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Feature Extraction for Face Recognition by using a Novel and Effective Color Boosting

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Abstract-This paper introduces the new color face recognition (FR) method that makes effective use of boosting learning as color-component feature selection framework. The proposed boosting color-component feature selection framework is designed for finding the best set of color-component features from various color spaces (or models), aiming to achieve the best FR performance for a given FR task. In addition, to facilitate the complementary effect of the selected color-component features for the purpose of color FR, they are combined using the proposed weighted feature fusion scheme. The effectiveness of my color FR method has been successfully evaluated on the following five public face databases (DBs): CMU-PIE, Color FERET, XM2VTSDB,SCface, and FRGC 2.0. Experimental results show that the results of the proposed method are impressively better than the results of other state-of-the-art color FR methods over different FR challenges including highly uncontrolled illumination, moderate pose variation, and small resolution face images.

Index Terms—Boosting learning, color face recognition, color space, color component, feature selection.

I. INTRODUCTION

RECENTLY, considerable research work in face recognition (FR) has shown that facial color information can be used to considerably improve FR performance, compared to the FR methods relying only on grayscale information. Most of the existing color FR methods are restricted to using a fixed color-component configuration comprising of only “two” or “three”[1] color components . In particular, currently used color-component choices are mostly made through a combination of intuition and empirical comparison without any systematic selection strategy. As such, existing methods may have a limitation to attaining the best FR result for given FR task. This is because specific color components effective for a particular FR problem could not work well for other FR problems under other FR operating conditions (e.g., illumination variations) that differ from those considered during the process of determining specific color components. A facial recognition system is a computer for automatically identifying or verifying a person from a digital image or a video frame from a video source.
One of the ways to do this is by comparing selected facial features from the image and a facial database. application It is typically used in security systems and can be compared to other biometrics such as fingerprint[2] or eye iris recognition systems.
The remaining of the paper is organized as follows. Section II describes feature extraction for face recognition within boosting learning framework.

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In particular, this section details the proposed selection criterion. In Section III, I explain the proposed modules for a FR purpose. Conclusions are presented in Section IV. In this paper, a multiclass boosting “Adaboost.M2” framework is adapted to implement color-component feature selection.

II. FEATURE EXTRACTION FOR FACE RECOGNITION

In this paper, a multiclass boosting “Adaboost.M2” framework is adapted to implement color-component feature selection. Differing from other boosting learning frame works, the key advantage of Adaboost.M2 framework is to force the weak learners to concentrate not only on the hard instances (or patterns), but also on the incorrect class labels that are hardest to classify.

Overall framework of the proposed color FR method which largely consists of two parts:1) color-component feature selection with boosting, 2) color FR solution using selected color component features.

To determine the best color component feature at each boosting round for recognizing the hard-to-classify sample subset of a training set, termed “learning set,” the effective selection criterion is proposed. The proposed selection criterion is in the form of penalty-based objective function with its associated weighting parameter for the purpose of selecting color-component features which not only produce small classification errors, but also keep their mutual dependence low. The proposed selection criterion is highly useful for achieving a low generalization classification error. In addition, to perform color FR, the color-component features chosen via our boosting framework are combined at the feature level. Specifically, selected color-component features are fused based on weighted feature fusion scheme depending upon the associated confidence of each color-component feature for achieving better FR performance.

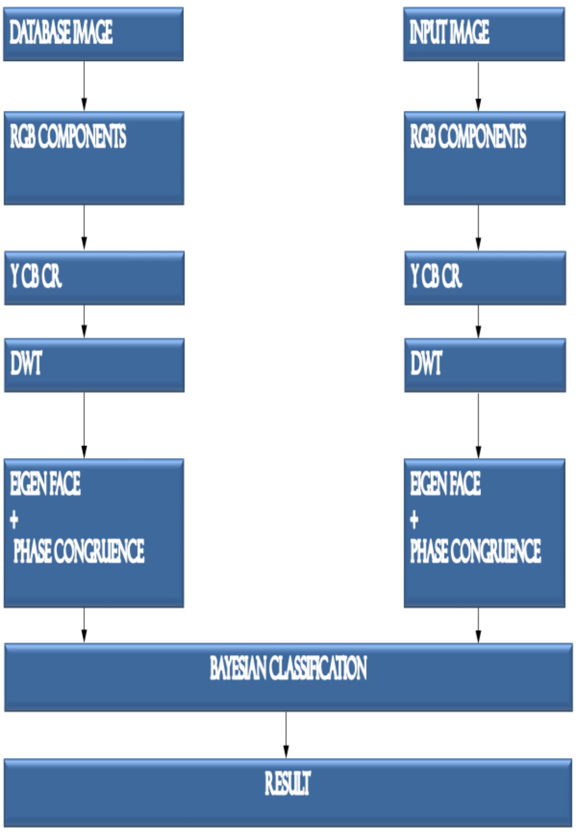
In order to evaluate the effectiveness of d extensive experiments have been carried out. For this, five public face databases (DB)CMU-PIE,FERET,XM2VTSDB,SCface,FRGC 2.0 are used.

A. Proposed Selection Criterion

At each boosting round, the best FR learner (i.e., the best color-component feature) should be determined from among constructed FR learners , each of which depends upon a single color-component feature. To this end, a selection criterion plays a crucial role in determining the “goodness”of feature selection. in ensemble classification (including boosting), it has been shown that, to achieve the lowest generalization error, we need to create ensembles (or classifiers) with low training classification error, while at the same time their mutual dependence should be kept minimal.

In particular, in our feature selection problem, mutual dependence between color-component features have to be carefully considered as different color channels may have similar properties from the view-point of classification. For instance, the and channels (from and color spaces, respectively) both encode the intensity information for green colors. To address the aforementioned issue, we develop an effective selection criterion which aims at making optimal balance between classification error and the degree of mutual dependence among selected FR learners.

B.System design



III. EXPERIMENTS

Most of the existing color FR methods are restricted to using a fixed color-component configuration comprising of only "two" or "three" color components. In particular, currently used color-component choices are mostly made through a combination of intuition and empirical comparison, without any systematic selection strategy. As such, existing methods may have a limitation to attaining the best FR result for given FR task. This is because specific color components effective for a particular FR problem could not work well for other FR problems under other FR operating conditions (e.g., illumination variations) that differ from those considered during the process of determining specific color components.

The existed color FR method which largely consists of two parts: 1) Color-component feature selection with boosting, 2) Color FR solution using selected color component features. We propose a new color FR method. Our method takes advantage of "boosting" learning as a feature selection mechanism, aiming to find the optimal set of color-component features for the purpose of achieving the best FR result with the help of DWT,Eigenface ,Face congruency.

To the best of our knowledge, our work is the first attempt to incorporate feature selection scheme underpinning boosting learning into FR methods using color information.

A. Discrete Wavelet Transform

The field of Discrete Wavelet Transforms (DWTs) is an amazingly recent one. The basic Principles of wavelet theory were put forth in a paper by Gabor in 1945 , but all of the definitive papers on discrete wavelets, an extinction of Gabor's theories involving functions with compact support, have been published in the past three years. Although the Discrete Wavelet Transform is merely one more tool added to the toolbox of digital signal processing, it is a very important concept for data compression. Its utility in image compression has been electively demonstrated. This paper discusses the DWT and demonstrates one way in which it can be implemented as a real-time signal processing system. Although this paper will attempt to describe a very general implementation, the actual project used the STAR Semiconductor SPROC lab digital signal processing system.

A wavelet, in the sense of the Discrete Wavelet Transform (or DWT), is an orthogonal function which can be applied to a finite group of data. Functionally, it is very much like the Discrete Fourier Transform, in that the transforming function is orthogonal, a signal passed twice through the transformation is unchanged, and the input signal is assumed to be a set of discrete-time samples. Both transforms are convolutions. Whereas the basis function of the Fourier transform is a sinusoid, the wavelet basis is a set of functions which are defined by a recursive difference equation,

$$\Phi(x)=\sum_{k=0}^{M-1} c_k\,\Phi(2x-k) \qquad (1)$$

Where the range of the summation is determined by the specified number of nonzero coefficients M. The number of nonzero coefficients is arbitrary, and will be referred to as the order of the wavelet. The value of the coefficients is, of course, not arbitrary, but is determined by constraints of orthogonality and normalization. A good way to solve for values of equation (1) is to construct a matrix of coefficient values. This is a square M x XI matrix where M is the number of nonzero coefficients. The matrix is designated L, with entries .This matrix always has an eigen value equal to 1, and its corresponding (normalized) eigen vector contains, as its components, the value of the <f> function at integer values of x. Once these values are known, all other values of the function <f>(x) can be generated by applying the recursion equation to get values at half integer x, quarter-integer x, and so on down to the desired dilation. This effectively determines the accuracy of the function approximation.

B. Phase Congruency

Phase congruency is a measure of feature significance in computer images, a method of edge detection that is particularly robust against changes in illumination and contrast.

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Phase congruency reflects the behaviour of the image in the frequency domain.

It has been noted that edge like features have many of their frequency components in the same phase. The concept is similar to coherence, except that it applies to functions of different wavelength.

Congruency of phase at any angle produces a clearly perceived feature . The angle at which the congruency occurs dictates the feature type, for example, step or delta. The Local Energy Model was developed by Morrone et al and Morrone and Owens. The local, complex valued, Fourier components at a location x in the signal will each have an amplitude An(x) and a phase angle Án(x). The magnitude of the vector from the origin to the end point is the Local Energy, jE(x)j. The measure of phase congruency developed by Morrone et al is

$$PC_1(\mathrm{x})=\frac{|E(X)|}{\sum_n A_{n(x)}}$$

Under this definition phase congruency is the ratio of jE(x)j to the overall path length taken by the local Fourier components in reaching the end point. If all the Fourier components are in phase all the complex vectors would be aligned and the ratio of jE(x)j=Pn An(x) would be 1. If there is no coherence of phase

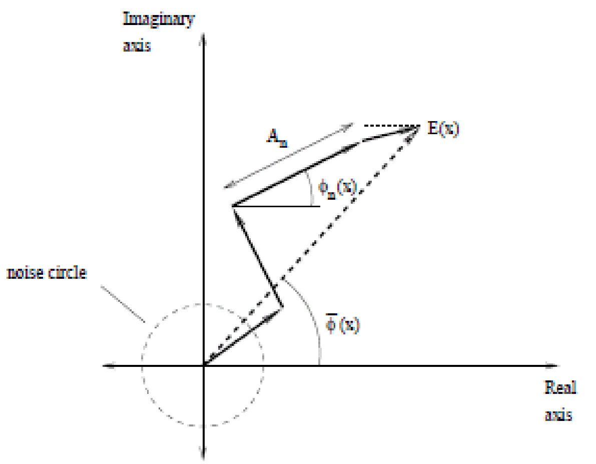

Figure 1: Polar diagram

Polar diagram showing the Fourier components at a location in the signal plotted head to tail. The weighted mean phase angle is given by A(x). The noise circle represents the level of E(x) one can expect just from the noise in the signal.The ratio falls to a minimum of 0. Phase congruency provides a measure that is independent of the overall magnitude of the signal making it invariant to variations in image illumination and/or contrast. Fixed threshold values of feature significance can then be used over wide classes of images.

The measure of phase congruency does not provide good localization and it is also sensitive to noise. Kovesi developed a modified measure consisting of the cosine minus the magnitude of the sine of the phase deviation; this produces a more localized response. This new measure also incorporates noise compensation.A small constant is incorporated to avoid division by zero. Only energy values that exceed T, the estimated noise influence, are counted in the result. The symbols b c denotes that the enclosed quantity is equal to itself when its value is positive, and zero otherwise.

The appropriate noise threshold, T is readily determined from the statistics of the filter responses to the image. Phase congruency is a measure of feature significance in computer images, a method of edge detection that is particularly robust against changes in illumination and contrast.

C. Eigen face

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. A set of eigenfaces can be generated by performing a mathematical process called principal component analysis (PCA) on a large set of images depicting different human faces. Informally, eigenfaces can be considered a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. For example, one's face might be composed of the average face plus 10% from eigenface 1, 55% from eigenface 2, and even -3% from eigenface 3. Remarkably, it does not take many eigenfaces combined together to achieve a fair approximation of most faces. Also, because a person's face is not recorded by adigital photograph, but instead as just a list of values (one value for each eigenface in the database used), much less space is taken for each person's face.

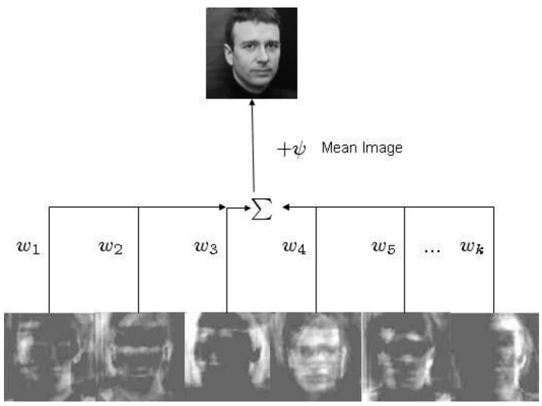

Fig 2. Eigen face reconstruction

To create a set of eigenfaces, one must:

Prepare a training set of face images. The pictures constituting the training set should have been taken under the same lighting conditions, and must be normalized to have the eyes and mouths aligned across all images. They must also be all resampled to a common pixel resolution (r × c). Each image is treated as one vector, simply by concatenating the rows of pixels in the original image, resulting in a single row with r × c elements. For this implementation, it is assumed that all images of the training set are stored in a single matrix T, where each row of the matrix is an image.Subtract the mean.

The average image a has to be calculated and then subtracted from each original image in T. Calculate the eigenvectors and eigenvalues of the covariance matrix S.

Each eigenvector has the same dimensionality (number of components) as the original images, and thus can itself be seen as an image.

The eigenvectors of this covariance matrix are therefore called eigenfaces. They are the directions in which the images differ from the mean image. Usually this will be a computationally expensive step (if at all possible), but the practical applicability of eigenfaces stems from the possibility to compute the eigenvectors of S efficiently, without ever computing S explicitly, as detailed below. Choose the principal components. The D x D covariance matrix will result in D eigenvectors, each representing a direction in the r × c-dimensional image space.

IV. CONCLUSION

In this paper, a novel and effective color FR method is proposed. It is based on the selection of the best color-component features (from various color models) using the proposed variant of boosting learning framework by discrete wavelet transform , Phase Congruency and eigen face. These selected color component features are then combined into a single concatenated color feature using weighted feature fusion. This makes the FR method to be effective. For an input represented by a list of 2n numbers, the Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale: finally resulting in 2n − 1 differences and one final sum. Phase congruency reflects the behaviour of the image in the frequency domain. It has been noted that edge like features have many of their frequency components in the same phase. 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.

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