Image Processing Based Smart System

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Abstract— 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. Using eigenfaces is very fast, and able to functionally operate on lots of faces in very little time. Unfortunately, this type of facial recognition does have a drawback to consider: trouble recognizing faces when they are viewed with different levels of light or angles. For the system to work well, the faces need to be seen from a frontal view under similar lighting. Face recognition using eigenfaces has been shown to be quite accurate. By experimenting with the system to test it under variations of certain conditions, the following correct recognitions were found: an average of 96% with light variation, 85% with orientation variation, and 64% with size variation.

I. Introduction

Eigenfaces:

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. The approach of using eigenfaces for recognition was developed by Sirovich and Kirby (1987) and used by Matthew Turk and Alex Pentland in face classification. It is considered the first successful example of facial recognition technology. These eigenvectors are derived from the covariance matrix of the probability distribution of the high-dimensional vector space of *possible faces of human beings*.

A. Eigenface generation

To generate a **set of eigenfaces**, a large set of digitized images of human faces, taken under the same lighting conditions, are normalized to line up the eyes and mouths. They are then all resample at the same pixel resolution. Eigenfaces can be extracted out of the image data by means of a mathematical tool called principal component analysis (PCA). Here are the steps involved in converting an image of a face into eigenfaces:

1. Prepare a training set. The faces constituting the training set **T** should be already prepared for processing.
2. Subtract the mean. The average matrix **A** has to be calculated and subtracted from the original in **T**. The results are stored in variable **S**.
3. Calculate the covariance matrix.
4. Calculate the eigenvectors and eigenvalues of this covariance matrix.
5. Choose the principal components.

There will be a large number of eigenfaces created before step 5, and far fewer are really needed. Select from them those that have the highest eigenvalues. For instance, if we are working with a 100 x 100 image, then this system will create 10,000 eigenvectors. Since most individuals can be identified using a database with a size between 100 and 150, most of the 10,000 can be discarded, and only the most important should remain.

The eigenfaces that are created will appear as light and dark areas that are arranged in a specific pattern. This pattern is how different features of a face are singled out to be evaluated and scored. There will be a pattern to evaluate symmetry, if there is any style of facial hair, where the hairline is, or evaluate the size of the nose or mouth. Other eigenfaces have patterns that are less simple to identify, and the image of the eigenface may look very little like a face.

The technique used in creating eigenfaces and using them for recognition is also used outside of facial recognition. This technique is also used for handwriting analysis, lip reading, voice recognition, sign language/hand gestures and medical imaging. Therefore, some do not use the term eigenface, but prefer to use 'eigenimage'. Research that applies similar eigen techniques to sign language images has also been made.

II USE IN FACIAL RECOGNITION

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. Using eigenfaces is very fast, and able to functionally operate on lots of faces in very little time. Unfortunately, this type of facial recognition does have a drawback to consider: trouble recognizing faces when they are viewed with different levels of light or angles. For the system to work well, the faces need to be seen from a frontal view under similar lighting. Face recognition using eigenfaces has been shown to be quite accurate. By experimenting with the system to test it under variations of certain conditions, the following correct recognitions were found: an average of 96% with light variation, 85% with orientation variation, and 64% with size variation.

III PRINCIPAL COMPONENT ANALYSIS:

Principal component analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis.

PCA was invented in 1901 by Karl Pearson. PCA involves the calculation of the eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA supplies the user with a lower-dimensional picture, a "shadow" of this object when viewed from it's (in some sense) most informative viewpoint.

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for a given data in least square terms.

PCA can be used for dimensionality reduction in a data set by retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data. However, depending on the application this may not always be the case.

➢ Application of PCA

- Face recognition
- Image processing
- Artificial intelligence (neural network)

➢ Properties and Limitations of PCA

PCA is theoretically the optimal linear scheme, in terms of least mean square error, for compressing a set of high dimensional vectors into a set of lower dimensional vectors and then reconstructing the original set. It is a non-parametric analysis and the answer is unique and independent of any hypothesis about data probability distribution. However, the latter two properties are regarded as weakness as well as strength, in that being non-parametric, no prior knowledge can be incorporated and that PCA compressions often incur loss of information.

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The applicability of PCA is limited by the assumptions made in its derivation. These assumptions are:

- Assumption on Linearity

We assumed the observed data set to be linear combinations of certain basis. Non-linear methods such as kernel PCA have been developed without assuming linearity.

- Assumption on the statistical importance of mean and covariance

PCA uses the eigenvectors of the covariance matrix and it only finds the independent axes of the data under the Gaussian assumption. For non-Gaussian or multi-modal Gaussian data, PCA simply de-correlates the axes. When PCA is used for clustering, its main limitation is that it does not account for class separability since it makes no use of the class label of the feature vector. There is no guarantee that the directions of maximum variance will contain good features for discrimination.

- Assumption that large variances have important dynamics

PCA simply performs a coordinate rotation that aligns the transformed axes with the directions of maximum variance. It is only when we believe that the observed data has a high signal-to-noise ratio that the principal components with larger variance correspond to interesting dynamics and lower ones correspond to noise.Essentially, PCA involves only rotation and scaling. The above assumptions are made in order to simplify the algebraic computation on the data set. Some other methods have been developed without one or more of these assumptions; these are briefly described below.

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