A Face's Parent/Offspring Determination using Geometric Features and PCA: A Novel Approach

C. N. Ravi Kumar
kumarcnr@yahoo.com

Anil Kumar
anilbhandary4u@gmail.com

Pramod G
pramodghegde@gmail.com

Dept. of CSE, SJCE
Mysore, Karnataka, India

***Abstract*-The problem of determining a parent/offspring of a given face: mother-daughter, mother-son, father-daughter, father-son relationships, from a dataset is a new problem. Finding the similarities in the parent/offspring pair is the key to solve this problem. In this paper we propose a novel approach to solve this problem using geometric features of the face and Principal Components Analysis on 2D frontal view faces with some constraints. The method has been found to be 90% accurate.**

Key words: **Determination, Similarity, Parent/Offspring, Geometric Features, Principal Components Analysis, Sequestration, Countenance Space, Region of Relevance**

1.0 INTRODUCTION

FACE recognition has been one of the most sought problems in applied Biometrics. After decades of research in this field, it has been possible to develop feasible technologies for real world applications. As mentioned in [1], if there is a gap between the efficiency of the fastest algorithm and the best lower bound known, the door for possible improvements remains open. This door leads to research in any problem, in our case to a problem related to face recognition. One of the most successful applications of image analysis and understanding is face recognition and similar related problems. Ref. [2] discusses two reasons for this trend; the first is the wide range of commercial and law enforcement applications, and the second is the availability of feasible technologies after 30 years of research.

Extensive research has been done to study the similar characteristics between the parent and the offspring genetically, psychologically and physiologically. Even though there has been a sincere effort to document the characteristics and relevant statistics, the problem of *spotting a subject's offspring/parent* from a dataset has not been solved. Solving the aforementioned problem could lead to development of significant applications.

Finding out the similarities or features exhibiting similarity among the parent/offspring pair could lead us to the solution for the problem in hand. As a part of orthodontic study, [3] makes an attempt to put light on the facial similarities between the parent and the offspring. The technique used in [4] to measure the similarity uses various ratios among the lengths between the facial traits. The facial expression is also found to be inherited as discussed in [5].

Principal Component Analysis (PCA) is defined as a way of identifying the patterns in data, and expressing the data in such a way as to highlight the similarities and differences is explained in [6] which is an elegant tutorial providing an insight on the theoretical and practical aspects of PCA. This definition shows clear indications of PCA supporting our problem as it deals with similarities and differences. We have used the face images as the data, the revolutionary papers [7] and [8] discuss one of the most successful techniques for face recognition, the Eigenface approach. PCA is the heart of Eigenface approach. This serves as the motivating factor for using PCA in the proposed approach. A clear insight on the properties of eigenvalues has been provided in [9] and [10] and terminology used in PCA has been discussed in [11].

The extensive studies to model the similarity between the parent and the offspring have been done in [3] and [4]. The results mentioned are: (a) The nose was the feature that was most significantly correlated between parents and offspring (b) The similarities between parents and offspring were closer for the relative positions of other features to the eyes than for individual features of the face. In general, the correlations between 'midparents' (the mean value of both parents) and offspring were higher than those between one parent and offspring. (c) The correlations between parents and offspring for size were higher than those for shape. (d) The similarities between mothers and offspring were closer than those between fathers and offspring. Furthermore: among four pairs of father/son, father/daughter, mother/son and mother/daughter, the mother/daughter pair had the highest correlation and the father/son pair had the lowest. The result (b) in the study conducted in [4] and the face measurements done using ratios in [3] are the motivating factors for using the ratios to train the system in the training phase.

Based on the above discussion an approach has been designed. The proposed approach consists of two stages:
(a) Training Phase
(b) Determination Phase

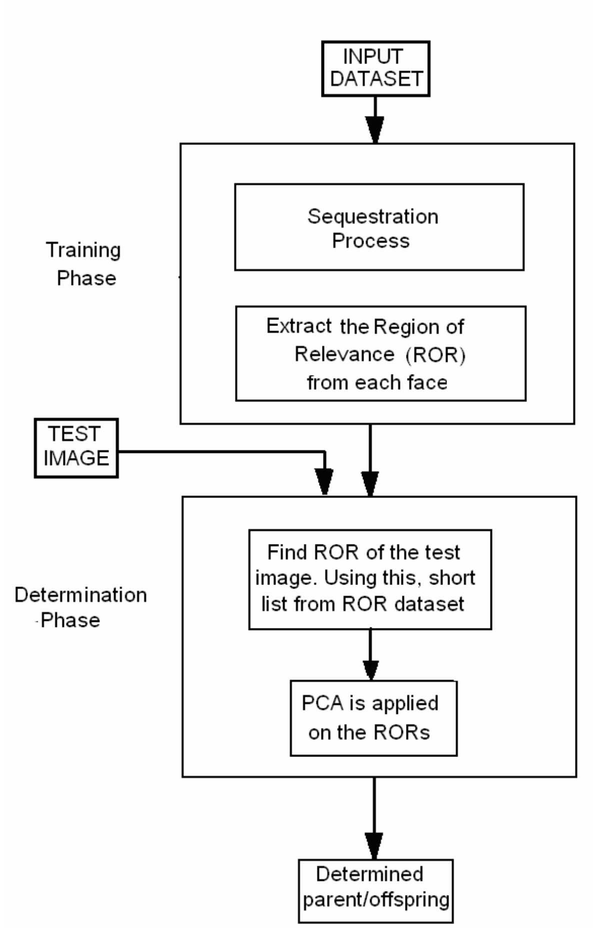


Fig. 1. The proposed approach showing the two stages.

The approach can be applied in various fields like criminal identification, parent dispute resolution and several other applications which require the verification of parent/offspring.

The block diagram of the proposed approach has been shown in Fig. 1. In Section 2.0 we discuss the results of our study of the data, Section 3.0 explains the training phase, Section 4.0 details the determination phase, Section 5.0 explains the experimental results and finally in Section 6.0 we conclude.

2.0 STUDY OF THE DATA

There was a need to create a database and study the characteristics since to the best of our knowledge, there was no reference available till date for this problem in the field of Pattern Recognition.

In the process of creation of database we photographed 124 volunteers' frontal view faces with artificial lighting and constraints on the alignment of the face. It was observed that some of the faces were nearer to most of the other faces, thereby increasing its probability of its nearness to the test image. Hence we need to sequestrate these faces. Furthermore, the results of our study of the dataset indicates that photos taken from the camera with flashlight on, always reflects the flash in the images at three positions: a) center of the pupil of the left eye b) center of the pupil of the right eye c) the tip of the nose. A little oil had been applied on the tip of the nose so that the area easily reflects any light incident on it.

The above aspects of applying oil and the results from the study will be used in Section 3.2.1 and Section 3.2.2 for locating eyes and tip of the nose.

Fig. 2. A typical face when photographed from a digital camera with flash. The reflection at the center (pupil) of both the eyes and at tip of the nose can be noticed.

3.0 TRAINING PHASE

3.1 Sequestration process

Each face in the dataset will be ratio modeled to an ordered *n*-tuple of ratios which will be detailed in Section 3.1.2. All faces are unique points in a *n*-dimensional space called countenance space. As stated in Section 2.0, some faces being nearer to many of the other faces makes the system less accurate. These faces would be tagged as sequestrated faces. The process aims at finding these faces.

3.1.1 Locating Facial features

Some of the features of the face are eyes, nose, mouth, face outline, skin intensity, hairs etc. The most prominent features which are detectable using shape/color/size etc are eyes, mouth, nose and face outline. The features which would be very useful in our problem of similarity are eyes, nose, lips and face outline as according to study [12]. The features which would not be very useful are hairs, as they are not invariant; ears, as the task of extracting the relevant information is laborious and strenuous.

3.1.1.1 Eye Locator

This section aims to locate the centre of the pupil in both left and right eyes. A typical eye is shown in Fig. 3.

The method to find the center of both eyes is:

a) The regions 1 to 7 in Fig. 3 are considered as states for the next step.
b) The Deterministic Finite Automata (DFA) for finding the pupil of the eye is illustrated in Fig. 4.
c) Using above two steps, when the state 7 is reached, the region 4 represents the pupil.

The output of this step for face F would be $I_F = [e_1, e_2]$, where $e_1 = (x_1, y_1)$ the location of left eye and $e_2 = (x_2, y_2)$ the right eye.

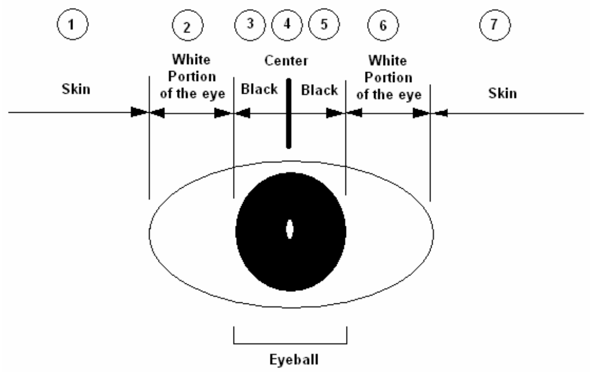


Fig. 3. A typical eye structure with the divisions in the colors numbered.

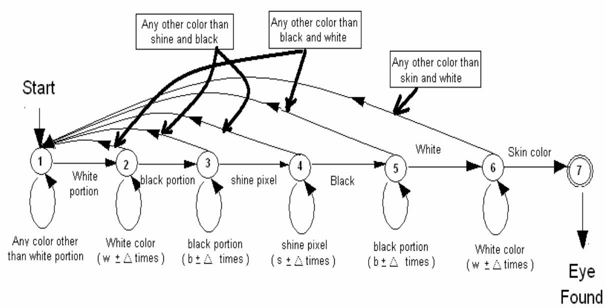


Fig. 4. DFA to find the center of the eye.

3.1.1.2 Nose Locator

For the face F with eyes I_F we find the coordinates of the midpoint of the eyes.

$$m_F = \left(\frac{e_1 + e_2}{2}\right)$$

The window k X k is moved in the column starting from m_F moving in the same column with one increase in y co-ordinate and no change in x co-ordinate as in Fig. 5. In every step, we check if any of the pixels enclosed inside the window is above a certain value of threshold then we

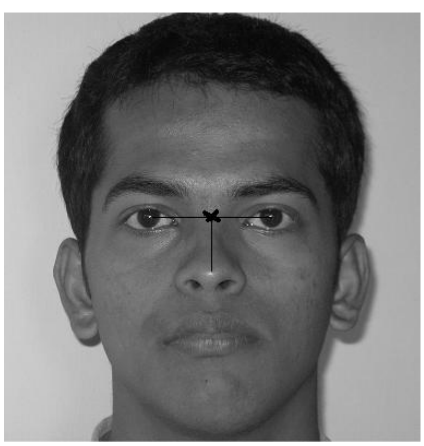


Fig. 5. The center of the line joining the eyes is cross marked and a perpendicular line shows the column through which the nose locating window would traverse.

output the center of the window as the tip of the inside the window is above a certain value of threshold then we output the center of the window as the tip of the nose. The value of k depends on the size of the image and only odd numbers are considered. We have taken k = 15.

3.1.1.3 Lip Locator

We locate the lip using the concept of region localization. We use the concept similar to the concept as mentioned in the Section 3.1.1.2. When we are inside the region of the lip we consider the intensity of the neighborhood pixels and decide the point which corresponds to the bottom middle point of the lower lip.

3.1.2 Ratio modeling the face

Geometric features of faces like ratios, gains significant importance in the problem of finding similarities. This has been supported by studies in [3] and [4]. The steps to ratio model a face F are:

a) Find the lengths a, b, c, d, e and f as in Fig. 6. Note that f is the length of the line joining the lower lip point and the mid point of the line joining the two eye points.
b) Construct a vector of ratios

$$V_F = \left[\left(a/f\right)\ \left(b/c\right)\ \left(d/e\right)\right]$$

Form the column vector for the dataset,

$$M = \begin{bmatrix} V_1 \\ V_2 \\ \ldots \\ V_N \end{bmatrix}$$

N = number of images in the dataset.

3.1.3 Find Euclidean matrix

Each face corresponds to a set of ratios. The set can be called as face ID. Each face ID is an ordered n-tuple where n represents the number of ratios in the set. All faces are unique points in n-dimensional space called countenance space. We have used a 3-D countenance space.

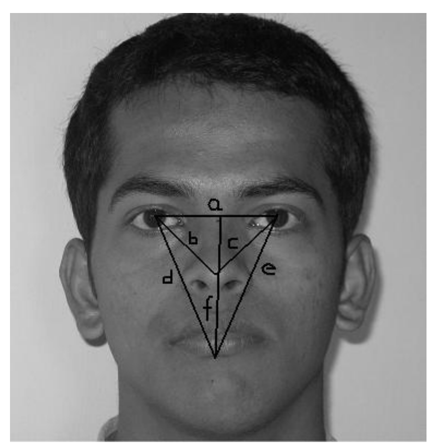


Fig. 6. The model of the face, shows various lengths.

The Euclidean distance, E between every two faces are determined and stored in a matrix.

3.1.4 Derive the IDs of sequestrated faces

For each face, the frequency is found by counting the number of values less than threshold of 0.0001 in its column or row of the Euclidean matrix. These faces can be considered as the spurious competitor images for a match. If the frequency of a face is more, the probability of it being falsely determined as parent/offspring is more.

A frequency threshold $f_T = (p * N)/ 100$ is calculated where p is decided by the user, N is the number of faces. Normally 40% to 60% value could be chosen for p. For each of face if the frequency found is greater than the threshold frequency f_T then it is added to the set of sequestrated face IDs. These faces are noted for use in the last step of determination phase.

The stepwise procedure for the section is as follows:
//Input: Face image dataset
//Output: The set of sequestrated faces, *S*.

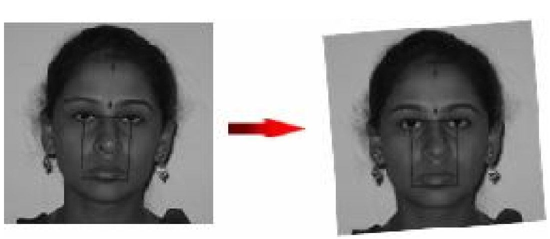
Step 1: For each face image in the input dataset find the co-ordinates of the eyes, the nose tip and bottom of the lower lip.
Step 2: Find the lengths between the two eyes, each of the eyes and nose tip, each of the eyes and bottom of the lower lip.
Step 3: Find the ratios.
Step 4: Find the Euclidean distance between every two faces between points in the countenance space.
Step 5: Sequestrate the faces based on the threshold value and store the identities in a set *S*.
Step 6: Output the sequestrated set *S*.

3.2 Extract the ROR

From each of the faces, a region which contains optimum information about the features required for the problem of similarity is obtained. This region is termed as Region of Relevance (ROR).

The ROR is a rectangle whose two consecutive end points are two eye points and one of the sides passes through the bottom middle point of the lower lip. ROR is found by applying transformations as in Fig. 7.

The two parallel proceedings of the phase are summarized:
a) A process called Sequestration is used to cloister the dataset faces which surpass a defined threshold.
b) A set of RORs is extracted corresponding to the dataset faces using transformation.



(a)

(b)

Fig. 7. The applications of transformation functions. (a) Rotation transformation with respect to the center of the left eye. (b) Extract the ROR from the transformed image.

4.0 DETERMINATION PHASE

4.1 Locate Facial features

The method of finding the facial features like eye points, nose tip and lower lip is the same as explained in Section 3.1.1

4.2 Short list the faces

The steps for the process of short listing are:

a) Find the vector of facial ratios of the test face as explained in 3.1.2
b) Find the Euclidean distance between the test face and all the faces in the dataset.
c) Select the faces which are at a Euclidean distance less than 0.0001 with the test face. These faces constitute the short listed faces.

4.3 Find test face's ROR

The test face's ROR is found as explained in Section 3.2

4.4 Find mean dimensions

The mean dimensions *Size* is a vector and is found by taking the average of rows and columns of the faces' RORs.

$$Size = [Row_{mean} \; Col_{mean}]$$

4.5 Transforming RORs

Transform all the short listed faces' RORs and test face's ROR to the mean dimensions *Size*.

4.6 Apply PCA

We have used the concept of PCA to categorize and determine the parent/offspring of a test face. Principal Component Analysis has six steps:

a) Collect the data.
b) Subtract the mean for making the data mean centered.
c) Calculate the covariance matrix.
d) Calculate the eigenvectors of the covariance matrix.
e) Form a feature vector by choosing the principal components.
f) Derive the new data.

The output of this stage is a set of weighted values known as weight vector of the input image.
A detailed explanation on PCA can be found in [6] and [11]. A discussion on application of PCA on the image data is found in [7] and [8].

4.7 Output the ranked matched faces

The distances of each of the short listed faces with the input face is done in the weight space. Two faces ranked priority wise are output. Lesser the distance between weight vectors, more is the priority to that pair.
Two cases arise:
Case 1: If any of the two nearest faces is present in the set *S*, the set of sequestrated faces, then the non sequestrated faces following them will be given more priority.
Case 2: The pairs with least distances would be ranked and displayed.

The sequence of steps for determining a test face's parent/offspring are summarized:
//Input: ROR Dataset and a test face image.
//Output: A set of ranked two matches.

Step 1: Locate facial features of the test face.
Step 2: Short list the faces from the dataset which are near to the test face, by calculating the Euclidean distances in the countenance space.
Step 3: Find the ROR of the test face.
Step 4: Find the mean of the dimensions of the RORs of the short listed faces.
Step 5: Transform all the short listed faces' RORs and the test face's ROR to the mean dimensions.
Step 6: Apply PCA for determining the test face's parent/offspring from the short listed faces.
Step 7: Leaving out the sequestrated faces, output the top two ranked matched faces.

5.0 EXPERIMENTAL RESULTS

The 800*x*600 resolution face images have been used for the experiments. The approach has been implemented using Matlab R2007b.

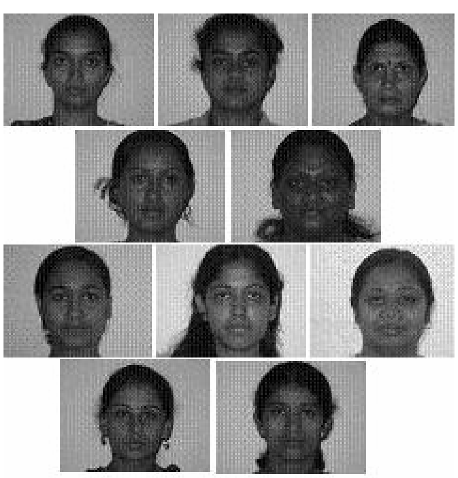


Fig. 8. The ten face images from the dataset used for experiment.

During the training phase, the sequestration process and the ROR extraction activity was performed in a sequence. After executing the algorithm, the frequencies obtained are

$$Freq = [6\ 3\ 3\ 2\ 4\ 5\ 2\ 3\ 2\ 1]$$

The value of p = 50% was considered which resulted into $f_T = 5$. In this case F_1 is the only sequestrated face.

$$S = [F_1]$$

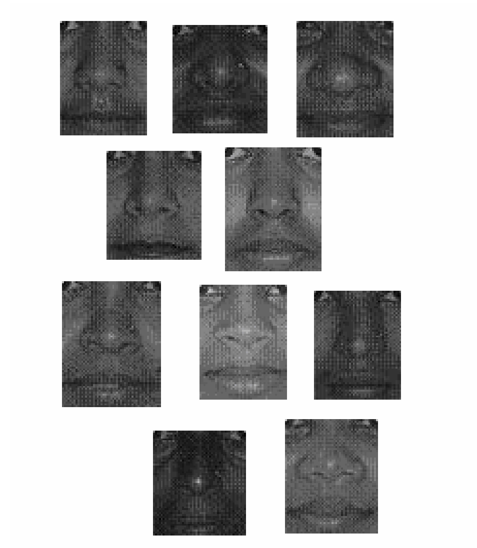
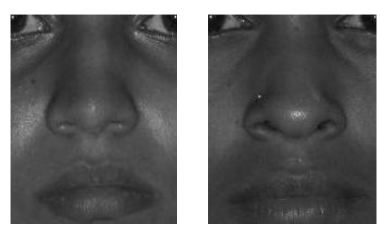


Fig. 9. The ten RORs extracted from the dataset which are of different sizes.

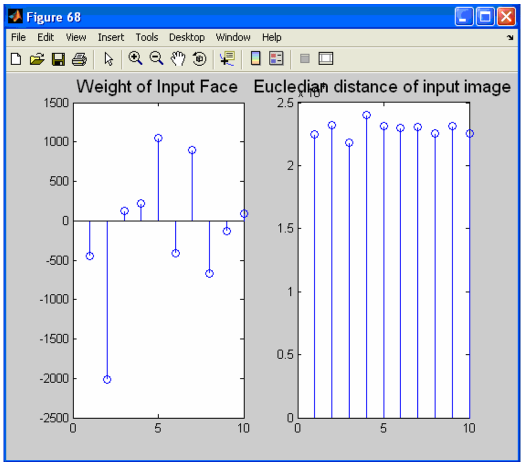
The RORs obtained from the training phase are of different sizes as in Fig. 9. The mean size was found to be *194x159*. The short listed RORs and the test image's ROR was scaled to the mean size.

PCA system takes the input test image T1.jpg as in Fig. 10(a). The resultant system output is in Fig. 11(a). In the figure, F_3 has the shortest vertical bar (least Euclidean distance), indicating the highest similarity. This is an example of ***Case 2***. Fig 10(b) and 11(b) show the ***Case 1*** scenario. In Fig. 11(b), F_1 has the shortest vertical bar. As $F_1 \in S$, the image F_6 which has the second shortest vertical bar is considered to be the best match.

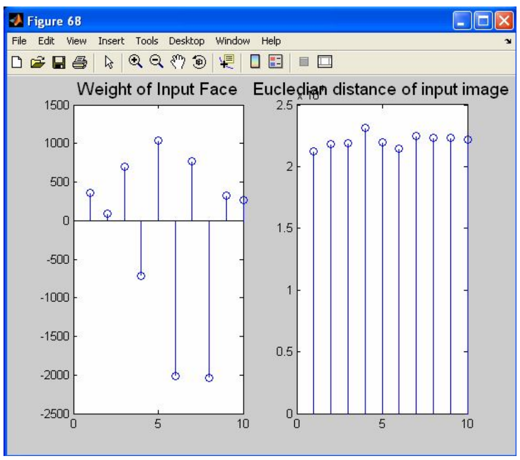


(a) **(b)**

Fig. 10. (a) The first test image T1.jpg. (b) The second test image T2.jpg.



(a)



(b)

Fig. 11. The images show the comparative plots of the Euclidean distances.
(a) *Case 2* match, F_3 (b) *Case 1* match, F_6

6.0 CONCLUSIONS

The objective of determining the parent/offspring of a face has been achieved using Geometric features and PCA. The system has been found to be 90% accurate on the frontal view of the synthetic images. To the best of our knowledge, the approach is a humble beginning in determining parent-offspring pairs. The approach opens the door for such similar problems.

ACKNOWLEDGMENT

We would like to thank Mrs. C. Nandini, Prof. and Head, Dept. of CSE, VVIET, Mysore for giving us invaluable suggestions. We like to thank Mr. Girish Chandra, Sr. Lecturer, GSSS, Mysore and Rashmi L, Student, SJCE for their help and support in our endeavor.

REFERENCES

[1] Anany Levitin, "Introduction to The Design & Analysis of Algorithms", *Pearson Education*, 2003.

[2] W. Zhao, R. Chellappa, A. Rosenfeld, "Face Recognition: A Literature Survey", *ACM Computing Surveys* (CSUR), vol 35, Issue 4, pp 399-458, December 2003.

[3] Chang C, Miyazono H, Komiya T, Nakasima A, "The similarity between parents and offspring in facial soft tissue: a frontal-view study", *Australian Orthodontic Journal*, March 1998, pp 85-92, www.ncbi.nlm.nih.gov/pubmed/9590923.

[4] Tamas Bereczkei, Gabor Hegedus, Gabor Hajnal, "Facialmetric similarities mediate mate choice: sexual imprinting on opposite-sex parents", *Proc. R. Soc. B 2009 276*, 91-98,doi: 10.1098/rspb.2008.1021

[5] Gili Peleg et al., "Hereditary family signature of facial expression", *PNAS*, vol. 103, no. 43, 15925.

[6] L. I. Smith, "A tutorial on Principal Component Analysis", www.cs.otago.ac.nz/cosc453/student_tutorials/principal_component.pdf

[7] M. Turk, A. Pentland, "Eigenfaces for Recognition", *Journal of Cognitive Neuroscience*, March 1991.

[8] M. Turk, A. Pentland, "Face Recognition Using Eigenfaces ", *Computer Vision and Pattern Recognition Journal*, 1991.

[9] Mariquita Flores Garrido, "Eigenvalues in a nutshell ", www.slideshare.net/guest9006ab/eigenlaues-in-a-nutshell

[10] Howard Anton, "Elementary Linear Algebra", *Publisher John Wiley & Sons Inc.*

[11] R. B. Smith, "Important terms in PCA".

[12] Ming-Hsuan Yang et al., "Detecting Faces in Images: A Survey", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol 24, no. 1, pp 34-58, 2002.

[13] James D Foley et al., "Computer Graphics: Principles & Practice", Second Edition in C, *Pearson Education*, 2007.

[14] www.pages.drexel.edu/~cis26/Face%20recognition.html, Drexel University Official Website,

[15] www.prip.tuwien.ac.at/teaching/ss/strupr/zweng_shapes.ppt, Zweng Shapes

[16] Rafael C Gonzalez, Richard Eugene Woods, "Digital Image Processing", *Prentice Hall.*

[17] Kyungnam Kim, "Face Recognition using Principal Component Anaylsis."

[18] J.G. Campbell, http://www.jgcampbell.com/ip/ip4.txt