Multiresolution Feature Based Subspace Analysis for Fingerprint Recognition

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ABSTRACT

The image intensity surface in an ideal fingerprint image contains a limited range of spatial frequencies, and mutually distinct textures differ significantly in their dominant frequencies. This paper presents a multiresolution feature based subspace technique for fingerprint recognition. The technique computes the core point of fingerprint and crops the image to predefined size. The multiresolution features of aligned fingerprint are computed using 2-D discrete wavelet transform. LL component in wavelet decomposition is concatenated to form the fingerprint feature. Principal component analysis is performed on these features to extract the features with reduced dimensionality. The algorithm is effective and efficient in extracting the features. It is also robust to noise. Experimental results using the FVC2002 and Bologna databases show the feasibility of the proposed method..

Categories and Subject Descriptors

I.5.4 [**Pattern Recognition**]: Applications- *Computer vision.*

General Terms

Algorithms, Design, Verification.

Keywords

Radon transform, Wavelet Transform, Face recognition.

1. INTRODUCTION

Accurate automatic person identification is needed in a wide range of civilian applications involving the use of passports, cellular telephones, automatic teller machines etc. Traditional knowledge based and token based identifications are prone to fraudulent activities. Biometric recognition or simply, biometrics refers to the automatic recognition of an individual based on his/her physiological and / or behavioral characteristics. By using biometrics, it is possible to confirm or establish an individual's identity based on, "who he/she is," rather than by, "what he/she possesses" (e.g., an ID card) or "what he/she remembers," (e.g., a password) [1].

Fingerprints are very unique, their details are permanent, even if they may slightly change due to cuts and bruises on the skin or weather conditions temporarily. The uniqueness of a fingerprint is determined by the topographic relief of its ridge structure and the presence of certain ridge anomalies termed as minutiae points. The global configuration defined by the ridge structure is used to determine the class of the fingerprint, while the distribution of minutiae points is used to match and establish the similarity between two fingerprints. Because of this, fingerprints are used to authenticate the person [1].

Fingerprint is represented by locally oriented ridges and valleys. The discontinuities in the ridges are called minutiae. The performance of minutiae based algorithms depend on the quality of images. An approach which uses adaptive filters computed from the orientation field has been used to extract the structural textural features [5].

The smooth flow pattern of ridges and valleys in a fingerprint can be viewed as an oriented texture field [8]. The image intensity surface in an ideal fingerprint image is comprised of ridges whose direction and height vary continuously and forms an oriented texture. The Most of textural images contain a limited range of spatial frequencies, and mutually distinct textures differ significantly in their dominant frequencies [7]

Texture regions possessing different spatial frequency can be easily discriminated by decomposing the texture in several spatial frequencies. This paper presents a pattern recognition framework based on multiresolution features and PCA for fingerprint recognition. The technique is capable to extract the efficient and effective global features from aligned and cropped fingerprint images. For classification, the nearest neighbor classifier using Euclidian distance has been used.

The paper is organized as follows. In Section 2, we briefly describe the multiresolution features, PCA technique and the proposed algorithm. Databases and experimental results are summarized in Section 3 followed by conclusions in Section 4.

2. FEATURE EXTRACTION

The proposed technique of fingerprint recognition detects the core point and crops the image to predefined size to extract the region of interest. The multiresolution features of these fingerprints are computed using 2-D Daubechies discrete wavelet transform. Average component (LL component) in wavelet decomposition is concatenated to form the fingerprint feature. Principal component analysis is performed on these multiresolution features to extract the features with reduced dimensionality. The nearest neighbor classifier is used to classify the images.

Fingerprints have many conspicuous landmark structures and a combination of them could be used for establishing a reference point of a fingerprint. A point of the most curvature in a fingerprint image has been detected and considered as a reference point as proposed in [2]. Figure 1 shows the core point detected cropped image.

(A) (B)

Figure 1. (A) Original image (B) Core point detected cropped image.

2.1 Multiresolution Features

Wavelet Transform (WT) has the nice features of space frequency localization and multiresolution. The main reasons for WT's popularity lie in its complete theoretical framework, the great flexibility in choosing the bases and low computational complexity.

Let $L^2(R)$ denote the vector space of a measurable, square integrable, one dimensional signal. Wavelet transform of $f(t) \in L^2(R)$ is defined as

$$(\mathrm{W}_a f)(b) = \int f(t)\phi_{a,b}(t)dt \tag{1}$$

where the wavelet basis function $\phi_{a,b}(t) \in L^2(R)$ can be expressed as

$$\phi_{a,b}(t) = a^{-\frac{1}{2}}\phi\left(\frac{t-b}{a}\right) \tag{2}$$

These basis functions are called wavelets and have at least one vanishing moment. The arguments a and b denote the scale and translation parameters respectively [8]. 2-D WT of images can be similarly defined by implementing the one dimensional WT for each dimension (row and column) separately. Figure 2 illustrates the decomposition of an image using Discrete Wavelet Transform (DWT) into four subimages via the high-pass and low-pass filter. H and L represent the high-pass and low-pass filter respectively, and ↓2 denotes the subsampling by 2.

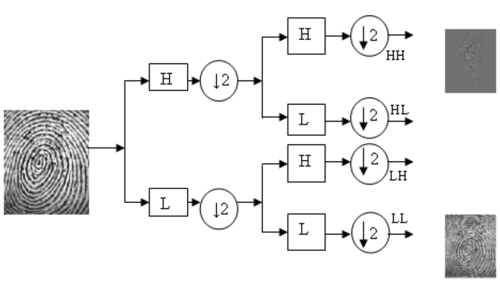

Figure 2. Multiresolution approach used for image decomposition

2.2 Principal Component Analysis

The present investigation is concerned with the general problem of characterizing, identifying, and distinguishing individual patterns drawn from well defined class of patterns. The treatment is based on a method known as the Karhunen-Loeve expansion in pattern recognition and principal component analysis (PCA) in the statistical literature. The applications of this procedure, especially in the analysis of signals in time domain, are extensive. This analysis demonstrates that any particular face can be economically represented in terms of a best coordinate system called as eigenpictures. These are the eigenvectors of the average covariance of the ensemble of faces. This is an information theory approach of encoding face images, emphasizing the significant local and global features.

A set of eigenfaces are computed from the eigenvectors of the ensemble covariance matrix C of the training set,

$$C = \sum_{i=1}^{M} (\bar{x}_i - \bar{m})(\bar{x}_i - \bar{m})^T \tag{3}$$

where, $\bar{m}$ is the mean of all samples. Eigenfaces are sorted by eigenvalues, which represent the variance of face distribution on eigenfaces. There are at most $M-1$ eigenfaces with non-zero eigenvalues [7].

2.3 The procedure of the proposed Technique

Following are the steps in proposed algorithm.

1. Detect the core point of image.

2. Crop the image to predetermined size.

3. Decompose the image using Daubechies wavelet DB3.

4. Decompose the LL component further.

5. Concatenate the rows of LL component to derive the multiresolution features of fingerprint images and form the data matrix.

6. Compute the eigenvalues and eigenvectors of covariance matrix C such that

$$CV = \lambda V . \tag{4}$$

7. Order the eigenvectors according to descending eigenvalues and normalize them.

8. Project the multiresolution features into eigenspace. These are stored in database as reference feature vectors.

9. Compute the Euclidean distance between training and test image feature vectors.

10. Classify the test image using the nearest neighbor classifier.

3. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

In this Section, we evaluate the performance of the proposed approach using two databases: FVC2000, and University of Bologna (part of FVC 2000). The FVC2000 database consists of DB1, DB2, and DB3 subparts and has been captured using optical scanner. We have selected 600 images of 100 subjects (six images per subject) from DB1_a database with image size of 388 X 374 for the experiments. University of Bologna database consists of images of 20 subjects with eight images per subject [8]. All the images from this database have been used in the experiments. In all the experiments two images per subject were used for training and remaining selected images were used for testing. The recognition is done using the nearest neighbor classifier on the basis of Euclidean distance.

Table 1. % Recognition rate of the algorithms

Algorithm	Database	
	FVC2000	University of Bologna
Minutiae based algorithm	82.3	87.5
PCA	85.6	84.3
Multiresolution	89.2	87.5
Multiresolution based PCA	95.7	96.3

In the first part of the experiments, the core point was detected and images were cropped to the size of 264 X 200. PCA algorithm was implemented on the cropped images. Two hundred images of 100 subjects derived 199 eigenvectors. In the second part we derived the multiresolution features of the cropped images using Daubechies wavelet DB3 (because of its symmetry, compact support and the use of overlapping windows to reflect all changes between pixel intensities). The LL part in the decomposition was selected for further decomposition. All the rows of LL parts were concatenated to derive the fingerprint features. The images were classified using these features.

The variations in recognition accuracy of the proposed approach with different types of Daubechies wavelets have been investigated. The highest recognition rate was obtained using DB3 wavelet. Hence only these results are presented in the paper.

In the subsequent experiment, we implemented PCA on the multiresolution feature. The recognition rates of all the experiments using both the databases are shown in Table 1. The proposed algorithm has attained the better performance because of removal of redundant information in wavelet decomposition and further reduction of dimension using PCA.

The variations in recognition rate were observed for different number of eigenvectors in deriving the features. Figure 3 shows the recognition rate for varying number of feature vectors. It has been observed that the recognition rate increases with increase in number of eigenvectors and remains almost constant after a certain number of eigenvectors. This is because of representation of maximum variance among the images by the eigenvector corresponding to the highest eigenvalue.

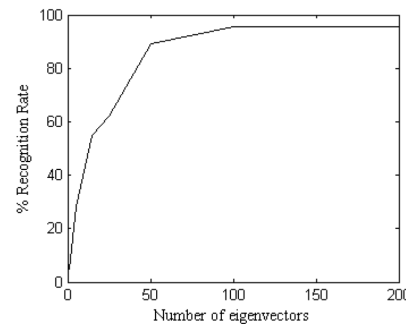

Figure 3: Recognition rate for varying number of eigenvectors

In the last part of the experiment, the performance of the algorithm has been evaluated using the False Acceptance Rate (FAR) and False Rejection Rate (FRR) at various thresholds. The correct recognition rate is obtained when two feature vectors of the same individual are compared and an imposter matching score is obtained when feature vectors of different individuals are compared. In this experiment one image per subject is selected for training and remaining five images of 100 subjects were used for testing. For an individual, images excluding his own images will be the impostors. The FRR is computed by counting the true claims rejected.

False Rejection Rate = (True claims rejected / Total true claims) x 100%.

FAR is computed by counting the number of imposter's claims accepted out of the total imposter's claims for given threshold. For an individual, remaining other person's images will be imposter images.

False Acceptance Rate = (Imposter claim accepted / total imposter claims) x 100%.

Figure 4 shows the FAR and FRR for different value of threshold. The equal error rate of the proposed algorithm is 4%.

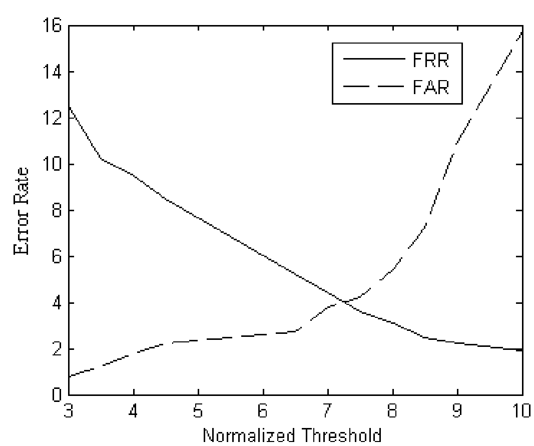

Figure 4. FAR and FRR of proposed algorithm for different values of threshold.

4. CONCLUSIONS

In this paper, we have proposed a technique for fingerprint recognition, which uses multiresolution features derived using Daubechies wavelet DB3. PCA algorithm implemented on these features has attained high recognition rate. The equal error rate is 4%. The feasibility of this algorithm has been successfully tested on FVC200 and University of Bologna databases. The proposed algorithm produce better result compared to minutiae based algorithms.

5. REFERENCES

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