**Facial Recognition Using Eigenfaces**

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**Abstract**

Facial recognition is a method of identifying a person based on a photograph of their face.  It is important for a number of reasons including forensics, surveillance, and security.  For example, facial recognition algorithms might be useful in order to identify particular people in crime investigations or it might provide quicker access to medical and/or criminal records.  Another important use of facial recognition software is for airport security and surveillance.  One such method of computer based facial recognition involves the use of eigenfaces.  Eigenfaces are sets of eigenvectors that are constructed out of a standard set of images of human faces. These can then be used to identify people by comparing a new photo of an individual and comparing it to the known photos that are in the original set. In this project, I will show how eigenfaces can be created by performing singular value decomposition on a set of images of human faces.  I will then provide a few examples to show how these eigenfaces can be used to identify both known and unknown individuals.

**Introduction**

The ability to identify and recognize objects – living or non-living – is a very important skill. Human beings in particular have an extraordinary capacity to remember and identify other people. It is remarkable that we are able to recognize people despite changes in appearance over the course of a lifetime. These changes might be deliberate such as changing hairstyles, growing facial hair or even wearing new sets of clothing. They also might be unintentional due to injury or age. Despite this though we are capable of remembering thousands of faces and are able to pick up on certain subtle features of an individual’s appearance in order to recognize them.

This leads us to wonder if we can gain some insight into how this process works by developing a mathematical model of facial recognition. There are many possible practical applications of facial recognition models today. For example, facial recognition software could be used in criminal investigations or as part of a security system. Airport security is one of particular concern today and these types of applications could be used to identify people on a no-fly list or could be used simply to accelerate the processing of individuals entering a country. Australia and New Zealand are already implementing an automated border processing system called SmartGate based entirely on facial recognition for Australian and New Zealand citizens ("SmartGate," n.d.). SmartGate takes a live picture of someone coming over the border and compares it to the picture stored in that individual’s digital passport and this makes the makes the process of entering the country much quicker ("SmartGate," n.d.). There are potential uses for it in social media as well as Facebook uses facial recognition software to suggest tagging friends in photos that an individual posts (Oswald, 2012). Facial recognition can also be used in advertisements and could be used as an ultimate customization to tailor an ad to a specific individual person (Li & Sarno, 2011).

Despite a wide range of applications it is difficult to develop a mathematical model for facial recognition because of the large variation among human faces. Just over the course of a lifetime an individual’s face undergoes constant and dramatic change whether due to age, injury, or intentional changes in appearance. In addition, human faces are multidimensional which makes the task of developing a mathematical model that much more difficult.

Other face models have attempted to interpret it as a geometric problem and have focused on detecting the common features of faces such as the eyes, ears, nose, and mouth. The relationships between these features are often described in terms of their size, distance from each other, and position on the face (Turk & Pentland, 1991). These models have had difficulty in being able to extend their findings to multiple views and have often had trouble in being able to account for the incredible variation among human faces (Turk & Pentland, 1991).

In this project, my goal is to develop a system that is able to quickly and accurately identify people. Before beginning, an original set of face images of different individuals must be collected. The main idea behind the mathematics of the eigenface approach is to extract the characteristic features from this original set of images and encode it in a small set of ghostly images that are called eigenfaces. These characteristic features can be thought of as the most important information across the original set of images. One advantage to this approach is that the characteristic features do not necessarily refer to facial features that humans tend to focus on such as the eyes, ears, nose or mouth. They simply represent stable elements within all images contained in the original set. Extracting the important information and representing it within the eigenfaces is an important step because it can then be used to quickly – because a small amount of eigenfaces are actually being used – and accurately – since the eigenfaces represent the characteristic features – identify people from a large database of images. Another advantage of this approach is that pictures of new people can be regularly added to the original set so the recognition process can be easily improved.

**Eigenface Approach**

First, a set of face images of different individuals must be collected. It is best if there are multiple images of the same people. For example, in my project, I took 4 pictures of 25 different people for a total of 100 images in my original set. Some example face images are shown in figure 1.

**Figure 1.** Six face images used in the original set.

  

  

The recognition procedure will then involve taking a new picture of an individual who is in the original set and then performing some calculations in order to identify the individual. It is important to clarify between known and unknown individuals in order to understand the project. When referring to a known individual, that means I am referring to a face image that is in my original set. What I mean by an unknown individual is a new face image of a known individual. This new face image is not in the original set, but other face images of that individual are. An image of an unknown individual is what we will use in the recognition process. We will use one more classification as well. Images of people who are not in the original set are completely unknown individuals. This method of facial recognition would not work well attempting to identify completely unknown individuals because there are no images in the original set for comparison.

As mentioned earlier, the main idea of the eigenface approach is to extract the characteristic features and encode them in such a way that allows for quick and accurate identification. In mathematical terms, I am looking for the eigenvectors of the covariance matrix. Covariance is simply a measure of how two random variables change together and a covariance matrix generalizes this measure to a large number of random variables. This covariance matrix measures the variability across all the face images in the original set. The eigenvectors that come out of the covariance matrix are the eigenfaces that represent the characteristic features. These eigenfaces can be ranked in order of importance by their eigenvalues. The higher an eigenface’s eigenvalue, the more useful it is in representing a face image from the original set. In practice, this allows us to throw out a relatively large number of eigenfaces and only use the most important ones so that most of the important information is preserved in a small number of eigenfaces. Each individual face image – known or unknown – can be represented in terms of a linear combination of the eigenfaces.

In order to find these eigenfaces, I used an approach utilizing a form of matrix factoring called Singular Value Decomposition (SVD). Let A be an matrix . Then A can be written as where U and V are orthogonal matrices and S is a diagonal matrix. The matrix U contains the eigenvectors of . The matrix V contains the eigenvectors of . The matrix S contains the singular values arranged on the main diagonal in order from largest to smallest. The singular values are the square roots of the eigenvalues of both and . In this project, singular value decomposition was performed on a particular matrix composed out of special column vectors which returned the eigenvectors of the covariance matrix. These eigenvectors are the eigenfaces which represent the characteristic features.

**The Eigenface Procedure**

The facial recognition procedure starts with collecting a set of face images. We need to obtain a set of images. All images are cropped to focus exclusively on the face, reshaped into pixels, and made black and white for manageable computations. In my case, 100 images (4 pictures of 25 different people) were taken and reshaped to be size pixels.

Now each pixel is represented by a number which determines the shade of that pixel. Since all the images are turned grayscale then there should be only one value per pixel. Now each face image can be thought of as a matrix where each element of that matrix represents the shade of color of the corresponding pixel. That matrix can be converted into a vector in dimensional space, or, in my case, a vector in dimensional space. Then the original set of face images is a set of vectors .

Now that we have collected our original set of face images and turned them into vectors, we begin our calculations. We must calculate the average face of the original set by performing the following calculation. Then and we must subtract the average face from each face image in the original set. Then for Figure 2 shows the average face () of the original set reshaped to a image.

**Figure 2.** The average face of the original set.



We then seek to find the eigenvectors, , of the covariance matrix (C) defined to be

where

Using singular value decomposition on the matrix , we were able to find the eigenvectors of . Now that we have the eigenvectors, we must explain how we are able to use only a small amount of these eigenvectors.

As mentioned previously, the eigenvectors of the covariance matrix represent the meaningful information of the original set of face images. Figure 3 shows the first 6 eigenfaces from our original set of images. The corresponding eigenvalues of allow us to order the eigenvectors according to how important they are in describing the variation among the original images. This allows us to actually use a small number of eigenfaces. Let’s say we are actually using only eigenfaces. In my case, despite a total of 100 eigenfaces, I only used 20 eigenfaces in the recognition procedure. This is an extremely important step because since we are only using a very small number of eigenfaces, this allows for much quicker calculations in the identification procedure.

Now that we have the eigenvectors from using singular value decomposition we can calculate the weights. Then for and The weights simply represent the contribution of each of the eigenfaces in representing the image. Now, we can form a vector using those weights. So ] for Finally, we can calculate the class vector by averaging all four of the weight vectors for each known individual.

**Figure 3.** The first 6 eigenfaces calculated from the original set.

  

  

**Recognition**

The goal of this project is for facial recognition. We want to be able to identify an unknown individual from an original set of images quickly and accurately. We need a method of taking an image of an unknown individual in order to perform some calculations and identify who that person is from our original set of images. We must then transform a new face image, , into its eigenface components. In other words, we need to calculate the weights of this new image by a calculation that we have seen previously. Then   where . We must again form a vector using those weights so that . We then seek to find the face class, , that minimizes the Euclidean distance. This tells how “close” the new face is to the known faces. This accomplished by performing the following calculation.

2

A face image is a member of a face class, , when the smallest is below some carefully chosen threshold . If a face does not belong to a face class then it is an image of an unknown person and can be added to the original database of images. This is one advantage to the eigenface approach because it allows for images to continually be added to the original set so the system can be improved relatively easily.

**Figure 3.** Four face images and their projections onto the eigenfaces. (a) is a picture of a known individual, (b) and (c) are of two unknown individuals and (d) is of a completely unknown individual.

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| 1. Known individual **Screen Clipping** **Screen Clipping** |
| 1. Unknown Individual Screen Clipping Screen Clipping |
| 1. Unknown Individual Screen Clipping Screen Clipping |
| 1. Completely Unknown Screen Clipping Screen Clipping |

**Future Work and Conclusions**

There are a number of problems that could be fixed in order to improve my results. The lighting should be the same in all of the original set of images as well as the orientation of each of the known individual’s faces. Facial expressions and characteristics such as smiling or glasses will often make computation much more difficult as well as the background of the images. It is important that the background is the same in all the images and blank as possible. It is also important that all images are centered and the results would be improved if it was possible to line up the known individual’s facial features. For example, if there was a way to line up all the known individuals’ eyes, noses, or mouths in the same position in each picture. Also, the quality of the photos taken as well as the total number of images could improve the results. Obviously, the larger our original set, the more accurate the facial recognition can be. One thing to note is that in many applications of facial recognition, taking a proper photo is difficult to do as there are a number of crucial features that must be kept constant in all of the images. In many such cases, this is extremely difficult or even impossible to do.

In conclusion, the goal of the eigenface approach was to develop a system to quickly and accurately identify unknown individuals. An original set of images of people was collected and we used singular value decomposition to find the eigenvalues and eigenvectors of the original set of images. These eigenvectors are the eigenfaces which represent the meaningful information across the original set of images.

The main idea behind the mathematics was to be able to extract the characteristic features of an original database of images. Since the characteristic features were encoded and condensed into a small number of eigenfaces, then we are able to throw away most of the eigenfaces and use only the most essential. We could then use the eigenfaces to identify images of unknown individuals quickly and accurately.

**References**

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