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Image Band-Distributive PCA Based Face Recognition Technique

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Abstract. This paper presents an Image Band-Distributive PCA (IBD-PCA) based technique for face recognition. The proposed method consists of four steps. In the first step, the reference image is pre-processed by converting its pixel values and performing histogram equalization to increase its contrast. In the second step, the equal-size boundary calculation method is used to calculate the boundary splitting values to divide the input image into multiple images with respect to band intensities of pixels. In the third step, Principal Component Analysis (PCA) is used to extract features from the images which will then be used as the input for the fourth step. In the last step, matching is performed by calculating the Euclidean distance between principal components. The proposed technique has been tested on the ORL face database and Yale face database. The experimental results demonstrate that the proposed technique outperforms other techniques on the same database.

Keywords: Face recognition, Principal component analysis, Image band-distributive PCA.

1 Introduction

Face recognition is a highly researched field within the realm of biometrics, focusing on the identification of individuals based on their facial images (Archana and Venugopal, 2015). It offers numerous advantages, particularly in areas such as security and surveillance, banking, database retrieval, law enforcement, criminal justice systems, and virtual reality (Archana, 2015). Despite the considerable amount of research dedicated to face recognition, there is still a significant need for improved techniques that can accurately and effectively recognize individuals.

Principal Component Analysis (PCA) is one of the techniques that has been extensively utilized for face recognition (Puyati et al., 2008). PCA is commonly employed to reduce the dimensionality of input image data while preserving its essential characteristics. By revealing vital aspects of the data, PCA enables the identification of patterns and the exploration of similarities and differences between features in the input data, facilitating feasible investigations.

However, it is important to note that face recognition is a complex and evolving field, and researchers continue to explore and develop new methods to overcome the challenges associated with accurate identification. While PCA has proven to be effective in many cases, it is not without limitations. One limitation is its sensitivity to variations in lighting conditions, facial expressions, and pose. In real-world scenarios, these factors can significantly affect the performance of PCA-based face recognition systems.

In recent years, researchers have proposed various face recognition methods (Abbas et al., 2017, Poon et al., 2009, Zhao et al., 1998). These methods can generally be categorized into two groups: holistic template matching and geometrical local feature-based techniques (Chellappa et al., 1995). Among these approaches, PCA-based methods employ the holistic template matching technique and have shown promising results for face recognition (Winarno et al., 2019).

1.1 PCA for Face Recognition

In face recognition, PCA is utilized as a technique for feature extraction and dimensionality reduction. In PCA-based face recognition, the face images are transformed into a lower-dimensional subspace, known as the eigenspace, using PCA. This subspace captures the most significant variations in the face images, and they serve as a basis for representing and recognizing faces. The eigenvectors, called eigenfaces, are the principal components extracted during the PCA process. These eigenfaces form a set of basis vectors that span the face image space, allowing for efficient representation and classification of face images.

1.1 Eigen faces

One of the pioneering works in PCA-based face recognition was introduced by Turk and Pentland (Turk et al., 1991). They developed an approach for using PCA for face recognition known as "eigenfaces" that involves applying PCA to a database of face images to derive eigenfaces, which are then used to represent and classify new face images. The eigenfaces technique represents each face in the database as a vector of weights, obtained by projecting the image onto eigenface components. When a test image is provided for identification, it is also represented by its vector of weights, and identification is performed by finding the image in the database with weights closest (in terms of Euclidean distance) to the test image's weights (Chellappa et al., 1995).

On the other hand, geometrical local feature-based methods focus on extracting specific facial features, such as the nose, eyes, and mouth, and utilize their locations for recognition (Chellappa et al., 1995). Jafri and Hamid (Jafri et al., 2009) employed a local feature-based approach for face recognition and reported encouraging results.

In this paper, we address the existing gap in the literature by introducing a novel approach for face recognition that combines image band-distributive generation with PCA. While researchers have made significant advancements in enhancing PCA-based face recognition methods, the incorporation of image band-distributive generation techniques has not been explored. The proposed method, called Image Band-Distributive PCA (IBD-PCA), fills this research gap and offers a robust solution for improving the performance of PCA-based face recognition systems. By generating multiple images from the input grayscale image based on pixel intensities, enables the extraction of facial features from different intensity ranges, leading to enhanced matching accuracy.

The rest of the paper is organized as follows: Section 2 describes the proposed technique. Section 3 provides details about the experiments performed and the results obtained in each case, and finally Section 4 draws the conclusion.

2. Proposed Technique

In this section, the proposed Image Band-Distributive PCA (IBD-PCA) for face recognition technique is presented.

The IBD-PCA technique introduces a unique and effective strategy to enhance the performance of traditional methods by leveraging the power of feature extraction. Unlike conventional approaches, the proposed method adopts a distinctive perspective by dividing the input grey image into multiple images, each capturing specific facial characteristics. This distribution of image data across multiple images enables the incorporation of both global and local facial details, resulting in a more comprehensive representation of the face features.

The core idea behind IBD-PCA lies in applying Principal Component Analysis (PCA) independently on each of the divided images. By extracting the principal components from these images, discriminative features encapsulating the essential facial information are obtained. This image band-distributive approach enables the exploitation of diverse facial appearance variations across different regions of the face, leading to improved recognition accuracy. A flowchart of the proposed technique is shown in Figure 1.

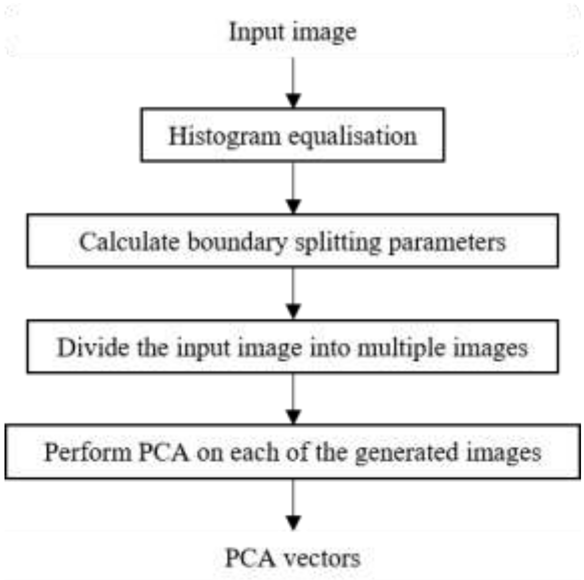

Figure 1. Flowchart of the proposed technique.

The proposed technique consists of four stages namely: Pre-processing, Multiple-Image Generation, conventional PCA, and Matching, which are detailed in the following sections:

2.1 Pre-processing

Let I represent a dataset of face images, with each image in \$I\$ of size $x \times y$. The input image $i \in I$ is assumed to be an 8-bit grayscale image. The input image pixels are first normalised to be mapped to the range of [0, 1]. The contrast of the resulting image is then increased using histogram equalization. This is done by first calculating the Probability Mass Function (PMF) PMF_X of the input image as follows:

$$PMF_X(x_j) = PMF(X = x_j)\text{for } j = 0,1,\dots,255 \quad (1)$$

where $X = x_0, x_1, \dots, x_{255}$ presents the pixels values and $PMF_X(x_j)$ represents the probability of coefficients in bin j. The resulting PMF is then used to derive the Cumulative Distribution Function (CDF) CDF_x by considering the following expression:

$$CDF_x(j) = PMF(X \le x_j) \text{ for } j = 0,1,\dots,255 \quad (2)$$

where $CDF_x(j)$ is the cumulative probability of $X \le x_j$. The pixels within the input image are mapped using the resulting CDF. The resulting histogram equalized image is then used for multiple-image generation.

2.2 Multi-Image generation

To generate multiple-images from the resulting histogram equalized input image, the proposed IBD-PCA method splits the input image into predefined number of images according to intensity of its pixels using an *equal size* boundary calculation method. If *i* is the input histogram equalized image and *N* is the predefined number of images desired from the input image *i*, the proposed algorithm calculates *N*-1 boundaries to split the pixels of the input image into *N* target images. The pixel value boundaries $B = \{b_1, b_2, \dots, b_{N-1}\}$ are then calculated using equation 3:

$$b_n = n/N \text{ for } n = 1,2, \dots, (N-1) \tag{3}$$

If $B = \{b_1, b_2, \dots, b_{N-1}\}$ represents the resulting boundary values, the input image *i* is then divided into *N* target images by:

1. Generating *N* images that have the same size as the input *i* image with pixel values of zero. Let's assume the generated images be: $R = [r_1, r_2, \dots, r_N]$.

2. Assigning all valued pixels p of *i* in the range $[0, b_1], [b_1, b_2], \dots, [b_{(N-1)}, 1]$ to image $r_1, r_2, \dots, r_N$, respectively.

Each resulting image in the image set of R has its own band intensity. The coefficients in each resulting image are then mapped to [0, 1]. This enables the algorithm to extract face features from different pixel intensity of the image, increasing the matching accuracy of the proposed IBD-PCA based face recognition technique.

2.3 Principal component analysis

Assume *R* is the set of the resulting multiple-images, which their coefficients have been mapped to [0 1], where $R = \{r_1, r_2, \dots, r_N\}$. Each image $r_j \in R$is mean adjusted, generating r'_j as follows:

$$r'_j = r_j - \overline{r}_j \tag{4}$$

where $\overline{r}_j$ represents the mean value of the pixels in image r_j.

Each resulting mean adjusted image r'_j is then converted to a column wise vector. Hence, *R* can be represented as a two-dimensional matrix *S*.

Principal Component Analysis (PCA) is then performed using Singular Value Decomposition (SVD) on the resulting matrix *S*, generating the following decomposition:

$$S = U\Sigma V^T \tag{5}$$

where *U* is a unity matrix, and the columns of *V* are the orthonormal eigenvectors of the covariance matrix of *S* and Σ is a diagonal matrix of their respective eigenvalues. The eigenvectors form a basis for an eigenspace for each set of images *R*. The resulting principal components in V are assumed to be the extracted features of the input image, which are used for finding the best match.

2.4 Matching

The matching process of faces is based on Euclidean distance measurement. Euclidean distance calculations can be used to determine the distance between any two points in a two-dimensional space, and to derive the absolute distance between points in N-dimensional space. In face recognition, smaller Euclidean distance values indicates more similarity between faces.

The face image to be detected is processed to obtain a N-dimensional face feature vector, which enables a condition for Euclidean distance calculations.

Let $\mathbf{A} = (x_1, x_2, \dots, x_n)$ be the principal components of an input face image **A** to be detected, and $\mathbf{B} = (y_1, y_2, \dots, y_n)$ is the principal components of an image **B** in a dataset of images, the Euclidean distance can be calculated as follows:

$$\mathbf{AB} = \sqrt{(x_1 - y_1)^2 + (x_2 - y_n)^2 + \cdots + (x_n - y_n)^2} \tag{6}$$

The resulting value from calculating AB represents the Euclidean distance between principal components of both face images.

After calculations of Euclidean distances between principal components have been done, their average is determined in the form of an average distance metric, as in the expression below, and used for finding the best match:

$$Av\mathbf{AB} = \sum \mathbf{AB}/(N-1) \tag{7}$$

3. Experiments and Results

This section presents the experiments performed to assess the validity and performance of the developed IBD-PCA technique in the domain of face recognition. The primary objective of these experiments is to establish the effectiveness of the proposed technique by benchmarking its performance against existing methods and thoroughly analyzing the obtained results.

3.1 Database

The proposed IBD-PCA method was used for face recognition and tested using two benchmark face image databases called: the ORL Face Database (ORL Face Databases, n.d.) and Yale Face Database (Yale Face Databases, n.d.). The ORL database was used to assess the performance of IBD-PCA under varying conditions of pose and sample size. The Yale database was used to assess the performance of the proposed method with varying facial expressions and illumination.

3.1.1 ORL Face Database

The ORL Face Database (ORL Face Databases, n.d.) contains ten face images of each of 40 distinct subjects, some of which were captured under different times, varying light, facial expressions (open/closed eyes, smiling/not smiling), and facial details (glasses/no glasses). The images are 8-bit grayscale of size 92×112 pixels. Figure 2 shows ten sample images of three individuals from the ORL Face Database.

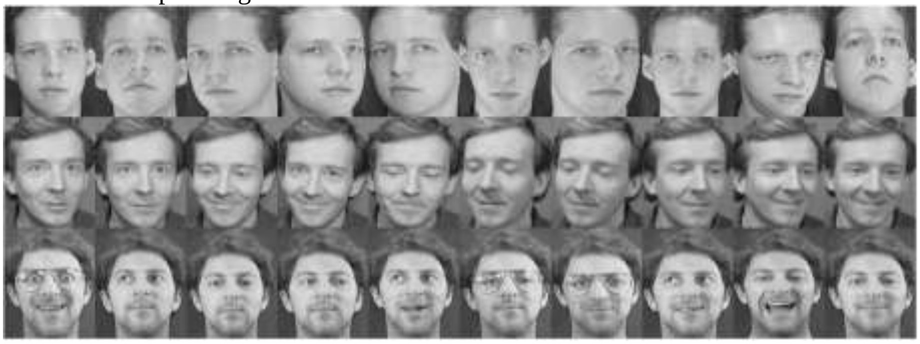

Figure 2. Sample images from ORL Face Database (ORL Face Databases, n.d.).

3.1.2 Yale Face Database

The Yale Face Database (Yale Face Databases, n.d.) contains 11 different face images of each of 15 distinct subjects. The images were also captured in different conditions like the ORL Face Database, and the images were in 8-bit grayscale and each of size 320×243 pixels. Figure 3 shows eleven sample images from of three individuals from the Yale Face Database.

Figure 3. Sample images from Yale Face Database (Yale Face Databases, n.d.).

To assess the performance of the proposed method, experiments were conducted on both databases for two main purposes. The first was to generate a baseline for comparison and the second was to determine the optimum matching accuracy.

3.2 Methodology

To establish a meaningful baseline for comparing the performance of the proposed IBD-PCA technique with other existing methods, a comprehensive evaluation using three algorithms: IBD-PCA, conventional PCA, and eigenfaces was conducted. These algorithms were applied to both the ORL and Yale datasets, allowing for the assessment of their respective performances and gaining insights into their unique strengths.

In the experimental setup, Rank-1 and Rank-5 evaluation criteria were employed to gauge the effectiveness of each algorithm. For the ORL dataset, ten captured face images per subject were utilized, with nine images serving as the database and one randomly selected image as the query. Similarly, the Yale dataset consisted of eleven face images per subject, with ten database images and one query image randomly chosen for each subject.

To determine the accuracy of the algorithms, the query image was compared against the database images. If the query image matched correctly with an image from the same subject in the database, it was labelled as a Rank-1 match. Similarly, if the subject was found among the top five closest images to the query image, it was labelled as a Rank-5 match. The percentage of Rank-1 and Rank-5 matches was then calculated based on the total number of query images, yielding the Rank-1 and Rank-5 accuracies.

To ensure the reliability of the findings, this process was repeated for multiple permutations, conducting three trials in total. The average accuracies of Rank-1 and Rank-5 across. These trials are then calculated, providing a robust assessment of each algorithm's performance.

By following this rigorous experimental procedure, a solid foundation for comparing the proposed IBD-PCA technique with conventional PCA and eigenfaces was established. The Rank-1 and Rank-5 accuracies obtained from these evaluations offer valuable insights into the relative strengths and weaknesses of each method, enabling a comprehensive understanding of their respective capabilities in face recognition tasks.

3.3 Experimental results and observations

The experimental results, as presented in Table 1 and 2, provide a comprehensive evaluation of the performance of the proposed IBD-PCA technique, conventional PCA, and eigenfaces algorithms using the Rank-1 and Rank-5 evaluation criteria.

Table 1. Rank-1 matching accuracies (%) for PCA, Eigenfaces, and Proposed IBD-PCA method.

Method/dataset	ORL Face Database	Yale Face Database
PCA	49%	75.15%
Eigenfaces	91.94%	75%
IBD-PCA	**99.25%**	**75.33%**

Table 2. Rank-5 matching accuracies (%) for PCA, Eigenfaces, and Proposed IBD-PCA method.

Method/dataset	ORL Face Database	Yale Face Database
PCA	70.75%	87.27%
Eigenfaces	97.78%	81.82%
IBD-PCA	**100%**	**85.33%**

In this study, the performance of three face recognition methods: PCA, Eigenfaces, and the proposed IBD-PCA method, using the ORL Face Database and Yale Face Database was evaluated. The Rank 1 and Rank 5 accuracy results were used as performance metrics to assess the effectiveness of these methods.

For the ORL Face Database, the PCA method achieved a Rank 1 accuracy of 49% and a Rank 5 accuracy of 70.75%. This indicates that while PCA captures some discriminative facial features, it struggles to provide precise identification, resulting in relatively low accuracy. In comparison, Eigenfaces achieved a significantly higher Rank 1 accuracy of 91.94% but a slightly lower Rank 5 accuracy of 81.82%. This suggests that Eigenfaces excel in accurately recognizing the most similar face images but exhibit challenges in distinguishing among more dissimilar faces.

Remarkably, the proposed IBD-PCA method outperformed both PCA and Eigenfaces, achieving a remarkable Rank 1 accuracy of 99.25% and a Rank 5 accuracy of 100% on the ORL Face Database. These results demonstrate the effectiveness of the IBD-PCA approach in capturing fine-grained facial variations and enabling highly accurate identification. By utilizing image band-distributive generation based on pixel intensity and incorporating PCA, the proposed method effectively leverages the complementary information contained in the images, resulting in superior performance.

Moving to the Yale Face Database, the comparative analysis yields interesting insights. The PCA method exhibited an improved Rank 1 accuracy of 75.15% and a Rank 5 accuracy of 87.27%. This indicates that the performance of PCA-based methods can vary depending on the complexity of the dataset. Eigenfaces achieved a Rank 1 accuracy of 75% and a Rank 5 accuracy of 81.82%, demonstrating competitive performance. Notably, the proposed IBD-PCA method showcased a promising Rank 1 accuracy of 75.33% and a Rank 5 accuracy of 85.33%. These results underscore the robustness and efficacy of the IBD-PCA approach in handling diverse facial variations, despite the challenges posed by the dataset.

Overall, the findings highlight the limitations of traditional PCA-based methods and the potential of the proposed IBD-PCA approach. By incorporating image band-distributive generation and leveraging the power of PCA, IBD-PCA method exhibits superior performance in face recognition tasks, particularly in achieving highly accurate identification even in complex datasets. These results contribute to the advancement of PCA-based methods and provide valuable insights for researchers and practitioners in the field of face recognition.

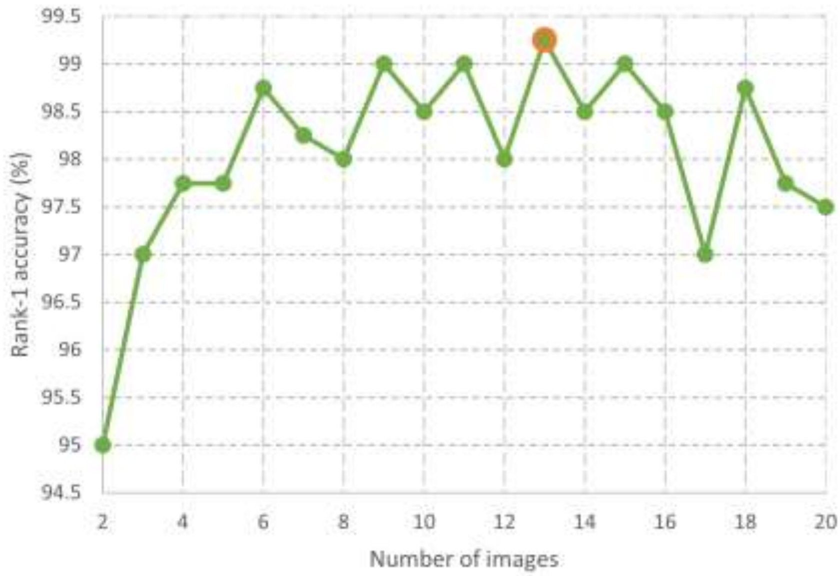

Figure 4. Rank-1 matching accuracies (%) for PCA, Eigenfaces, and Proposed IBD-PCA method.

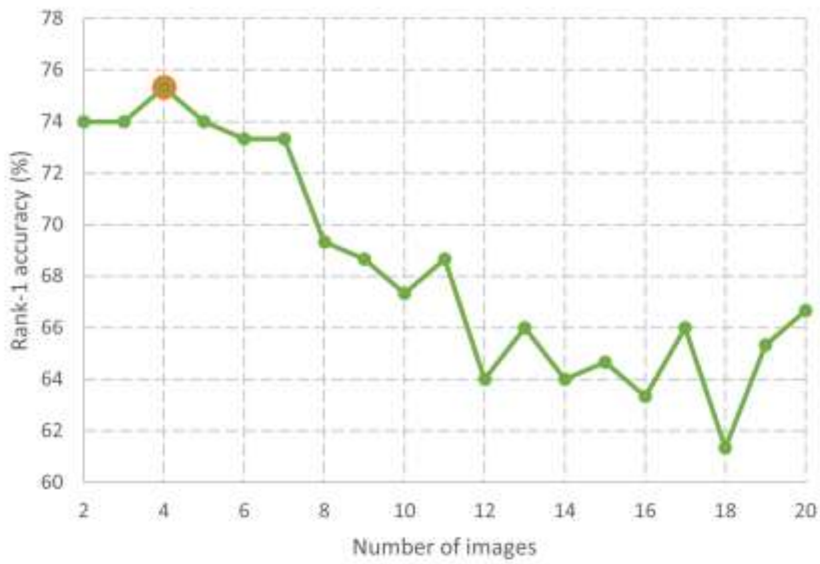

Figure 5. Rank-1 matching accuracies (%) for PCA, Eigenfaces, and Proposed IBD-PCA method.

4. Conclusion

In this paper, an Image Band-Distributive PCA (IBD-PCA) based method for face recognition was presented. With a face image as input, the proposed algorithm first performs histogram equalization on the image, it then generates multiple images from the resulting histogram-equalized image using the equal-size boundary selection method. The eigenvectors of the resulting images are then extracted by applying standard PCA, and the resulting eigenvectors were then used for feature matching.

The experimental results obtained from comparing the proposed IBD-PCA method with PCA and eigenfaces methods using ORL Face database and Yale Face Database show that the proposed method is superior and outperforms other techniques, giving improved matching accuracy.

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