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Gender Specification Using Touch less Fingerprint Recognition

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Abstract: Fingerprint recognition or fingerprint authentication refers to the automated method of verifying a match between two human fingerprints.Fingerprints are one of many forms of biometrics used to identify individuals and verify their identity. This article touches on two major classes of algorithms (minutia and pattern) and four sensor designs (optical, ultrasonic, passive capacitance, and active capacitance).Most of the current security and attendance systems are shifting towards automated biometric systems, the most popular biometrics being fingerprints. In Automated Fingerprint Identification Systems (AFIS), the fingerprint of an individual needs to be identified with that stored in the database. In this is a method which deals with fingerprint identification in the transform domain is considered and the main focus is on the reduction of the processing time. First, the mean of rows (or columns) of the fingerprint image is computed, this converts a two dimensional image signal into one dimension. The one dimensional Walsh transform of the row (or column) vector is generated and is distributed in a complex plane which is subjected to sectorization to generate the feature vector.The feature vector of a given test image is compared to those present in the database. The scores from row and column transform methods are fused using OR and MAX functions. The results with accuracy of more than 73% (for 16 sectors) and high computational speed show that the method can be used in fingerprint identification in application with requirements of less processing time.

Keywords: DWT, SVM, STFT, Gabor filter, SVD, Walsh transform

1. INTRODUCTION

For over a century, fingerprints have been one of the most highly used methods for human recognition. The determination and commitment of the fingerprint industry, government evaluation and needs, and organized standards bodies have led to the next generation of fingerprint recognition, which promises faster and higher quality acquisition devices to produce higher accuracy and more reliability. Automatic fingerprint recognition technology has now rapidly grown beyond forensic applications into civilian applications. In fact, fingerprint-based biometric systems are so popular that they have almost become the synonym for biometric systems.

Biometrics has three broad uses –

1. Verification, i.e. confirming another identifier such as a password, PIN or a photograph.
2. Identification, providing a discrete identifier (or identifiers) that are independent of what the individual knows/remembers (e.g. a password) or what the individual carries (e.g. an identity document or card).
3. Screening, enabling surveillance and sorting of groups of people (e.g. finding a person in a crowd or selecting travellers for detailed examination of passports).

Gender and Age information is important to provide investigative leads for finding unknown persons. Existing methods for gender classification have limited use for crime scene investigation because they depend on the availability of teeth, bones, or other identifiable body parts having physical features that allow gender and age estimation by conventional methods. Various methodologies has been used to identify the gender using different biometrics traits such as face, gait, iris, hand shape, speech and fingerprint. In this work, gender and age of a person is identified from the fingerprint using DWT and SVD.

2. EXISTING TECHNOLOGIES

Gender and age classification can be me made using the spatial parameters or frequency domain parameters or using the combination of both. Most of the findings are based on the spatial domain analysis and few were based on the frequency domain. Many studies were carried out for the human face gender classification by using frequency domain and various classifiers.

There are basically two methods of fingerprint feature extraction:

2.1. Discrete Wavelength Transform Based Fingerprint Feature extraction [3]

2.2. Singular Value Decomposition based Fingerprint Feature extraction [3]

2.1. Discrete Wavelet Transform based fingerprint feature extraction

Wavelets have been used frequently in image processing and used for feature extraction, de- noising, compression, face recognition, and image super-resolution. Two dimensional DWT decomposes an image into sub-bands that are localized in frequency and orientation. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain sub-bands. This process results in isolating small changes in an image mainly in high frequency sub-band images. Hence, DWT is a suitable tool to be used for designing a classification system. The 2-D wavelet decomposition of an image is results in four decomposed sub-band images referred to as low–low (LL), low–high (LH), high–low (HL), and high–high (HH).Each of these sub-bands represents different image properties. Typically, most of the energy in images is in the low frequencies and hence decomposition is generally repeated on the LL sub band only (dyadic decomposition). For k level DWT, there are (3*k) + 1 sub-bands available. The energy of all the sub-band coefficients is used as feature vectors individually which is called as sub-band energy vector (E). The energy of each sub-band is calculated by using the equation (1).Where is the pixel value of the kth sub-band and R, C is width and height of the sub-band respectively.

$$E_k = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}|x_k(i,j)| \qquad \text{.......(1)}$$

2.2. Singular Value Decomposition based fingerprint feature extraction

The Singular Value Decomposition (SVD) is an algebraic technique for factoring any rectangular matrix into the product of three other matrices. Mathematically and historically, it is closely related to Principal Components Analysis (PCA). In addition it provides insight into the geometric interpretation of PCA. As noted previously, the SVD has long been considered fundamental to the understanding of PCA. The SVD is the factorization of any k × p matrix into three matrices, each of which has important properties.

That is, any rectangular matrix A of k rows by p columns can be factored into U, S and V by using the equation (2).

$$A = U\,S\,V^T \qquad \text{.......(2)}$$

Where

$$U = AA^T \qquad \text{.......(3)}$$

$$V = A^T A \qquad \text{........(4)}$$

As the internal database contains images of size 260x300 pixels, the feature vector of SVD is of the size 1x260. The spatial feature extraction by using SVD is shown in Figure 1.

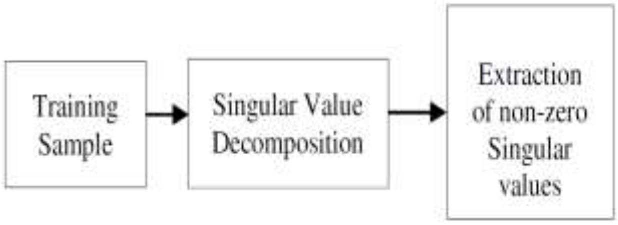

Figure 1. SVD based fingerprint feature extraction

3.TOUCH-LESS FINGERPRINT RECOGNITION

3.1. Overview

In this paper we will be discussing about the touch-less fingerprint recognition system. Most of the sensors available today use "touch" method since it is simple and little training is required. However, the touch-based electronic fingerprint scanner will lead to the weakening of durability if the device is used heavily. In addition, the pressure of the physical contacts will normally cause the touch-based fingerprint images to be degraded. On the other hand, images captured with touch-less devices are distortion free and present no deformation because these images are free from the pressure of contact. Touch-less fingerprint acquisition is a remote sensing technology to capture the ridge-valley pattern which provides essential information for recognition. Several approaches for touch-less fingerprint recognition system have been reported.

3.2. Algorithm

The block diagram of the proposed touch less fingerprint recognition system is shown below.

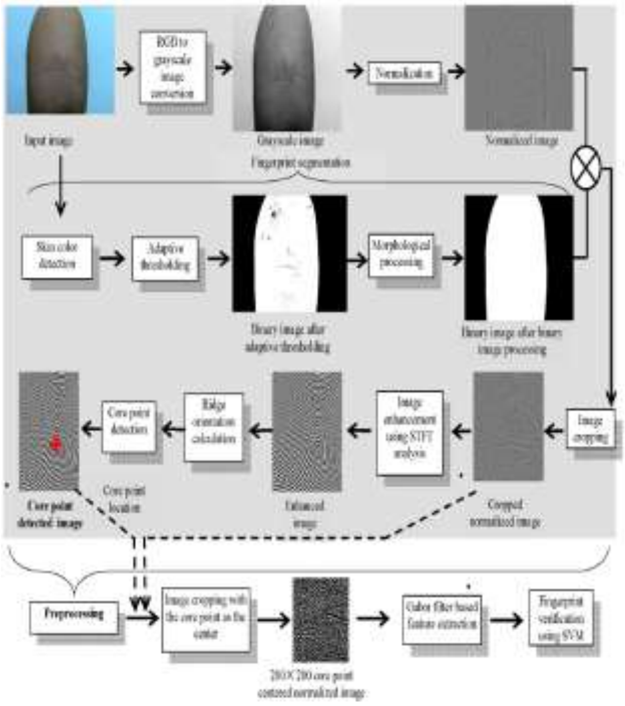

Figure 2. Block Diagram of Touchless Fingerprint Recognition System

3.3. Proposed System

The steps involved in implementation of this system are as follows:

1. Image acquisition
2. Image Preprocessing
3. Verification of results

3.3.1. Image acquisition:

Due to the lack of any standard database of images the fingerprint images are captured using digital camera. The digital camera used is Canon the PowerShot Pro1, with 8 mega pixels of effective resolution and a 7x optical zoom canon “L” series lens. The L-series lens’ macro capabilities allow capturing high resolution images while “super macro mode” permits close focus to 1.2 inches enables to get clearer foreground pattern and blurred background pattern.

Table 1. Configuration of the camera.

ISO Speed	400
Image Size/ Resolution	640x480
Image Quality	Superfine
Super Macro	On
Colour Space	RGB
Drive Mode	Continuous shooting (Speed priority)

3.3.2 Image pre-processing:

The main sub- modules of the system are :

a. Pre-processing: The fingerprint images are pre-processed using proposed method which includes skin color detection normalization fingerprint segmentation image enhancement and core point detection. [1]

b. Gabor filter based feature extraction: The feature vectors are extracted by Gabor- filter from the images after pre-processing

c. Fingerprint verification using SVM: The fingerprint verification by using SVM classifier.

3.3.2.1. Pre-processing:

The first step in preprocessing is to convert the image from RGB format to grey scale [0-255]. The image is then normalized by changing the dynamic range of the pixel intensity values in order to reduce the damage caused by the illumination. The next step is segmentation done by skin color detection, adaptive thresholding and followed by the morphological processing. The fingerprint image thus obtained is multiplied with the binary mask from segmentation. The resultant image is cropped and enhanced by using Short Time Fourier Transform (STFT) analysis.
Finally, the core point is detected on the enhanced image.

3.3.2.2. Gabor filter based feature extraction:

It is desirable to obtain representations for fingerprints which are scale, translation, and rotation invariant. The present implementation of feature extraction assumes that the fingerprints are vertically oriented. In reality, the fingerprints in our database are not exactly vertically oriented; the fingerprints may be oriented up to away from the assumed vertical orientation.

The four main steps in our feature extraction algorithm are [2]:

1) Determine a reference point and region of interest for the fingerprint image

2) Tessellate the region of interest around the reference point

3) Filter the region of interest in eight different directions using a bank of Gabor filters (eight directions are required to completely capture the local ridge characteristics in a fingerprint while only four directions are required to capture the global configuration

4) Compute the average absolute deviation from the mean (AAD) of grey values in individual sectors in filtered images to define the feature vector or the Finger Code.

To meet these conflicting requirements of an accurate and reliable localization, we propose a new method of reference point determination based on multiple resolution analysis of the orientation fields. Our new method locates the reference point more precisely than the algorithm proposed by Hong and Jain.

Let us first define the orientation field, O, for a fingerprint image. The orientation field, O, is defined as a P×Q image, where O(i,j) represents the local ridge orientation at pixel (i,j). Local ridge orientation is usually specified for a block rather than at every pixel; an image is divided into a set of w×w non- overlapping blocks and a single orientation is defined for each block

A summary of our reference point location algorithm is presented below [2].

1) Estimate the orientation field O as described above using a window size of w×w.

2) Smooth the orientation field in a local neighborhood. Let the smoothed orientation field be represented as O’. In order to perform smoothing (low-pass filtering), the orientation image needs to be converted into a continuous vector field.

3) Compute an image containing only the sine component of O’.

4) Initialize A, a label image used to indicate the reference point.

5) For each pixel (i,j), integrate pixel intensities (sine component of the orientation field) in regions and assign the corresponding pixels in A, the value of their difference

$$A(i,j) = \sum_{R_I} \mathcal{E}(i,j) - \sum_{R_{II}} \mathcal{E}(i,j) \quad \text{....(5)}$$

The regions were determined by applying the reference point location algorithm. The geometry of regions is designed to capture the maximum curvature in concave ridges. Although this successfully detects the reference point in most of the cases, including double loops but is not very precise and consistent for the arch type fingerprints.

6) Find the maximum value in A and assign its coordinate to the core, i.e., the reference point.

7) For a fixed number of times, repeat steps 1–6 by using a window size of w’×w’, where and w’<w and restrict the search for the reference point in step 6 in a local neighbourhood of the detected reference point.

3.3.2.3. Fingerprint verification using Singular Value Decomposition:

It is a binary classifier based on principle of structural risk minimization that maps an input sample to high dimensional feature space. SVM [1] is adopted as it could optimally separate the two classes of genuine and imposters by constructing a hyper plane. The hyper plane is defined by

x * w + b = 0 **….(6)**

where,
w: is normal to the plane
b: is bias term.

The extension to non linear boundaries is achieved through transforming each data point to a higher dimensional space. Better seperability between two classes is achieved with proper transformation which is done by polynomial kernel or radial basis function (RBF) kernel.

$$K(x_i, x_j) = (x_i \cdot x_j + 1)^n \quad \text{…(7)}$$

Where n : order of the polynomial

$$K(x_i, x_j) = \exp\left[-\frac{1}{2}\left(\frac{\|x_i - x_j\|}{\sigma}\right)^2\right] \quad \text{…...(8)}$$

Where

σ :the width of the radial basis function.

Another technique for the above process is filterbank based matching.

3.3.2.4. Filterbank based matching:

Fingerprint matching is based on finding the Euclidean distance between the corresponding finger codes. The translation invariance in the finger code is established by the reference pointer achieved by cyclically rotating the features in the Finger Code itself. A single step cyclic rotation of the features in the Finger Code described by (21)–(23) corresponds to a feature vector which would be obtained if the image were rotated by 22.5°. A rotation by R steps corresponds to a R×22.5° rotation of the image. A positive rotation implies clockwise rotation while a negative rotation implies counterclockwise rotation. The Finger Code obtained after R steps of rotation is given by [2],

$$V_{i\theta}^{R} = V_{i'\theta'} \quad \text{….(9)}$$

i' = (i + k + R) mod k + (i div k) ×k ….(10)

θ' = (θ + 180° + 22.5° × R) mod 180° ….(11)

The process has been depicted in the following figure.

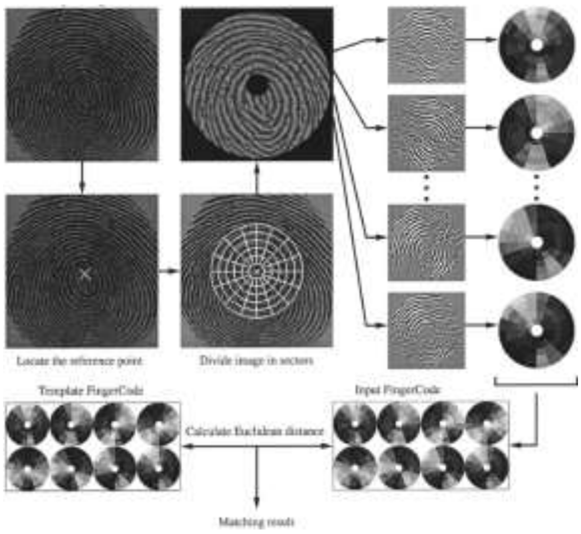

Figure 3. System diagram of fingerprint authentication system

4. FINGERPRINT GENDER CLASSIFICATION

4.1. Overview

The proposed system for gender classification is built based on the fusion of fingerprint features obtained by using DWT and SVD. This section describes two different stages named as learning stage and classification stage and the KNN classifier used for the gender classification [3].

4.2. Algorithm

4.2.1. Learning stage:

The feature vector V of size 1x260 obtained by SVD and the sub band energy vector E of size 1x19 obtained by DWT are fused to form the feature vector and used in the learning stage. The fusion of feature vector V and E is done by concatenation of features that are widely used for feature level fusion. The resulting feature vector is of the size 1x279 (1x260 +1x19).The learning stage is shown in Figure 4.

The learning algorithm is as follows:

[Input] all samples of fingerprint with known class (Gender).

[Output] the feature vector of all samples as database.

a) Decompose the fingerprint with 6 level decomposition of DWT.
b) Calculate the sub-band energy vector (E) using (1).
c) Calculate the Eigen vector (V) using (2).
d) Fuse the vectors E and V to form the feature vector for the particular fingerprint.
e) Insert this feature vector and the known class into the database.
f) Repeat the above steps for all the samples.

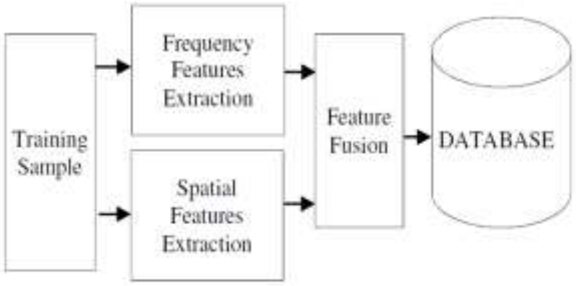

Figure 4. Learning Stage of the Proposed Gender Classification System

4.2.2. KNN Classifier:

In pattern recognition, the k-nearest neighbour algorithm (K-NN) is the generally used method for classifying objects based on closest training examples in the feature space. KNN is a type of instance-based learning where the function is only approximated locally and all computation is deferred until classification. In K-NN, an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbour. The neighbours are taken from a set of objects for which the correct classification is known. This can be thought of as the training set for the algorithm, though no explicit training step is required [3].

4.2.3. Classification Stage:

In the classification phase, the fused feature vector of the input fingerprint is compared with the feature vectors in the database by using the KNN classifier. The distance measure used in the classifier is 'Euclidean Distance'. The classification process is as follows.

***Classification algorithm* [3]:**

[Input] unknown fingerprint and the feature database

[Output] the class of the fingerprint to which this unknown fingerprint is assigned

a) Decompose the given unknown fingerprint with 6 level decomposition of DWT.
b) Calculate the sub-band energy vector (E) using (2).
c) Calculate the Eigen vector (V) using (1).
d) Fuse the vectors E and V to form the feature vector for the given unknown fingerprint.
e) Apply KNN classifier and find the class of the unknown fingerprint by using the database generated in the learning phase.

5. EXPERIMENTAL RESULTS

5.1. Gender classification using DWT only

The code is tested from 2nd level to 7th level and the success rate for the classification is identified. No appreciable results were obtained for the levels 2 to 4 and beyond the level 7, the results were not convincing. Significant success rate is obtained for the levels 5, 6 and 7. The sub-band energy vector for the level 5 is of the size 1x16 and these features are compared with templates stored in the database obtained during the learning stage. Similarly, the sub-band energy vectors are of the size 1x19 and 1x22 for the level 6 and 7 respectively. The results achieved by the 2-D DWT for the levels 5, 6 and 7 are listed in table 2 for each finger of the male and female [3].

Table 2. Gender Classification Rate For Different Levels Of DWT.

Finger No.	Level 5		Level 6		Level 7	
	Male	Female	Male	Female	Male	Female
1	86.99	91.67	87.67	94.32	87.67	90.63
2	89.04	86.46	89.86	90.88	89.04	83.33
3	90.41	81.25	92.79	85.88	91.10	86.46
4	93.15	79.17	95.46	79.68	89.73	78.13
5	91.78	73.96	94.92	75.92	93.15	72.92
6	93.84	72.92	92.8	73.87	93.15	71.88
7	89.73	77.08	93.17	80.69	91.78	78.13
8	91.78	83.33	92.57	84.28	91.10	79.17
9	89.73	86.46	90.73	89.78	93.15	87.50
10	86.99	85.42	86.76	93.58	87.67	87.50
Average	90.34	81.77	91.67	84.89	90.75	81.56

The overall classification rate for the level 5, 6 and 7 are 84.61%, 85.46% and 86.41% respectively. It is also observed that the success rate of right thumb finger (numbered as 6) of male are quite higher than the other fingers. Similarly, the success rate of left hand little finger (numbered as 1) of female are higher than the other fingers.

5.2. Verification results for touchless fingerprint recognition [1]

Verification experiments are conducted by using core point center normalized fingerprint images. After the preprocessing o\f the fingerprints the features derived from gabor filter are used for subsequent SVM verification.

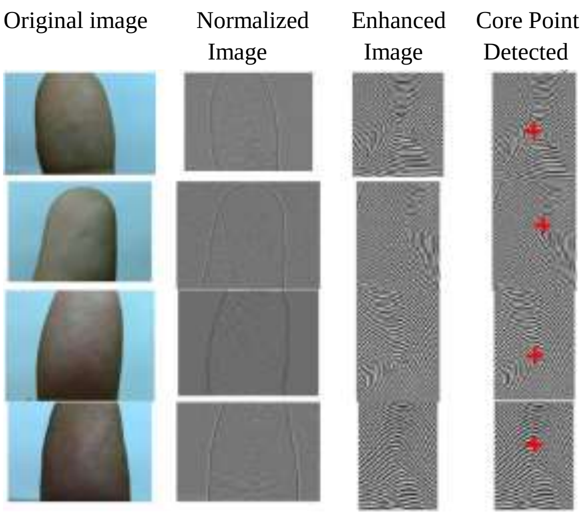

Figure 5. Results Of Proposed Preprocessing

Above are the results for successful core point detection.

Original Image Core Point Detected

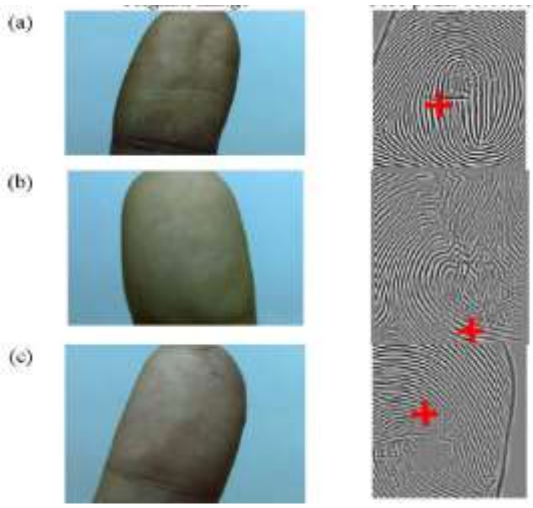

Figure 6. Samples of false core point detection. (a) Deep wrinkle image (b) motion blurriness image (c) defocus image.

There are two classes of errors in verification system False Acceptance Rate (FAR). False Reject Rate (FRR). System performance is determined by using Equal Error Rate (EER) i.e. FAR=FRR.
In filter based recognition the fingerprint images were collected of size 508x480 pixel. The age distribution was as follows:
1) Younger than 25 years: 46.5%;
2) Between the ages of 25 and 50: 51%;
3) Older than 50 years: 2.5%.
The images were taken in the order of right index, right middle, left index, left middle. These images were stored in the database MSU_DBI. The fingerprints were taken at the interval of 6 months. In practice, the ROC curve behaves in between these two extremes [2].

Table 3. FAR and FRR with different threshold values for MSU_DBI database.

Threshold Value	**False Acceptance Rate (%)**	**False Reject Rate (%)**
30	0.10	19.32
35	1.07	7.87
40	4.59	2.83

6. CONCLUSION

Average statistics along fingers for every pattern type was calculated together with different concordance and asymmetry properties for the corresponding fingers. The variation among females and males in the membership of the fingerprints to the different pattern types, and the average ridge count for fingers belonging to each pattern type, are very small, and thus are statistically insignificant. But there is no significant difference in the degree of asymmetry between males and females, and thus the asymmetry is not a good candidate for the classification process. The pattern type concordance between left and right corresponding fingers doesn't show significant statistical variations between females and males.

While the present approach tolerates small magnitudes of elastic distortion and local scaling (due to finger-pressure variations), it does not take care of significant nonlinear elastic distortion in the fingerprints. The inter-ridge densities in a fingerprint could be used to obtain a canonical representation to compensate for the large distortions due to shear and pressure variations caused by the contact of the finger with the sensing device.

The touch-less fingerprint recognition system is presented here where the experiment results signifies an improvement using the proposed algorithm in the segmentation, enhancement and core point detection for the fingerprint images captured by the digital camera. Moreover it has also presented an effective verification technique that employs SVM where feature vectors are extracted using the Gabor filter.

7. REFERENCES

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