Towards Enhancement of Gender Estimation from Fingerprints

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Accurate gender prediction brings benefit to several applications. In biometrics, beyond filtering large databases, a gender recognizer can be combined with the output of primary identifiers to increase the recognition accuracy in challenging scenarios (e.g., partial evidence) [1]. In criminal investigation, gender classification may minimize the list of suspects. Although the development of reliable gender estimators is needed, most of the existing approaches are not highly accurate, and often the process is not fully automated. Epidermal ridges are formed during the first three / four months of the gestational period and the resulting ridge configuration remains stable. Ridges and their arrangement, referred to as *dermatoglyphics*, are determined not only based on environmental factors but also on genetics [2, 3]. In the scientific literature, fingerprints of females are assumed to have thinner epidermal ridge details which leads females having a higher ridge density compared to males. Subsequently, existing methods tend to relate gender determination to a direct measure of the ridge density [4]. However, this approach may not be robust to image degradation (e.g., partial impressions, low quality).

In 2006, Badawi *et al.* achieved an accuracy of 88.8% on fingerprint data pertaining to $1,100$ males and $1,100$ females by combining the ridge thickness to the valley thickness ratio, white lines count, pattern type concordance and ridge count asymmetry [5]. However, some of the features were manually extracted. Later, Natural images are modeled as non-stationary signals, characterized by patterns of long period at low frequencies (e.g., background), and developments of short-period at high frequencies (e.g., discontinuities, edges) [6]. In 2011, Gnanasivam and Muttan used Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD) on data pertaining to 225 males and 175 females, and reported accuracy of 93.86 % [4]. In 2013, Tom *et al.* efficiently combined Principal Components Analysis (PCA) and 2-D Discrete Wavelet Transform (DWT) [7]. In 2014, Marasco *et al.* fused LBP, LPQ, image quality, minutiae count and energy values pertaining to forty different frequency bands determined through Fourier analysis [8]. An accuracy of 88.7% was achieved by the K-Nearest Neighbor classifier after performing Principal Component Analysis on data pertaining to 500 subjects. In 2015, Gornale *et al.* proposed an approach based on Haralick texture features classified via Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). They evaluated data pertaining to 300 males and 300 females and reported an accuracy of 92% and 94% was achieved with LDA and QDA, respectively [9].

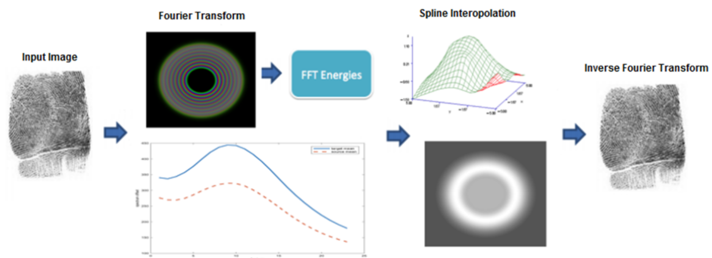

Figure 1. Architecture of the proposed approach.

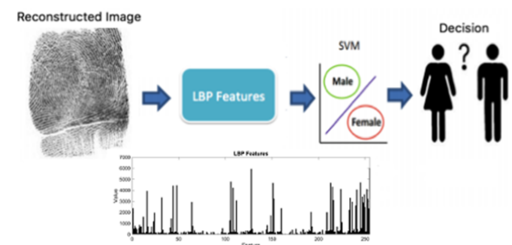

Figure 2. Classification process.

In this work, we push boundaries for achieving an accurate automatic gender estimation from fingerprints. The proposed method first estimates enhanced frequency features in the Fourier domain by using a spline model. Then, Local Binary Patterns are extracted from the reconstructed image and classified with SVM.

The architecture of our approach is illustrated in Fig. 1 and Fig. 2.

- The fingerprint image is transformed into the Fourier domain where frequency components express a rate of change in grey-level intensity in the image. Specifically, higher variations are associated to faster frequency components. Given an image $I(x, y)$, the Discrete Fourier Transform (DFT) of size $M \times N$ can be computed as follows:

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

where $i = \sqrt{-1}$, 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. The selected Region Of Interest (ROI) consists in frequency components ranging from 50 Hz to 250 Hz. In order to have a fine-grained distribution of energy for each fingerprint, we analyzed 40 equally-spaced bands of 5 Hz. Each band is determined through the difference between two consecutive Butterworth low-pass filters. The energy concentration local to each band is then computed.

- The magnitude of the Fourier Transform is modified and the original image is recovered with modified magnitude and original phase. Specifically, a target distribution is built in order to reach desired values for the energy distributions. The centers of the Fourier bands correspond to pre-defined points. The Spline interpolation estimates the frequency components corresponding to the target energy distribution. The inverse of the Fourier Transform is computed in order to reconstruct the image with modified magnitude but same phase spectrum. Frequency components are modified such that the overlap between the energy distributions pertaining to males and females are maximized. The corresponding magnitude of the Fourier spectrum is estimated through Spline interpolation.

- Texture features are extracted from the reconstructed image. Texture is characterized by repeating patterns of local variations in image intensity. We seek for a texture descriptor which is invariant to monotonic transformations of grey-levels such as the *Local Binary Patterns (LBP)* operator[1]. Texture 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. (2)),

$$T = t(g_c, g_0, ..., g_{P-1}) \tag{2}$$

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. Features (e.g., statistics) are extracted directly from LBP histograms, obtained as described in Eqn. (3) [10],

$$LBP = \sum_{p=0,\ldots,P-1} s(g_p - g_c)2^p \tag{3}$$

where s is defined as: $s(x) = 1$ if $x \geq 0$, else $s(x) = 0$. Uniform LBP features are used to train a SVM classifier.

The performance of the proposed algorithm was evaluated on fingerprint data pertaining to two different data sets both collected at West Virginia University. The first data set has 494 users, 238 females and 256 males. The second data set has 1074 users, where 501 are females and 573 are males. Users provided two sets of fingerprints, in sequence, each consisting of rolled individual fingers on both hands, left slap, right slap, and thumbs slap. In our experiments we only used the right index finger. In cross-sensor scenario, gender is still identified with an improved average accuracy by 5%.

[1] http://www.cse.oulu.fi/CMV/Downloads/LBPMatlab

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