Study of Eigenface Algorithm for Face Detection

Prof. Divya Mahadik¹, Harshal Raut², Shivam Talekar³, Akash Sonawane⁴, Aishwarya Nanekar⁵ ¹(Professor, SRCOE, Department of Computer Engineering Pune) ²,^{3,4,5}(Student, SRCOE, Department of Computer Engineering Pune)

Abstract: This paper presents a face recognition methodology that combines Principal Component Analysis (PCA) and a neural network to effectively recognize and differentiate faces. The approach consists of two main stages: feature extraction using PCA, which reduces the dimensionality of face data, and recognition through a feedforward backpropagation neural network, allowing the system to recognize specific faces from a large set, even with slight variations. The Eigenface method uses PCA to create a lower-dimensional space for face recognition. However, Fisherface, which combines PCA with Linear Discriminant Analysis (LDA), is more effective as it maximizes the separation between different faces (or classes) during training. The Fisherface approach, using LDA, extracts distinguishing features and applies Euclidean distance for face identification, showing improved accuracy over Eigenface, especially when handling variations across different individuals.

Key Word: Face Recognition, Feature Extraction, Pattern Recognition, Image Normalization, Feed-forward Backpropagation Neural Network.

I. Introduction

Face recognition technology has emerged as a versatile and transformative tool across various domains, offering innovative solutions for identity verification and management. This paper describes a face recognition system that can recognize both static and dynamic images. Dynamic images are converted to static ones, then analyzed using an information theory-based approach. This method reduces face images to a set of characteristic images called Eigenfaces, derived from the principal components of the initial face data set. Recognition happens by projecting new images onto the "face space" created by Eigenfaces, and then classifying the image based on its position relative to known faces. The Principal Component Analysis (PCA) method, introduced by Turk and Pentland in 1991, is commonly used for this feature extraction, emphasizing the directions of greatest data variation. However, PCA has limitations in class separation. To improve class separation, Linear Discriminant Analysis (LDA), introduced by Cheng in 1991, optimizes class separability using the Fisher Criterion. LDA works well when data dimensions are lower but may face issues with high-dimensional data due to matrix singularity.

II. Literature Review

1. This study by Prof. Y. Vijaya Lata et al. (2009) provides an introduction to using PCA for face recognition, focusing on reducing data dimensionality and enhancing classification accuracy. Face Recognition Using Eigenface Approach - Vinaya Hiremath and Ashwini Mayakar highlight the application of PCA for face recognition, emphasizing how Eigenfaces serve as feature vectors to represent and classify faces.

2. Face Recognition Using Eigenfaces and Neural Networks - Mohd Rozailan Mamat and co-authors (2006) explore the combination of Eigenfaces and neural networks, showing how PCA can preprocess images for more effective neural network training.

3. Face Recognition Using Eigenfaces and Artificial Neural Networks - Mayank Agarwal et al. (2010) examine the use of neural networks with Eigenface-based features, achieving enhanced accuracy in face recognition tasks. Mahmud et al. (2015) - This study combines Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to enhance face recognition accuracy. The authors emphasize the value of combining PCA's dimensionality reduction with LDA's class separation to improve recognition performance.

4. Puja and Rajput (2016) - This research focuses on feature extraction using Support Vector Machine (SVM) combined with Local Binary Patterns (LBP), which enhances facial feature detection. The technique is applied to distinguish unique features more accurately, thus improving recognition.

5. Belhumeur, Hespanha, and Kriegman (1997) - This foundational study introduces the Fisherface method, a combination of PCA and LDA. Fisherface addresses PCA's limitations in class separation, improving recognition under variations in lighting and expression by focusing on maximizing inter-class variance.

Find the face class Start Calculate the with minimum covariant matrix Euclidian distance Subtract Test Image with Train Image Read the testing End face image Calculate Covariant value Calculate feature vector of the test image Calculate Eigenvalue and Compute the Eigenvector Euclidian distance

III. Algorithm

Fig.1 Flowchart Of Eigenface Algorithm.

Start

The process begins with initializing the required inputs, such as the training and test images.

Subtract Test Image with Train Image

- Each training image and the test image are converted into a vector.
- The average face (mean image) of the training dataset is calculated.
- The test image is mean-centered by subtracting the average face from it. This step helps remove the overall illumination and improves face detection.

Calculate Covariant Value

- The covariance matrix of the training images is calculated.
- This captures how the intensity of each pixel varies with respect to others across all training images.

Calculate Eigenvalue and Eigenvector

- **Eigenvalues** and **eigenvectors** are computed from the covariance matrix.
- The eigenvectors represent the principal components of the face space (known as "Eigenfaces"). These are essentially a set of features that capture variations between faces.

Calculate the Covariant Matrix

- The covariance matrix is used again to refine the feature space.
- Training data is projected onto the "Eigenfaces" to obtain a set of weights for each image.

Read the Testing Face Image

- The test image is processed in a similar manner as the training images.
- The test image is projected into the same face space using the calculated eigenvectors, producing a feature vector.

Calculate Feature Vector of the Test Image

• The test image is represented as a feature vector in the Eigenface space.

Compute the Euclidean Distance

- The Euclidean distance between the feature vector of the test image and each feature vector of the training images is computed.
- This distance quantifies how similar the test image is to each training image.

Find the Face Class with Minimum Euclidean Distance

- The training image with the smallest Euclidean distance to the test image is identified.
- The test image is classified as belonging to the same class (person) as this closest training image.

End

• The process concludes with the identification of the face class.

IV. Advantages

1. Eigenfaces reduce the high-dimensional image data (e.g., pixel intensities of images) into a much smaller subspace (Eigenface space) while retaining the most important features.

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- 2. Eigenfaces capture the major variations in facial features and structure, which helps distinguish between different faces.
- **3.** The algorithm is conceptually straightforward and relies on well-understood mathematical tools like Principal Component Analysis (PCA).
- 4. Eigenfaces can adapt to new faces by simply recalculating the average face and updating the Eigenface space with new data.
- 5. By focusing only on the most significant components (eigenvectors with the largest eigenvalues), the model avoids overfitting to the noise or irrelevant details in the training data.

V. Disadvantages

- 1. The algorithm is highly sensitive to variations in lighting conditions. Changes in illumination can significantly alter the pixel intensities, leading to poor recognition accuracy.
- 2. The algorithm performs poorly when parts of the face are occluded (e.g., by glasses, masks, or hair).
- **3.** Noisy or low-quality images can significantly affect the calculation of eigenvalues and eigenvectors, leading to inaccuracies in face classification.

VI. Application

1. Access Control and Security

- Authentication Systems: Eigenfaces can be used in secure access systems, such as door locks, attendance systems, or computer login interfaces. A user's face is scanned and compared to stored images for verification.
- Visitor Management: Used to identify authorized personnel or restrict entry to sensitive areas.

2. Surveillance and Monitoring

- Criminal Identification: Eigenfaces can help match surveillance footage against a database of known individuals.
- Crowd Monitoring: Useful for identifying faces in a group and matching them to known identities for law enforcement purposes.

3. Human-Computer Interaction (HCI)

- Customized Interfaces: Recognizing users to adapt the interface or personalize the system's response.
- Face-Driven Applications: For example, detecting user identity and mood to provide tailored interactions.

4. Education and Research

- Teaching Tool: Fisherfaces is often used in academia to teach concepts of dimensionality reduction and discriminative analysis in pattern recognition.
- Prototype Development: Used in research as a baseline face recognition system before moving to more complex models.

VII.Conclusion

In this study, we used the eigenfaces to represent the features vectors for human faces. The features are extracted from the original image to represents unique identity used as inputs to the neural network to measure similarity in classification and recognition. The eigenfaces has proven the capability to provide the significant features and reduces the input size for neural network. Thus, the network speed for recognition is raise.Face recognition system using fisherface methods able to recognize the image of face testing correctly with 100% percentage for the test image the same as the training image and able to recognize the image of face testing correctly with 93% when the test image different from the training image. Face recognition with fisherface method not only capable of performing an introduction to the test face images with different color components of the training image and a sketch of the original image. This method is also immune to noise-induced images and the blurring effect on the image.

VIII. References

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