Exploiting Quality and Texture Features to Estimate Age and Gender from Fingerprints

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ABSTRACT

Age and gender of an individual, when available, can contribute to identification decisions provided by primary biometrics and help improve matching performance. In this paper, we propose a system which automatically infers age and gender from the fingerprint image. Current approaches for predicting age and gender generally exploit features such as ridge count, and white lines count that are manually extracted. Existing automated approaches have significant limitations in accuracy especially when dealing with data pertaining to elderly females. The model proposed in this paper exploits image quality features synthesized from 40 different frequency bands, and image texture properties captured using the Local Binary Pattern (LBP) and the Local Phase Quantization (LPQ) operators. We evaluate the performance of the proposed approach using fingerprint images collected from 500 users with an optical sensor. The approach achieves prediction accuracy of 89.1% for age and 88.7% for gender.

Keywords: Fingerprint Recognition, Soft Biometrics, Age / Gender Estimation, Image Quality, Image Texture

1. INTRODUCTION

Although soft biometric characteristics, gender and age for example, are not discriminative enough to distinguish individuals, they provide additional evidence that may complement primary biometric identifiers such as fingerprints, faces, irises. Therefore, they can contribute to recognition accuracy. Recently, frameworks for fusing ancillary information with the output of traditional biometric systems have been proposed. In these systems automatic extraction of soft biometrics enables performance enhancements in recognition systems based on primary biometric identifiers. In the case of fingerprints, in adverse acquisition conditions (e.g., low quality images, spoof attacks, non-universality) it may become challenging to image a well-defined ridge structure, which is essential for reliable minutiae extraction and, subsequently, accurate matching. It is known that fingerprint recognition performance is confounded by various physiological and technological factors. For example, the age of individuals and sensor wear-out may negatively affect the quality of fingerprint capture. Inherent physical features of the subject and ageing effects pertain to the character view point of the fingerprint, while the utility measures the impact of the sample on the overall matching performance. The character contributes to the utility of the sample and, subsequently, to the matching. In particular, studies demonstrate that elderly people have a higher probability of being falsely rejected by the system, compared to the younger individuals. An assessment of differences between fingerprints collected from males and females was carried out by Frick et al.. They compared image quality and minutiae counts to capture variations in elasticity and in the ability of the skin to retain moisture. Existing approaches for predicting age and gender exploit features such as ridge count, ridge thickness-to-valley-thickness ratio and white lines count all of which are typically manually extracted. Automatic extraction of these fingerprint features which are relevant for age and gender estimation remains a challenge especially from elderly female subjects.

In this study, we first examine the impact of gender and age in fingerprint images by observing differences in match scores, image quality and texture; then, we propose automatic age and gender estimators for fingerprints.
Our model exploits three categories of features: i) image quality, captured as the ridge strength and estimated by computing the energy concentration pertaining to forty different frequencies; ii) image texture, captured by the Local Binary Pattern (LBP) and the Local Phase Quantization (LPQ) descriptors with optimized division of the whole image in sub-regions; iii) characteristics related to the extractability of features (e.g., minutiae count, contrast, etc.).

The paper is organized as follows. In Section 2, we describe the state-of-the-art pertaining to the estimation of age and gender from fingerprints. Section 3 presents the proposed age and gender estimation method. Section 4 presents the experimental results. Section 5 draws our conclusions.

2. RELATED WORK

Extensive research has been performed in the area of gender and ethnicity inference of individuals based on face images. Age determination presents quite a challenging problem. There are also studies which examined the impact of age groups and gender diversity on fingerprints. The effects of ageing affect the quality of fingerprints mainly due to changes in character. Over the life of the individual, the skin becomes drier and thinner, and reduction of collagen causes skin wilting. These factors affect the sample provided to the fingerprint sensor. Age affects the differences in quality of the fingerprint image, but the ridge / valley pattern is believed to remain stable over the life time of the individual. Research on age estimation through fingerprints has analyzed textural characteristics. A recent method, although automatic, results in a low prediction accuracy for subjects 36 years or age and above.

Regarding gender, most authors pursue ridge analysis in the spatial domain. Some studies assumed that females exhibit a higher ridge density due to finer epidermal ridge details compared to males. Ridge density is defined as the number of ridges within a unit of space. Ridge density is characterized by ridge breadth and ridge-to-ridge distance. Correlations between ridge-counts on the ten fingers, stratified by race, have been compared in a small study of 11 samples from different populations. The samples of European population showed no consistent difference in mean correlation that can be attributed to subject’s sex, although female American Whites appeared to significantly exceed male ridge counts. The pattern of sex differences suggests that the Y-chromosome may play a role in dermal ridge development. Fingertips do not seem to be completely random patterns, there appears to be some relationship with the genes. In particular, ridge configurations seem to be under genetic control. Past studies on the influence of genes on dermatoglyphic development highlighted, for example, a correlation between the total fingerprint count and sex chromosomes. Additionally, in 1968 Hunter reported significant differences in ridge counts between genders. Later, in 1995 Kunter and Ruhl analyzed a Central European population sample (Giessen, Hessen) of 625 persons (273 males and 352 females) and reported significant differences of ridge counts in males and females as well. In 1999, Acree experimentally demonstrated this trend by counting ridges in a well-defined area. In subsequent studies, the mean epidermal ridge breath (MRB) was used as indicator of sex given that MRB in males was found to be 9% greater than females. The hypothesis that women tend to have a greater ridge density than men was supported also by Gungadin who found out that fingerprints of females exhibit a higher ridge density due to finer epidermal ridge details compared to males. Recently, an opposite observation was reported by Bharadwaj et al.. Their analysis uncovered no difference in ridge count in relation to gender. However, the analyzed population had a total of 100 subjects. Namouchi showed as well that ridge count does not differ for Tunisian population. Gutierrez-Romero et al. counted epidermal ridges in three well-defined fingerprint areas and found that, in data pertaining to 200 subjects of a Spanish Caucasian population, females present higher ridge density compared to males. Such a study was extended to a different population. Nithin et al. classified fingerprints based on gender using finger ridge count in a well-defined area. Results on rolled fingerprints from 550 subjects belonging to the South Indian population show that females present a significant higher ridge count than males. Gnanasivam et al. investigated the impact of gender on ridge density as well. They found a statistically significant difference between males and females in the ulnar fingerprint area. In 2013, a North Indian population of 194 female subjects was found to exhibit statistically significant higher ridge density in all the three areas (radial, ulnar and lower).

In forensic applications, gender classification from fingerprints has been proposed by Badawi et al. The method is based on manual extraction of five features: ridge count, ridge thickness to valley thickness ratio, white
lines count, pattern type concordance and ridge count asymmetry. The reported accuracy on a data set made of 1,100 males and 1,100 females was 88.8%, achieved by a Neural Network classifier. Recently, a method based on discrete wavelet transform (DWT) and singular value decomposition (SVD) has been proposed by Gnanasivam et al. for gender and age estimation from fingerprints. In this work, images are decomposed into different frequency ranges to isolate small changes, mostly at high frequencies. The reported gender classification rate was 88.28%, while the reported age classification rate was unacceptably low for females 36 and older (16.79%).

3. THE PROPOSED APPROACH

In order to capture variations in fingerprint images due to differences in gender / age, we combine different types of features, image quality and texture extracted at global and local levels. The classification is carried out using machine learning algorithms after applying a feature reduction technique.

**Frequency Domain Filtering.** Image filtering in the frequency domain allows us to exploit some basic properties. Frequency components of the Fourier Transform (FT) are generally related to spatial characteristics of the image. In particular, frequency expresses the rate of change in the image such that higher frequency components pertain to patterns in the image corresponding to the occurrence of higher variations in grey level intensity.

- **Global Fourier Transform Analysis.** Given an image $I(x, y)$, the Discrete Fourier Transform (DFT) of size $M \times N$ can be computed as indicated in Eqn. (1).

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) e^{-i2\pi \frac{ux}{M} + \frac{vy}{N}}, \quad i = \sqrt{-1},$$

where $x$ and $y$ are spatial variables, $I(x, y)$ represents the gray level intensity value at pixel $(x, y)$ of the image, $u$ and $v$ are frequency variables. Let $B = 40$ be the number of equally spaced frequency bands considered. We define a Region Of Interest (ROI) in the power spectrum with bands ranging from 50 Hz to 250 Hz in order to extract ring features. Each ring is constructed by computing the difference of two equally-spaced low-pass Butterworth filters. Butterworth filters are defined by two parameters, i.e., the cutoff frequency and the filter order. The filter order indicates the sharpness degree of the transition from the passband to the stopband. The Butterworth filter used in this work has order $n = 20$, see Eqn. (2).

$$H(u, v) = \frac{1}{1 + D(u, v)/D_0}^{2n}$$

with cutoff frequency at a distance $D_0$ from the origin, $D(u, v)$ is the distance of point $(u, v)$ from the origin of the frequency plane defined by $D(u, v) = (u^2 + v^2)^{1/2}$.

$$G_k(u, v) = H_k(u, v) - H_{k-1}(u, v)$$

The frequency response of the Butterworth filter in the passband is as flat as possible depending on the order of the designed filter. The description of the image is given in terms of energy computed in the frequency bands. For each band, the energy concentration is given by Eqn. (4).

$$E_k = |G_k(u, v)F(u, v)|^2$$

where $k = 1, \ldots, B$. Young people and females, generally, present strong ring patterns in the power spectrum, see Fig. 1.

- **Local Fourier Transform Analysis.** Spectral content may vary spatially. When using the FT applied to the entire image there is no information about which frequencies occur at which position in the original image. This limitation can be overcome by using the Short-Term Fourier Transform (STFT) which analyzes the frequency content locally, by considering image patches. The local FT $G_s(u, v)$, with $s$ being the patch...
Figure 1. Fingerprint images taken from the WVU dataset: (a) fingerprint of a male (22 years old); (b) fingerprint of a female (22 years old); (c) fingerprint of an elderly person (54 years old); (d) (e) (f) show corresponding power spectra; (g) (h) (i) illustrate the energy distribution across different frequency bands. Visually, ridge density of the female fingerprint is higher compared to the fingerprint of the male. For young males the power spectrum is concentrated in about ten central frequency bands, while for females the spectrum is wider and higher frequency values are assumed as well. For elderly people most of the frequency components are low.
index, is obtained by applying a linear filtering technique. The local transform is a weighted sum of the frequency components of the image patch in which weights are determined by frequency coefficients of the filter.\textsuperscript{34,35,36} For every pixel of the image, \( I(x, y) \), the phase of the local DTF is computed in a \( M \times M \) neighborhood. Data pertaining to the local descriptor is reduced using the quantizer defined in Eqn. (5) to obtain the Local Phase Quantization (LPQ)\textsuperscript{∗}:

\[
q_j = \begin{cases} 
1, & \text{if } g_j \geq 0 \\
0, & \text{otherwise}
\end{cases}
\]

(5)

where \( g_j \) is the \( j^{th} \) component of \( G \). The quantizer results in a 2-bit integer representation for a single frequency component at every point \( x \). The \( L \) quantized coefficients are presented as histograms according to the following binary coding:

\[
b = \sum_{j=1}^{L} q_j 2^{j-1},
\]

(6)

which ranges between 0 and \( 2^L - 1 \) and describes the local texture at location \( x \).

Spatial Domain Filtering. In most approaches to texture classification, probe samples are assumed to exhibit identical spatial scale, orientation and gray-scale properties. In practical applications, these conditions are difficult to achieve. Texture is characterized by the spatial distribution of gray levels in a neighborhood. Its details cannot be captured in a single point. The local binary pattern operator (LBP)\textsuperscript{†} is able to efficiently characterize the spatial configuration of local image texture by detecting spatial structures, referred to as local binary texture patterns. LBP is robust to gray-scale variations, in particular it is invariant to monotonic transformation of the gray scale which can be due for example to changes in illumination conditions. The texture \( T \) is defined as the joint distribution of gray values of a circularly symmetric neighbor set of \( P \) image pixels on a circle of radius \( R \) (see Eqn. (7)).

\[
T = t(g_c, g_0, ..., g_{P-1}),
\]

(7)

where \( g_c \) is the gray value of the center pixel of the local neighborhood and \( g_0, ..., g_{P-1} \) are the gray values of \( P \) equally spaced pixels on the considered circular symmetric neighbor set. Pixels of a given image are transformed by thresholding each \( 3 \times 3 \) pixel neighborhood with the center value and multiplying the thresholded values by powers of two; their sum corresponds to the label assigned to pixel, see Eqn. (8)\textsuperscript{37,38} Histograms of LBP images estimate the distribution of local structures detected by the LBP operator. In this paper, we use the basic LBP operator without considering its extensions based on uniform pattern detection or rotation invariance.

\[
LBP_{P,R} = \sum_{p=0, ..., P-1} s(g_p - g_c)2^p,
\]

(8)

where \( s \) is defined as: \( s(x) = 1 \) if \( x \geq 0 \), else \( s(x) = 0 \).

4. EXPERIMENTAL RESULTS

4.1 Data set

The data set used in this study consists of fingerprints from 494 users collected at West Virginia University. Fingerprints were acquired using a live-scan optical sensor with resolution factor of 500 dpi. Users provided two sets of fingerprints, in sequence, each consisting of rolled individual fingers on both hands, left slap, right slap, and thumbs slap. Fingerprints were collected without controlling the quality in acquisition, i.e., no fingerprint images were rejected and recaptured at that stage. Match scores between all image pairs were generated using the Identix BioEngine Software Development Kit. Quality measures were extracted with NFIQ, part of National Institute of Standard Technology (NIST) Biometric Image Software (NBIS)\textsuperscript{‡}. The quality value given by NFIQ to a fingerprint image is a scalar in the range 1-5, where 1 is given to images with highest quality. Recent studies highlighted that NFIQ is effective in discriminating between good and bad quality images.\textsuperscript{39}

\textsuperscript{∗}http://www.cse.oulu.fi/CMV/Downloads/LPQMAtlab

\textsuperscript{†}http://www.cse.oulu.fi/CMV/Downloads/LBPMatlab

\textsuperscript{‡}http://www.nist.gov/itl/iad/ig/nbis.cfm
4.2 Evaluation Procedure
For each fingerprint image, we extracted the following set of features:

- 1 value obtained from the NFIQ algorithm;
- 1 value representing the number of minutiae in the fingerprint (not used for gender estimation);
- 40 values representing the ring features extracted in the frequency domain;
- 1 value of the entropy computed from the ring features;
- 256 values obtained from the histogram of the LPQ descriptor;
- 256 values representing the frequency histogram of the LBP descriptor.

These values are concatenated to form a feature vector. Such vector has the size of 554 for gender and 555 for age. In order to analyze the correlation between the features and reduce the dimensionality of the feature set, Principal Component Analysis (PCA) was applied to the data set. PCA is a method for dimensionality reduction which projects the original feature vectors into a lower dimensional subspace determined by the principal components. The principal components are a linear combination of features, and they represent the direction of maximum variance in the data set. By analyzing the correlation matrices for LBP and LPQ histograms (Pearson’s linear correlation), we observed that each bin is strongly correlated with neighboring bins. The same observation is made for the energy distribution across the 40 specified bands: the energy for each band is highly correlated with that of its neighboring bands. PCA takes advantage of the dependencies between the variables in order to project the high-dimensional data into a lower-dimensional subspace without losing too much information. Given the high correlation in our data set, PCA is able to reduce the number of features from 555 to 44 for age and from 554 to 43 for gender. We experimented with different classification algorithms, all of which were trained by performing a 10-Fold Cross Validation. Weka 3.6 was used for implementing both the PCA and classification algorithms.

4.3 Results
We observed that match score distributions vary based on age groups. Fig. 2 shows that genuine match scores for elderly people are generally lower compared to young. In the experiments, young subject is someone 18 to 29 years old and elderly are 30 years of age and older. In the data set of 494 users 283 are young and 211 belong the elderly group. Several factors such as finger conditions, sensor imperfection and improper finger placement affect image quality. In particular, ageing effects and skin conditions (i.e., wet or dry) represent inherent impairments in the biometric source, which impact its suitability for matching. We also analyzed how image quality values vary based on age, see Fig. 3. We computed NFIQ scores using National Institute of Standards and Technology (NIST) Fingerprint Image Software 2 (NFIS2). Quality measures range between 1 and 5, where 1 indicates the best fingerprint image quality. The average quality value for the young group was 1.9; 2.8 for the elderly group. Fingerprint image quality quantifies the utility of a fingerprint image in an automatic comparison operation. A high image quality measure is assigned to an image with distinguishable patterns and features of interest. Fig. 4 illustrates the probability density functions of energy for two different frequency bands. We can see that there is little overlap area between the distribution for female subjects and that for male subjects. This is proof that those frequency bands have high discriminative power with respect to gender, although not all the 40 bands exhibit the same level of separation. Fig. 5 shows LBP and LPQ histograms for individuals belonging to the classes considered in this study. We performed experiments with different classification algorithms: Support Vector Machine, Random Forest, K-Nearest Neighbor. The classifier that performed best was K-Nearest Neighbor, with K=1, for both cases: accuracy of 89.1% for age and 88.7% for gender; see Tables 1 and 2 respectively.
Identix Genuine Match Scores for Age Groups

![Histogram of genuine match scores for two different age groups](a)

Identix Genuine Match Scores for Gender

![Histograms of genuine match scores for males and females](b)

Figure 2. Impact of age and gender on Identix match scores: (a) Histograms of genuine match scores for two different age groups; (b) Histograms of genuine match scores for males and females.

Figure 3. Histogram of NFIQ quality measures for two different age groups.

**Table 1. Classification performance for age estimation.**

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<tr>
<th>Classifier</th>
<th>Parameters</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Polynomial kernel</td>
<td>75.5</td>
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<tr>
<td>Random Forest</td>
<td>50 trees</td>
<td>76.3</td>
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<tr>
<td>K-Nearest Neighbor</td>
<td>K = 1</td>
<td>89.1</td>
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</table>
Figure 4. Energy distribution across two different frequency bands which are discriminative with respect to gender.

Figure 5. (a) LBP-based histogram of a fingerprint image pertaining to a male (22 years old); (b) LBP-based histogram of a fingerprint image pertaining to a female (22 years old); (c) LBP-based histogram of a fingerprint image pertaining to an elderly male (54 years old); (d) LBP-based histogram of a fingerprint image pertaining to a male (22 years old); (e) LBP-based histogram of a fingerprint image pertaining to a female (22 years old); (f) LBP-based histogram of a fingerprint image pertaining to a 54 years old male. LBP distributions assume higher values for young males; the maximum value of LPQ histograms for this category is generally higher.

<table>
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<tr>
<th>Classifier</th>
<th>Parameters</th>
<th>Accuracy (%)</th>
</tr>
</thead>
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<tr>
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<td>K-Nearest Neighbor</td>
<td>K = 1</td>
<td>88.7</td>
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Table 2. Classification performance for gender estimation.
5. CONCLUSIONS

In this paper we built models which are able to automatically predict age and gender from a fingerprint image. The models exploit quality-based features extracted from the frequency domain, and textural features captured by the Local Binary Pattern and Local Phase Quantization descriptors. By applying Principal Component Analysis we were able to reduce complexity and increase the discriminative power of our designed feature set. Classification for gender and age is accomplished using several Machine Learning algorithms. In both cases the K-Nearest Neighbor classifier provided the highest accuracy: 89.1% and 88.7% for age and gender, respectively.

We plan to extend our experiments using additional features and classification algorithms, in order to raise accuracy above 90% for both age and gender.

REFERENCES


