View-Based and Modular Eigenspaces for Face Recognition

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Abstract: ***In this work we describe experiments with eigen-faces for recognition and interactive search in a large-scale face database. Accurate visual recognition is demonstrated using a database of O(103) faces. The problem of recognition under general viewing orientation is also examined. A view-based multiple-observer eigenspace technique is proposed for use in face recognition under variable pose. In addition, a modular eigenspace description technique is used which incorporates salient features such as the eyes, nose and mouth, in an eigenfeature layer. This modular representation yields higher recognition rates as well as a more robust framework for face recognition. An automatic feature extraction technique using feature eigen templates is also demonstrated.***

Keywords: h/w requirement, s/w requirement

1. Introduction

In recent years considerable progress has been made on the problems of face detection and recognition, with controlled illumination and scale. The best results have been obtained for 2-D, view-based techniques based on either template matching (e.g., [1], [2]), or matching using eigenfaces," i.e. template matching using the Karhunen-Loeve transformation of a set of face pictures (e.g., [10, 11,5]).For real-world applications, we must be able to reliably discriminate among thousands of individuals. Moreover, the problem of recognizing a human face from a general view remains largely unsolved, because transformations such as position, orientation, scale, and illumination cause the face's appearance to vary substantially. It is therefore important to ask if we can extend these successful 2-D, view-based recognition approaches to large databases with more general viewing conditions. In this paper we explore how the eigenface technique of Turk and Pentland [11] scales when applied to much larger recognition problems. We then generalize the approach to view-based and modular eigenspaces for detection and recognition. The view-based formulation allows for recognition under varying head orientations and the modular description allows for the incorporation of important facial features such as eyes, nose and mouth. The general applicability of eigenvector decomposition methods for appearance-based 3D object recognition has recently been convincingly demonstrated by Murase and Nayar [7].

1.1 Biometrics

Biometrics is used in the process of authentication of a person by verifying or Identifying that a user requesting a network resource is who he, she, or it claims to be, and vice versa. It uses the property that a human trait associated with a Person itself like structure of finger , faces details etc. By comparing the existing data with the incoming data we can verify the identity of a particular person.

There are many types of biometric system like fingerprint recognition, face detection and recognition, iris recognition etc., these traits are used for human identification in surveillance system, criminal identification. Advantages of using these traits for identification are that they cannot be forgotten or lost. These are unique features of a human being which is being used widely [1].

2.2 Face Recognition

Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching identification of a human being is traced. Facial features are extracted and implemented through algorithms which are efficient and some modifications are done to improve the existing algorithm models.

2. Eigen Face Approach

The Eigen faces are Principal Components of a distribution of faces, or equivalently, the Eigen vectors of the covariance matrix of the set of the face images, where an image with N by N pixels is considered a point in N2 dimensional space. Previous work on face recognition ignored the issue of face stimulus, assuming that predefined measurement were relevant and sufficient. This suggests that coding and decoding of face images may give information of face images emphasizing the significance of features. These features may or may not be related to facial features such as eyes, nose, lips and hairs. We want to extract the relevant information in a face image, encode it efficiently and compare one face encoding with a database of faces encoded similarly. A simple approach to extracting the information content in an image of a face is to somehow capture the variation in a collection of face images. The number of possible Eigen faces is equal to the number of face image in the training set. The faces can also be approximated by using best Eigen face, those that have the largest Eigen values, and which therefore account for most variance between the set of face images. The primary reason for using fewer Eigen faces is computational efficiency.

3. General Viewing Geometries

There are two ways of approaching the problem of face recognition under general viewing conditions. Given N individuals under M different views, one can do recognition and pose estimation in a universal eigenspace computed from the combination of NM images. In this way a single parametric eigenspace" will encode both identity as well as viewing conditions. Such an approach, for example, has recently been used by Murase and Nayar [7] for general 3D object recognition. An alternative formulation is to build a view-based set of M separate eigenspaces, each capturing the variation of the N individuals in a common view. The view-based eigenspace is essentially an extension of the eigenface technique to multiple sets of eigenvectors, one for each combination of scale and orientation. One can view this architecture as a set of parallel observers each trying to explain the image data with their set of eigenvectors (see also Darrell and Pentland [3].)

In this view-based, multiple-observer approach, the first step is to determine the location and orientation of the target object by selecting the eigenspace which best describes the input image. This is accomplished by calculating the residual description error (the distance-from-face-space metric [11]) using each viewspace's eigenvectors. Once the proper viewspace is determined, the image is encoded using the eigenvectors of that viewspace, and then recognized.

3.1 View based vs parametric methods

The main advantage of the parametric eigenspace method is its simplicity. The encoding of an input image using n eigenvectors requires only n projections. In the view-based method, M different sets of n projections are required, one for each view. However, this does not imply that a factor of M times more computation is necessarily required. By progressively calculating the eigenvector coefficients while pruning alternative viewspaces, the cost of using M eigenspaces can be greatly reduced.

The key difference between the view-based and parametric representations can be understood by considering the geometry of facespace. In the high-dimensional vector space of an input image, multiple-orientation training images are represented by a set of M distinct regions, each defined by the scatter of N individuals. Multiple views of a face form non-convex (yet connected) regions in image space [1]. Therefore the resulting ensemble is a highly complex and non-separable manifold. The parametric eigenspace attempts to describe this ensemble with a projection onto a single low-dimensional linear subspace (corresponding to the first n eigenvectors of the NM training images). In contrast, the view-based approach corresponds to M independent subspaces, each describing a particular region of the facespace (corresponding to a particular view of a face). The relevant analogy here is that of modeling a complex distribution by a single cluster model or by the union of several component clusters. Naturally, the latter (view-based) representation can yield a more accurate representation of the underlying geometry.

4. Recognition Performance

We have evaluated both the view-based and parametric techniques with data similar to that shown in This data consists of 189 images consisting of nine views of 21 people. The nine views of each person were evenly spaced from -900 to +900 along the horizontal plane. Data were provided by Westinghouse Electronic Systems. Our experimental results show a slightly superior performance obtained with the view-based method. Two different testing methodologies were used to judge the relative performance of the parametric and view-based eigenspace methods. In the first series of experiments the interpolation performance was tested by training on a subset of the available views and testing on the intermediate views. The average recognition rates obtained were 90% for the view-based and 88% for the parametric eigenspace methods. A second series of experiments tested the extrapolation performance by training on a range of views (e.g., -90to +45) and testing on novel views outside the training range (e.g., +68 and +90). For testing views separated by +230 and -230 from the training range, the average recognition rates were 83% for the view-based and 78% for the parametric eigenspace method. For +450 and -450 testing views, the average recognition rates were 50% (view-based) and 43%(parametric).

Figure 1: Some of the images used to test accuracy at face recognition despite wide variations in head orientation. Average recognition accuracy was 92%, the orientation error had a standard deviation of 150

5. Eigen Features

The eigenface technique is easily extended to the description and coding of facial features, yielding eigeneyes, eigennoses and eigenmouths. Eye-movement studies indicate that these particular facial features represent important landmarks for taxation, especially in an attentive discrimination task [14]. Therefore we should expect an improvement in recognition performance by incorporating an additional layer of description in terms of facial features. This modularity in face description also has distinct advantages for face coding in teleconferencing. For example, a layered representation consisting of the face and eigenmouths has recently been implemented for low bit-rate transmission of visual telephony by Welsh and Shah[13].

6. Hardware and Software Requirement

Hardware and Software requirements are those which are essential to implement the working of this technique and these are:

6.1 Hardware Requirement

Microsoft Visual Studio is an integrated development environment (IDE) from Microsoft. It is used to develop computer programs for Microsoft Windows, as well as web sites, web applications and web services. Visual Studio uses Microsoft software development platforms such as Windows API, Windows Forms, Windows Presentation Foundation, Store and Microsoft Silverlight. It can produce both native code and managed code.

Minimum Requirements

- Computer that has a 1.6GHz or faster processor
- 1 GB (32 Bit) or 2 GB (64 Bit) RAM (Add 512 MB if running in a virtual machine)
- 3GB of available hard disk space
- 5400 RPM hard disk drive

DirectX 9 capable video card running at 1024 x 768 or higher-resolution display

- DVD-ROM Drive.

6.2 Software Requirement

The software required for Android development is free and readily available on the Web:

- Visual Studio 2010
- .NET FRAMEWORK 4

6.3 Research Design

“An Optimized and Smarter Face Recognition Using Eigen Visual Perception” is developed in C#, which mainly focuses on basic face recognition operations. It is a C# application written for biometric devices & systems, designed to help users to identify a person through its face. The software has 4 main modules.

- Face Detection and Available face
- Add Faces and Names
- Train Faces
- Display Information

Face Available and Detection: - Used to show the Available faces that are already exist.

Add Faces: - This option is used to create a new details of person in which we have to insert:

- Person Image
- Name Of Person
- Account Holders

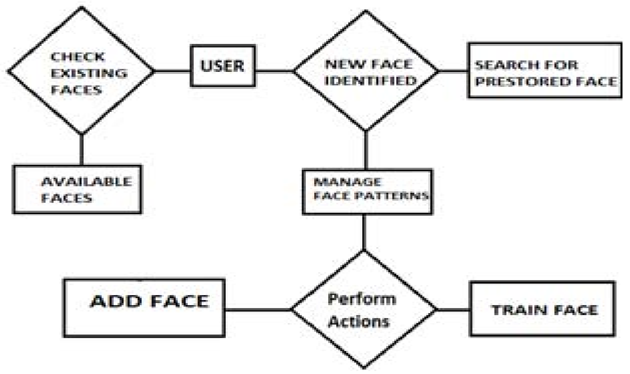
Train faces: - Option provided to store a Face Pattern based on Eigen values. It contains:-

- Face Patterns
- Mean Face

Display Information: - It provides the details of Person identified by its face and also provide its name.

7. System Design

7.1 ER Diagram



8. Purpose

This “an optimized and smarter face recognition Using Eigen visual perception” Test Report provides a summary of the results of test performed as outlined within this document. Testing is the practice of making objective judgments regarding the extent to which the system (device) meets, exceeds or fails to meet stated objectives.There are two fundamental purposes of testing: verifying procurement specifications and managing risk. First, testing is about verifying that what was specified is what was delivered: it verifies that the product (system) meets the functional, performance, design, and implementation requirements identified in the procurement specifications. Second, testing is about managing risk for both the acquiring agency and the system's vendor/developer/integrator. The testing program is used to identify when the work has-been “completed” so that the contract can be closed, the vendor paid, and the system shifted by the agency into the warranty and maintenance phase.

8.1 Test Summary

- Test Case1: Connect a Device
- Test Case2: Detect and Recognize
- Test Case3: Add a face
- Test Case4: Start Recognition

8.2 Test Result

- Program is compatible for the given OS.
- No Error Found.

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