A Novel Fingerprint Quality Assessment Based on Gabor Filters

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***Abstract*—Fingerprints are the most widely deployed biometric characteristics. However, the recognition of a fingerprint may be influenced by a lot of factors (e.g., skin conditions, sensor conditions) and a matching algorithm is highly affected by the quality of the images involved. This work proposes a novel method for Fingerprint Quality Assessment (FQA) based on the analysis of the Gabor filters response on a fingerprint image. The correlation between the worst quality templates and the matching score has also been analyzed. The method is validated on FVC2000DB3, FVC2004DB2, FVC2004DB3, and FVC2006DB3 databases. This work was compared to other FQAs in order to evaluate performance and with different matching algorithms for fair comparison. The results found pointed that the proposed method is able to identify the images which most affect the error rates of an AFIS, better than the other methods presented in the literature.**

I. Introduction

The humans are able to identify each other based on their voice, appearance, or gait since the first signs of rationality and social conviviality. Over the years, social development has resulted in the increase of biometric identification usage, mainly to identify criminal recurrence and access control [1].

With the development of technology, biometric verification and identification in large-scale have become a trivial task, being used for criminal identification, perform remote financial transactions or boarding a commercial flight [2].

The use of token-based (e.g., ID cards) or knowledge-based (e.g., passwords) systems have become common. However, these traditional mechanisms of establishing a person's identity can be easily lost, shared, manipulated or stolen. It is possible, by using biometrics, to establish an identity based on who you are, rather than by what you possess or what you remember. In some applications, biometrics can be used to supplement the traditional methods, imparting an additional level of security (dual-factor authentication) [2].

Fingerprints are the most extensively used biometric characteristics because of the well-known persistence and distinctiveness properties of fingerprints, as well as the cost and the maturity of products [3]. Due to its advantages towards other methods, fingerprint recognition has become a usual standard routine in forensics. Besides, agencies have been set up worldwide, and criminal databases have been established. For instance, the FBI fingerprint identification division was set up in 1924 with a database of 810,000 fingerprint samples [2], [4].

With the rapid expansion of fingerprint in forensics, the manual fingerprint identification became unfeasible. Thus, 40 years later, the agencies began to invest a significant amount of effort in developing Automatic Fingerprint Identification Systems (AFIS). Nowadays AFISs are used by most law enforcement agencies in the world [3].

A wide variety of factors influence the quality of a fingerprint image, such as skin conditions (e.g., dryness, moisture, dirt, cuts, and bruises), sensor conditions (e.g., dirt, noise, size), and other acquisition conditions like user cooperation or crime scene preservation in forensic settings, etc. The recognition performance of a fingerprint matcher is strongly affected by the quality of the images involved [3], [5]–[7]. Depending on the quality, the ridges-valley flow is well evident and a reliable set of minutiae can be extracted. If the fingerprint is very noisy, the minutiae extraction algorithm may detect a large number of spurious minutiae and miss several genuine minutiae [8], [9].

Methods to measure the quality of fingerprint images have high importance to control matching error by, for instance, requesting additional sample data in case of a low-quality acquisition or adapting feature extraction and matching schemes to low-quality areas. As a consequence of the importance of fingerprint image quality assessment, a considerable number of studies have been dealing with the question of how to best estimate the quality of fingerprints for AFIS [9]–[11] and recently also for latent (forensic) fingerprints [12], [13], where the impact of different sensor devices is considered in the latter work.

In the advent of assessing the predictive power of a particular quality index, the correlation of recognition accuracy (e.g., given regarding EER) and the quality index of the involved images play a key role [14]. This work presents a novel Fingerprint Quality Assessment (FQA) based on the analysis of the Gabor filters response on a fingerprint image. The main advantages of this approach are:

(i) the detection of low-quality images which can decline even state-of-art matching approaches;
(ii) EER can be improved by 50% removing less than 6% of worst quality images;
(iii) additional processing is not required beyond widely used techniques for fingerprint enhancement.

The rest of this paper is organized as follows. Section 2 gives a brief literature survey of the Fingerprint Quality Assessment methods, followed by the full description of the proposed algorithm in Section 3. Experiments and results are shown in Section 4 and the last section presents our conclusions from this work.

II. Related Works

The Fingerprint quality assessment has attracted efforts from both academic and industrial area. The existing studies may be classified into three categories: (i) segmentation-based approaches; (ii) single feature-based approaches; and (iii) solutions carried out by using multi-feature fusion, which can be achieved via a linear fusion or classification [15].

Segmentation-based approaches. The approaches of the first category could be either represent the quality of the foreground area or to segment foreground from the image at first. Shen *et al.* [16] proposed a method based on Gabor features. Each block of the image is filtered using a Gabor filter with m different directions. If a block has high quality (*i.e.*, strong ridge direction), the responses of some filters are larger than the others. In poor-quality blocks or background blocks, the m filter responses are similar. The standard deviation of the m filter responses is then used to determine the quality of each block (good or poor). The quality index (*QI*) of the whole image is finally computed as the percentage of foreground blocks marked as good. If *QI* is lower than a predefined threshold, the image is rejected. Poor-quality images are additionally categorized as smudged or dry [16].

Yao *et al.* [17] proposed an approach with minutiae template only by using convex-hull and Delaunay triangulation. They are adapted to measure the area of an informative region. This algorithm is hence dependent on a minutiae extracting operation.

Single feature-based approaches. Chen *et al.* [18] estimated the power spectrum ring with Butterworth functions instead of observing the pixel information directly in the spectrum image. In [19], Lee *et al.* reviewed approaches based on the local standard deviation, the directional contrast of local block and the Gabor features. A feature was proposed by analyzing the Fourier spectrum of a fingerprint image. Their approach depends on the pixels information of the Fourier spectrum image which is a floating measure for different kinds of image settings.

Multi-feature fusion methods. The work presented by Lim *et al.* [20] is an example of the final category. They compute the following features in each block: Orientation Certainty Level (OCL), ridge frequency, ridge thickness and ridge-to-valley thickness ratio. Blocks are then labeled as good, undetermined, bad or blank by setting thresholds for the four features. A local quality score *SL* is finally computed based on the total number of good, undetermined and bad quality image blocks in the image.

The state-of-the-art quality metric, NIST fingerprint image quality (NFIQ) was proposed by Tabassi *et al.* [21]. Their approach employs 11-dimensional feature (exploiting several characteristics such as ridge orientation flow, local ridge curvature and local contrast) to estimate a matching score and classify results to five levels through a trained model of a neural network.

III. Fingerprint Quality Assessment

The approach proposed in this work is based on an iterative fingerprint enhancement algorithm presented by Turroni *et al.* [8]. However, the presented method requires just some computations from the first iteration of [8]. The proposed approach is composed of four main steps: (i) filter-bank convolution, (ii) combined image computation, (iii) homogeneity image combination, and (iv) metric computation. Each step is detailed in the following sub-sections. Figure 1 shows an overview of the proposed method.

A. Convolution with Gabor filter-bank

According to Turroni *et al.* [8], a Gabor filter is defined by a sinusoidal plane wave (second term in (1)) tapered by a Gaussian (first term in (1)). The two-dimensional Gabor filter is defined by:

$$g(x, y : \theta, f) = \exp\left\{ -\frac{1}{2}\left[\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right]\right\} \cdot \cos(2\pi f \cdot x_\theta) \quad (1)$$

where θ is the orientation of the filter and $[x_\theta, y_\theta]$ are the coordinates of $[x, y]$ after a clockwise rotation by an angle of $(90° - \theta)$. Such filter depends on four parameters $(\theta, f, \sigma_x, \sigma_y)$, where σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y axes, respectively.

A Gabor filter-bank is defined as a set $G = \{g_{i,j}(x, y)|i = 1..n_o, j = 1..n_f\}$ of Gabor filters, where n_o is the number of discrete orientations $\{\theta_i|i = 1..n_o\}$ and n_f is the number of discrete frequencies $\{\theta_j|j = 1..n_f\}$.

Let I a $h \times w$ fingerprint image, the output of convolution between I and the filter-bank G is a set V of $n_o \cdot n_f$ images where $V^{i,j} = [v^{i,j}_{x,y}], x = 1..w, y = 1..h$ denotes the response image to a filter $g_{i,j}$ with orientation θ_i and frequency f_j. In this work is used $n_o = 12$ and $n_f = 4$. Figure 2 shows an example of a Gabor filter-bank builded with six orientations and three frequencies.

B. Combined Image

The set of responses V, obtained after the previous step, is used to compute a single combined image $C = [c_{x,y}], x = 1..w, y = 1..h$, where the combination is performed according to the max filter response:

$$c_{x,y} = v^{l,t}_{x,y} \quad (2)$$

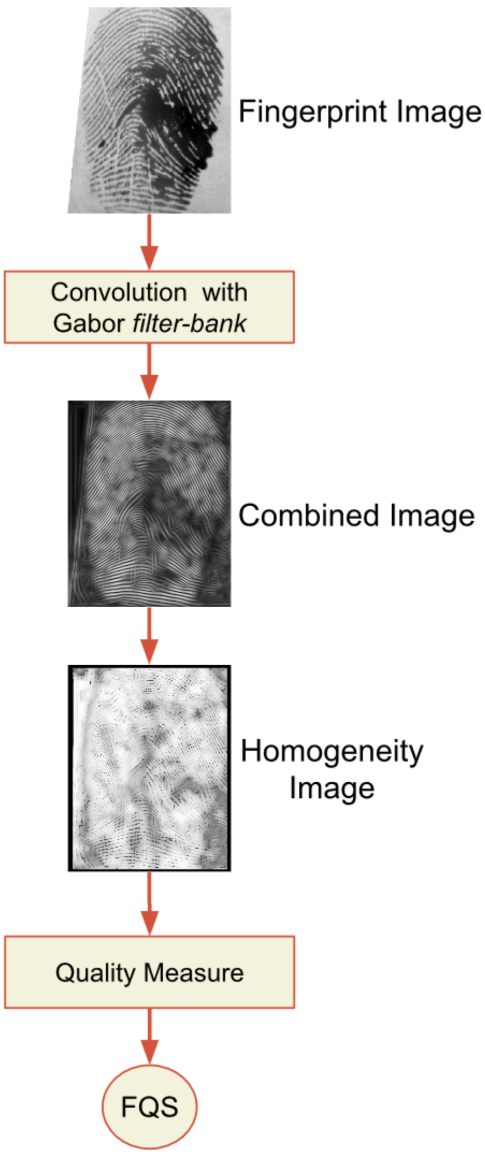

Fig. 1. An overview of the proposed method.

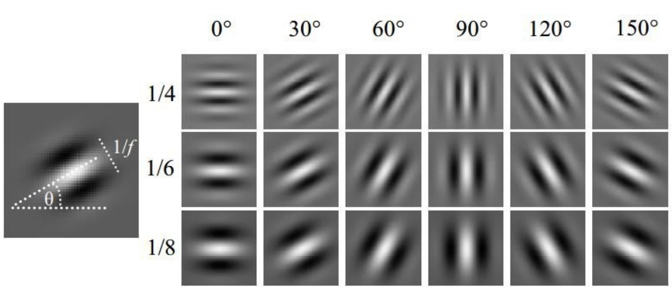

Fig. 2. A Gabor filter-bank with six orientations θ (columns) and three frequencies f (rows) [8].

where $l, t = argmax_{i,j}\{|v_{x,y}^{i,j}|\} i = 1..n_o, j = 1..n_f$. Negative values correspond to ridge regions response, likewise positive values correspond to a valley region response. As side effect of this stage, a pixel-level frequency image is also obtained $F = \{f_{x,y}|x = 1..w, y = 1..h\}$ and orientation image $O = \{o_{x,y}|x = 1..w, y = 1..h\}$.

C. Homogeneity Image

The homogeneity image $H = \{h_{x,y}|x = 1..w, y = 1..h\}$ encodes the local ridge flow homogeneity. In theory, except for singularity regions, ridges run smoothly across the fingerprint pattern, and sudden changes in the orientation and frequency should not exist. In practice, such discontinuities are determined by noise or ridge alteration [8]. The homogeneity at $[x, y]$ is defined as follows:

$$h_{x,y} = \frac{\sum_{(p,k)} |C_{p,k}| \cdot S_{p,k}}{\sum_{(p,k)} |C_{p,k}|} \tag{3}$$

where $p, k = -\frac{m}{2}, .., \frac{m}{2}$ and $S_{p,k}$ is an orientation homogeneity measure defined as:

$$S_{p,k} = \frac{\pi}{2} - |d\phi(O_{x,y}, O_{p,k})| \tag{4}$$

$$d\phi(\theta_1, \theta_2) = \begin{cases} \theta_1 - \theta_2 & \text{if } -\frac{\pi}{2} \leq \theta_1 - \theta_2 < \frac{\pi}{2} \\ \pi + \theta_1 - \theta_2 & \text{if } \theta_1 - \theta_2 < -\frac{\pi}{2} \\ \pi - \theta_1 - \theta_2 & \text{if } \theta_1 - \theta_2 \geq -\frac{\pi}{2} \end{cases} \tag{5}$$

Finally, H is normalized to fit values in the range [0,1] as defined by Turroni *et al.* [8]. Lower values denote a lower homogeneity.

D. Quality Measure

Aiming to decrease the importance of the pixels in low-homogeneous regions a pixel-wise multiplication is performed between C and H. Let $P = \{p_{x,y}|x = 1..w, y = 1..h\}$ be computed as:

$$p_{x,y} = |c_{x,y}| \cdot h_{x,y} \tag{6}$$

In this stage, the filter response is what is taken into consideration, not the fact of the pixel is an edge or a valley. Therefore, the absolute value is analyzed. Then, the histogram of P is computed. When a fingerprint image has a good quality, the values of p are higher. Thus the histogram is denser on the right side. Otherwise, if the fingerprint image has low-quality, the histogram is denser on the left side (lower values). This is shown in Figure 3.

In order to identify this behavior, Skewness is computed. Skewness is a measure of the asymmetry of the probability distribution of real-valued variable about its mean. Negative skew indicates that the tail on the left side is longer or fatter than the right, and a positive skew indicates the opposite. Skewness is defined by the following equation:

$$S = \frac{\mu_3}{\sigma^3} \tag{7}$$

where μ_3 is the third central moment and σ is the standard deviation.

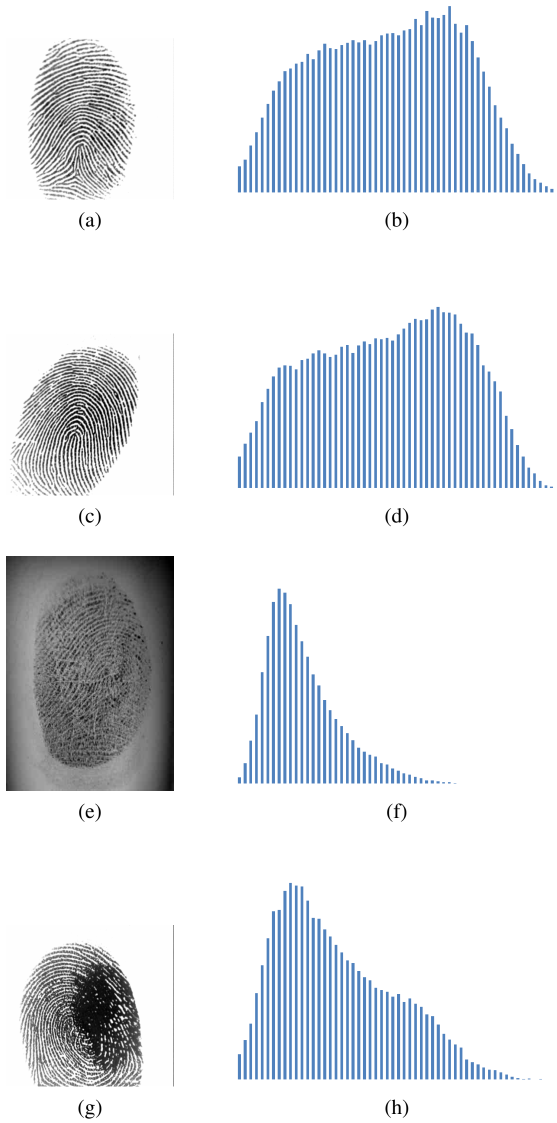

Fig. 3. Illustration of the analysis of P. The left column are examples of fingerprint and the right column is the histogram of P computed from the respective fingerprint image. The images (a) and (c) are better quality fingerprints than (e) and (g).

The skewness is computed over the resulting histogram of the previous step. In order to compute the final fingerprint quality, the negative of skewness is taken. Then, the value between a predefined range is clipped and normalized from 0 to 100. The higher this value, the better the fingerprint quality. The Fingerprint Quality Score (FQS) can be defined as follows:

$$FQS = \begin{cases} 0 & \text{if } -S < min \\ -\frac{100(S+min)}{max-min} & \text{if } min \geq -S \geq max \\ 100 & \text{if } -s > max \end{cases} \quad (8)$$

where min and max are the parameters used in the clip operation. In the experiments, it was used -2 and 0 for min and max, respectively.

IV. Experiments and Results

In order to validate the presented fingerprint quality assessment approach, two different analysis were performed. First, the correlation between the FQS and the resulting EER is analyzed. Then, the effect of removing the worst quality images regarding the final EER is measured. This method can also be compared to two other well known Fingerprint Quality Assessment (FQA) methods: NIST Fingerprint Image Quality (NFIQ) [21] and the commercial VeriFinger SDK's FQA, developed by Neurotechnology. Two different commercial SDKs were used for template extraction and matching: BioPass SDK from VSoft Tecnologia, and VeriFinger from Neurotechnology. It was decided to use these SDKs to allow a fair comparison between FQAs.

A. Database and Protocol

In this work, four databases of Fingerprint Verification Competition (FVC) [22] with different resolutions have been used for the experiments: FVC2000DB3, FVC2004DB2, FVC2004DB3, and FVC2006DB3. These databases were selected since they are commonly used in the literature. In addition, the quality problems presented in these datasets are known to affect the performance of automatic fingerprint identification system (AFIS) [23]. Each dataset is composed of 800 images (100 fingers with 8 samples per finger). However, the FVC2006DB3 dataset has 140 fingers with 12 samples per finger, totaling 1680 images. Further details about the databases can be seen in Table I.

TABLE I
Details of databases.

DB	Sensor	Image Dim	Resolution
00DB3	Optical	448x478	500 dpi
04DB2	Optical	328x364	500 dpi
04DB3	Thermal	300x480	512 dpi
06DB3	Thermal	400x500	500 dpi

B. Correlation Coefficient Analysis

The matching of genuine samples is known to produce high scores than fraudulent samples. However, genuine matching may result in a low score due to some facts as missing common information, acquisition failure or low-quality images. In order to increase the method precision, one may decrease the amount of genuine matching errors (false rejection). This paper proposes to reject these samples by using an own FQA algorithm. The correlation score is used in order to associate the scores of a genuine matching and FQS. The Pearson Correlation coefficient between the matching score and the mean quality of two templates are computed. Usually, the matching score between genuine samples will result in a higher value than fraudulent samples. However, results have suggested that when the matching between genuine samples have a low value,

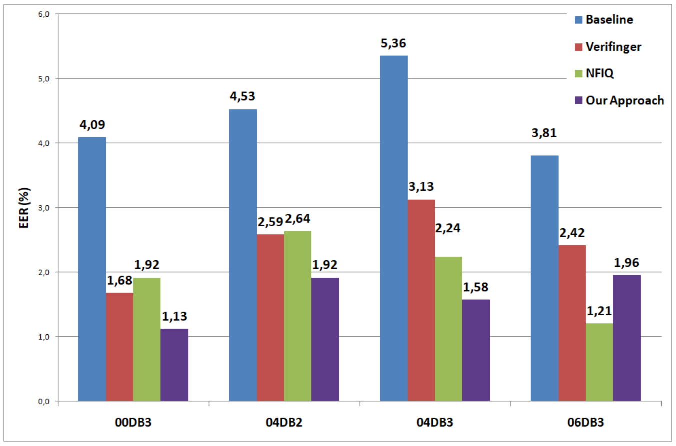

Fig. 4. EER removing worst 10% samples and using BioPass SDK.

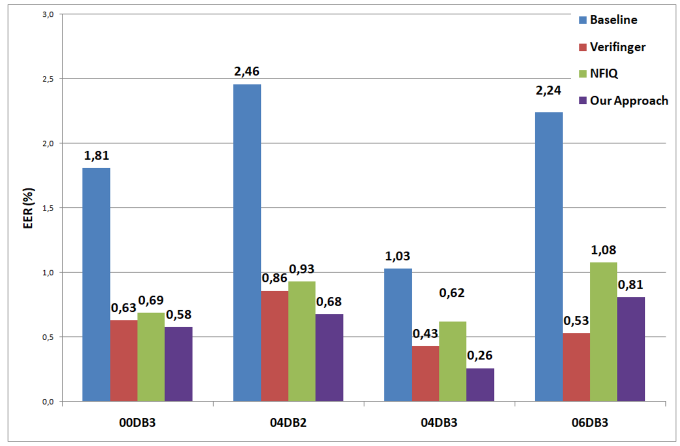

Fig. 5. EER removing worst 10% samples and using VeriFinger SDK.

there is a high correlation between the quality score and the matching score.

The evaluation of this method first begins by analyzing the correlation between the scores of matching and the fingerprint qualities (see Table II). The matching between genuine samples may result in a higher score than fraudulent samples. Therefore, the lower the quality score, the lower the matching score.

TABLE II
MEAN OF CORRELATION COEFFICIENTS BETWEEN THE FQS AND THE MATCHING SCORE.

AFIS	FQA	00DB3	04DB2	04DB3	06DB3
BioPass	VeriFinger	0.59	0.48	0.57	**0.55**
	NFIQ	0.52	0.49	0.45	0.23
	Our method	**0.67**	**0.59**	**0.63**	**0.55**
VeriFinger	Verifinger	0.62	0.49	**0.60**	**0.52**
	NFIQ	0.58	0.54	0.46	0.25
	Our method	**0.63**	**0.56**	0.57	0.51

The computed mean of the values from Table II for VeriFinger, NFIQ and our approach are 0.55, 0.44 and 0.58, respectively. The results presented show that this method achieved moderate or strong correlation for all test sets regardless of the AFIS.

C. Evaluation Over Equal Error Rate

The first step was analyzing the results when 10% of the worst quality templates were removed by BioPass SDK. The EER of the proposed method achieved the highest improvement in comparison with baseline results. The performance was improved from 48.55% (FVC2006DB3) up to 72.37% (FVC2000DB3). On average, this algorithm decreased EER by 60.57%, while NFIQ and Verifinger decreased by 41.61% and 52.91%, respectively. Figure 4 compares the results of each method for all the four datasets.

Removing the 10% of worst quality templates with VeriFinger SDK, the presented algorithm achieved better performance in 3 out of 4 databases. As can be seen in Figure 5, the EER was improved from 63.83% (FVC2006DB3) to

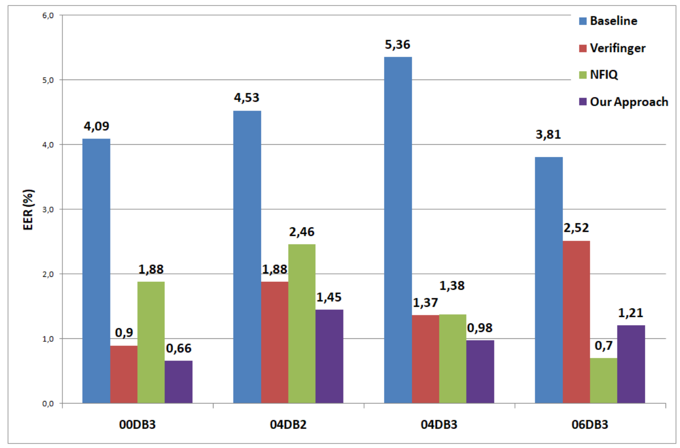

Fig. 6. EER removing worst 20% samples and using BioPass SDK.

74.75% (FVC2004DB3). In average, the EER was improved by 69.72% through this method and by 53.91% and 66.20% using NFIQ and VeriFinger, respectively. Finally, it can be seen that the presented FQA method is better than the VeriFinger even when the VeriFinger SDK is used to template matching.

When the 20% of worst quality templates are removed by BioPass SDK, the EER was able to be improved by 74.40% on average for all datasets. Figure 6 shows that the best improvement was achieved in FVC2000DB3 (83.86%), while the lowest was in FC2004DB2 (67.99%.). The NFIQ and VeriFinger algorithm decreased EER by 62.42% and 60.38%, respectively.

The proposed method has improved the EER from 77.67% (FVC2006DB3) to 85.63% (FVC2000DB3) with an average improvement of 80.33%. Otherwise, the NFIQ and VeriFinger methods decreased the EER by 64.65% and 81.14%, respectively.

In Table III, the percentage of templates required to be removed was measured in order to improve EER performance by a certain factor. It can be noticed that this method removes only 3.61% of worst templates in order to achieve an EER improvement of 40%. To decrease EER by 80%, the NFIQ

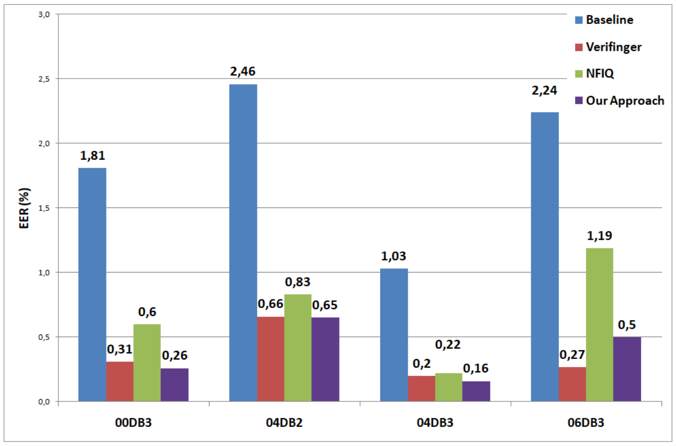

Fig. 7. EER removing worst 20% samples and using VeriFinger SDK.

TABLE III
PERCENTAGE OF REMOVED TEMPLATES BY EACH SDK TO ACHIEVE A GIVEN EER IMPROVEMENT.

EER Improvement	NFIQ	VeriFinger	Our Approach
40%	5.71%	4.96%	**3.61%**
50%	8.84%	8.31%	**5.68%**
60%	8.62%	12.82%	**8.26%**
70%	27.98%	24.63%	**10.41%**
80%	38.19%	35.89%	**22.43%**

and VeriFinger algorithm had to remove more than 35% of templates with low-quality, while this method removed only 22.43%. Therefore, these results showed the method proposed is able to identify the images which most affect the error rates of an AFIS for both SDK's.

V. CONCLUSION

This work presented a new Fingerprint Quality Assessment method to reduce EER. The method is evaluated on four FVC Datasets and compared with others FQAs algorithms (VeriFinger and NFIQ). Our results showed that genuine comparisons from low-quality templates usually have low scoring, yielding a false rejection result. When 10% of the worst-quality templates were removed from the dataset by our method, the EER was decreased in comparison to all the methods analyzed.

For future works, we first intend to analyze the performance with other filter banks, metrics, and SDKs (e.g., NBIS SDK) presented in the literature. We may also try extending our method, developing a local quality measure to be computed at the template generation.

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