# Racial Inconsistency in Face Recognition

Kishor S Kinage and S. G. Bhirud

*Abstract:* **There has been significant progress in improving the performance of computer-based face recognition algorithms over the last decade. Race and gender also play an important role in face-related applications. Humans are better at recognizing faces of their own ethnicity/race than faces of other races. This phenomenon is sometimes referred to as cross-group deficit or own–group bias effect. In this paper, we investigated whether face recognition, using Eigenface show different racial effects in terms of verification error on the subjects. We performed experiments on a face database containing 143 subjects (1,849 face images, Indian and Non-Indian classes), experimental results indicate that, for Indian data, verification accuracy proved to be highest as compared to Non-Indian data and Mixed data. It was clearly revealed that there is racial inconsistency in terms of verification error.**

*Index Terms*-- **Biometrics, Face recognition, Eigenface, Own –group bias effect.**

## I. INTRODUCTION

It is a common experience that faces from “other races” look more similar than faces from “one's own race”. This phenomena associated with face recognition is referred to as “cross-race recognition deficit” or “own-group bias effect”, whereby people have difficulty in recognizing members of a race different from their own. The size of the other-race effect decreases as the amount of experience with faces from other races increases[1].

The task of facial recogniton is discriminating input signals (image data) into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.), yet the input images are not completely random and in spite of their differences there are patterns which occur in any input signal. Such patterns, which can be observed in all signals could be in the domain of facial recognition, the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain (or principal components generally). They can be extracted out of original image data by means of a mathematical tool called Principal Component Analysis (hereafter PCA). Eigenface is a facial pattern representation scheme that employs PCA to efficiently encode the intensity features.

In case of minority race, should there be a wanted criminal whose facial population is not fully reflected in the design of the verification system, all possible subjects of that minority race would likely to suffer from racial discrimination[2]. These issues motivated us to investigate cross-racial differences with respect to the accuracy of biometrics verification algorithms. In this work, the power to discriminate different faces was tested on an experimental basis using PCA and a comparison was made between the two conditions: face discrimination within the same race and among different races.

We performed face identification experiments using comparatively small databases of both Indian and Non-Indian faces, using Eigenface technique. In this paper, we report some of the results on cross-racial face identification experiments by this scheme, in which rather different race effects were observed.

## II. PRINCIPAL COMPONENT ANALYSIS

PCA (or Karhunen-Loeve expansion) identifies variability between human faces. PCA does not attempt to categorise faces using familiar geometrical differences, such as nose length or eyebrow width. Instead, a set of human faces is analysed using PCA to determine which 'variables' account for the variance of faces. In face recognition, these variables are called eigenfaces[3].

Any grey scale face image $I(x,y)$, is a two dimensional N by N array of intensity values (usually 8 bit gray scale). This may be considered a vector of dimension $N^2$, so that an image of size 256 by 256 becomes a vector of dimension 65,536 or equivalently. A point in 65,536 dimensional space. An ensemble of images then maps to a collection of points in this huge space. The central idea is to find a small set of faces (the eigenfaces) that can approximately represent any point in the face space as a linear combination. Each of the eigenfaces is of dimension $N \times N$, and can be interpreted as an image[4].

We expect that some linear combination of a small number of eigenfaces will yield a good approximation to any face in a database, and (of course) also to a candidate for matching. An

Kishor Kinage is working as Associate Professor and Head of Electronics and Telecommunication Engineering department at D. J. Sanghvi College of Engineering Mumbai.

S. G. Bhirud is working as Asst. Professor. in Computer Tech. Department at V. J. T. I. Mumbai.

image can therefore be reduced to an eigenvector $\vec{B} = b_i$ which is the set of best-fit coefficients of an eigenface expansion. Now we can compare a candidate's eigenvector against each of those in a database through a distance matching, for example, a Cartesian measure. The distances found against the database yield both a rank-ordering and a linear closeness measure. [4]

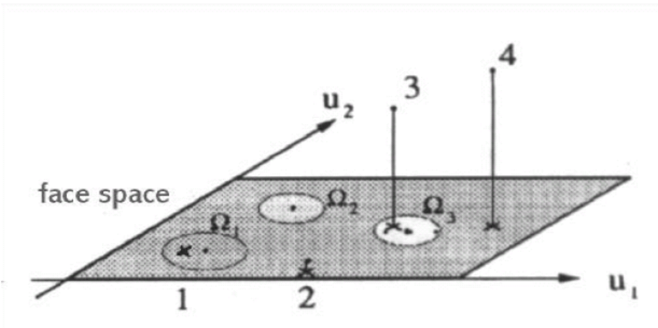


Figure 1: The four possible results when projecting an image into faces space. The face space is formed by just two eigenfaces ( $\mu_1$ and $\mu_2$ ) and contains the faces of three known individuals (Ω1, Ω2 and Ω3).[3]

For each new face image to be identified, calculate its feature vector and compare it with the stored feature vectors of the face library members. If the comparison satisfies the threshold for at least one member, then classify this face image as "known", otherwise a miss has occurred and classify it as "unknown" and add this member to the face library with its feature vector. Figure 1 shows four possibilities for simple example of two eigenfaces: (1) Projected image is a face and is transformed near a face in the face database. (2) Projected image is a face and is not transformed near a face in the face database. (3) Projected image is not a face and is transformed near a face in the face database. (4) Projected image is not a face and is not transformed near a face in the face database

## III. DATA USED FOR THE VERIFICATION EXPERIMENT

In this study, we used three types of face image databases: the Indian data and two Non-Indian data, to analyze racial effects in personal verification.

### A. Indian data

For Indian face images, we used the database provided by Computer Science and Engineering Department, IIT Kanpur. This database is a collection of face images of 61 Indian people, including 39 male faces and 22 female faces. There are eleven different images of each of 40 distinct subjects. For each subject we used 11 images. For some subjects, there are additional photographs. Figure 1 shows examples of face images from this data. There are the following orientations of the face : looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, looking down. Emotions: neutral, smile, laughter, sad/disgust are also included.

### B. Non-Indian data

*As f*or the Non-Indian face images, we used Georgia Tech face database and California Institute of Technology, frontal face dataset

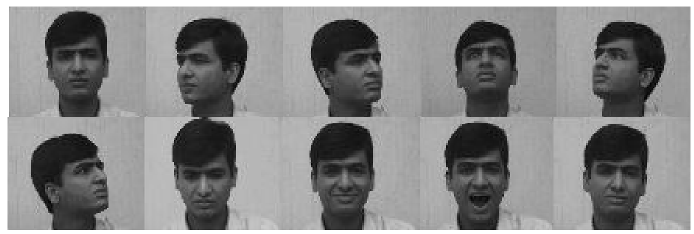

Figure 1: Examples of face images from Indian data ( IIT Kanpur )

Figure 2: Examples of face images from Non-Indian data. (Georgia Tech ).

Figure 3: Examples of face images from Non-Indian data. (Cal. Inst. of Tech.) .

Georgia Tech face database contains 750 images of 50 people taken in two or three sessions at the Center for Signal and Image Processing at Georgia Institute of Technology. All people in the database are represented by 15 color JPEG images with cluttered background taken at resolution 640x480 pixels. The average size of the faces in these images is 150x150 pixels. Figure 2 shows examples of face images from this data. The pictures show frontal and/or tilted faces with different facial expressions, lighting conditions and scale.

California Institute of Technology, frontal face dataset, collected by Markus Weber consists of 446 face images, 896 x 592 pixels, JPEG format, 26 unique people with different lighting/expressions/backgrounds. Figure 3 shows examples of face images from this data.

TABLE 1: THE OUTLINE OF EACH DATABASE USED FOR TRAINING AND TESTING

| Race | Learning Sample | Test Sample |
|---|---|---|
| Indian | 61 | 653 |
| Georgia Tech | 50 | 750 |
| California Tech | 32 | 446 |
| Mix | 143 | 1849 |

TABLE 2

| TABL E 2 Thre-shold | False Rejections | | | |
|---|---|---|---|---|
| | Indian | Geo Tech | Cal Tech | Mix |
| 3.0 | 199 | 400 | 342 | 1483 |
| | 4.47 % | 62.01 % | 85.50 % | 80.20 % |
| 3.5 | 186 | 365 | 327 | 1402 |
| | 28.48 % | 56.58 % | 81.75 % | 75.82 % |
| 4.0 | 177 | 336 | 311 | 1317 |
| | 27.10 % | 52.09 % | 77.75 % | 71.23 % |
| 4.5 | 153 | 306 | 289 | 1194 |
| | 23.43 % | 47.44 % | 72.25 % | 64.57 % |
| 5.0 | 119 | 262 | 258 | 1069 |
| | 18.22 % | 40.62 % | 64.50 % | 57.81 % |
| 5.5 | 96 | 239 | 233 | 964 |
| | 14.70 % | 37.05 % | 58.25 % | 52.13 % |
| 6.0 | 67 | 217 | 197 | 874 |
| | 10.26 % | 33.64 % | 49.25 % | 47.27 % |

TABLE 3

| Thre-shold | False Acceptances | | | |
|---|---|---|---|---|
| | Indian | Geo Tech | Cal.Tech | Mix |
| 3.0 | 0 | 0 | 0 | 13 |
| | 0 % | 0 % | 0 % | 0.70% |
| 3.5 | 0 | 8 | 0 | 18 |
| | 0 % | 1.24 | 0 % | 0.97% |
| 4.0 | 0 | 11 | 0 | 35 |
| | 0 % | 1.70 | 0 % | 1.89% |
| 4.5 | 1 | 17 | 1 | 76 |
| | 0.15 % | 2.63 | 0.25 % | 4.11% |
| 5.0 | 8 | 23 | 3 | 115 |
| | 1.22 % | 3.56 | 0.75 % | 6.22% |
| 5.5 | 19 | 29 | 4 | 153 |
| | 2.91% | 4.49 | 1.00 % | 8.27% |
| 6.0 | 36 | 43 | 7 | 196 |
| | 5.51 % | 6.67 | 1.75 % | 10.60% |

## IV. EXPERIMENTS

We evaluated the accuracy of the verification over the test samples of the different races with the “Indian data”, the “Non-Indian data” and by using the “Mixed data” as test samples. We used image data on the front face as the learning sample and designed a verification system. The test samples were pictures with frontal and/or tilted faces with different facial expressions, lighting conditions and scale.

A threshold is applied in order to derive the rejection/acceptance decision. Hence, each FRR (percentage of incorrect rejections), and FAR (percentage of incorrect

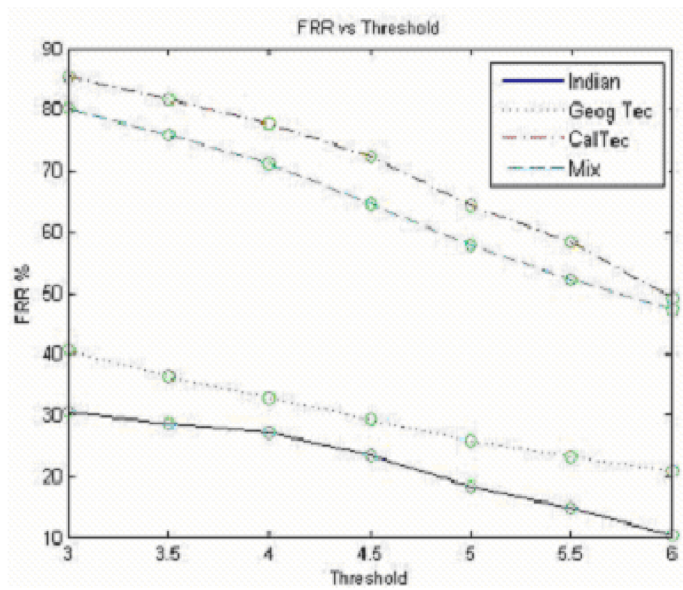


Figure 4: Plot of False Rejection Rate for the databases used, for various values of Threshold.

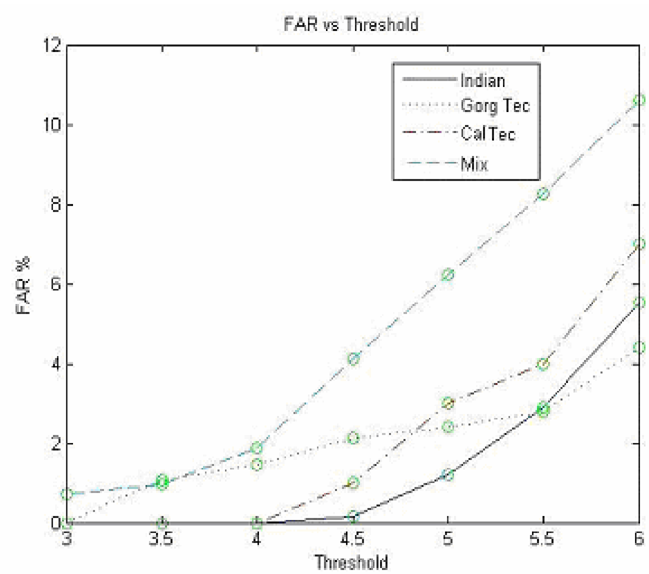


Figure 5: Plot of False Acceptance Rate for the databases used, for various values of Threshold.

acceptances) pair is calculated from 3698 verification operations. By varying the threshold we produce a set of FRR FAR plots, as shown in figure 4 and figure 5. Table 2 and Table 3 show the corresponding experimental results of False Rejection Rate and False Acceptance Rate (FAR) distributions obtained for 7 different values of threshold i.e. 3.0, 3.5, 4.0, 4.5, 5.0, 5.5 and 6.0 for all the databases used. One can notice from that these curves have similar shapes. As the threshold value increases (toward the right), the FRR decreases slowly while the FAR increases more quickly. In case of mixed data the probability of error caused by accepting other faces will increase sharply as compared to Indian data and Non-Indian data as seen in figure 5.

Effectiveness of the face recognition methods is evaluated using receiver operating characteristic ( ROC ) curve or error rate curves (FRR against FAR) for the verification operation as shown in figure 6. From the ROC curve we then take the EER (point at which FRR equals FAR) as a single comparative value for each of the four databases. The EER is derived from the point at which the ROC curve intersects the diagonal of the co-ordinate system. The closer ROC curve lies to the axes, the better the recognition performance.

The EER for Indian, Georgia Tech, California Tech and Mixed data are found to be 10.0%, 18.0%, 34.5% and 34.5% respectively. The results clearly show that the mixed data has a significantly higher EER than the three databases, particularly Indian database.

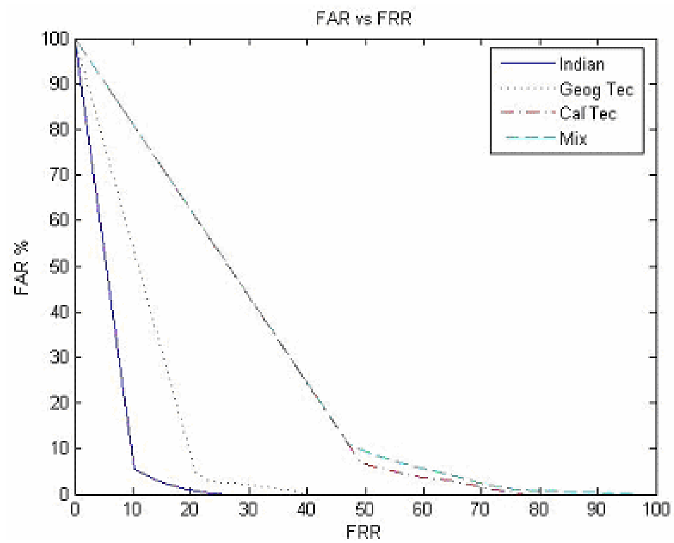

Figure 6: Plot of Receiver Operating Characteristics (ROC) for the databases used.

## V. DISCUSSION

We compared the verification accuracy of the same race data and the different race data for face recognition based on Eigenface feature-representation scheme. For Indian data verification accuracy in terms of False Rejection Rate and False Acceptance Rate is proved to be highest as compared to Non-Indian data and Mixed data as seen in figure 4, figure 5 and figure 6. Results clearly reveal that there is racial inconsistency in terms of verification error.

There might be several reasons for why such a result was obtained. Features such as skin color, which are informative when it comes to discriminating own-race faces, may not be equally applicable when encoding other-race faces. While encoding other-race faces, attention may be directed to facial properties that are useful for discriminating between own-race faces. When faces are categorized as out-group faces, and are less self- relevant, less effort may be spent on processing these faces in depth and in an elaborate manner. This in turn, may lead to face recognition deficits for out-group faces.

## VI. REFERENCES

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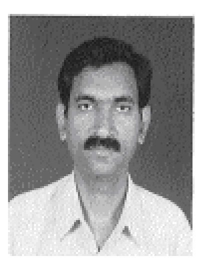
## VII. BIOGRAPHIES

**Kishor Kinage** graduated from S. S. G. M. College of Engineering Shegaon in 1989 and completed his post graduation from V. J. T. I., Mumbai in 1998.

Currently he is working as Associate Professor and Head of Electronics and Telecommunication Engineering department at D. J. Sanghvi College of Engineering Mumbai. His special fields of interest include digital signal processing, face recognition, microwave engineering.



**S. G. Bhirud** obtained his B. E. and M. E. and Ph.D.in 1987, 1995 and 2001 respectively from S. G. G. S. College of Engg. and Tech. Nanded, India. He worked with Bush India Ltd., M. I. T. College of Engg. Pune, J. T. M. College of Engg. Faizpur, and S. G. G. S. College of Engg. and Tech. Nanded. Presently he is Asst. Professor. in Computer Tech. Department at V. J. T. I. Mumbai.
His areas of interest include Neural Networks, Load Forecasting, and Image Processing. He is a Life member of ISTE and CSI.