

# Application of Eigenvalues and Eigenvectors in Face Recognition

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DOI: <https://doi.org/10.51244/IJRSI.2026.1304000056>

Received: 06 April 2026; Accepted: 12 April 2026; Published: 29 April 2026

## ABSTRACT

Face recognition is now an essential part of human–computer interaction, surveillance systems, and biometric authentication. The eigenvalue–eigenvector based Eigenface methodology has been popular among different computing techniques because of its high performance in controlled situations and mathematical simplicity. The contribution of eigenvalues and eigenvectors to dimensionality reduction and feature extraction in face recognition is examined in this work. Principal Component Analysis (PCA) is used to convert facial images into a lower-dimensional eigenspace where robust and efficient recognition is achieved. The paper also examines developments, difficulties, and enhancements to the initial eigenface model.

**Keywords:** Eigenfaces, Eigenvalues, Eigenvectors, Principal Component Analysis, Face Recognition, Covariance Matrix, Image Classification, Linear Algebra

## INTRODUCTION

One of the most extensively researched issues in computer vision and image processing is face recognition. By identifying key face features in digital photos, it seeks to identify people. In order to transform complicated visual input into useful mathematical structures, linear algebra is essential. Turk and Pentland (1991) developed the Eigenface approach, which effectively uses eigenvectors obtained from a covariance matrix to express facial patterns.

The mathematical underpinnings of eigenvalues and eigenvectors in face recognition are explained in detail in this work, which also examines how PCA condenses high-dimensional image data without significantly losing information.

## Mathematical Background

A grayscale face image of size  $m \times n$  can be represented as a vector in a high-dimensional vector space:

$$\mathbf{x} \in \mathbb{R}^{mn}$$

A dataset with  $N$  face images forms a matrix:

$$X = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N]$$

The covariance matrix is computed as:

$$C = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \boldsymbol{\mu})(\mathbf{x}_i - \boldsymbol{\mu})^T$$

Where  $\boldsymbol{\mu}$  is the mean image. Solving the eigenvalue equation:

$$C\mathbf{v} = \lambda\mathbf{v}$$

Produces eigenvalues ( $\lambda$ ) showing variance and eigenvectors ( $\mathbf{v}$ ) representing the principal components of facial features.

Only eigenvectors with the largest eigenvalues are selected → These are called **Eigenfaces**.

Images are projected into eigenspace for recognition:

$$\omega = V^T(x - \mu)$$

Where  $V$  is the matrix of eigenfaces and  $\omega$  is the feature vector used for classification.

### Eigenface-Based Face Recognition Process

Step	Description
Image Acquisition	Collect facial images in uniform format
Preprocessing	Aligning, cropping, and converting to grayscale
PCA Computation	Calculate covariance matrix & eigenvectors
Dimensionality Reduction	Select top eigenfaces based on eigenvalues
Feature Projection	Convert input face into eigenspace
Classification	Recognize using distance metrics such as Euclidean distance

The method reduces computational load and improves recognition speed significantly.

## LITERATURE REVIEW

- Turk and Pentland (1991) introduced the Eigenface technique using PCA for near-real-time face recognition, marking a major breakthrough in appearance-based methods.
- Belhumeur et al. (1997) compared PCA with Linear Discriminant Analysis (LDA) and found LDA provides better class separability in varying lighting conditions.
- Pentland (2000) emphasized that eigenfaces are efficient but highly sensitive to illumination, expression, and occlusion.
- Zhao et al. (2003) reviewed face recognition advancements and suggested hybrid approaches for improved robustness.
- Sangeeta & Gupta (2016) improved eigenface recognition accuracy using image normalization and noise reduction techniques.
- Deep learning approaches (e.g., CNNs) have recently surpassed classical PCA models; however, eigenfaces remain crucial for theoretical understanding and lightweight systems (Parkhi et al., 2015).

### Summary of Literature Gaps

- Sensitive to pose and illumination variations
- Performance declines as dataset diversity increases
- Requires enhancement for real-world deployment

## Advantages and Limitations

Advantages	Limitations
Fast computation	Sensitive to lighting/pose variations
Requires smaller storage	Not effective with occlusions
Strong mathematical foundation	Performance limited on large datasets
Works well for frontal images	Less effective in unconstrained environments

## Applications

- Biometric authentication systems
- Security and surveillance
- Phone unlocking mechanisms
- Attendance and identity verification systems
- Human-computer interaction

## CONCLUSION

In traditional face recognition methods, eigenvalues and eigenvectors are fundamental. The Eigenface method effectively extracts useful characteristics for identification while reducing dimensionality. Eigenface-based recognition is still useful in computationally limited settings and as a solid theoretical foundation for contemporary algorithms, despite deep learning's increasing popularity. Future developments could include hybrid models that combine neural networks and PCA for reliable real-world performance.

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