Gender Classification System Derived from Fingerprint Minutiae Extraction

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ABSTRACT
Fingerprint evidence is undoubtedly the most reliable and acceptable evidence till date in the court of law. Due to the immense potential of fingerprints as an effective method of identification an attempt has been made in the present work to analyze their correlation with gender of an individual. This prospective study was carried out over a period of 2 months among 500 public people(250 male & 250 female) belonging to the various age groups between 1 - 90. Features extracted were; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance. For gender classification Support Vector Machines (SVM) was used for the classification using the most dominant features. Results are calculated by our proposed method. This analysis makes the proposed method better accurate than existing methods.

Keywords
Gender Classification, Finger Print, Support Vector Machines (SVM), Minutiae Extraction.

1. INTRODUCTION
Identity is a set of physical characteristics, functional or psychic, normal or pathological that defines an individual. Recently, there has been an increased interest in biometric technologies that is human identification based on one's individual features. The various identification data used are fingerprints, handwriting, bite marks, DNA fingerprinting etc. Fingerprints are constant and individualistic and form the most reliable criteria for identification. [1], A fingerprint is an impression of the friction ridges of all part of the finger. A friction ridge is a raised portion of the epidermis on the digits or on the palmar and plantar skin, consisting of one or more connected ridge units of friction ridge skin. The fig. 1 shows the sketch of ridge units and an area of a finger print showing friction ridges.

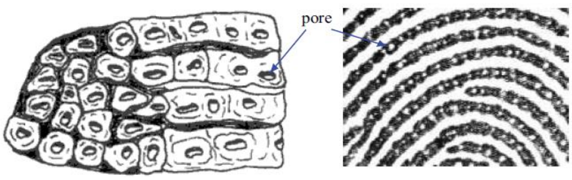


Figure 1: Ridge units, the building blocks of friction ridges: (a) a sketch of ridge units; (b) an area of a fingerprint showing friction ridges fused by ridge units, each containing a pore.

Fingerprints may be deposited in natural secretions from the eccrine glands present in friction ridge skin or they may be made by ink or other contaminants transferred from the peaks of friction skin ridges to a relatively smooth surface. Fingerprint patterns are genotypically determined and remain unchanged from birth till death. [2] Fingerprints collected at a crime scene can be used to identify suspects, victims and other persons who touched the surface, fingerprint scans can be used to validate electronic registration, cashless catering and library access especially in schools and colleges. The most common ridge characteristics are shown in the below fig. 2.

Figure 2: The most common ridge characteristics.

The performance of a fingerprint feature extraction and matching algorithm depends critically upon the quality of the input fingerprint image. While the 'quality' of a fingerprint image cannot be objectively measured, it roughly corresponds to the clarity of the ridge structure in the fingerprint image [3]. Direct binarization using standard techniques renders images unsuitable for extraction of fine and subtle features such as minutiae points. Therefore it is necessary to improve the clarity of ridge structures of fingerprint images, maintain their integrity, avoid introduction of spurious structures or artifacts, and retain the connectivity of the ridges while maintaining separation between ridges. As the distance between minutiae is normalized by ridge frequency at each minutia, the distance variation by nonlinear deformation is minimized. The positions and ridge orientations of minutiae that are located in near region also are less affected by nonlinear deformations since nonlinear deformation appears in some local areas and changes gradually. Classification performance highly depends on the preprocessing steps where various ways to extract and represent distinguishable features among classes can be applied. The main purpose of fingerprint classification is to facilitate the management of large fingerprint databases and to speed up the process of fingerprint matching. As the database of fingerprints increased manual identification became tedious and automated methods became more widespread. Fingerprint verification and identification algorithms can be classified into two categories: image-based and minutiae-based. Image-based methods include methods involving optical correlation and transform-based features. Other aspects of fingerprint identification are orientation, segmentation and core point detection.

Gender classification is an important problem with a variety of practical applications. For example, a robust gender classification system could provide a basis for performing passive surveillance using demographic information or collecting valuable consumer statistics in a shopping center. It could also be used to improve the performance of biometric systems such as face authentication and recognition [4]. Based on the varieties of the information available from the fingerprint we are able to process its identity along with gender, age and ethnicity. The primary dermal ridges (ridge counts) are formed during the gestational weeks 12-19 and the resulting fingerprint ridge configuration (fingerprint) is fixed permanently . Within a single individual, the breadth of finger print ridges varies within the hand and between hands, but the differences are quite small on the order of 0.05mm and less [5]. The gender of each person must be based on different combinations of these features. The overall features include ridge count, RTVTR, fingerprint pattern type, white lines count, pattern type concordance between the corresponding left-right fingerprints, and ridge count asymmetry between the left-right corresponding fingerprints. Male's and female's fingerprints are characterized by an average rightward asymmetry in the ridge count, i.e. the ridge count of a finger in the right hand is most likely greater than the ridge count of its corresponding finger in the left hand, 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.

2. REVIEW OF LITERATURE

Hui-Cheng Lian and Bao-Liang Lu [6] suggested a novel technique to multi-view gender classification by considering both shape and texture information to represent different facial images. The face area was divided into small regions, from which local binary pattern (LBP) histograms were extracted and concatenated into a single vector efficiently which represents the facial image. The classification is performed by using support vector machines (SVMs), which have shown to be superior to traditional pattern classifiers in gender classification problem. The experiments clearly show the superiority of the proposed method over support gray faces on the CASPEAL face database and a highest correct classification rate of 96.75% is obtained. In addition, the simplicity of the proposed method leads to very fast feature extraction, and the regional histograms and global description of the face allow for multi-view gender classification.

Ahmed Badawi *et al*. [7] have proposed that, gender classification from fingerprints was an important step in forensic anthropology to identify the gender of a criminal and also to minimize the list of suspects search. A dataset of 10-fingerprint images for 2200 persons of different ages and gender (1100 males and 1100 females) was analyzed. The different features extracted included; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry and pattern type concordance. Fuzzy CMeans (FCM), Linear Discriminant Analysis (LDA), and Neural Network (NN) were used to classify by using the most dominant features. They have obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, respectively. Results of that analysis make that method a prime candidate to utilize in forensic anthropology for gender classification in order to minimize the suspects search list by getting a likelihood value for the criminal gender**.**

G. Ramaswamy *et al*. [8] have proposed that the purpose was real time, high confidence recognition of a person's identity by using mathematical analysis of the random patterns which are visible within the finger prints from some distance. Finger prints were a protected internal organ whose random texture was stable throughout life, it had served as a kind of living password that one need not remember but one always carries along. Because the randomness of fingerprint patterns had very high characteristics such as dimensionality, recognition decisions were made with different confidence levels which were high enough to support rapid and reliable exhaustive searches through national-sized databases. Finger print recognition has shown to be very accurate for human identification. The metric used in performance of identification techniques are directly scanned fingerprints or inked impression of fingerprints. To obtain a better accuracy in matching the images of different decomposition of matching was performed. These parameters perform better in comparing the resultant fingerprints. When tested on a database of images this system was faster and more

In [9] sought to determine if gender had an impact on fingerprint ridge density. They worked under the assumption that fingerprints of females tended to have a thinner epidermal ridge detail compared those of males. The thinner detail would lead to females having a higher ridge density compared to males. The study found that the ridge density was statistically significant in the differences between males and females. The research described in [10] followed up the research performed in [9] and applied it to evaluate the differences in loop ridge count of male and female subjects. The FBI 1984 standards of ridge counting were used to compare the fingerprint loop ridge counts from 40 males and 40 females. The study found that there were no statistically significant differences in loop ridge counts between genders. [11] attempted to classify gender based on fingerprint images. They used fingerprint features like ridge count, ratio of ridge thickness to valley thickness, ridge count asymmetry, and pattern type concordance. The report was specific to their population, application and environment, but it indicated the need to understand the impact of gender on other biometric systems.

3. FINGER PRINT MINUTIAE EXTRACTION

Block-diagram of the automatic fingerprint verification system and its diverse parts can be seen in Figure 1.3. The template is a pre-stored point pattern of extracted minutiae from authentic fingerprint. It is produced in the same way as the point pattern of the fingerprint in the Figure 1.3 on the left.

The major step in this system is minutiae extraction and its various steps are shown in the fig. 3

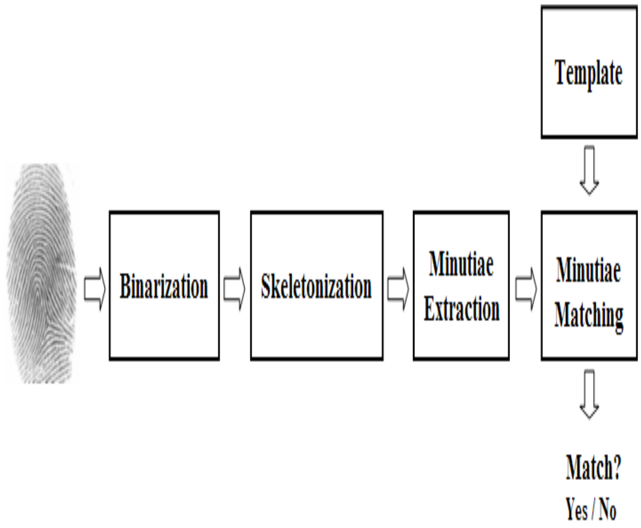


Figure 3 Block-diagram of the total system design.

Fingerprint process includes histogram equalization, noise reduction, and binarization, thinning and filtering.

3.1 Image Enhancement

The fingerprint is first converted into grayscale. Local histogram equalization is used for contrast expansion. Histogram equalization defines a mapping of gray levels q into gray level p such that the distribution of gray level p is uniform. This expands the range of gray levels near the histogram maxima. The transformation improves the detectability of the image features since the contrast is expanded for most of the image pixels. The probability density function of a pixel intensity level l_k is given by:

$$l_k = \frac{m_k}{m} \qquad (1)$$

Where $0 \leq m \leq 1, k = 0,1, \dots\dots 255, m_k$the number of pixels at intensity is level m_k and n is the total number of pixels.

3.2 Histogram equalization

Histogram equalization is a general process used to enhance the contrast of images by transforming its intensity values. We apply the histogram equalization locally by using local windows of 11×11 pixels. This results in expanding the contrast locally, and changing the intensity of each pixel according to its local neighborhood.

3.3 Noise Reduction

In order to reduce the noise pixel-wise wiener filtering is proposed. The filter is based on the estimated local statistics from a local neighborhood $'a'$ of size 3×3 of each pixel, and is given by:

$$w(m_1, m_2) = \tau + \frac{\mu^2 - \sigma^2}{\mu^2}\left(I(m_{1,} m_2) - \tau\right) \qquad (2)$$

Where σ^2 is noise variance, τ and μ^2 are local mean and variance, where we represented the gray level intensity in $(m_1, m_2) \in a$.

3.4 Binarization

Most minutiae extraction algorithms operate on binary images where there are only two levels of interest: the black pixels that represent ridges, and the white pixels that represent valleys. Binarisation is the process that converts a grey level image into a binary image. This improves the contrast between the ridges and valleys in a fingerprint image, and consequently facilitates the extraction of minutiae. Image binarization converts an image of up to 256 gray levels to a black and white image. The simplest way to use image binarization is to choose a threshold value, and classify all pixels with values above this threshold as white, and all other pixels as black. The operation that converts a grayscale image into a binary image is known as binarization. Each pixel is assigned a new value 1 or 0 according to the intensity mean in local neighborhood of 13×13 pixels. The binarization clears the background, and preserves all the thin details. We carried out the binarization process using the following an adaptive threshold.

$$I_{new}(m_1, m_2) = \begin{Bmatrix} 1\ if\ I_{old}(m_1, m_2) \geq Local\ Mean \\ 0\ otherwise \end{Bmatrix} \qquad (3)$$

3.5 Thinning

During this stage, the characterization of each feature is carried out by determining the value of each pixel. Some techniques exist based on thinning the pixel neighborhood having a maximum value initially and filtered in final step in order to eliminate the false lonely points and breaks; an algorithm is presented which eliminates the false information by slide neighborhood processing in a first step followed by thinning without any additional filtering.

3.6 Post processing and filtering

Algorithm is developed in order to handle two typical kind of noise which occur in the thinned binary image: false ridgeline connections and gaps within a true ridgeline, The false ridgeline connections are perpendicular to local ridge direction, and empirically found to be of length less than 10pixels. Thus, lines with similar features are automatically removed by the algorithm. By matching pairs of ridgeline termination, gaps within a true continuous ridgeline are also eliminated.

3.7 Ridge and Valley thickness

The fingerprint image is divided into 30×30 non overlapping blocks. Within each block the local ridge orientation is calculated. The average ratio between the ridge thickness and the valley thickness for each of the fingerprints was calculated automatically and an average ratio was calculated for every subject. The resultant binary profile represents the ridges and the valleys in this block, the high binary value represents the valleys and the low binary value represents the ridges. The average RTVTR was calculated for each block. The blocks having the best quality should contribute to the average RTVTR calculated for this fingerprint. For each block, a quality index was calculated as the average difference between the values of successive singular points (minimas and maximas) of the projection profile, blocks of good quality have higher quality index than those of bad quality. The blocks were arranged in descending order based on their quality index, and the RTVTR of the best 15 were averaged and taken as the averaged and taken ad m the average RTVTR foe this fingerprint.

For each fingerprint the white lines count and ridge count are extracted manually and then average white lines count as well as the ridge count was calculated for each subject. Pattern type was extracted manually for each fingerprint, and the pattern type concordance was calculated for the fingerprints of each right-left corresponding fingerprint pair for the subject, such that the concordance value is 1 if the corresponding fingerprints have the same pattern type, and is 0 otherwise, then the sum of the five fingerprint pairs concordance values was calculated. The ridge count asymmetry between the right-left corresponding fingerprints for a subject was calculated, the asymmetry is 1 for a left-right corresponding fingerprint pair if the ridge count of the left fingerprint is greater than the right one, is -1 if it is smaller, and is 0 if both ridge counts are equal. The sum of the asymmetry values of the five fingerprint pairs of the subject was calculated.

4. GENDER CLASSIFICATION USING SVM

In gender classification from fingerprints ridge breadth and white lines are calculated. The gender classification is done based on different combinations of these features. The features include ridge count, ridge thickness to valley thickness ratio (RTVTR), fingerprint pattern type, white lines count, pattern type concordance between the corresponding left-right fingerprints, and ridge count asymmetry between the left-right corresponding fingerprints. Support Vector Machines are used to classify the gender from the given fingerprints. It is based on the concept of decision planes that defines the decision boundaries. A set of objects having different class memberships are separated by a decision plane. SVM is a nonlinear classifier often used for producing superior classification. An example for SVM classifier is as shown in the fig. 2.

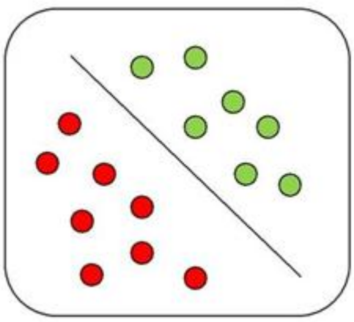


Fig. 2 SVM Classifier

Classification task is based on separating lines to distinguish between objects of different class memberships, here its male and female classification. Here let ‘red’ color represents ‘male’ gender and ‘green’ color represents ‘female’ gender.

5. RESULT AND DISCUSSION

In this section, we have investigated the performance of our proposed method of classification. For gender classification SVM classifier is used

Initially four person’s fingerprints are extracted. The input images of the four fingerprints are converted into the binary image as shown in the fig. 4(b). Binary images contain only two values either 0 or 1. Fig. 4(c) shows the filtered image of the binary fingerprint image.

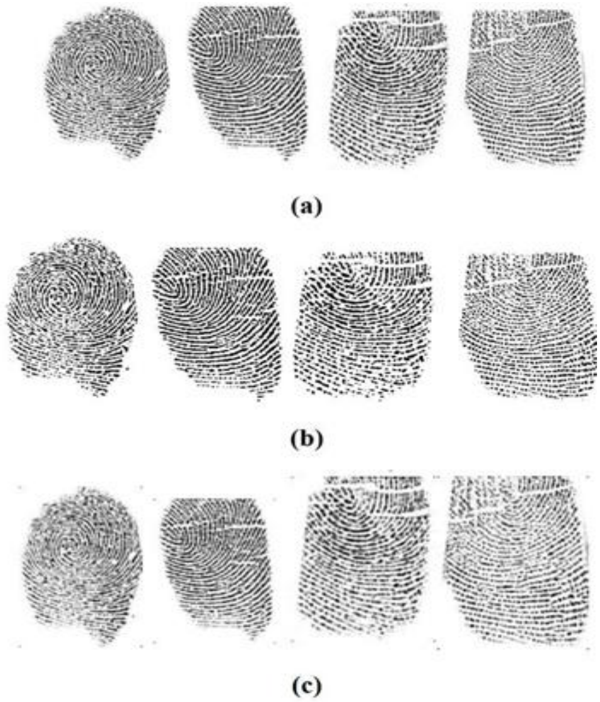


Fig. 4 (a) Input Images (b) Binary Image (c) Filtered Images of four fingerprints

Fig.5 (b) & (c) shows the skeletonized and thinned images of the four input fingerprints.

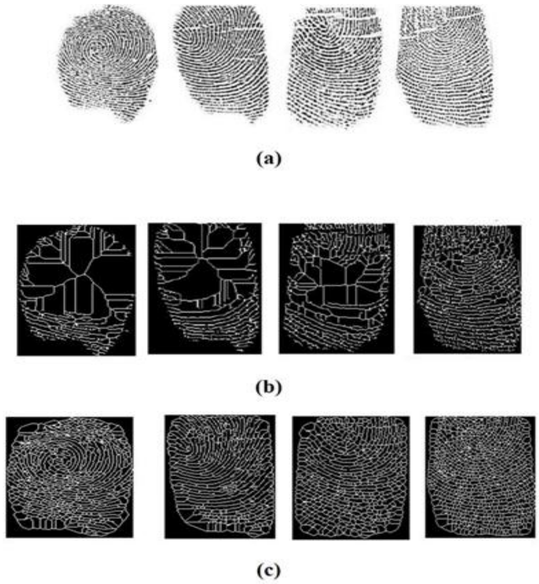
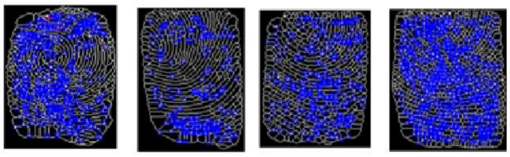


Fig. 5 (a) Input images (b) Skeletonized images (c) Thinned images of four fingerprints

Fig.6 (a) & (b) shows the input images and corresponding minutiae extracted images.

(a)

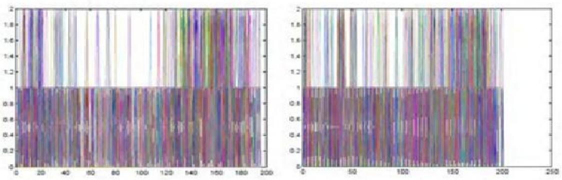


(b)

Fig. 6 (a) Input images of four fingerprints and (b) corresponding minutiae extraction

From the fig. 7 (b) number of ridges are calculated and plotted from the input fingerprint image as in fig. 7(a). And the fig. 8 (b) shows the ridge count plot of the corresponding input fingerprint image as shown in fig. 8 (a). From the plots in fig.7 and fig. 8 it is observed that the ridge count is high in fig. 7 than in latter fig.8 Thus it is concluded that the fingerprint having high number of ridge count belongs to female gender. This is the same in case of white lines count too. Female fingerprints have higher white lines count.

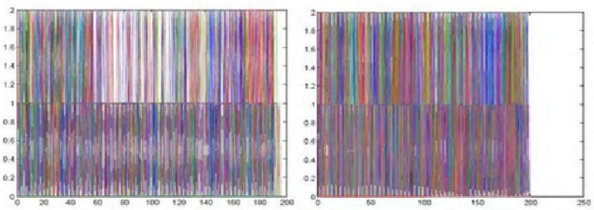
(a)



(b)

Fig. 7 (a) Input images and (b) Ridge Count plot of corresponding input fingerprints of female

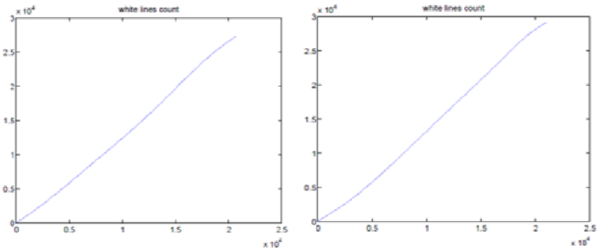
(a)



(b)

Fig. 8 (a) Input image and (b) Plot of ridge count of corresponding input images of male fingerprint

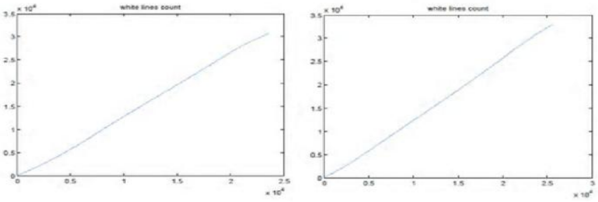
(a)



(b)

Fig.9 (a) Input images, (b) White lines count plot of female fingerprint

(a)



(b)

Fig. 10 (a) Input images and (b) Plot of white lines count of male fingerprint

5. CONCLUSION

In this paper gender classification is carried by using SVM classifier. For our method male and female fingerprint of good quality are selected. Optimal threshold is chosen for better results. The results confirm a difference in fingerprint image quality across age groups. Inherent feature issues, such as poor ridge flow, and interaction issues, such as inconsistent finger placement, have an impact on captured fingerprint quality, which eventually affects overall system performance. Our proposed method gives more accuracy than existing methods.

6. REFERENCES

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