Evaluation of Texture Descriptors for Automated Gender Estimation from Fingerprints

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Abstract. Gender is an important demographic attribute. In the context of biometrics, gender information can be used to index databases or enhance the recognition accuracy of primary biometric traits. A number of studies have demonstrated that gender can be automatically deduced from face images. However, few studies have explored the possibility of automatically estimating gender information from fingerprint images. Consequently, there is a limited understanding in this topic. Fingerprint being a widely adopted biometrics, gender cues from the fingerprint image will significantly aid in commercial applications and forensic investigations. This study explores the use of classical texture descriptors - Local Binary Pattern (LBP), Local Phase Quantization (LPQ), Binarized Statistical Image Features (BSIF) and Local Ternary Pattern (LTP) - to estimate gender from fingerprint images. The robustness of these descriptors to various types of image degradations is evaluated. Experiments conducted on the WVU fingerprint dataset suggest the efficacy of LBP descriptor in encoding gender information from good quality fingerprints. The BSIF descriptor is observed to be robust to noisy and partial fingerprints, while LPQ is observed to work well on blurred fingerprints. However, the gender estimation accuracy in the case of fingerprints is much lower than that of face, thereby suggesting that more work is necessary on this topic.

Keywords: Soft biometrics, fingerprints, gender estimation, LBP, LPQ, BSIF, LTP

1 Introduction

Gender[1] classification is a fundamental task for human beings, as many social interactions are gender-based [1]. The problem of gender classification has been investigated from both psychological [2] and computational perspectives [3]. It plays an important role in many applications such as human-computer interaction, surveillance, context-based indexing and searching, demographic studies

[1] The more accurate term would be *sex* rather than *gender* in the context of this paper.

and biometrics [1, 4]. In the context of biometrics, gender can be viewed as a soft biometric trait that can be used to index databases or enhance the recognition accuracy of primary biometric traits.

The problem of automated gender estimation is typically treated as a two-class classification problem in which features extracted from a set of images corresponding to male and female subjects are used to train a two-class classifier. The output of the gender estimator is the classification of a test image as a male or female subject [1, 4–6]. A number of studies suggest that gender can be robustly estimated from face images with relatively high accuracies [7, 8].

However, only a limited number of studies have investigated the estimation of gender information from fingerprint images [9–12]. In most of these studies [9–11], gender estimation using fingerprints was based on the observation that females exhibit a higher ridge density due to finer epidermal ridge details compared to males. In [13], a method for gender classification based on Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) was proposed. Recently, in [14], quality-based features extracted from the frequency domain using Fourier Transform Analysis (FTA) and texture-based features captured by the Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) descriptors, were used for gender estimation. These studies suggested that gender can be deduced from fingerprint images with an accuracy of about 82% [13, 14]. However, these studies do not clearly indicate if the *subjects* in the training and test sets are non-overlapping - an important requirement for evaluating gender classifiers. The local texture information of a fingerprint should offer gender cues [13, 14] because it can encode the ridge density structure that varies between males and females [9]. Deducing gender from fingerprints can be useful in forensic investigations and security applications where additional intelligence may be obtained from the fingerprint of a person. Further, gender information can also be used to enhance the recognition accuracy of a fingerprint matcher in commercial applications. However, there is a limited understanding of this topic which is partially due to the superficial nature of existing studies.

In this work, we investigate several aspects of gender estimation from fingerprint images. Firstly, we evaluate the ability of four commonly used texture descriptors to extract gender information from fingerprints. Secondly, we analyze if a gender estimator developed for one finger (e.g., left index) can be used to predict the gender of fingerprints originating from a different finger (e.g., right index). In previous studies, experiments were conducted by either training and testing the gender estimator on each finger individually [13] or by analyzing the differences in fingerprint ridge density between males and females over all the fingers and reporting aggregate statistics [9–11]. Thirdly, we evaluate the effect of degraded and partial fingerprint images on the performance of the gender estimator. To facilitate this analysis, we simulate noisy, blurred and partial fingerprint images. Finally, we investigate if the texture descriptors used for fingerprints can be used in the context of gender estimation from face images.

In summary, the contributions of this work are as follows:

- Exploring multiple textural descriptors to encode gender information from fingerprints.
- Evaluating the interoperability of the gender estimator across different fingers.
- Evaluating the performance of gender estimator on degraded fingerprint images.
- Utilizing the same set of texture descriptors for encoding gender information in both face and fingerprint images.

Experiments are conducted on the WVU multimodal face and fingerprint database [15].

This paper is organized as follows: Section 2 explains the textural descriptors used to encode gender information from fingerprint images. Section 3 presents the experimental investigations and results. Conclusions are drawn in section 4.

2 Texture Descriptors Used for Encoding Gender Information

The textural descriptors used to extract gender information from fingerprint images are summarized below.

1. **Local Binary Pattern (LBP):** It is a textural descriptor that assigns a label to every pixel of an image by thresholding the neighborhood of each pixel based on the center pixel value and converting the resultant binary number to a decimal value. Then histograms are computed from tessellated blocks and concatenated to form a descriptor [16]. The LBP operator can be extended with neighborhoods of different sizes. Using a circular neighborhood and bilinear interpolation at non-integer pixel coordinates allows for any radius and number of pixels in the neighborhood. The notation (P,R) will be used to denote a pixel neighborhood consisting of P points on a circular neighborhood of radius R. The LBP code of a pixel g_c is given by:

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

$$s(x) = \begin{cases} 1 \text{ if } x \geq 0; \\ 0 \text{ otherwise.} \end{cases} \tag{2}$$

   Here, g_c and g_p denote the center pixel and neighboring pixels, respectively. Further, $LBP^{u2}_{P,R}$ represents uniform rotation invariant LBP which can be used to reduce the number of codes, and hence the length of the feature vector[16].
   In our work, each image is tessellated into non-overlapping blocks of size 18×25 and each block is represented with a feature vector which is a concatenation of histograms corresponding to $\mathrm{LBP}^{u2}_{8,1}$, $\mathrm{LBP}^{u2}_{16,2}$ and $\mathrm{LBP}^{u2}_{24,3}$. The feature vectors of all block are concatenated to obtain the final feature descriptor.

2. **Local Phase Quantization (LPQ):** It is based on the quantization of Fourier transform phase in local neighborhoods [17]. Short Time Fourier Transform (STFT) is computed over a $M \times M$ neighborhood, N_x, at each pixel position x of the image $f(x)$ as follows:

$$F_{u,x} = \sum_{y \in N_x} f(x-y)e^{-j2\pi u^T y} = w_u^T f_x. \tag{3}$$

   Here, w_u is the basis vector of the 2-D DFT at frequency u, and f_x is a vector containing all M^2 image pixels from N_x. We used a window size of 5×5 to extract LPQ features. Then, a LPQ histogram was computed for each tessellated block of size 18×25 from an image.
3. **Binary Statistical Image Features (BSIF)**: This method computes a binary code for each pixel by linearly projecting local image patches onto a subspace, whose basis vectors are learnt from natural images via independent component analysis, and by binarizing the coordinates in this basis via thresholding. The length of the binary code string is determined by the number of basis vectors. Image blocks are represented by histograms of binary codes. This method is different from other descriptors which produce binary codes, such as LBP and LPQ, in the sense that the proposed approach is based on statistics of natural images and this improves its modeling capacity [18]. We extracted BSIF features using a predefined filter of size 7×7 learnt from natural images and a 12-bit string.
4. **Local Ternary Pattern (LTP)**: This is a texture descriptor that creates a ternary code for every pixel based on its neighborhood as follows [19].

$$s'(g_p, g_c, t) = \begin{cases} 1 & g_p \geq g_c + t \\ 0 & |g_p - g_c| < t \\ -1 & g_p \leq g_c - t \end{cases} \tag{4}$$

   Here, g_p is the neighborhood pixels, g_c is the center pixel and t is the threshold value. As stated in [19], LTP is less sensitive to noise since the threshold is not purely based on the center pixel, unlike LBP. A 59-bin histogram is extracted from each block of size 18×21.

To extract these textural features, a fingerprint image is first tessellated into non-overlapping blocks, and then textural histograms are computed from each block. The histograms of all the blocks are concatenated to obtain a final feature descriptor. The extracted feature vectors from a set of training images corresponding to male and female subjects are used to train a gender estimator based on two-class linear SVM [8]. Figure 1 illustrates the steps involved in gender estimation from a fingerprint image.

3 Gender Estimation from Fingerprints

In this section, we will describe the dataset used, the experiments conducted and the obtained results.

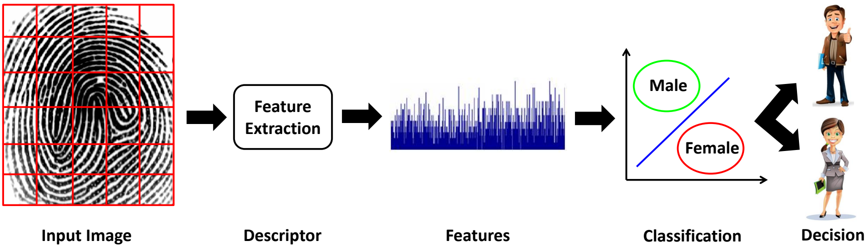

Fig. 1. The steps involved in gender estimation from a fingerprint image.

3.1 WVU Multimodal Dataset

We utilized the WVU multimodal dataset consisting of face and fingerprint images of 166 male subjects and 71 female subjects. For every subject, five samples from each of four fingers (left index (L1), left middle (L2), right index (R1) and right middle (R2)) and five face samples were obtained. Sample images from this dataset are shown in Figure 2. Eye regions of the face have been masked to preserve the privacy of the subjects.

(a) Male Subjects (b) Female Subjects

Fig. 2. Sample images from the WVU multimodal dataset. Each subject has both face and fingerprint samples. The eye regions have been masked in order to preserve the privacy of users.

The images corresponding to 50 male and 50 female subjects were used to extract the histograms (LBP, LPQ, BSIF, LTP) and to train a two-class SVM based gender estimator. The remaining 111 male and 21 female subjects were used to evaluate the performance of the gender estimator. In order to perform cross-validation, this random partitioning into training and test sets was done 20 times. Each fingerprint image is 248×292 and the dimensionality of the obtained feature vectors are 7776, 36864, 4096, 14160 for LBP, LPQ, BSIF and

LTP, respectively. The performance of the gender estimator was evaluated using the correct overall classification rate (COCR), correct male classification rate (CMCR) and correct female classification rate (CFCR). Correct overall classification rate (COCR) is the percentage of test images whose gender was correctly estimated. Correct male (female) classification rate (CMCR and CFCR) is the percentage of images corresponding to males (females) correctly classified as males (females).

3.2 Evaluation of the Textural Descriptors to Encode Gender Information

First, we tested the performance of LBP, LPQ, BSIF and LTP based textural descriptors in extracting gender information from fingerprint images. Table 1 tabulates the COCR of the LBP, LPQ, BSIF and LTP based descriptors in estimating gender information from fingerprint images. These results are summarized over 20 test runs (as $\mu \pm \sigma^2$) and shown for the four fingers i.e., left index (indicated as L1), left middle (indicated as L2), right index (indicated as R1) and right middle (indicated as R2), individually. It can be seen that LBP performs marginally better than other textural descriptors in encoding gender information from fingerprint images (COCR is 71.7%). The second best performance is obtained by BSIF (COCR is 71.0%). The average COCR over all the four descriptors and fingers is 70.0%.

Table 1. Correct overall classification rate (COCR) of the LBP, LPQ, BSIF and LTP based textural descriptors in encoding gender information from fingerprint images.

Methods	COCR [%]				
	L1	L2	R1	R2	**Average**
LBP+SVM	70.8 ± 2.1	72.4 ± 3.4	70.2 ± 3.6	73.4 ± 2.5	71.7 ± 2.9
LPQ+SVM	66.6 ± 3.3	66.2 ± 3.6	64.7 ± 3.2	65.7 ± 3.5	65.8 ± 3.4
BSIF+SVM	70.1 ± 2.7	72.2 ± 3.7	70.4 ± 2.9	70.5 ± 3.7	71.0 ± 3.3
LTP+SVM	70.9 ± 3.2	72.1 ± 2.9	69.1 ± 3.3	70.2 ± 2.5	70.0 ± 2.9

Further, Table 2 tabulates the correct male and female classification rates of the LBP, LPQ, BSIF and LTP based descriptors for the four fingers. The LBP based descriptor obtained the best correct male (71.2%) and female (74.6%) classification rates. The average correct male and female classification rates (CMCR and CFCR) over all four descriptors and four fingers are 69.5% and 72.9%, respectively.

Next, we evaluated the performance when fusing the outputs of the gender estimators corresponding to the four fingers of a subject. The majority rule was used for fusion. Table 3 tabulates the correct male, female and overall classification rates of LBP, LPQ, BSIF and LTP. In case of ties, a label was randomly assigned. It can be seen that fusion of gender cues from multiple fingerprints

Table 2. Correct male classification rate (CMCR) and correct female classification rate (CFCR) of the LBP, LPQ, BSIF and LTP based textural descriptors.

Methods	CMCR [%]				CFCR [%]			
	L1	L2	R1	R2	L1	L2	R1	R2
LBP+SVM	69.7 ± 2.4	72.1 ± 4.6	70.1 ± 4.2	72.9 ± 3.2	76.8 ± 6.6	74.3 ± 2.4	70.7 ± 8.9	76.6 ± 6.2
LPQ+SVM	66.2 ± 3.8	65.9 ± 4.5	64.2 ± 4.1	65.3 ± 3.6	68.7 ± 5.3	68.1 ± 7.4	67.9 ± 6.5	68.7 ± 9.8
BSIF+SVM	69.9 ± 3.7	71.7 ± 4.6	69.7 ± 3.7	70.1 ± 4.3	71.0 ± 7.5	74.9 ± 5.8	73.6 ± 7.4	73.4 ± 7.5
LTP+SVM	70.5 ± 4.4	73.9 ± 4.5	69.4 ± 3.9	69.7 ± 3.2	72.9 ± 7.6	74.7 ± 6.1	68.4 ± 7.7	72.9 ± 6.8

enhanced the accuracy of the gender estimator. For instance, COCR of the LBP based descriptor increased from 71.7% (see Table 1) to 80.4%. Similar observations can be made for other descriptors as well.

Table 3. Correct male classification rate (CMCR), correct female classification rate (CFCR) and correct overall classification rate (COCR) of the LBP, LPQ, BSIF and LTP based textural descriptors when outputs from the left index, left middle, right index and right middle fingerprints were fused using the majority rule.

Methods	CMCR [%]	CFCR [%]	COCR [%]
LBP+SVM	82.2 ± 3.1	70.7 ± 8.4	80.4 ± 2.7
LPQ+SVM	80.3 ± 2.2	77.5 ± 1.8	77.5 ± 1.8
BSIF+SVM	83.7 ± 3.6	68.6 ± 7.3	81.4 ± 2.9
LTP+SVM	84.5 ± 2.7	67.3 ± 8.3	80.1 ± 2.5

3.3 Interoperability of the Gender Estimator Across Fingers

In this section, we evaluate the interoperability of the gender estimator across different fingers. The aim is to analyze if the gender can be estimated from the fingers different from those used for training the gender estimator.

Table 4 tabulates the COCR of the gender estimator trained using one finger (say left index) and tested on all others (say left middle, right index and right middle). It can be seen that performance of all the descriptors dropped across fingers. For instance, COCR of the LBP dropped from 71.7% (see Table 1) to 66.4%, and BSIF dropped from 71.0% (see Table 1) to 63.2%. However, LBP performed better than other descriptors in this case as well. Lowest average COCR was observed for LTP. Table 5 shows the CMCR and CFCR of these descriptors when evaluated across fingers.

3.4 Performance of the Gender Estimator on Degraded and Partial Fingerprint Images

In this section, we evaluate the performance of the gender estimator when tested on degraded and partial fingerprint images. We simulated fingerprint degrada-

Table 4. Correct overall classification rate (COCR) of the LBP, LPQ, BSIF and LTP based gender estimators across fingers.

Training	Testing	LBP	LPQ	BSIF	LTP
L1	[L2 R1 R2]	72.9 ± 7.4	59.4 ± 10.9	66.2 ± 5.5	49.6 ± 6.8
L2	[L1 R1 R2]	63.8 ± 13.5	62.0 ± 9.5	64.2 ± 4.9	70.4 ± 5.1
R1	[L1 R1 R2]	78 ± 6.1	66.1 ± 10	69.4 ± 4.9	54.2 ± 6.0
R2	[L1 L2 R1]	50.8 ± 9.1	55.3 ± 10.1	52.8 ± 8.6	63.7 ± 4.9
Average		66.4 ± 9.1	60.7 ± 10.1	63.2 ± 5.9	59.4 ± 5.7

tions such as noise and blur. These type of fingerprint degradations are more likely to be encountered in some operational scenarios and forensic investigations. The process of lifting latent print by dusting the surface with fingerprint powder (black granular, aluminum flake, black magnetic, etc.) followed by photographing and lifting with clear adhesive tape also introduces noise and blur effect in the fingerprints. For this study, the gender estimator was always trained on the original (without degradations) fingerprints. Next, we evaluate the impact of degraded and partial prints on the gender estimator.

Table 5. Correct male classification rate (CMCR) and correct female classification rate (CFCR) of the LBP, LPQ, BSIF and LTP based gender estimators across fingers.

Training	Testing	LBP		LPQ		BSIF		LTP	
		CMCR [%]	CFCR [%]	CMCR [%]	CFCR [%]	CMCR [%]	CFCR [%]	CMCR [%]	CFCR [%]
L1	[L2 R1 R2]	77.2 ± 9.2	48.2 ± 13.2	60.9 ± 16.1	50.6 ± 11.2	49.6 ± 6.8	55.8 ± 13.4	79.6 ± 6.8	44.2 ± 13.4
L2	[L1 R1 R2]	62.8 ± 18.6	69.3 ± 18.6	61.9 ± 13.5	62.1 ± 13.5	62.0 ± 9.5	69.8 ± 9.1	73.4 ± 4.1	53.6 ± 11.1
R1	[L1 R1 R2]	84.6 ± 8.9	39.3 ± 12.2	69.9 ± 15.1	44.7 ± 22.3	66.1 ± 10	55.9 ± 12.9	69.3 ± 7.4	51.5 ± 10.7
R2	[L1 L2 R1]	82.1 ± 9.1	43.2 ± 17.5	53.4 ± 14.5	54.2 ± 8.9	77.56 ± 5.7	55.3 ± 10.1	63.7 ± 4.9	60.8 ± 10.0

When Fingerprint Images are Noisy: We simulated noisy fingerprint images by applying a Gaussian noise with a mean value of 0.07. The variance varies from 0.04 to 0.07, with a step size of 0.01. An example of applying Gaussian noise to a fingerprint image is shown in Figure 3.

Table 6 shows the COCR of the LBP based gender estimator when test fingerprint images are noisy. The performance is evaluated for four noise levels (column 1). It can be seen that performance of the gender estimator drops significantly from 71.7% (see Table 1) to 33.1% (averaged over all the four noise levels and four fingers). The performance drops are obvious because LBP-based textural descriptors are not robust to noise [20].

Further, Table 7 shows the COCR of the BSIF based gender estimator when test fingerprint images are noisy. It can be seen that performance of the BSIF based gender estimator also dropped from 71.0% (Table 1) to 52.6% (averaged over all four noise levels and four fingers). However, BSIF (COCR is 52.6%) performed better than LBP (COCR is 33.1%) on noisy fingerprint images. COCR of LPQ and LTP are 50.5% and 45.6%, respectively, over all the four fingers.

Fig. 3. An illustration of applying Gaussian noise to a fingerprint image. From left to right, the noise level increases with the standard deviation.

Table 6. Correct overall classification rate (COCR) of the **LBP** based gender estimator when test fingerprint images are noisy. Noisy fingerprint images are simulated by applying a Gaussian noise with a mean value of 0.07. The variance varies from 0.04 to 0.07, with a step size of 0.01 (shown in column 1).

Noise level	L1	L2	R1	R2	**Average**
$(\mu = 0.07, \sigma^2 = 0.04)$	32.9 ± 5.7	56.1 ± 3.8	28.6 ± 7.6	27.7 ± 8.8	36.3 ± 6.4
$(\mu = 0.07, \sigma^2 = 0.05)$	31.5 ± 6.2	42.7 ± 3.7	37.4 ± 5.6	26.2 ± 4.8	34.5 ± 5.2
$(\mu = 0.07, \sigma^2 = 0.06)$	31.4 ± 7.9	44.2 ± 4.5	20.9 ± 4.9	24.5 ± 5.3	30.3 ± 5.6
$(\mu = 0.07, \sigma^2 = 0.07)$	30.1 ± 5.6	45.7 ± 6.4	18.2 ± 7.4	31.6 ± 9.7	31.4 ± 7.2

Table 7. Correct overall classification rate (COCR) of the **BSIF** based gender estimator when test fingerprint images are noisy. Noisy fingerprint images are simulated by applying a Gaussian noise with a mean value of 0.07. The variance varies from 0.04 to 0.07, with a step size of 0.01 (shown in column 1).

Noise level	L1	L2	R1	R2	**Average**
$(\mu = 0.07, \sigma^2 = 0.04)$	50.1 ± 9.7	44.5 ± 8.0	66.2 ± 5.8	52.9 ± 9.2	53.4 ± 8.2
$(\mu = 0.07, \sigma^2 = 0.05)$	50.5 ± 9.1	42.6 ± 9.9	62.3 ± 6.1	54.5 ± 9.7	52.5 ± 8.7
$(\mu = 0.07, \sigma^2 = 0.06)$	51.8 ± 9.5	42.1 ± 9.1	63.4 ± 6.1	51.4 ± 9.2	52.2 ± 8.4
$(\mu = 0.07, \sigma^2 = 0.07)$	50.8 ± 9.4	42.3 ± 9.5	64.4 ± 5.1	52.5 ± 9.7	52.5 ± 8.4

When Fingerprint Images are Blurred: We simulated blurred fingerprint images by applying a Gaussian low pass filter using a window size of 15×15. The variance varies from 3.0 to 24.0, with a step size of 6.0. An example of applying Gaussian blur to a fingerprint image is shown in Figure 4.

Table 8 shows the COCR of the LPQ-based gender estimator when test fingerprint images are blurred. The performance is evaluated at four different blur levels (column 1). It can be seen that the LPQ-based gender estimator is quite robust to blur (COCR is 68.4%). This is because the LPQ descriptor itself is resilient to blur [17].

Further, Table 9 shows the COCR of the LTP based gender estimator when test fingerprint images are blurred. It can be seen that performance of the LTP

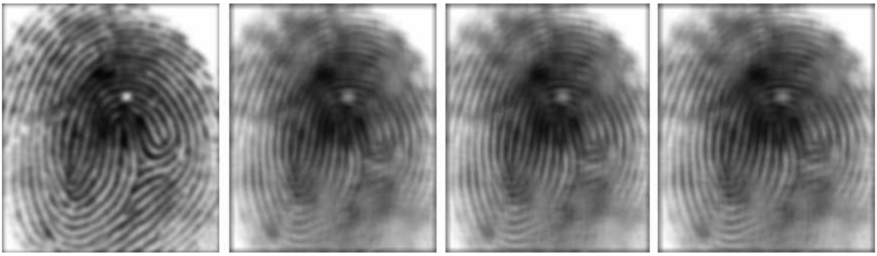

Fig. 4. An illustration of applying Gaussian low pass filter with a window size of 15×15 to a fingerprint image. From left to right, the blurring effect increases with the variance.

Table 8. Correct overall classification rate (COCR) of the **LPQ** based gender estimator when test fingerprint images are blurred. Blurred fingerprint images are simulated by applying Gaussian low pass filter using a window size of 15×15. The standard deviation varies from 3.0 to 24.0, with a step size of 6.0. (shown in column 1). The gender estimator was trained on original non-blurred fingerprint images.

Noise level	L1	L2	R1	R2	**Average**
$(\text{block} = 15, \sigma = 3)$	66.5 ± 9.6	67.7 ± 9.5	74.7 ± 9.1	56.4 ± 9.5	66.3 ± 9.4
$(\text{block} = 15, \sigma = 9)$	66.4 ± 9.2	74.5 ± 8.5	74.1 ± 9.3	66.2 ± 7.5	70.3 ± 8.6
$(\text{block} = 15, \sigma = 15)$	69.1 ± 7.3	71.7 ± 8.2	68.5 ± 6.5	63.8 ± 7.7	68.3 ± 7.4
$(\text{block} = 15, \sigma = 24)$	69.2 ± 9.5	71.8 ± 8.4	70.9 ± 9.7	63.8 ± 9.6	68.9 ± 9.3

based gender estimator drops from 70.0% (see Table 1) to 61.6% (averaged over all four blur levels and four fingers). COCR of LBP and BSIF are 31.4% and 54.3%, respectively. LPQ (COCR is 68.4%) performs better than other descriptors on blurred fingerprint images.

Table 9. Correct overall classification rate (COCR) of the **LTP** based gender estimator when test fingerprint images are blurred. Blurred fingerprint images are simulated by applying Gaussian low pass filter with a window size of 15×15. The standard deviation varies from 3.0 to 24.0, with a step size of 6.0. (shown in column 1). The gender estimator was trained on original non-blurred fingerprint images.

Noise level	L1	L2	R1	R2	**Average**
$(\text{block} = 15, \sigma = 3)$	62.1 ± 9.3	66.6 ± 5.6	67.2 ± 7.5	56.3 ± 6.3	63.0 ± 7.2
$(\text{block} = 15, \sigma = 9)$	67.1 ± 6.3	58.3 ± 4.3	62.3 ± 6.4	54.1 ± 7.1	60.4 ± 6.1
$(\text{block} = 15, \sigma = 15)$	65.8 ± 6.1	63.4 ± 7.2	55.4 ± 5.6	59.8 ± 7.6	61.1 ± 6.6
$(\text{block} = 15, \sigma = 24)$	65.6 ± 8.8	59.7 ± 9.7	65.9 ± 8.6	57.7 ± 7.5	62.2 ± 8.6

When Fingerprint Images are Partial: Partial prints were generated by using half and one-fourth portion of the original fingerprint image as shown in Figure 5. The gender estimator was trained on full fingerprints.

Fig. 5. An illustration of (a) Original print (b) One-half of original print and (c) One-fourth of original print (from left to right).

It can be seen in Table 10 that COCR of LBP, BSIF, LPQ and LTP (averaged over all the four fingers) on partial prints generated using half of the original prints are 59.1%,71.7%, 65.4% and 64.2%, respectively. Further, COCR of these descriptors on partial prints generated using one-fourth of the original prints are 54.5%, 70.5%, 62.9% and 54.0%, respectively. BSIF is fairly robust to partial fingerprints compared to other descriptors. In fact, the COCR of the BSIF on partial prints is almost equal to those obtained on original fingerprints (see Table1). This clearly conveys the importance of the BSIF operator in estimating gender from fingerprint images.

Table 10. Correct overall classification rate (COCR) of the LBP, BSIF, LPQ and LTP based gender estimator when tested on partial fingerprint images (generated using half and one-fourth portion of the original fingerprint). These gender estimators were trained on full fingerprint images.

Finger	LBP		BSIF		LPQ		LTP	
	Half	One-fourth	Half	One-fourth	Half	One-fourth	Half	One-fourth
L1	60.1 ± 7.7	60.6 ± 9.2	70.8 ± 2.7	71.5 ± 4.4	68.8 ± 3.8	67.7 ± 3.6	67.4 ± 5.8	45.7 ± 8.4
L2	65.2 ± 9.1	62.3 ± 9.8	70.7 ± 8.4	75.2 ± 9.1	62.6 ± 9.2	58.5 ± 10.6	62.6 ± 4.1	65.6 ± 9.4
R1	53.4 ± 6.7	52.4 ± 6.5	72.4 ± 6.2	69.1 ± 7.6	69.8 ± 9.8	70.4 ± 8.7	64.5 ± 3.9	55.6 ± 6.2
R2	57.7 ± 8.7	43.5 ± 4.7	73.3 ± 9.3	67.2 ± 8.4	60.5 ± 5.4	65.6 ± 4.2	62.1 ± 5.2	47.6 ± 8.3
Average	59.1 ± 8.1	54.5 ± 7.5	71.7 ± 6.6	70.5 ± 7.4	65.4 ± 7.1	62.9 ± 6.7	64.2 ± 4.7	54.0 ± 8

These experimental results suggest that the performance of all four descriptors dropped when encountering degraded or partial fingerprints. However, BSIF performed better than LBP, LPQ and LTP on noisy and partial fingerprint images and LPQ performed better than LBP, BSIF and LTP on blurred fingerprint images.

3.5 Common Textural Descriptors to Encode Gender Information from Face and Fingerprints

Next we investigate if the same textural descriptors used for encoding gender information in fingerprint images can be used on face images. In this regard, we tested the performance of the LBP, LPQ, BSIF and LTP based textural descriptors on face images. The size of each cropped face image was 150×130 (block size was 18×21) and the dimensions of the obtained feature vectors were 2160, 12288, 4096 and 7434 for LBP, LPQ, BSIF and LTP, respectively. Further, to better understand the performance of these texture descriptors on face images, a state-of-the-art gender classifier named Intraface[2] was utilized for comparison.

Table 11 tabulates the CMCR, CFCR and COCR of the LBP, LPQ, BSIF and LTP based gender estimators from face images. It can be seen that LTP outperforms the other textural descriptors (LBP, LPQ and BSIF) in encoding gender information from face images. Further, the performance difference of LTP over Intraface is only 4.2%. The second best performance is obtained by LPQ. These results suggest that these textural descriptors can potentially be used for encoding gender cues from both face and fingerprint images.

Table 11. CMCR, CFCR and COCR rates of the LBP, LPQ, BSIF and LTP based textural descriptors for gender estimation from face images.

Methods	CMCR [%]	CFCR [%]	COCR [%]
LBP+SVM	85.8 ± 3.27	85.3 ± 5.02	85.7 ± 2.65
LPQ+SVM	92.4 ± 2.36	93.6 ± 4.53	92.6 ± 1.91
BSIF+SVM	88.0 ± 3.11	91.4 ± 4.40	88.5 ± 2.39
LTP+SVM	92.5 ± 1.99	93.1 ± 4.04	92.6 ± 1.47
Intraface	98.4 ± 0.61	88.5 ± 5.32	96.8 ± 0.95

However, gender can be deduced from face images with relatively high accuracy than fingerprints. The COCR of the gender estimator based on face images is 89.8% (averaged over all the four descriptors), while the COCR of the gender estimator based on fingerprint is 71.7% (averaged over all the four descriptors (see Table 1)).

Further, the performance of individual texture descriptors varies across modalities. For instance, LBP outperformed LPQ, BSIF and LTP in encoding gender information from fingerprint image. However, LTP outperformed LBP, BSIF and LTP in encoding gender information from face images. The possible reason is

[2] Intraface: http://www.humansensing.cs.cmu.edu/intraface/

the radically different nature of the information used for sex determination from face and fingerprint images. Facial features play a dominant role in gender determination from face images [1, 4], while studies suggest that ridge density reflects gender information in fingerprint images [9–12].

4 Conclusion and Discussion

This study evaluates the performance of four texture descriptors - LBP, LPQ, BSIF and LTP - for the task of gender estimation from fingerprint images. Further, the performance of the estimators is evaluated on degraded fingerprints that are noisy and blurred, as well as partial prints. Experimental results suggest that

- LBP descriptor is efficient in encoding gender information from high quality fingerprint images in comparison to LPQ, BSIF and LTP.
- The performance of all four gender estimators drops, when training is done using one set of fingers (e.g., left index) and testing is done on a different set of fingers (e.g., right index). LBP exhibited the least drop in performance.
- The performance of the gender estimator degrades when noisy and blurred fingerprint images are observed. BSIF performs much better than other descriptors on noisy and partial fingerprints. The reason could be that BSIF uses predefined filters learned from a set of natural images and this improves its modeling capacity. LPQ performs better than other descriptors on blurred images. This is because it is resilient to blur.
- Finally, the texture descriptors that were used to encode gender information in fingerprint images could also be used to encode face images. However, the performance of these descriptors varies depending on the modality used. This is because face and fingerprint contain different type of information used for gender determination.

As a part of future work, more robust features will be investigated for gender estimation from fingerprint images; experiments will be repeated on a large scale multi-modal face and fingerprint datasets; and results will be compared against existing schemes for gender estimation from fingerprints. We will consider ways to fuse the outputs of the four descriptors in a systematic way. We will also investigate fusion of the gender estimators based on face and fingerprints at the feature, score and decision levels.

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