# Heuristic based Face Recognition using Image Processing Techniques

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## ABSTRACT
This paper introduces a new technique for face recognition in controlled domains by learning additional information using heuristics. Multiple faces, some of which with very low resolution and blurred onws are recognized by learning heuristics over time. Heuristics derived from seat to student correlation, student to student correlation, dress color, and skin color have been proposed. The algorithm Heuristic Supplemented PCA (HSPCA) has been tested over several hours of different video sequences gathered from classrooms with around 30 students in each class. It has been observed that the performance improves over time, with the recognition rate using heuristics contributing significantly as time progresses.

## General Terms

Face recognition, PCA(Principal Component Analysis), EIGEN faces, EMD

## Keywords
PCA Algorithm, EMD, Heuristics.

## 1. INTRODUCTION
During the last decade, face recognition has drawn significant attention from the perspective of different applications. Despite the fact that there are more reliable biometric recognition techniques such as fingerprint and iris recognition,these techniques are intrusive and their success depends highly on user cooperation, since the user must position her eye in front of the iris scanner or put her finger in the fingerprint device [1]. On the other hand, face recognition is non-intrusive since it is based on images recorded by a distant camera, and can be very effective even if the user is not aware of the existence of the face recognition system. The face recognition problem can be formulated as follows. Given still or video images of a controlled environment scene, the problem is to identify or verify one or more persons in the scene using a stored database of faces.

A large number of facial recognition techniques have been derived from PCA algorithm with EIGEN faces [2], EBG [3], skin based recognition [4], etc. However, most of the works concentrate on systems with one or two faces using still images. Also, the illumination conditions are made ideal. Typically, the multiple faces are at same resolution. Our proposed technique Heuristic Supplemented PCA (HSPCA) uses as its base an existing algorithm such as Eigen faces and the results are enhanced by supplementing it with information learnt from heuristics. The results demonstrate how even up to 30 faces can be recognized and the recognition rate is improved over time using efficient heuristics. In this paper the output results and some of the images from the database are shown. The results have been compared with the previous algorithm results. The purview of the technique is limited to controlled environments like a seminar hall, classroom, etc., where the students are facing the camera and the data of the same set of students is available for extended periods of time. This technique Heuristic Supplemented PCA (HSPCA) cannot be extended to general environments like airports, railway stations or public places which are uncontrolled environments.

## 2. PCA ALGORITHM
PCA was invented by the Karl Pearson in 1901. The PCA algorithm is one of the most successful techniques that have been used for face recognition and face compression. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables). Face recognition has many applicable areas. So many features are added to the existing PCA for better results. The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace [5] is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images called vectors. The PCA algorithm [6, 7] does not work very well for several faces as can be seen in Fig 1 where the unrecognized faces have been highlighted. Our current technique aids in recognizing such faces. The existing multi face recognition systems typically work with 15 or less. As can be observed in Fig 1, the current set of videos have over 30 faces and has recognition rates for students seated in the last rows, or of students whose images are occluded, would be pretty poor using PCA and its extensions. A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Suppose we have *M* vectors of size *N* (= rows of image × columns of image) representing a set of sampled images.
’s represent the pixel values.

$$x_i = [p_1 \ldots \ldots p_n]^T \quad , \text{i=1,---------,m} \tag{1}$$

The images are mean centered by subtracting the mean image from each image vector. Let *m* represent the mean image.

mean m $=1/m(1+2+..M)/M$ (2)

And let $w_i$ be defined as the mean centred image.

$w_i = x_i$-m (3)

Our goal is to find a set of $e_i$'s which have the largest possible projection on each of the $w_i$'s. To find the set of M orthonormal vectors $e_i$. For which the quantity is maximized with the orthonormality constraint.

$\rho_i = 1/\mathrm{M} \sum_{n=1}^{M} ( e_i^T . w_n)^2$ (4)

$e_l^T . e_k = \delta_{lk}$ (5)

The $e_i$ and $\rho_i$ are given by the eigen vectors and eigen values of the convariance matrix .

$\mathrm{C}= WW^T$ (6)

The size of *C* is enormous so we find the EIGEN vectors and EIGEN values by the common theorem in linear algebra.

The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues [9]. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions.

A facial image can be projected onto $M^{\sim}$ (<< *M*) dimensions by computing.

$\Omega = Transpose([V_1 V_2 \ldots\ldots V_{M^{\sim}}]$ (7)

By calculating the Euclidean distance the face is recognized.

## 2. PCA ALGORITHM WITH HEURISTICS

The PCA algorithm with EIGEN faces and EIGEN values can recognize some of the faces in the images [8]. Especially, the faces those are at larger distances from the camera, or occluded are more difficult to recognize. A new algorithm is proposed and can be used for recognizing the faces in a controlled environment more reliably. This system learns newer information and improves the performance over time. The proposed system is shown with the framework and how it works. In the heuristics part the system is applied one by one. Whenever a new data is found then the corresponding data is updated in the database for future use. The heuristics and the database are communicated directly. The algorithm HSPCA flow is controlled by the decision control present in the center of the proposed system. The PCA algorithm is applied to the data and then the heuristics has follows. The system is updated the database for some stages. But later on, the database is not updated huge, because the changes will be less. Heuristics plays the major role in the proposed technique HSPCA.

**Figure-1: The faces which was not recognized by PCA algorithm is highlighted.**

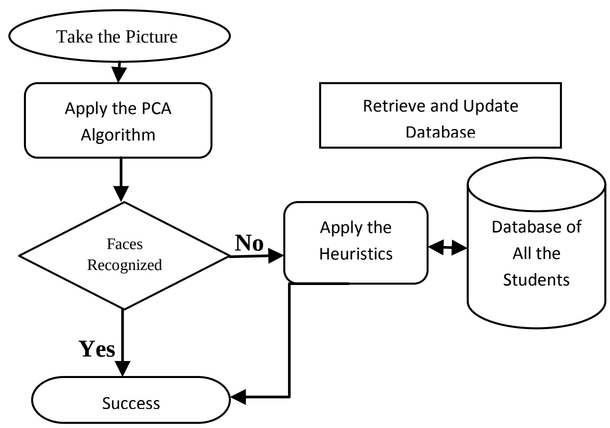



**Figure-2: The flow of PCA algorithm with Heuristics.**

Different heuristics are used and here in this technique two are implemented. The usage of the heuristics is explained with the student database taken from the controlled environment (college). The database of 90 days is taken to implement the system. Every day the heuristics are updated of every individual student record depends on the changes occurred to the student environment. Every student has an independent record to maintain the details of his own. Mainly heuristics are used to reduce the search space. The heuristics are explained as follows**.**

### 2.1 Neighbors:

The proposed technique "Heuristic Supplemented PCA (HSPCA)" will use the controlled environment database like class room student database to explain the heuristics clearly. In a classroom environment some of the students are usually sit together as a group regularly. This can be observed easily with the help of 90 days of database. With this commonsense the neighbor of a student is taken as the heuristic. From that 90

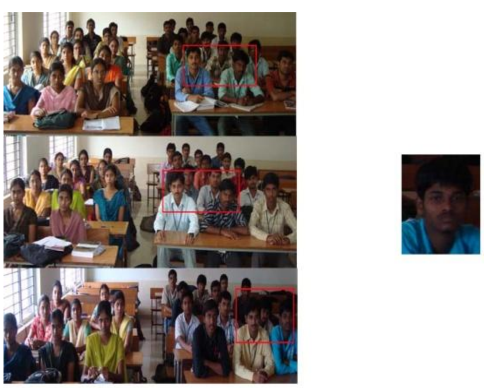

days student database a sample dataset is shown in Fig. 3 in that with some parts are highlighted that some of the students sat

**FIGURE-3: Highlighted portion to show that two students are sit together for 3 days.**

together for some different days in a month. Then the records of the corresponding students are updated. This heuristic can be explained by taking some few days dataset. Fig. 3 shows that some students are highlighted in those two students are usually sat together regularly then the database has been updated. From Fig. 4 in the last photograph the face is not clear. The PCA algorithm has not been recognized the face. But the proposed technique “Heuristic Supplemented PCA (HSPCA)” will recognize that face with the help of the heuristics. The result after the Heuristic Supplemented PCA (HSPCA) is applied will show in the Fig. 4.

## 2.2 Texture and color of clothes:

This is the other heuristic which is used in this algorithm. In any controlled environment like classrooms all the students are used to wear a limited collection of cloths with texture and color [9]. With the help of the above statement this proposed technique “Heuristic Supplemented PCA (HSPCA)” is collected the student records of the database with the corresponding color of the dress. This database is regularly updated. The HSPCA is



used this database for the recognition. The recognition rate is increased with this heuristic. This can be explained with the help of the student database.


**FIGURE-4: The unrecognized face is recognized with the help of neighbor (heuristic1).**

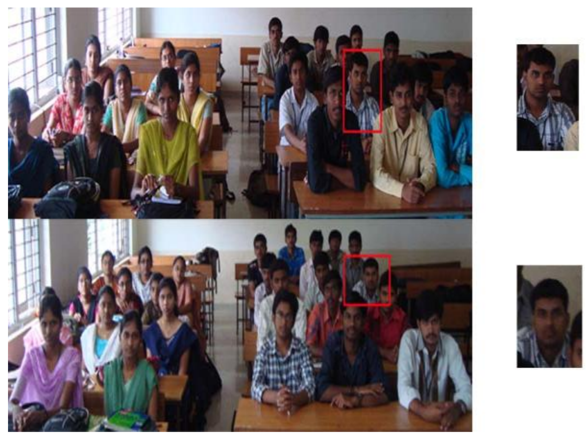


**FIGURE-5: Faces are highlighted which is not recognized by the existing algorithm**

**FIGURE-6: The student is recognized with the help of texture from two different days.**

The student database is updated for 90 days and later the HSPCA is applied then the results are good. Fig.5 shows that some of the faces are not recognized that has been highlighted. The HSPCA will recognize the faces with this heuristic. The results are shown in Fig. 6. The results are drawn from the student database and from that a dataset is taken and shown here. In Fig. 6 the highlighted portion shows a face which is not recognized with the help of the PCA.

# 3. EMD ALGORITHM

## 3.1 Introduction

In probability theory, the earth mover's distance (EMD) is a measure of the distance between two probability distributions over a region D. Informally, if the distributions are interpreted as two different ways of piling up a certain amount of dirt over the region D, the EMD [11] is the minimum cost of turning one pile into the other; where the cost is assumed to be amount of dirt moved times the distance by which it is moved . Definition is valid only if the two distributions have the same integral (informally, if the two piles have the same amount of dirt), as in normalized histograms or probability density functions. In that case, the EMD is equivalent to the 1st mallows distance or 1st Wasserstein distance between the two distributions. Some applications may require the comparison of distributions with different total masses. One approach is to allow for a partial match, where dirt from the most massive distribution is rearranged to make the least massive, and any leftover "dirt" is discarded at no cost. Under this approach, the EMD is no longer a true distance between distributions. Another approach is to allow for mass to be created or destroyed, on a global and/or local level, as an alternative to transportation, but with a cost penalty. In that case one must specify a real parameter σ, the ratio between the cost of creating or destroying one unit of "dirt", and the cost of transporting it by a unit distance. This is equivalent to minimizing the sum of the earth moving cost plus σ times the L1 distance between the rearranged pile and the second distribution.

If the domain D is discrete, the EMD can be computed by solving an distance transportation problem, which can be solved by the so-called Hungarian algorithm [11]. In particular, if D is a one-dimensional array of "bins" the EMD can be efficiently computed by scanning the array and keeping track of how much dirt needs to be transported between consecutive histogram. The Histogram has shown in the figure 7.

$$D(I,J) = \sum_{i,j} g_{ij}\, d_{ij} \Big/ \sum_{ij} g_{ij} \qquad (8)$$

$g_{ij}$ ground distance two bins i and j, $d_{ij}$ distance between two bins i and j.

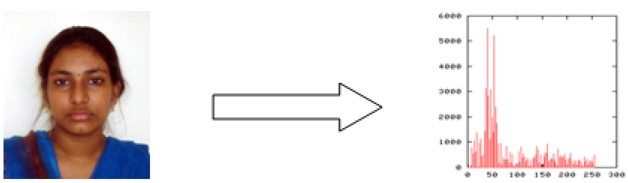



**Figure- 7: Image to Histogram.**

The Earth Mover Distance is the discrete way of writing the famous problem of optimal transport, also called the Wasserstein metric or Monge-Kantorovich. It is a distance between probability density functions, or, on discrete data, histograms. Two histograms P and Q are given, as well as a distance affinity matrix D(i; j). This matrix computes the cost of transporting one element of mass (i.e. one pixel) of the ith bin of P to the jth bin of Q. It computes a flow matrix F where F(i; j) is the amount of mass in the ith bin of histogram P transported to the jth bin of histogram Q. The goal of optimal transport is then to find F that minimizes the cost of every transports D(i; j) to warp histogram P to histogram Q. The EMD gives two interesting outputs, the first one is the distance value which gives a matching score between histograms. It has the physical meaning as the amount of mass displaced. In the statistics community, compared to other famous scores between histograms such as Kullback-Leibler divergence or Hellinger distance it is one of the only cross-bin distance. This means that it does not assume the bin values are correctly aligned as in bin-wise comparisons. This is a particularly desired feature in computer vision since changes of illuminations or viewpoints can shift the values of the histogram. However, as opposed to other distance between histograms, the complexity of EMD is higher since it has to solve a combinatorial problem of matching N bins to N other bins. Plus, it is designed to work efficiently on histograms which are not a very discriminative feature of the image. Some works have tried to solve the optimal transport directly on the image pixels but it results in a complex PDE and brings new problems since there is no regularity constraint in the flow F. The contribution of this paper is a way of computing the transport on image pixels, with the complexity cost of matching 1-D histograms and without losing the geometry and the topological structure.

The same image data set which is used for the PCA algorithm is used as an input for the EMD. The output of the EMD has shown in the figure 8.

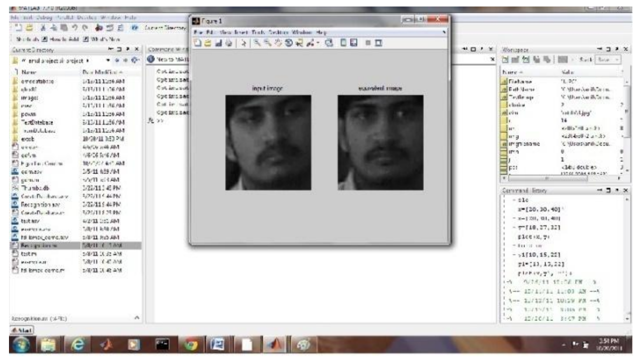


**Figure-8: The output of the EMD**

## 4. RESULTS

This technique is implemented on a 90 days database of the classroom which contains 30 students. The proposed system "Heuristic Based Face Recognition algorithm" using both PCA and EMD applied on heuristics. This system has been tested over several hours of different video sequences gathered from classrooms with around 30 students in each class. It has been observed that the performance improves over time with the recognition rate using heuristics contributing significantly as time progresses. All the results are shown in this section with the help of bar chart. Fig 9 shows the performance comparison between PCA based facial recognition, PCA with heuristics, EMD and the "Combination of these three (Heuristic Based Face Recognition Algorithm)". It can be observed that the performance of PCA and EMD is constant, with little random variations from day to day data. On the other hand Heuristic based PCA and EMD improves with time initially and the performance remains constant once the learning has been accomplished. TABLE I shows performances of results are displayed in percentages. All the percentages are calculated and shown for comparing the algorithms. The table is drawn for the algorithms to show how they gave the results for every 15 days. And here the TABLE I have shown for 90 days results. From the table the Heuristic based PCA with heuristics the recognition rate is increased continuously for every 15 days but the PCA and EMD has not increased. By combining the PCA, EMD and Heuristics will improve the results.

From the TABLE I it has been clear that the results are different for the algorithms. The PCA and EMD algorithms are constant and the proposed system is varied continuously and increases the recognition results.

TABLE II shows the experimental results of the classroom database. The total faces present in the image are 30. The proposed system is applied to the database and then the results are recorded and have shown in TABLE II.

**Table I: The table to show the results of the algorithms in percentages**

| | Number of Faces recognized | | |
|---|---|---|---|
| | **PCA** | **PCA With Heuristics(HSPCA)** | **EMD** |
| **1-15 days** | 63.5% | 63.7% | 63.6% |
| **16-30 days** | 64.8% | 85% | 68% |
| **31-45 days** | 62.9% | 92% | 63% |
| **46-90 days** | 63.1% | 94% | 69% |

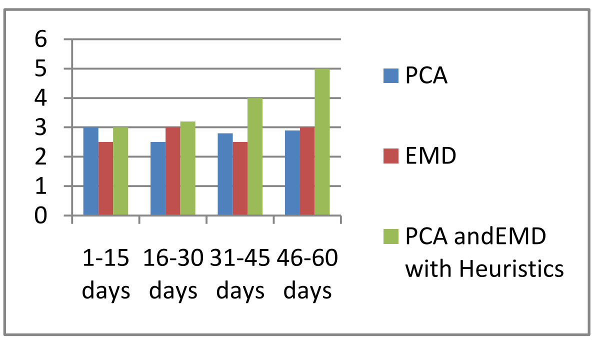



**Figure-9: Bar chart to show the comparisons of PCA, EMD and The Proposed System.**

## 5. CONCLUSIONS AND FUTURE WORKS

The problem of multiple face recognition has been an ongoing subject of research for more than 20 years. Although a large number of approaches have been proposed in the literature and have been implemented successfully for real-world applications, robust face recognition is still a challenging subject in real life scenarios, mainly because of large facial variability, pose variations, etc. In this paper a heuristic based technique has been proposed that enhances the facial recognition results and learns vital information over time in controlled environments. In the future, more heuristics can be added to the currently used heuristics and the technique can also be extended to uncontrolled domains like airports, etc., by developing suitable heuristics.

**Table II: The table to show the results of the algorithms in percentages**

| Total Database =30 faces | |
|---|---|
| **Technique** | **Identified faces** |
| **PCA** | 18 |
| **EMD** | 21 |
| **PCA With Heuristics** | 25 |
| **PCA,EMD and Heuristics** | 28 |

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