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A Novel Face Recognition Algorithm using PCA

Shravan Kumar Chandrasekaran
Amrita School of Engineering
Bangalore,

T Senthil Kumar
Amrita School of Engineering
Coimbatore,
Tamil Nadu 641 112

ABSTRACT
The PCA based face recognition algorithm has short-comings like sensitivity to illumination, facial expressions and importantly, not taking into consideration the high level features of the face among others. The discrete wavelet transformation of an image helps enhance the high frequency content and smoothen the lower frequencies. The primary objective of this paper is to present a generic algorithm which utilizes the advantages of the wavelet transformation complimenting it with base-line PCA.

General Terms
Face Recognition, PCA, Wavelets.

Keywords
Face Recognition, PCA, Wavelets.

1. INTRODUCTION
Face recognition is the process of recognizing/verifying a face given an image. There are two steps to do this;

- Detect a face in the image
- Recognize/verify the face using database

There are scores of algorithms that can be applied on an image to achieve these two steps. But each has its own down side. For one, many of these algorithms are computationally expensive and take a lot of time[1].

The human face poses more problems than any normal object. This is primarily because; the human face comes in many forms, textures, features and colors[2][3]. If we design an algorithm to detect a face, it has to be generic. It essentially needs to be one which is not constrained by the features of a human face.

The basic steps of face recognition however, can be described in the block diagram given below.

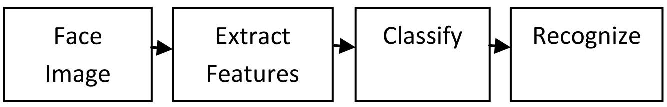

Fig. 1 Face Recognition Block Diagram

In this paper, one of the most popular algorithms; the Principle Component Analysis is suggested. It is analyzed with its performance using standard databases like the YALE face database and looked at ways to improve the algorithm. We then looked at Wavelets and how the properties of wavelets could complement the PCA and better it, in terms of accuracy

2. ALGORITHMS
2.1 *Face Detection with AdaBoost*
. Boosting is a powerful iterative procedure that builds efficient classifiers by selecting and combining very simple classifiers. Good theoretical results have been demonstrated, so we have some theoretical guarantees for achieving good detection rates. This idea is interesting in the sense that a combination of simple classifiers may intuitively give a rapid detection without deteriorating the detection rates. So it seems to be one of the best compromises between efficiency in term of detection and speed.

Consider a mono-stage classifier and given a set of features, a face detector is built by applying all the masks at each image location (each shift and each scale) .For this many different learning methods could be used. Moreover, there are a complete set of 37520 features[4] which is far larger than the number of pixels, so even if the features responses are very simple to compute (notably with the integral image representation), applying the all set of features would be too expensive, computationally. The next stage, in building an algorithm around this, is to use a learning function which selects a small set of these features: the ones which separate the best positive and negative examples. The resulting final classifier would be a simple linear combination of these few Haar-like features. AdaBoost (Adaptive Boosting), precisely does this. AdaBoost has two main goals:

- Selecting a few set of features which represents as well as possible faces.
- Train a strong final classifier with a linear combination of these best features.

This new method given by Viola is a combination of more traditional methods like geometrical and image based detection. It is a geometrical; in that it uses general features of human faces: position of particular features among which the eyes the nose and the mouth. On the other hand, it is also image based because it uses a statistical learning with the use of a consequent data set needed to build the face model. Viola has developed this face detector based on works of Papageorgious[8]. It seemed to be the fastest and the most robust algorithm for face detection. It still is. The speed of the detection is notably given by the simplicity of the features chosen and the good detection rates are obtained by the use of the fundamental boosting algorithm AdaBoost which selects the most representative feature in a large set. To have a concrete idea of the performances of the detection, Viola's detector can process 15 frames of 384x288 pixel images per second on a conventional 700 MHz Intel Pentium.[4]

The AdaBoost algorithm is used to capture the face area and select it out, for further processing.

2.2 *Principle Component Analysis*

The Principal Component Analysis (PCA) is a statistical method for reducing the dimensionality of the data set while retaining the majority of the variation present in the dataset. It is used for handling and analyzing data. And because it is a statistical decision, a PCA based face recognition system needs an algorithmic support structure. It is dependent on several decisions.

Each of these decisions affects the performance of the system on the whole. Using PCA we can;

- Represent a face effectively in an Eigen face space.
- Approximately reconstruct the face using few Eigen face vectors.

To achieve this, a face image is projected to several face templates which are a set of variations in the face. Once the set of Eigen faces are computed, a face image can be approximately reconstructed using weighted combinations of Eigen faces[4]. The projection weights form a feature vector for face representation and recognition. When a new test image is given the weights are computed by projecting the image onto the Eigen face vectors[5]. The classification is then carried out by comparing the distances between the weight vectors of the test image and the images from the database.

We start with the p dimensional feature vector and want to summarize them by projecting in a q dimensional subspace. Our summary would be the projection of the original vectors onto q directions which sum up the sub-space. The simplest way of deriving the principle components is by finding the projections which maximize the variance.[6][7] The first principle component is the direction in the feature space alo ng which projections have largest variance. The second one would be maximizing in all directions orthogonal to the first projection.

Each face in the database can be thought of as a point in space. This space can be called the Face space[8][9]. Now, as there would be many faces in the database, the number of points would be large. So, mapping would be very difficult. Hence we would do PCA and reduce the dimensions of the face space.[10][11][12] The inputs to the PCA would be the images in the database. We would then calculate those faces which can be used to best describe all the faces in the database by linear combination[13][14].

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2.3 *Discrete Wavelet Transformation*

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency *and* location information (location in time).

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by filtering operations, and the scale is determined by upsampling and downsampling operations.

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal. This is called Mallet algorithm[15]. Its significance is in the manner it connects continuous-time multiresolution to discrete-time filters. In the figure the signal is denoted by the sequence x(n), where n is an integer. The low pass filter is denoted by G while the high-pass filter is denoted by H. at each level, the high pass filter produces detail information, d(n), while the low pass filter associated with scaling function produces coarse approximations.

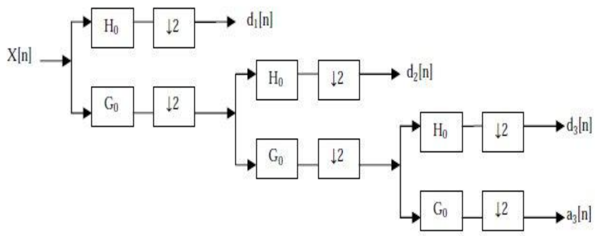

Fig. 2 Wavelet Decomposition

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in the frequency is reduced to half. Nyquist principle states that if the highest frequency of signal is 'w' then the minimum sampling frequency should be '2w'. But it then has the highest frequency of 'w/2'. It can now be sampled at the frequency of 'w' thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now

represented by only half of the frequencies and thus halves the resolution, the

decimation by 2 doubles the scale. With this, the time resolution becomes arbitrarily good at high frequencies and the frequency resolution becomes arbitrarily good at low frequencies. The DWT of the original signal is then obtained by concatenating all the coefficients starting from the last level.

Reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in decomposition process to obtain the original signal.

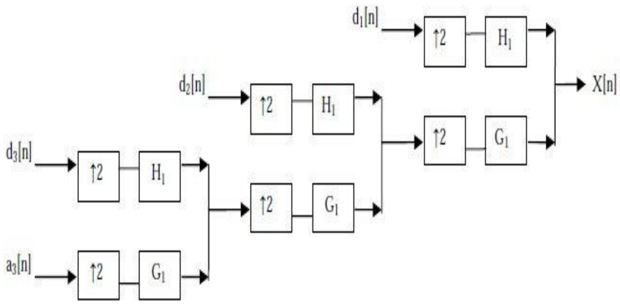

Fig. 3 Wavelet Recomposition

2.4 *DWT based Face Recognition using PCA*

While doing an image-based DWT, the original image is high-pass filtered, yielding the three large images, each describing local changes in brightness (details) in the original image. It is then low-pass filtered and downscaled, yielding an approximation image; this image is high-pass filtered to produce the three smaller detail images, and low-pass filtered to produce the final approximation image in the upper-left corner.[15][16]

The input image is decomposed into three-level wavelet frame tree. The first level of the tree contains the wavelet coefficient images A (approximation), H(horizontal), V (vertical) and D (diagonal). The next level is obtained from further decomposition of each node as AA, AH, AV, AD, HA, HH, HV, HD etc.[15][17][18]

Based on a large number of experiments, it has been noticed that the AHH band provides a stable signal for the eyes and mouth. The nose feature proved to be very unstable in all the wavelet bands. Hence we can conveniently say that the eyes and mouth feature can be extracted or enhanced from the AHH band.[19][20][21]

The DWT based PCA algorithm is a hybrid algorithm which uses the PCA to reduce the number of dimensions of the image, and at the same time appends a DWT of the initial image to the later to enhance the feature bits of the image.

We take an image from the database and run a PCA initially. We then take a Wavelet transformation of this image, isolate the AHH band and append the image to the PCA. Similarly, we build the entire database with these newer images.

As we get a fresh image to compare it with our database, we run it through the same algorithm. We then compare the euclidean distances between each image from the database and this image, and check if it is within an acceptable range.

3. RESULTS

For the purpose of testing the algorithm, it was run on the YALE and CMU face databases.

The Yale Face Database contains 165 grayscale images in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink.

The Yale Face Database consists of only frontal views and is monochromatic.

The CMU database consists of 41,368 images of 68 people, with each person under 13 different poses, 43 different illumination conditions and with 4 different expressions.

Only 15 individual persons were used from the CMU database to standardize the tests.

The following results were deduced. DWT was taken with Daubechies wavelet with N taken as 3. We could find that, the Daubechies series were particularly more effective than the rest.

Table 1. PCA v/s DWT based PCA Accuracy Table

Images in test Database	PCA	DWT based PCA
5	40%	40%
7	56%	60%
10	82%	85%

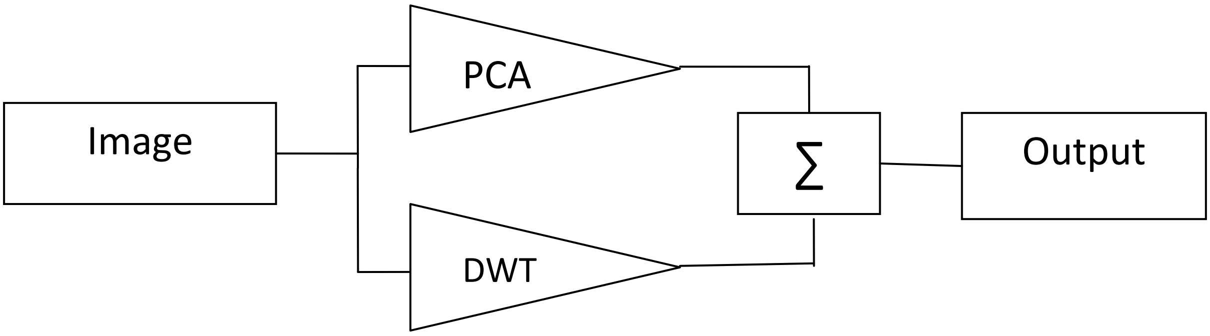

Figure 4: Block Diagram: Wavelet based PCA face recognition

4. CONCLUSION

There is notable improvement in the accuracy of recognition while we vary the coefficient of the weights applied on the DWT part of the image. Although the size of each image gets considerably larger, we could perhaps trade that, with better efficiency in recognition. The size of the image being greater would have a direct correlation with the size of the entire database. And this would ultimately have a cascading effect on the average time of recognition of an image and the memory the database would consume. But with faster and faster processors the time factor could be reduced. Also, with memory becoming cheaper and more easily available, the memory consumption problem could be alleviated\

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