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Authorization of Face Recognition Technique Based on Eigen Faces

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Abstract: Face recognition has been one of the most interesting and important research fields in the past two decades. The existing algorithm represents some face space with higher dimensionality and it is not effective too. Our approach treats face recognition as two dimensional recognition problems. The face is represented as the eigenfaces which is eigenvectors. The goal is to implement the system (model) for a particular face and distinguish it from a large number of stored faces with some real-time variations as well. The Eigen face approach uses Principal Component Analysis (PCA) algorithm for the recognition of the images. It gives us efficient way to find the lower dimensional space. The experimental result shows the performance of the algorithm with the plot for the variation and image recognition.

Keywords: Computer Security, Eigen Face Recognition, Eigen Vectors, Information Security, Principle Component Analysis.

I. INTRODUCTION

Face recognition presents a challenging problem in the field of image analysis and computer vision, and as such has received a great deal of attention. It is one of the prominent research areas due to its numerous practical applications in the area of biometrics, information security, access control, law enforcement, smart cards and surveillance system. Face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology:

methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red imagery.

Surveillance systems rely on passive acquisition by capturing the face image without the cooperation or knowledge of the person being imaged. Face recognition also has the advantage that the acquisition devices are cheap and are becoming a commodity. With the widespread deployment of security cameras, and the increasing financial and technological feasibility of automating this surveillance, public fears have also increased about the potential for invasion of privacy that

this technology can bring about. It has to become easy and cheap to connect a face recognition system to a blanket video surveillance system with great potential for crime prevention. The human face is not a unique, rigid object. There are numerous factors that cause the appearance of the face to vary. The sources of variation in the facial appearance can be categorized into two groups: intrinsic factors and extrinsic ones. A) Intrinsic factors are due purely to the physical nature of the face and are independent of the observer. These factors can be further divided into two classes: intrapersonal and interpersonal. Intrapersonal factors are responsible for varying the facial appearance of the same person, some examples being age, facial expression and facial paraphernalia (facial hair, glasses, cosmetics, etc.). Interpersonal factors are responsible for the differences in the facial appearance of different people, some examples being ethnicity and gender. B) Extrinsic factors cause the appearance of the face to alter via the interaction of light with the face and the observer. These factors include illumination, pose, scale and imaging parameters (e.g., resolution, focus, imaging, noise, etc.).

II. RELATED WORK

Eigen Faces based Face Detection

Eigen faces are the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. The eigenvectors are ordered to represent different amounts of the variation, respectively, among the faces. Each face can be represented exactly by a linear combination of the eigen faces. It can also be approximated using only the “best” Eigen vectors with the largest Eigen values. The best M eigen faces construct an M dimensional space, i.e., the “face space”.

This method approximates the multi-template by a low-dimensional linear subspace F, usually called the face space. Images are initially classified as potential members of T, if their distance from F is smaller than a certain threshold. The images which pass this test are projected on F and these projections are compared to those in the training set. However, it runs into problems if one tries to detect objects under arbitrary rotation and possible other distortions.

Face Recognition

There is a great diversity in the way facial appearance is interpreted for recognition by an automatic system. A

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major difference in approaches is whether to represent the appearance of the face, or the geometry. Brunelli and Poggio [5] have compared the two approaches, but ultimately most systems today use a combination of both appearance and geometry. Geometry is difficult to measure with any accuracy, particularly from a single still image, but provides more robustness against disguises and aging. Appearance information is readily obtained from a face image, but is more subject to superficial variation, particularly from pose and expression changes. In practice for most purposes, even appearance-based systems must estimate some geometrical parameters in order to derive a 'shape free' representation that is independent of expression and pose artifacts.

This is achieved by finding facial land marks and warping the face to a canonical neutral pose and expression. Facial features are also important for geometric approaches and for anchoring local representations. Face appearance representation schemes can be divided into local and global, depending on whether the face is represented as a whole, or as a series of small regions. Most global approaches are based on a principal components representation of the face image intensities. This representation scheme was devised first for face image compression purposes and subsequently used for recognition purposes.

The latter coined the term Eigen faces for this type of representation. A face image is represented as a vector of intensities and this vector is then approximated as a sum of basis vectors (Eigen faces) computed by principal component analysis from a database of face images. These principal components represent the typical variations seen between faces and provide a concise encapsulation of the appearance of a sample face image, and a basis for its comparison with other face images. This principal components representation is, like for example the Fourier Transform, a de correlating transform to an alternative basis where good representations of the salient characteristics of an image can be created from only a few low-order coefficients despite discarding many of the higher-order terms.

Major Steps for Face Recognition

The step begins with face detection method. After a face has been detected, the task of feature extraction is to obtain features that are fed into a face classification system. Depending on the type of classification system, features can be local features such as lines or fiducial points, or facial features such as eyes, nose, and mouth. Face recognition is considered as successful if the presence and rough location of face has been identified. In a face detection problem, two statistics arises: true positives and false positives. A true recognition system would have high true positives and low false positives.

The methods become challenging when feature changes such as closed eyes, eyes with glasses, open mouth etc. An even more challenging situation for feature extraction is feature restoration, which tries to recover features that are invisible due to large variations in head pose. The best solution here might be to hallucinate the missing features either by using the bilateral symmetry of the face or using learned information.

Face Recognition Tasks

The three primary face recognition tasks are:
1. Verification
2. Identification
3. Watch List

1. Verification

Verification task is aimed at applications requiring user interaction in the form of an identity claim, i.e. access applications. The verification test is conducted by dividing persons into two groups:

Clients- people trying to gain access using their own identity.

Imposters- people trying to gain access using a false identity, i.e. an identity known to the system but not belonging to them.

The percentage of imposters gaining access is reported as the False Acceptance Rate (FAR) and the percentage of client rejected access is reported as the False Rejection Rate (FRR) for a given threshold.

2. Identification

The identification task is mostly aimed at applications not requiring user interaction,
i.e. surveillance applications. The identification test works from the assumption that all faces in the test are of known persons. The percentage of correct identification is then reported as the Correct Identification Rate (CIR) or the percentage of false identification is reported as the False Identification Rate (FIR).

3. Watch List

The watch list task is a generalization of the identification task which includes unknown people. The watch list test is like the identification test reported in CIR or FIR, but can have FAR and FRR associated with it to describe the sensitivity of the watch list, meaning how often is an unknown classified as a person in the watch list (FAR).

III. LITERATURE REVIEW

Most work on segmentation was focused on single-face segmentation from a simple or complex background. These approaches included using a whole-face template, a deformable feature-based template, skin color, and a neural network. Compared to feature-based methods and template-matching methods, appearance or image-based methods that train machine systems on large numbers of samples have achieved the best results.

Over the past 15 years, research has focused on how to make face recognition systems fully automatic by tackling problems such as localization of a face in a given image or video clip and extraction of features such as eyes, mouth, etc.

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Feature Extraction

There are of feature extraction methods can be distinguished: (1) generic methods based on edges, lines, and curves; (2) feature-template-based methods that are used to detect facial features such as eyes; (3) structural matching methods that take into consideration geometrical constraints on the features.

A template-based approach to detecting the eyes and mouth in real images was presented in [Yuilleetal. 1992]. This method is based on matching a predefined parameterized template to an image that contains a face region. Two templates are used for matching the eyes and mouth respectively. Energy function is defined that links edges, peaks and valleys in the image intensity to the corresponding properties in the template, and this energy function is minimized by iteratively changing the parameters of the template to fit the image. The statistical shape model (Active Shape Model, ASM) proposed in [Cootes et al. 1995] offers more flexibility and robustness. The advantages of using the so-called analysis through synthesis approach come from the fact that the solution is constrained by a flexible statistical model. Among the various approaches there are feature based, holistic, and hybrid approaches for face recognition.

Feature based Approach

Feature-based approach is the elastic bunch graph matching method proposed by Wiskott et al.. This technique is based on Dynamic Link Structures. A graph for an individual face is generated as follows: a set of fiducial points on the face are chosen. Each fiducially point is a node of a full connected graph, and is labeled with the Gabor filters' responses applied to a window around the fiducial point. Each arch is labeled with the distance between the correspondent fiducial points. A representative set of such graphs is combined into a stack-like structure, called a face bunch graph. Once the system has a face bunch graph, graphs for new face images can then be generated automatically by Elastic Bunch Graph Matching. Recognition of a new face image is performed by comparing its image graph to those of all the known face images and picking the one with the highest similarity value.

Holistic Approaches

Holistic approaches attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. In the simplest version of the holistic approaches, the image is represented as a 2D array of intensity values and recognition is performed by direct correlation comparisons between the input face and all the other faces in the database. The major hindrance to the direct matching methods' recognition performance is that they attempt to perform classification in a space of very high dimensionality. To counter this curse of dimensionality, several other schemes have been proposed that employ statistical dimensionality reduction methods to obtain and retain the most meaningful feature dimensions before performing recognition.

Sirovich and Kirby [] were the first to utilize Principal Components Analysis (PCA) to economically represent face images. They demonstrated that any particular face can be efficiently represented along the Eigen pictures coordinate space, and that any face can be approximately reconstructed by using just a small collection of Eigen pictures and the corresponding projections along each Eigen picture.

Moghaddam et al. [] propose an alternative approach which utilizes difference images, where a difference image for two face images is defined as the signed arithmetic difference in the intensity values of the corresponding pixels in those images. Two classes of difference images are defined: intrapersonal, which consists of difference images originating from two images of the same person, and extra personal, which consists of difference images derived from two images of different people. It is assumed that both these classes originate from discrete Gaussian distributions within the space of all possible difference images. Then, given the difference image between two images I1 and I2, the probability that the difference image belongs to the intrapersonal class is given by Bayes Rule.

PCA

The Eigen face algorithm uses the Principal Component Analysis (PCA) for dimensionality reduction to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of face images and the subspace is called face space. All faces in the training set are projected onto the face space to find a set of weights that describes the contribution of each vector in the face space. To identify a test image, it requires the projection of the test image onto the face space to obtain the corresponding set of weights. By comparing the weights of the test image with the set of weights of the faces in the training set, the face in the test image can be identified.

The key procedure in PCA is based on Karhumen -Loeve transformation. If the image elements are considered to be random variables, the image may be seen as a sample of a stochastic process. The Principal Component Analysis basis vectors are defined as the eigenvectors of the scatter matrix ST, The transformation matrix WPCA is composed of the eigenvectors corresponding to the d largest Eigen values. After applying the projection, the input vector (face) in an n-dimensional space is reduced to a feature vector in a d-dimensional subspace.

ICA

Independent Component Analysis (ICA) [22] is similar to PCA except that the distributions of the components are designed to be non-Gaussian. Maximizing non-Gaussianity promotes statistical independence. Bartlett et al. provided two architectures based on Independent Component Analysis, statistically independent basis images and a factorial code representation, for the face recognition task. The ICA separates the high-order moments of the input in addition to the second-order moments utilized in PCA. Both the architectures lead to a

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similar performance. The obtained basis vectors are based on fast fixed-point algorithm for the ICA factorial code. There is no special order imposed on the ICA basis vectors.

LDA

In LDA the goal is to find an efficient or interesting way to represent the face vector space. But exploiting the class information can be helpful to the identification tasks. The Fisher face algorithm [16] is derived from the Fisher Linear Discriminant (FLD), which uses class specific information. By defining different classes with different statistics, the images in the learning set are divided into the corresponding classes. Then, techniques similar to those used in Eigen face algorithm are applied. The Fisher face algorithm results in a higher accuracy rate in recognizing faces when compared with Eigen face algorithm.

Neural Networks

The attractiveness of using neural networks could be due to its non linearity in the network. Hence, the feature extraction step may be more efficient than the linear Karhunen-Loève methods. One of the first artificial neural networks (ANN) techniques used for face recognition is a single layer adaptive network called WISARD which contains a separate network for each stored individual. The way in constructing a neural network structure is crucial for successful recognition. It is very much dependent on the intended application. For face detection, multilayer preceptor and convolution neural network have been applied. For face verification, is a multi-resolution pyramid structure. [ ] proposed a hybrid neural network which combines local image sampling, a self-organizing map (SOM) neural network, and a convolution neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimension reduction and invariance to minor changes in the image sample. The convolution network extracts successively larger features in a hierarchical set of layers and provides partial invariance to translation, rotation, scale, and deformation.

IV. METHODOLOGY

The task of facial recognition is discriminating input signals (image data) into several classes. The input signals are highly noisy 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, and mouth) in any face as well as relative distances between these objects. These characteristic features are called Eigen faces 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 (PCA). By means of PCA one can transform each original image of the training set into a corresponding eigen face. An important feature of PCA is that one can reconstruct reconstruct any original image from the training set by combining the eigen faces. Each eigen face represents only certain features of the face, which may or may not be present in the original image. If the feature is present in the original image to a higher degree, the share of the corresponding eigen face in the"sum" of the eigen faces should be greater. If, contrary, the particular feature is not present in the original image, then the corresponding eigen face should contribute a smaller (or not at all) part to the sum of eigen faces. So, in order to reconstruct the original image from the eigen faces, one has to build a kind of weighted sum of all eigen faces. That is, the reconstructed original image is equal to a sum of all eigen faces, with each eigen face having a certain weight. This weight specifies, to what degree the specific feature (eigen face) is present in the original image.

Mathematically, the algorithm calculates the eigenvectors of the covariance matrix of the set of face image. Each image from the set contribute to an eigenvector, these vectors characterize the variations between the images. When we represent these eigenvectors, we call it eigen faces. Every face can be represented as a linear combination of the eigen faces; however, we can reduce the number of eigen faces to the ones with greater values, so we can make it more efficient.

The basic idea of the algorithm is develop a system that can compare not images themselves, but these feature weights explained before. The algorithm can be reduced to the next simple steps.

1. Acquire a database of face images, calculate the eigenfaces and determine the face space with all them. It will be necessary for further recognitions.
2. When a new image is found, calculate its set of weights.
3. Determine if the image is a face; to do so, we have to see of it is close enough to the face space.
4. Finally, it will be determined if the image corresponds to a known face of the database of not.

V. ALGORITHMIC STEPS

The algorithm for recognition of authorized used is divided in two parts. The first part describes about the checking whether the image is face or not. And the second part provides description about the Recognition whether it is authorized or non authorized user.

The algorithmic steps are outlined as:

1. Prepare the training set consisting of faces Fi.
2. Perform the average matrix and subtract from the original faces to get the resultant.

$$M = \frac{1}{F_m} \sum_{n-1}^{F_m} F_i$$

FR=Fi - M

3. Calculate the covariance matrix C

$$C = \frac{1}{F_m} \sum_{n-1}^{F_m} F_R F_R{}^T$$

4. Calculate the Eigen values and Eigen Vectors of the covariance matrix

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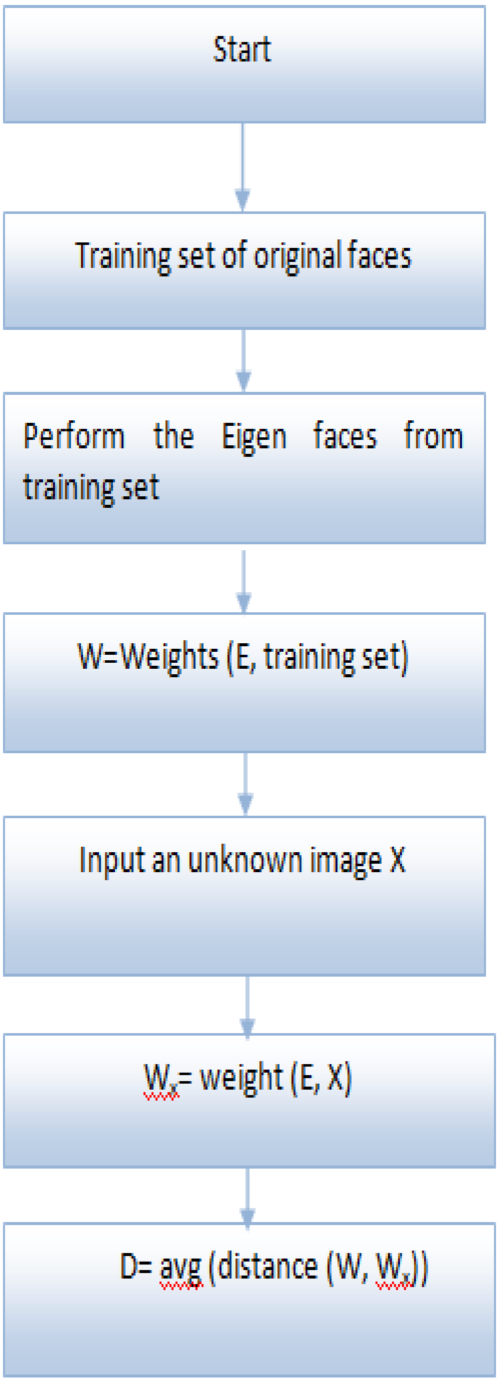
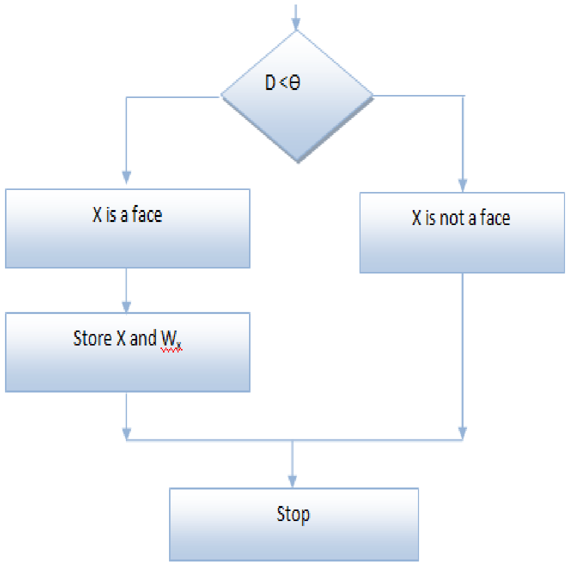
5. Calculate the weight for each image in the Training set and stores it in set W.
6. Consider the unknown image and calculate Weight for it and store it in vector *Wx*.
7. Compare *Wx* with *W*. Calculate distance Between them using Euclidian distance.
8. If the average distance exceeds the Threshold value then it is not a face.
9. Compare the distance between the inputs Image and the images of the training set.
10. If the distance is minimum and the Weight is maximum then the input image is a known Face else it is an unknown Face.

FLOWCHART





VI. RESULTS AND ANALYSIS

The algorithm used a training set of 10 different face images of a person.

- Training Set of 10 different face images of a person
- All the face images of a training set are normalized in pre-processing phase in order to reduce the error due to lighting conditions.
- Mean image can be calculated for all the normalized training images.
- Transform Training set images to Eigen Faces.
- Test image is reconstructed using the mean value and eigenvector of the training set.
- Calculate the weight and distance of test image for each image in the training set. If the distance is minimum and the weight is maximum then the input image is a known Face.

Fig 1: Training Set

Fig 3: Mean Image

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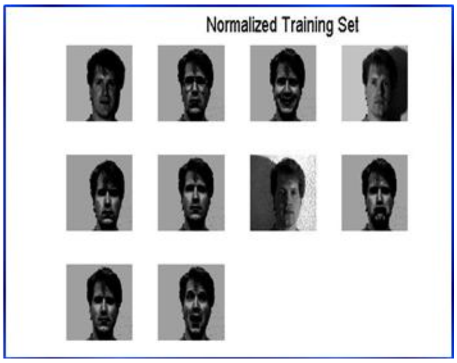

Fig 2: Normalized Training Set

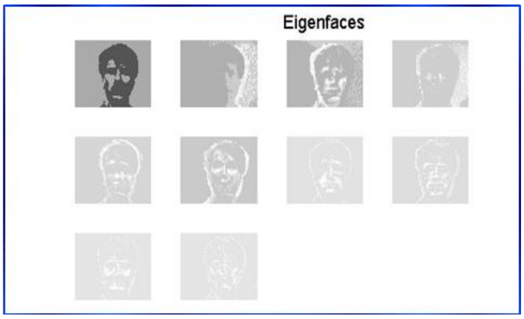

Fig 4: Eigen Faces of the Training Set

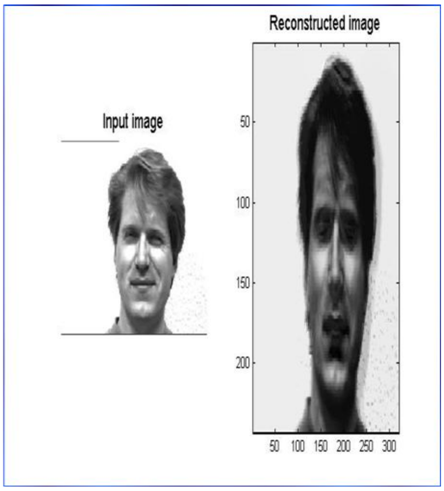

Fig 5: Reconstructed Test Image

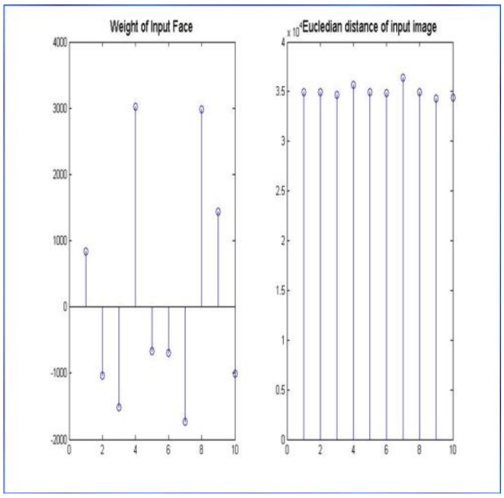

Fig 6: Weight and Distance of Test Image

First a PCA is performed on the shape free images and then on the shapes. The obtained results were then combined and a third PCA was performed yielding a subspace containing both the geometric and photometric information. When combining the results obtained from the first two PCA's the weighting between texture and shape is one.

To access the visibility of this approach to face recognition, we have performed experiments with stored face images and built a system to recognize faces in dynamic environment. Over 10 face images have been digitized under variations of lighting, scale and orientations. Various groups of images are selected and used as training set. The mean of the training set is calculated for calculation of the Eigen vectors. With the training set the image of one person is taken under orientation and head positions. Experiments show an increase of performance accuracy with the threshold value. With the change in lighting conditions performance drops dramatically. The Euclidean distance between two weight vectors d (i, j) provides a measure of similarity for recognition the test images with the training set between the corresponding images i and j. The distance of the training image with the test image shows the recognition rate. The less is the distance value the more similar is the image. Hence the recognition rate is higher.

Problem Formulation

Occlusion may cause error in authentication if the captured image has certain features that are hidden or are blocked and are different from the face templates stored in the database.

Face recognition in which the features of the employee differ with their age. Due to this there are errors in authentication if the features do not match with the face templates stored in the database.

We have seen the standard Eigen face Approach for Face Recognition. Here we find out M Eigenvectors for representing training set images. Now it is important to choose only M' Eigenvectors from these M Eigenvectors, such that M' is less than M, to represent face space spanned by images. This will reduce the face space dimensionality and enhance speed for face recognition. Here we are reducing the dimensionality of face images.

VII. CONCLUSION

Eigen faces is a rapidly evolving technology that is being widely used in security; prevent unauthorized access in bank or ATMs, in cellular phones, smart cards, PCs, in workplaces, and computer networks. For given set of images, due to high dimensionality of images, the space spanned is very large. But in reality, all these images are closely related and actually span a lower dimensional space. By using eigenfaces approach, we try to reduce this dimensionality. The eigenfaces are the eigenvectors of covariance matrix representing the image space. The lower the dimensionality of this image space, the easier it would be for face recognition. Any new image can be expressed as linear combination of these eigenfaces. This makes it easier to match any two images and thus face recognition.

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