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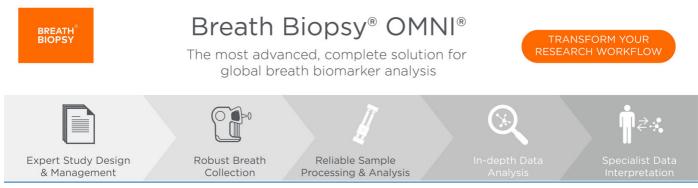
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A Study about Principle Component Analysis and Eigenface for Facial Extraction

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Abstract. Facial recognition is one of the most successful applications of image analysis and understanding. This paper presents a Principal Component Analysis (PCA) and eigenface method for facial feature extraction. Several performance metrics, i.e. accuracy, precision, and recall are taken into account as a baseline of experiment. Furthermore, two public data sets, namely SOF (Speech on faces) and MIT CBCL Facerec are incorporated in the experiment. Based on our experimental result, it can be revealed that PCA has performed well in terms of accuracy, precision, and recall metrics by 0.598, 0.63, and 0.598, respectively.

1. Introduction

Facial recognition has become a favored subject in computer vision and one of the most successful applications of image analysis and understanding. Since a set of eigenfaces can be updated or recalculated, not only computer science researchers are interested on this field. The goal of applying a system model to some faces differentiate it from many faces stored with some real time variations, thus providing an efficient way to find a lower dimension space. Furthermore, this algorithm is able to extend to recognize the gender of the person or interpret the expression of a person's face [1], [2],[3].

A face recognition system usually possesses four main parts, i.e. face detection, face alignment, feature extraction, and recognition process [4]. In the past few years, many researchers have been working on solving several problems related with face recognition, yet some issues are still unresolved. For instance, different lighting on scenery, facial pose change, recognition of facial recognition, and facial expressions are some of the issues that must be taken into consideration earnestly [5]. The eigenfaces method can change any face image to vector. Some of the tested facial images are transformed into vector representations, after which they are used to find a vector image that is stored and closest to a testing vector, so that the face can be recognized [6].

Facial extraction in face recognition requires large computational cost because of complex calculation. Face features reduce memory in symbolic feature computation time, for example color and intensity in numerical terms. Features in the image are usually not directly related with the part of the image. The feature is an extraction algorithm on face images. Feature extraction provides a set of features in the classification process, reduces input data, minimizes redundancy, and produces dimensional representations [7][8].

A set of eigenfaces is derived from most of the eigenvectors because there is a decomposition process in the covariance matrix of face images that are converted to vector. A collection of eigenfaces form a face representation space on a smaller dimension than a face image. Normalized inter-facial relationships can be represented by covariance matrices. Covariance of the matrix can produce an eigenvector by decomposing its eigen vector. The principle component analysis (PCA) is used to simplify data with linear transformations and then forming new coordinates with maximum variation. PCA consists of a

collection of eigenface vectors. It calculates the covariance matrix from several parts in a set of training face images [9].

The rest of the paper is structured as follows. Section 2 briefly discusses facial extraction process, whilst Section 3 provides an overview of eigenfaces and principle component analysis. Section 4 presents the experimental result and discussion. Finally, the paper is summarized in Section 5.

2. Facial Extraction Process

Many of the proposed facial detection methods have realized that faces and backgrounds are considered as constraints, which make the proposed method cannot be applicable for common cases. This is why face detection remains an unresolved issue. There are many methods are available in this field. Many proposed methods are available to identify and recognize the shape of the human face given in a database. A feature extraction performs the required features in an image that is detected and represented at an advanced level. It is the most critical step in most computer vision and image processing as it is able to mark the form of representative data transition from pictorial to non-pictorial [10], [11], [12].

The PCA method is used as it is good in constructing facial recognition systems. It allows for a system to extract facial features more efficiently and more appropriately, by narrowing the face distance to face detection, and the ability of the face detection method cannot be lower [4]. One of the simplest and most effective PCA approaches used in facial recognition systems is also called the eigenface approach. This approach transforms the face into a small series of core characteristics, eigenface, which are the principal components of the initial train image series [13].

3. Eigenface and Principle Component Analysis: An Overview

3.1. Eigenface

The use of eigenface provides an advantage in improving the face recognition process since it generates facial patterns from face data sets, that is able to significantly reduce the dimensions of the input image. The training image is then represented by a combined vector. Next, an eigenvector extraction is performed and stored. The training image is then projected on the facial feature space based on its eigenvector. Parameters used in feature extraction eigenface include average image value (Eq.1), covariance matrix (Eq.2), mean image value (Eq.3), eigenvalue and eigenvector (Eq.4). The following is the process of calculating feature extraction parameters:

• Calculation of average image value.

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma^i \tag{1}$$

where Γ^i is image vector, whilst *M* is number of sample image.

• Calculation of covariant matrices.

$$C = A^T A \tag{2}$$

where $A = \{ \Phi_1, \Phi_2, ..., \Phi_M \}$

• Subtract all of the image vector by average image value.

$$\Phi_i = \Gamma^i - \Psi \tag{3}$$

• Calculation of eigenvalue and eigenvector.

$$A^{T}AX_{i} = \lambda_{i}X_{i} \tag{4}$$

where λ_i and X_i is eigen value and eigen vector, respectively.

Eigenface flowchart shown below to explain the flow of the process form the Eigenface method. Eigenface method for feature extraction process can be seen as Figure 1 below, the method consist of some processes including subtraction, covariant, projection, and so on.

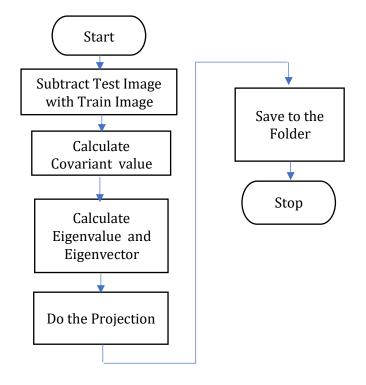


Figure 1. The steps involved in eigenface method

3.2. Principal Component Analysis

A principal component analysis (PCA) is used to simplify data by transforming linearly and forming new coordinates with maximum variation. It is a collection of vectors from eigenface. In addition, it calculates the covariance matrix from several parts of a collection of training face images [14]. The ability to extract this feature can be used to recognize facial images. 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. It gives us efficient way to find the lower dimensional space. Further this algorithm can be extended to recognize the gender of a person or to interpret the facial expression of a person. The ability to extract this feature can be used to recognize facial images. The advantage of this approach over other face recognition systems is in its simplicity, speed and insensitivity to small or gradual changes on the face. The problem is limited to files that can be used to recognize the face. Namely, the images must be vertical frontal views of human faces. PCA flowchart for feature extraction process can be seen as Figure 2.

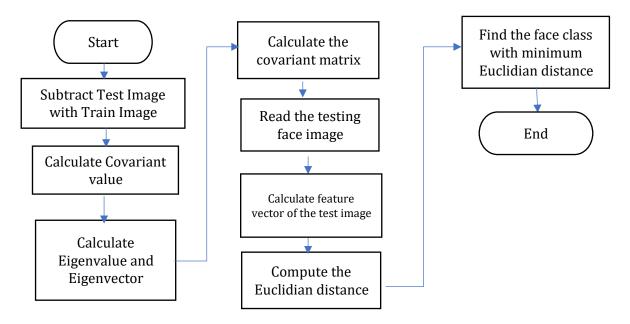


Figure 2. The Flowchart of PCA

4. Experimental Result

In the learning phase, there are several processes, i.e. preprocessing, feature extraction with PCA, and finally store the captured data into a database. Subsequently, in recognition phase, the system performs the main steps, i.e. image detection, face detection, and feature extraction. Result of facial recognition experiment using PCA and eigenface is determined by calculating accuracy, recall, and precision metrics as follows [15].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$
(5)

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$Precision = \frac{IP}{TP + FP} \tag{7}$$

By using the above-mentioned equations, the obtained result is presented in Table 1 and Figure 3. From the experimental results, it is obvious that the proposed method has lower accuracy than the prior works. It is assumed that it is happened because of the constraints in the face detection algorithm used in the *Opencv* library used in our experiment. Examples of such constraints are the detection of objects that are not faces but are recognized as faces (false positives is quite high). In the future work, we will put our attention to improve the detection performance using other techniques, i.e. convolutional neural network (CNN).



Figure 3. The result of eigenface method

Table 1. The results of recall, precision, and accuracy calculations for face database

	TP	TN	FP	FN	Recall	Precision	Accuracy
PCA	7.3	6.6	2.7	3.4	0.598	0.63	0.595

5. Conclusion

This paper implemented a facial recognition system with PCA and eigenface approach. A principle component analysis on facial recognition problems is studied and facial recognition based eigenface technique was proposed. The test is performed on PNG image and JPEG images, which gave a good facial classification even though it possessed constrain on varying image sizes. The eigenface approach provided a highly practical solution to facial recognition problems. For future work, we will further extend this study on the performance of convolutional neural network (CNN) for image classification.

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