Wavelet Transform based Feature Extraction for Face Recognition

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Sangeeta Kakarwal, Ratnadeep Deshmukh

Abstract - In this paper, we propose a Wavelet Transform based analysis method for Face Recognition. This algorithm has been used to extract the features of the FERET face database. Results indicate that the proposed methodology is able to achieve excellent performance with only a very small set of features being used, and its error rate is calculated using FAR and FRR. The choice of the Wavelet transform in this setting is motivated by its insensitivity to large variation in light direction, face pose, and facial expression. In the experiments we used Correlation and Threshold values to assure high consistency of the produced classification outcomes. The encouraging experimental results demonstrated that the proposed approach by using frontal and side-view images is a feasible and effective solution to recognizing faces, which can lead to a better and practical use of existing forensic databases in computerized human face-recognition applications.

KeyWords- *AFR (Automatic Face Recognition), FERET, FAR (False Acceptance Rate), FRR (False Rejection Rate).*

I. INTRODUCTION

Face recognition from still images and video sequence has been an active research area due to both its scientific challenges and wide range of potential applications such as biometric identity authentication, human-computer interaction, and video surveillance. Within the past two decades, numerous face recognition algorithms have been proposed as reviewed in the literature survey. Even though we human beings can detect and identify faces in a cluttered scene with little effort, building an automated system that accomplishes such objective is very challenging. The challenges mainly come from the large variations in the visual stimulus due to illumination conditions, viewing directions, facial expressions, aging, and disguises such as facial hair, glasses, or cosmetics [1].

Face Recognition focuses on recognizing the identity of a person from a database of known individuals. Face Recognition will find countless unobtrusive applications such as airport security and access control, building surveillance and monitoring Human-Computer Intelligent interaction and perceptual interfaces and Smart Environments at home, office and cars [2].

Within the last decade, face recognition (FR) has found a wide range of applications, from identity authentication, access control, and face-based video indexing/browsing, to human-computer interaction/communication. Two issues are central to all these algorithms: 1) feature selection for face representation and 2) classification of a new face image based on the chosen feature representation. This work focuses on the issue of feature selection. Among various solutions to the problem, the most successful are those appearance-based approaches, which generally operate directly on images or appearances of face objects and process the images as two-dimensional (2-D) holistic patterns, to avoid difficulties associated with three-dimensional (3-D) modeling, and shape or landmark detection [3]. The initial idea and early work of this research have been published in part as conference papers in [4], [5].

A recognition process involves two basic computational stages: In a first stage a suitable representation is chosen, which should make the subsequent processing not only computationally feasible but also robust to certain variations in images. One method of face representation attempts to capture and define the face as a whole and exploit the statistical regularities of pixel intensity variations [6]. We have used Wavelet transform to decompose face images and classified it with correlation and different threshold values.

The remaining part of this paper is organized as follows. Section II extends to the feature mapping, which also introduces and discusses the Wavelet Transform in detail. In Section III, extensive experiments on FERET databases are conducted to evaluate the performance of the proposed method on face recognition. Finally, conclusions are drawn in Section IV with some discussions.

II. PATTERN MATCHING

A. Pattern Recognition Methods

In communication with the outer world, one of the most important goals for human beings is to recognize objects. For example, from an image, image set, or image sequence of objects, we need to recognize that the objects are oriented toward, where they are located, how they are arranged, what size and shape they have, and what sort of things they are.

During the past 30 years, pattern recognition has had a considerable growth. Applications of pattern recognition now include: character recognition; target detection; medical diagnosis; biomedical signal and image analysis; remote sensing; identification of human faces and of fingerprints; machine part recognition; automatic

inspection; and many others.

Pattern recognition is, in general, a complex procedure requiring a variety of techniques that successively transform the iconic data to information directly useable for recognition. Traditionally, these methods are grouped into two categories: structural methods and feature space methods. Structural methods are useful in situation where the different classes of entity can be distinguished from each other by structural information, e.g. in character recognition different letters of the alphabet are structurally different from each other. The earliest-developed structural methods were the syntactic methods, based on using formal grammars to describe the structure of an entity. Some other methods, which may be structural, are machine vision methods such as those based on point distribution models, active contours, etc [7].

In feature-space methods, a set of measurements (typically numerical) is made on each real-world entity (pattern), and from the measurement set there is extracted a set of features which together characterize the class of patterns t which the given pattern belongs.

The traditional approach to feature-space pattern recognition is the statistical approach, where the boundaries between the regions representing pattern classes in feature space are found by statistical inference based on a design set of sample patterns of known class membership [7]. Feature-space methods are useful in situations where the distinction between different pattern classes is readily expressible in terms of numerical measurements of this kind. The traditional goal of feature extraction is to characterize the object to be recognized by measurements whose values are very similar for objects in the same category, and very different for objects in different categories. This leads to the idea of seeking distinguishing features that are invariant to irrelevant transformations of the input. The task of the classifier component proper of a full system is to use the feature vector provided by the feature extractor to assign the object to a category [8]. Image classification is implemented by computing the similarity score between a target discriminating feature vector and a query discriminating feature vector [9].

B. Wavelet Transform
Wavelet is an increasingly popular tool in image processing and computer vision. Many applications, such as compression, detection, recognition, image retrieval have been investigated. Wavelet transform has nice features of space-frequency localization and multiresolutions. The main reasons for Wavelet transforms popularity lie in its complete theoretical framework, the great flexibility for choosing bases and the low computational complexity [6]
Wavelets decompose complex signals into sums of basis functions – in this respect they are similar to other discrete image transforms. However, wavelets are local in both frequency and time and are able to analyze data at different scales or resolutions much better than simple sine and cosine can [10].

Wavelets are an extension of Fourier analysis. As with the Fourier transform, the point of wavelets is not the wavelets themselves; they are a means to an end. The goal is to turn the information of a signal into numbers – coefficients – that can be manipulated, stored, transmitted, analyzed, or used to reconstruct the original signal. Not only there two big classes of wavelet transforms - continuous and discrete - but discrete transforms can be redundant, orthogonal, or biorthogonal. Each category contains innumerable possibilities, Daubechies wavelets alone constituting a very big class [11].

DWT for an image as a 2-D signal can be derived from 1-D DWT. The easiest way for obtaining scaling and wavelet functions for two dimensions is by multiplying two 1-D functions. The scaling functions for 2-D DWT can be obtained by multiplying two 1-D scaling functions:

$\phi(x, y) = \phi(x)\phi(y)$ Wavelet functions for 2-D DWT can be obtained by multiplying two wavelet functions. For the 2-D case, there exist three wavelet functions that scan details in horizontal $\psi^{(I)}(x, y) = \phi(x)\psi(y)$ vertical $\psi^{(II)}(x, y) = \psi(x)\phi(y)$ and diagonal directions: $\psi^{(III)}(x, y) = \psi(x)\psi(y)$ [12].

As in any pattern classification task, feature extraction plays a key role in face recognition process. In feature extraction stage, a proper face representation is chosen to make the subsequent face processing not only computationally feasible but also robust to possible intrinsic and extrinsic facial variations [13]. In this paper, 2D Discrete Wavelet Transform is used to extract the features from the faces.

C. Correlation
Here we consider it as basis for finding matches of a subimage w(x,y) of size J X K within an image f(x,y) of size M X N, where we assume that J<=M and K<=N.
In its simplest form, the correlation between f(x,y) and (x,y) is $c(x, y) = \sum_{s} \sum_{t} f(s,t) w(x+s, y+t)$ …(1)

For x=0,1,2,…,M-1, y=0,1,2,..,N-1 and the summation is taken over the image region where w and f overlap. Figure 1 illustrates the procedure, where we assume that the origin of f is at its top left and the origin of w is at its center. For one value of (x,y), say, (x0,y0) inside f, application of Eq. (1) yields one value of c. As x and y are varied, w moves around the image area, giving the function c(x,y). The maximum value(s) of c indicate the position (s) where w best matches f. Note that accuracy is lost for values of x and y near the edges of f, with the amount of error being in the correlation proportional to the size of w. The correlation function given in equation (2) has disadvantage of being sensitive to changes in the amplitude of f and w. For example, doubling all values of f doubles the value of c(x,y).
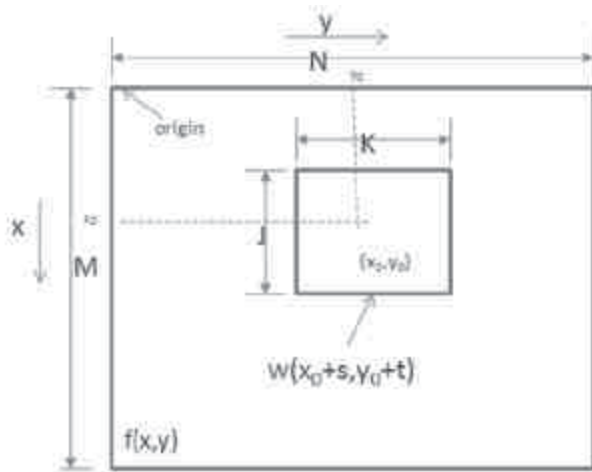
Figure1 Arrangement for obtaining the correlation of f and w at point (x_0, y_0)

An approach frequently used to overcome this difficulty is to perform matching via the correlation coefficient, which is defined as specified in Eq. (2)

$\gamma(x,y)$ =

…(2)

where x=0,1,2,,..,M-1, y=0,1,2,..,N-1, w' is the average value of the pixel in w (computed only once), f' is the average value in the region coincident with the current location of w, and the summations are taken over the coordinates common to both f and w. The correlation coefficient γ (x,y) is scaled in the range –1 to 1, independent of scale changes in the amplitude of f and w[14].

III. EXPERIMENTS

A. Facial Database

There are many facial databases available for evaluating face recognition algorithms. The FERET facial database consists of 13539 facial images corresponding to 1,565 subjects. Since images are acquired during different photo sessions, the illumination conditions and the size of the face may vary. The diversity of the FERET database is across gender, ethnicity, and age. The images are acquired without any restrictions imposed on facial expression and with at least two frontal images shot at different times during the same photo session. The FERET database has become the de facto standard for evaluating face recognition technologies [2]. The FERET dataset used in our experiments includes 250 face images corresponding to 20 subjects. In order to extract the facial region, the images are normalized to the size 512 x 512. All images are gray-scale images.

Image1: Genuine faces used for training.

Image2: Genuine faces used for testing.

Image3: Imposter faces used for testing

In our experiment, Daubechies wavelet 'db3' with 5 number of decomposition is used to compress and decompress the facial images.

10 persons with 15 images each are used for training and 5 images of same persons are used for testing. Image1 shows faces of only 3 persons with 5 subjects. It is the set of images used during training. In Image2, the genuine faces used during testing are shown. In addition to this, testing is performed with impostor faces. Imposter's faces are shown in Image3. Results of classification are obtained by using correlation and different threshold values.

B. Steps used in Face Recognition
1. Read the Images
2. Convert the color images into gray scale images
3. Normalize the images
3. Apply Daubechies Wavelet to extract the features
4. Obtain Correlation of the images
5. Classify the images by using different values of thresholding
6. Analyse the performance by computing FAR and FRR at different values of threshold

C. Performance Evaluation
A typical biometric verification system commits two types of errors: *false match* and false *non-match*. Note that these two types of errors are also often denoted as *false acceptance* and *false rejection*; a distinction has to be made between positive and negative recognition; in positive recognition systems (e.g., an access control system) a false match determines the false acceptance of an impostor, whereas a false non-match causes the false rejection of a genuine user. On the other hand, in a negative recognition application (e.g., preventing users from obtaining welfare benefits under false identities), a false match results in rejecting a genuine request, whereas a false non-match results in falsely accepting an impostor attempt. The notation "false match/false non-match" is not application dependent and therefore, in principle, is preferable to "false acceptance/false rejection." However, the use of false acceptance rate (FAR) and false rejection rate (FRR) is more popular and largely used in the commercial environment [15].

Traditional methods of evaluation focus on collective error statistics such as EERs and ROC curves. These statistics are useful for evaluating systems as a whole. *Equal-Error Rate* (EER) denotes the error rate at the threshold *t* for which false match rate and false non-match rate are identical: $FAR(t) = FRR(t)$ [16].

FRR is False Rejection Ratio, which means the fault when someone which registered in the system was refused by system [17]. Table I presents the FRR values of genuine person faces.

FAR is False Acceptance Rate, which is the fault where someone of user which does not enlist will be held true by the system. FAR values for impostor persons are presented in Table II.

Finally, Table III presents the FAR and FRR values for all persons with different threshold values. The FRR and FAR for number of participants (N) are calculated as specified in Eq. (3) and in equation Eq. (4)[17]:

$$FRR = \frac{1}{N}\sum_{n-}^{N} FRR(n) \qquad \ldots(3)$$

$$FAR = \frac{1}{N}\sum_{n-}^{N} FAR(n) \qquad \ldots(4)$$

TABLE I
FRR OF GENUINE PERSONS

T	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
0.6	0.2	0.4	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
0.65	0.2	0.4	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
0.7	0.2	0.4	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
0.75	0.2	0.4	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0
0.8	0.4	0.4	0.0	0.4	0.4	0.0	0.2	0.4	0.4	0.2
0.85	0.6	0.6	0.0	0.8	0.6	0.0	0.2	0.2	0.6	0.8

TABLE II
FAR OF IMPOSTOR PERSONS

T	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
0.6	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.2	0.0	0.0
0.65	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0
0.7	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
0.75	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.85	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: T denotes Threshold value and P indicates person

TABLE III
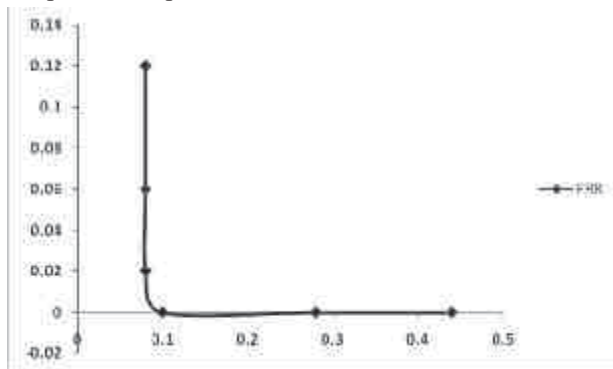RECOGNITION PERFORMANCE FOR DIFFERENT THRESHOLD VALUES

Threshold	FRR	FAR
0.6	0.08	0.12
0.65	0.08	0.06
0.7	0.08	0.02
0.75	0.1	0.0
0.8	0.28	0.0
0.85	0.44	0.0

The FAR-FRR diagram is shown in Graph1:
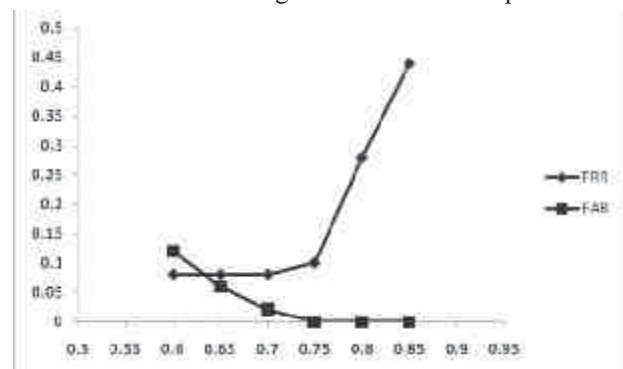
Graph1: FAR-FRR Diagram

A ROC (Receiver Operating Characteristic Curve) is a plot of FAR against FRR, for various decision thresholds [11]. Graph 2 shows plot of ROC.

Graph2: Receiver Operating Characteristics

IV. CONCLUSIONS

This paper investigates the feasibility and effectiveness of using correlation and threshold values for face description and recognition. A 2D Discrete Wavelet Transform is proposed to capture the variations in faces. Face recognition based on correlation can be performed by using thresholding. Experimental results on an extensive set of face databases, FERET databases, demonstrate that the proposed Correlation and thresholding outperforms in identification. Experiments conducted on various face conditions, including different angles, expressions etc.

It is shown that the proposed method of face recognition gives satisfying results for threshold-0.7. At t=0.7, the value obtained for FAR is 0.02 and FRR is 0.08 There is a trade-off between FAR and FRR values. The optimum thresholds value i.e. the value where FAR=FRR, is 0.65 as shown in Graph1. But threshold value can be set as per requirement of application. For example, in some forensic applications such as criminal identification, it is the false rejection rate that is major concern and not the false acceptance rate: that is, we do not want to miss a criminal even the risk of manually examining a large number of potential matches identified by the biometric system. There are several civilian applications where both FAR and FRR need to be considered.

ACKNOWLEDGEMENTS

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