PCA EIGENFACE:
An Approach to Appearance-Based Face detection and Recognition

Machine Learning

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Abstract

In this paper, an appearance based principal component analysis (PCA) is developed for image detection and recognition. Images are transformed into 1D vectors, named as face images. Then Average of the face space is calculated to gain all the common features from the images. Image covariance matrix is generated from the difference matrix using the original image matrices, and its eigenvectors are derived for image feature extraction. To test PCA and assess its performance, some experiments were performed on one face image database: ORL.

1. *Introduction*

Principal component analysis (PCA) is used in the area of pattern recognition for computer vision and it is a classical feature extraction technique. Sirovich and Kirby [1], [2] have implemented PCA to efficiently represent images of human faces. They claimed that any face picture can be recreated as a weighted sum of a small collection of images that characterize a facial basis (Eigen images), and a mean image of the face. In this framework, Turk and Pentland [3] presented method for face recognition in 1991 also known as Eigenfaces. Since then, Principal component analysis has been broadly investigated which resulted in one of the most prominent and successful approaches in face recognition. Penev and Sirovich [4] argued the problem of the dimensionality of the “face space” A space consist of vector faces where each face vector represents one image vertically. There were some problem with the method (PCA) for which some researchers have done a lot of work. Basically the problems were that PCA method was not friendly with the various effects of illumination. However, Wiskott et al. [5] pointed out that PCA cannot capture even the tiny invariance unless the information is clearly provided in the training data.

As of late, two PCA-related techniques, independent part investigation (ICA) and portion foremost part examination (Kernel PCA) have been of wide concern. some researchers proposed to use ICA for face representation and found that, it was superior to anything PCA when cosines were utilized as the comparability measure (be that as it may, their execution was not altogether extraordinary if the Euclidean distance is utilized). Yang (A researcher) utilized Kernel PCA for face include extraction and acknowledgment and demonstrated that the Kernel Eigenfaces strategy beats the established Eigenfaces technique. Be that as it may, ICA and Kernel PCA are both computationally more costly than PCA.

2. **facial recognition**(*background)*

***Motivation*:**

Facial recognition was the source of motivation behind the creation of eigenfaces. For this use, eigenfaces have advantages over other techniques available, such as the system's speed and efficiency. As eigenface is primarily a dimension reduction method means it uses the concept of PCA, by which a system can represent many objects with a small set of data. As a face recognition system is also invariant to large reductions in image dimensions.

3. *Method (Steps involved to recognize face images)*

a) First we should prepare a training set of face images. The pictures establishing the training set should have been taken under the same lighting conditions if not, this technique will not work. Then it must be normalized to have the features (eyes, mouth) aligned across all images. The all must be of same size (resolution). Each image will be treated as one vector. We assumed that all images of the training set are stored in a single matrix T, where each column of the matrix is an face vector(image).

The average of training set is defined by:

$$\mathbf{m} = (1/m) \sum_{i=1}^{m} x_i$$

b) Subtract the mean **m**:

The average image **m (of the face vector space)** has to be calculated and then subtracted from each original image in **T**.

$$r_i = x_i - m$$

c) Calculate the eigenvectors and eigenvalues of the covariance matrix C. The eigenvectors of this covariance matrix are called eigenfaces. Eigenfaces are the directions in which the images differ from the mean (Averaged image) image. Usually this is computationally expensive step, but practically eigenfaces stem from the possibility to compute the eigenvectors of C efficiently. The covariance matrix is constructed as given below.

$$C = A\,A^t \qquad \text{where } A = [r_1, \ldots, r_m]$$

Finding eigenvectors of n^2 x n^2 matrix is intractable. Hence, use the matrix A^tA of size m x m and find eigenvectors of this small matrix**.**

- Consider the eigenvectors vi of ATA such that

$$A^t A v_i = \mu_i v_i$$

- Premultiplying both sides by a, we have

$$AA^t (Av_i) = \mu_i (Av_i)$$

The eigenvectors of covariance matrix are

$$U_i = Av_i$$

- $\mathbf{U_i}$ resemble facial images which look ghostly, hence called eigenfaces

d) Projection into Face Space: A face image can be projected into this face space by

$$P_k = u^t(x_k - m) \quad \text{where } k=1,\ldots,m$$

Recognition:

To recognize faces, gallery images, those seen by the system, are saved as collections of weights describing the contribution each eigenface has to that image. When a new face is presented to the system for classification, its own weights are found by projecting the image onto the collection of eigenfaces. This provides a set of weights describing the probe face. These weights are then classified against all weights in the gallery set to find the closest match.

Intuitively, recognition process with eigenface method is to project query images into the face-space spanned by eigenfaces we have calculated and in that face-space find the closest match to a face class.

- The test image x is projected into the face space to obtain a vector p:
  - **$P = u^t(x - m)$**
- The distance of p to each face class is defined by
  - **$\epsilon_k^2 = ||p-p_k||^2; k = 1,\ldots,m$**
- A distance threshold θ_c, is half the largest distance between any two face images:
  - **$\theta_c = \frac{1}{2} \max_{j,k} \{||p_j-p_k||\}; j,k = 1,\ldots,m$**
- Find the distance ϵ between the original image x and its reconstructed image from the eigenface space, xf,
  - **$\epsilon 2 = || x - xf ||2$, where $xf = u * x + m$**
- **Recognition process:**
  - If **$\epsilon \geq \theta c$**
    then input image is not a face image;
  - If **$\epsilon < \theta c$ AND $\epsilon\ k \geq \theta c$ for all k**
    then input image contains an unknown face;
  - If **$\epsilon < \theta c$ AND $\epsilon k^* = \min k\{ \epsilon k \} < \theta c$**
    then input image contains the face of individual k*

4. Results

From the dataset of ORL two different classes were taken for the experiment purpose and then the PCA method was tested with various number of samples to determine its accuracy.

From the experiments we have concluded that as we increases the number of samples per class the accuracy rate also increases. As show in below figure.1.

# Training samples / class	1 *	2 *	3	4 *	5
PCA (Eigenfaces)	66.9 (39)	84.7 (79)	88.2 (95)	90.8 (60)	93.5 (37)

Figure.1

5. Conclusion

Advantages of Eigenfaces Approach

It is acknowledged that the accuracy rate increases much faster which indicates that PCA Eigenface technique is very much efficient in recognizing images for less dataset. It is because of the weights that are pre-calculated at the stage of projecting the eigenface into the face space.

- Training process is completely automatic and easy.
- Eigenface reduces statistical complexity in face image representation.
- Face recognition can be achieved in real time.
- Can handle large databases.

Limitations of Eigenfaces Approach

- Eigen face is very sensitive to lighting, also not scale, rotation and translation invariant.
- It has difficulty to capture expression changes.
- The most important eigenfaces are about illumination encoding.

References

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