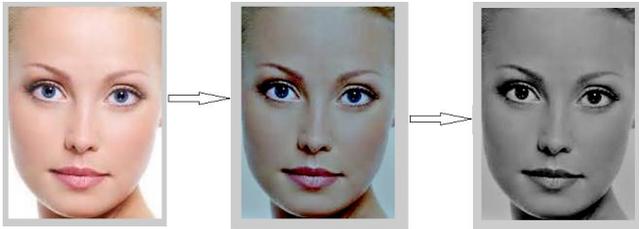


Fig. 5 The face image after enhanced and gray scaled

The resulted image is used for geometrical features extraction after being turned to grayscale image, while the original image is used for skin color matching, see Fig. 5.

B. Feature Extraction

1. geometrical feature

The primary features of the face (eyes, nose, mouth) are found from grayscale images by dividing the face into three part to make ease of detection and illuminate errors as in Fig. 6:

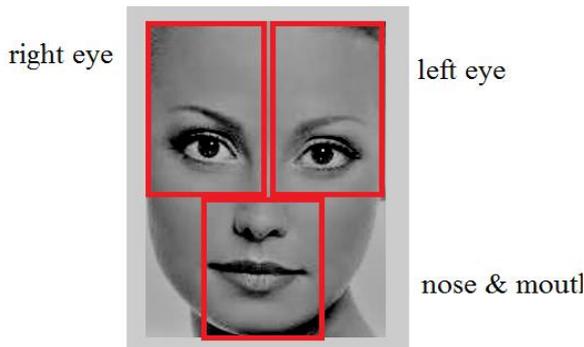


Fig. 6 Face Feature Partitions

- **Finding Eyes** :we cut the upper part of the face and split it to two quarter (left and right),for each part **HalfOfFace** with dimensions (m*n) and Intensity (I_{ij}, i=1,2,...,m, j=1,2,...,n) we do as follow:

a) $I_{ij} = I_{ij} + 0.8 \quad (5)$

b) Calculate L which is :
$$L_i = \sum |I_{j+1} - I_j| \quad (6)$$

c) Calculate H that is:
$$H_j = \sum I_i \quad (7)$$

The maximum value of L is used to detect x-coordinate while the minimum value of H is used to detect y-coordinate of the eye, see Fig. 7:

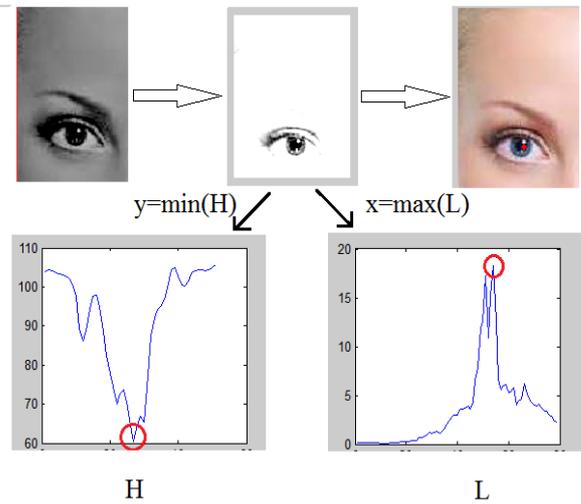


Fig. 7 Finding Left Eye

- d) Then each coordinate is projected on whole face to place it in its position.
- e) The same operations is made to find other eye.
- **Finding mouth and nose**: a bottom region from face is taken as a rectangle with limited start from x-coordinate of left eye to x-coordinate of right eye and from half of face to chin as showed above in fig5, then following below steps :
 - o Calculate the x-coordinate of both mouth and nose as the middle point between the eyes:
$$X_{middle} = ((x_{right} - x_{left})/2) + x_{left} \quad (8)$$
 - o Calculate the the vector B as:
$$B_i = \sum I_j \quad (9)$$
 - o Finding y-coordinate of the mouth as a minimum value of B.
 - o The y-coordinate of the nose is the second minimum value of B, see Fig. 8

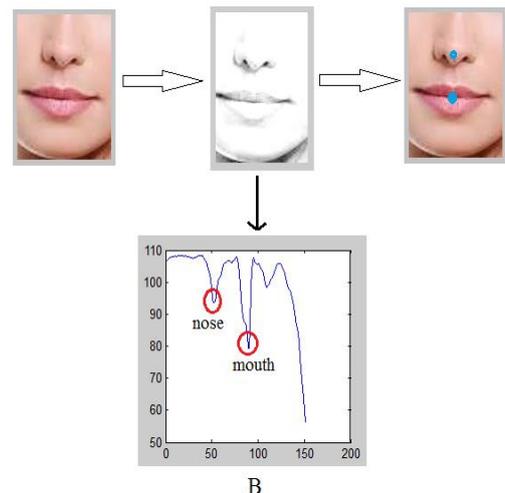


Fig. 8 Finding Mouth and Nose

- **Finding nose length and width:** one of feature that differentiate Asian and African is nose length which calculated as below:

- Cutting an area around nose as a rectangle and finding vector N as:

$$N_j = \sum |I_{i+1} - I_i| \quad (10)$$

- Finding the ending point of nose from left and right as the highest values in N.
- The width is the difference between nose ends ,see Fig.9.
- The length of nose is calculated from y-coordinate of the eye to the y-coordinate of the nose estimated as in Fig. 8.

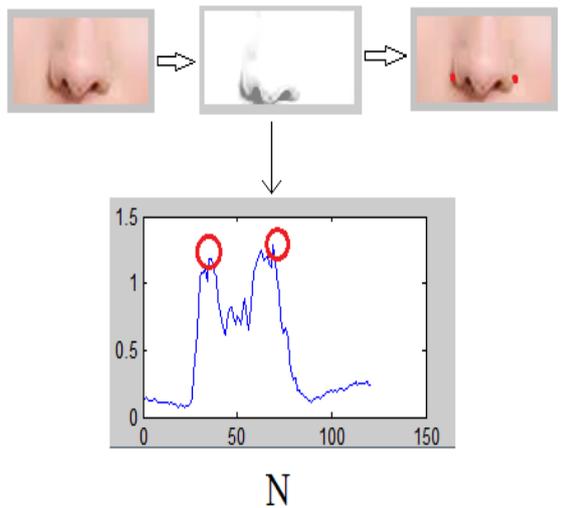


Fig. 9 Calculating the Width of Nose

Then we have a face with detected feature as Fig. 10



Fig. 10 Detected Features

2. Skin Color

other influential feature is the color of skin and how to vary in darkness to lightness from one race to other ,in our system we took a piece of face (cheek) to calculate color feature for each component of the image in RGB scale as :

$$R = \frac{\sum r_{ij}}{WH} , i=1,2,\dots,W \quad j=1,2,\dots,H \quad (11)$$

$$G = \frac{\sum g_{ij}}{WH} , i=1,2,\dots,W \quad j=1,2,\dots,H \quad (12)$$

$$B = \frac{\sum b_{ij}}{WH} , i=1,2,\dots,W \quad j=1,2,\dots,H \quad (13)$$

3. **Calculating Ratios:** There are five ratios that are used to classify the race category . These five ratios are computed by detecting well defined features coordinates namely:(eyes, mouth, nose), Ratio1 is the ratio formed by two segments: segment1 joining two eyes and the segment2 is the width of nose. Ratio2 is the width of nose. Ratio3 is the ratio formed by the two segments: segment1 as above and segment3 which represent the length of nose . Ratio4 the sum of R,G,B (color mean) while Ratio5 is the B (blue color mean).Fig11

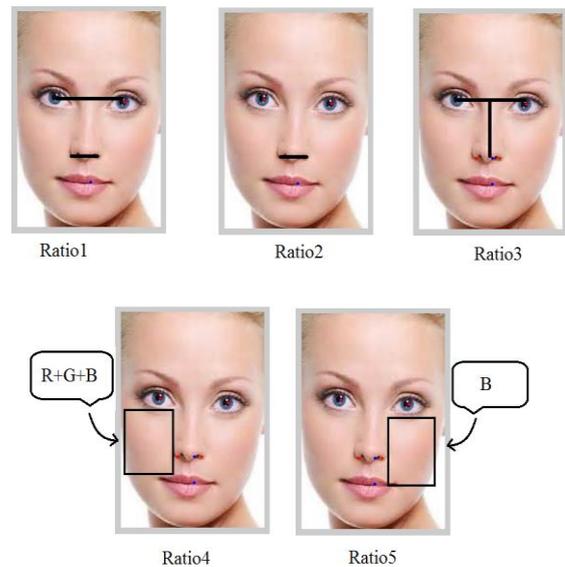


Fig. 11 The Five Ratios

Table I shows the distinguishing ratios of four races groups after five ratios computation with images selected from the system database.

C. Decision maker:

We can notice from table1 how the calculated ratios can determine the difference between races ,the ratio1, ratio2 and ratio5 can isolate the race 'African' with threshold about > 0.32 , ≥ 34 and < 100 for each while the ratio4 with threshold < 460 takes two races 'Asian' and 'middle east' that we can use ratio3 to separate between them ,and for race 'white' the ratio4 can differentiate between 'white' and 'Asian' if ratio4 more than 508 . These thresholds programmed within our system in order (if...then...else) to give the race for the input image and it calculated after experienced 200 images for different races (50 for each) arranged and gathered from databases like FG-NET and CPIR and some other private images for people around.

Table I Showed the five ratios with its effected values

images	R1	R2	R3	R4	R5
	0.254902	26	1.3076	<u>554.650</u> 4	161.546 5
	0.217822	22	1.2948	<u>528.390</u> 9	138.377
	0.252427	26	1.6093	<u>512.411</u> 5	123.459
	<u>0.336634</u>	<u>34</u>	1.6557	377.111 5	<u>82.3179</u> 9
	<u>0.410256</u>	<u>48</u>	1.4810	349.342 4	<u>83.4823</u> 3
	<u>0.463158</u>	<u>44</u>	1.1445	345.928 5	<u>80.6507</u> 5
	0.218182	24	<u>1.4667</u>	490.558 5	132.690 3
	0.3125	30	<u>1.21519</u>	317.825 9	83.0594 1
	0.39604	40	<u>1.29487</u>	382.678 6	103.117 2
	0.168142	19	2.01785	<u>400.071</u>	113.795 2
	0.155963	17	1.21111	<u>439.993</u> 7	128.975 3
	0.634615	33	0.7023	<u>336.058</u> 1	81.6871 7

Input as	Recognized as				
	African	white	asian	middle	s.rate
80 African	75	1	3	1	93.75%
75 white	1	65	5	4	86.66667%
60 asian	3	6	45	6	75%
88 middle	6	7	9	66	75%

The error of recognizing some images backs to the telescopic feature of appearance for some people which makes even the human himself can misjudge it, Table III explicates some false recognized images and how its feature causes that.

Table III ,False recognized images with its ratios						
image	R1	R2	R3	R4	R5	Input as Output
	0.38	38	1.16 279 1	<u>561.37</u> 78	180.688 9	Asian as white
	<u>0.387</u> 097	<u>36</u>	1.29 166 7	133.79 96	<u>66.8997</u> 9	Asian as African
	0.244 898	24	<u>1.22</u> 5	<u>219.91</u> 98	109.959 9	African as Asian
	0.437 5	28	<u>0.62</u> 745 1	<u>246.57</u> 52	123.287 6	White as Asian
	0.239 583	23	0.94 117 6	<u>170.64</u> 2	85.3209 8	White as Middle
	0.153 846	18	1.58 108 1	<u>556.07</u> 42	128.037 1	Middle as white
	0.326 923	34	<u>1.46</u> 478 9	<u>221.45</u> 86	110.729 3	Middle as Asian

V. RESULTS

After calculating the thresholds the system was tested with over than 300 images included four races and it gave a result about 82% of success in recognizing races ,as shown in Tabel II.

VI. CONCLUSION

We had designed a system for recognizing races of four types (White, Asian, African, Middle) by using local features extracted from facial images and these features are (eyes, nose, mouth, skin color) the best recognized images those images with perfect features detection, our experienced results lead to this conclusions:

- The best race in recognition is African due to strongest geometrical features of the face with consideration to skin color.
- The skin color is the best feature for recognizing white race with more than 86% percentage of success .
- There are many interference between races which is touched by plastic surgery, inheritance and living style.
- To raise the performance of the system we need to feed it with clear photo with no expression and pose that are representing races clearly.

For future work, we plan to experiment with more types of local features and feature selection algorithms , as well as using race detection as part of face recognition systems.

VII. ACKNOWLEDGMENT

We would like to thank our family for their support .One of us(E.W.A) would like to thank her dearest Ashraf.A.T. for his encourages.

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