Touchless Fingerprint Sample Quality: Prerequisites for the Applicability of NFIQ2.0

Jannis Priesnitz[1 2], Christian Rathgeb[1], Nicolas Buchmann[2], Christoph Busch[1]

Abstract: The impact of fingerprint sample quality on biometric performance is undisputed. For touch-based fingerprint data, the effectiveness of the NFIQ2.0 quality estimation method is well documented in scientific literature. Due to the increasing use of touchless fingerprint recognition systems a thorough investigation of the usefulness of the NFIQ2.0 for touchless fingerprint data is of interest.

In this work, we investigate whether NFIQ2.0 quality scores are predictive of error rates associated with the biometric performance of touchless fingerprint recognition. For this purpose, we propose a touchless fingerprint preprocessing that favours NFIQ2.0 quality estimation which has been designed for touch-based fingerprint data. Comparisons are made between NFIQ2.0 score distributions obtained from touch-based and touchless fingerprint data of the publicly available FVC06, MCYT, PolyU, and ISPFDv1 databases. Further, the predictive power regarding biometric performance is evaluated in terms of Error-versus-Reject Curves (ERCs) using an open source fingerprint recognition system. Under constrained capture conditions NFIQ2.0 is found to be an effective tool for touchless fingerprint quality estimation if an adequate preprocessing is applied.

Keywords: Biometrics, Fingerprint, Touchless Fingerprint, Sample Quality.

1 Introduction

In the past decade, many research efforts have been devoted to robust fingerprint quality estimation, for comprehensive surveys the reader is referred to [OŠB16, BVS14]. It is generally conceded that fingerprint quality assessment is vital to achieve competitive recognition accuracy, *i.e*. quality estimation serves as a predictor of biometric performance. NIST published the first open algorithm for finger image quality assessment which is referred to as NIST Fingerprint Image Quality (NFIQ) in 2004 [TWW04]. Its improved successor, NFIQ2.0 [NI], represents a well-established tool for quality estimation which is used in many operational fingerprint recognition systems. NFIQ2.0 has been specifically designed to assess the quality of fingerprints acquired by touch-based sensors which are optical capture devices and provide fingerprint images of 500dpi spacial resolution.

Touchless fingerprint recognition represents a rapidly growing field of research, for overviews of published scientific literature the reader is referred to [La14,Ma17]. A comparison of a touch-based and touchless fingerprint representation is depicted in Figure 1. In touchless fingerprint recognition methods, effective quality control is of utmost importance as

[1] da/sec - Biometrics and Internet Security Research Group, Hochschule Darmstadt, Schöfferstraße 9, 64295 Darmstadt, Germany, firstname.lastname@h-da.de
[2] Freie Universität Berlin, Takustraße 9, 14195 Berlin, Germany, firstname.lastname@fu-berlin.de

(a) touch-based (b) touchless

Fig. 1: Touch-based and touchless fingerprint representations of a single finger: touch-based fingerprint acquired with a Crossmatch Guardian 200 (left); touchless fingerprint image captured with a Samsung Galaxy S8 smartphone (right).

numerous factors may negatively impact fingerprint quality.In many proposed touchless systems captured fingerprint images are pre-processed in a way that these resemble properties of touch-based fingerprint imagery, *e.g.* in terms of contrast or image resolution. This entails two major advantages: on the one hand, sub-systems of touch-based recognition systems for quality control, feature extraction, and comparison can be maintained; on the other hand, acquired touchless imagery can be compared to legacy data.

Focusing on touchless fingerprint recognition, some dedicated quality estimation methods have been proposed, *e.g.* [YLB13, LPS10, Li13]. Labati *et al.* [LPS10] showed that a direct application of NFIQ (version 1) to touchless fingerprint images generally yields low quality scores. The authors conclude that NFIQ1.0 is not usable for touchless fingerprint imagery. In contrast, Salum *et al.* [Sa17] showcased that good NFIQ1.0 scores can be obtained in case touchless fingerprints are pre-processed adequately. To the best of the authors' knowledge the applicability of NFIQ2.0 to touchless fingerprint data has not been investigated.

This work investigates the usefulness of NFIQ2.0 in the context of touchless fingerprint recognition. First, the NFIQ2.0 score distributions of well-known touch-based fingerprint databases and publicly available touchless fingerprint databases are compared. For this purpose, a pre-processing pipeline is proposed which favours the extraction of NFIQ2.0 scores from touchless fingerprints. Further, the predictive power of NFIQ2.0 on touchless fingerprint data is estimated in terms of Error-versus-Reject Curves (ERCs) as suggested by Grother and Tabassi [GT07]. Based on biometric performance rates, quality score distributions, and shapes of ERCs different conclusions w.r.t. the applicability of NFIQ2.0 for touchless fingerprint data are reached.

Tab. 1: Overview of used fingerprint databases. The DPI value is listed if it is specified in the database description.

Database	**Subset**	**Type**	**Sensor**	**Color**	**Resolution**	**Instances**	**Samples**
FVC06	DB2-A	touch-based	optical	grayscale	400×560 (569 dpi)	140	1,680
	DB3-A	touch-based	thermal sweeping	grayscale	400×500 (500 dpi)	140	1,680
	DB4-A	synthetic	–	grayscale	288×384	140	1,680
MCYT	dp (Digital Persona)	touch-based	optical	grayscale	256×400 (500 dpi)	3,300	39,600
	pb (Precise Biometrics)	touch-based	capacitive	grayscale	300×300 (500 dpi)	3,300	39,600
PolyU	CB-S1 (contact-based session 1)	touch-based	optical	grayscale	328×356	336	2,016
	CB-S2 (contact-based session 2)	touch-based	optical	grayscale	328×356	160	960
	CL-S1 (contactless session 1)	touchless	digital camera, LED light	RGB	1,400×900	336	2,016
	CL-S2 (contactless session 2)	touchless	digital camera, LED light	RGB	1,400×900	160	960
ISPFDv1	LS (live scan)	touch-based	optical	grayscale	544×253 (250 dpi)	128	1,024
	NI (natural indoor)	touchless	Apple iPhone 5	RGB	3,264×2,448	128	1,024
	NO (natural outdoor)	touchless	Apple iPhone 5	RGB	3,264×2,448	128	1,024
	WI (white indoor)	touchless	Apple iPhone 5	RGB	3,264×2,448	128	1,024
	W0 (white outdoor)	touchless	Apple iPhone 5	RGB	3,264×2,448	128	1,024

This paper is organized as follows: Section 2 summarizes the used fingerprint databases. In Section 3 the proposed evaluation pipeline is described in detail. Experimental results are presented in Section 4. Finally, Section 5 concludes.

2 Databases

We employ four different databases, which comprise touch-based as well as subsets of touchless fingerprint images. The use of touch-based fingerprint databases allows for a detailed comparison of NFIQ2.0 quality scores as well as their predictive power w.r.t. biometric performance on touchless and touch-based data. Used databases and their properties are listed in Table 1 and briefly summarized as follows:

- *FVC06* [Ca07]: the database of the fourth international Fingerprint Verification Competition (FVC), containing four disjoint fingerprint subsets. The first three subsets are each collected with a different touch-based sensor while the fourth database is generated using Synthetic Fingerprint Generator (SFinGe) [Ma09]. Example images of the FVC06 database are depicted in Figure 2 (a)-(c).
- *MCYT* [Or03]: the fingerprint subcorpus of the MCYT bimodal database contains fingerprint images captured with two different touch-based sensors. Figure 2 (d)-(e) show example fingerprints of this database.
- *PolyU* [LK18]: the Hong Kong Polytechnic University contactless 2D to contact-based 2D fingerprint images database version 1.0 comprises touchless and touch-

(a) FVC06 DB2-A (b) FVC06 DB3-A (c) FVC06 DB4-A (d) MCYT dp (e) MCYT pb

Fig. 2: Example fingerprint images of used subsets of the FVC06 database (a)-(c) and of the MCYT fingerprint subcorpus (d)-(e).

(a) CB-S1 (b) CB-S2 (c) CL-S1 (d) CL-S2

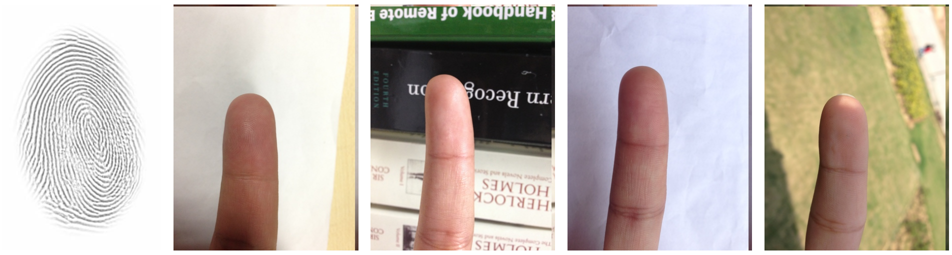
Fig. 3: Example fingerprint images of the subsets of the PolyU database.

based fingerprint images of the same data subjects. In two sessions, touch-based fingerprints were captured with an optical sensor while touchless were acquired using a digital camera with LED illumination. Touchless images, which are provided in pre-segmented form, appear to be captured in a constrained environment. Fingerprint images of this databases are shown in Figure 3.

- *ISPFDv1* [Sa15]: the IIITD SmartPhone Fingerphoto Database v1 consists of touch-based fingerprints captured with an optical sensor as well as touchless fingerprint images collected with a smartphone in four different environmental conditions, including indoor and outdoor images with natural and white background. Figure 4 depicts example images of the ISPFDv1 database. It should be noted that the 250dpi resolution of sensor used to capture the live scan database does not correspond to the NFIQ2.0 target resolution of 500dpi.

3 Evaluation Pipeline

In the proposed evaluation pipeline, touchless fingerprint data is pre-processed, NFIQ2.0 quality scores are estimated, and their predictive power is estimated.



(a) LS (b) WI (c) NI (d) WO (e) NO

Fig. 4: Example fingerprint images of the subsets of the ISPFDv1 database.

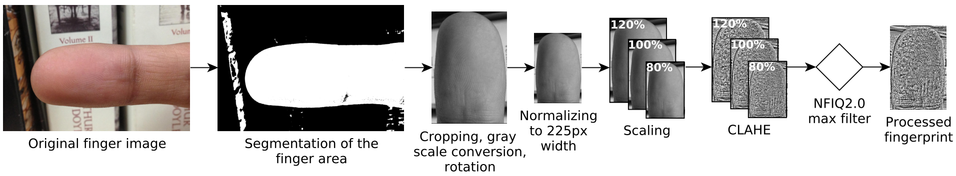


Fig. 5: Proposed touchless fingerprint pre-processing pipeline.

3.1 Touchless Fingerprint Pre-processing

To enable a processing of touchless data with a tool designed for the touch-based domain a pre-processing has to be applied which transforms a touchless fingerprint image to a touch-based equivalent fingerprint image [Sa17,LK18]. The equivalence relates to the resolution of the image respectively to the ridge-to-ridge distance, that can be expected with 10-11 pixels for a 500dpi adult fingerprint. This pre-processing pipeline is necessary since a direct application of a touch-based fingerprint recognition system to touchless fingerprint imagery is not possible [Li13]. Figure 5 depicts the pre-processing pipeline which is used for touchless fingerprint data.

Focusing on the employed touchless databases, two acquisition scenarios can be distinguished: (1) unconstrained acquisition in terms of sensor-to-finger distance, finger rotation, illumination and background properties, which is the case for the ISPFDv1 database, and (2) constrained acquisition, which is the case for the PolyU database. In the latter database, the fingerprint images are already segmented, *c.f.* Figure 3 (c, d). That is, on the PolyU database we skip the segmentation part of the pre-processing pipeline.

To extract the finger area from the background a color-based segmentation method is used [SVC17]. To achieve an accurate segmentation performance, the threshold parameters are adapted for the different environmental situations, *i.e.* subsets of the ISPFDv1 database. In order to present only the fingerprint region to NFIQ2.0 and the feature extractor, a fingertip detection and cropping is performed. Here a brightness-based approach as proposed by Raghavendra *et al.* [RBY13] is used, which searches for the most prominent local minimum on the smoothed gray scale distribution along the horizontal axis. This minimum corresponds to the first finger knuckle. After the cropping step the finger image only contains the relevant fingertip region. Since the samples of the ISPFDv1 database are represented in a horizontal orientation, samples are rotated by 90 or 270 degree in order to achieve consistency in terms of orientation, *i.e.* upright fingerprint impression. Then the angle between the longitudinal axis of the finger and the horizontal axis is 90 degree.

As can be seen in Table 1, considered touchless datasets consist of color images. Hence, a conversion to gray scale is computed using the very common RGB to gray scale conversion parameters: $Y \leftarrow 0.299R + 0.587G + 0.114B$. Touchless fingerprint samples might be captured at various distances leading to a varying ridge-line frequency. However, the NFIQ2.0 algorithm is designed to achieve optimal results on touch-based fingerprint data captured with a resolution of 500dpi [NI]. For this reason, all touchless samples are normalized to an image width of 225pixel which resembles a ridge-line frequency comparable to that of touch-based fingerprint data captured at a resolution of 500dpi. Due to varying finger sizes and inaccuracies during the finger segmentation a further scaling of ±20% on the normalized image is executed. Assuming that NFIQ2.0 reveals the best scores on 500dpi images we present all three versions of the sample to the NFIQ2.0 method expecting that the one with the highest quality score is the one which is most equivalent to a touch-based capture condition with 500dpi. A max filter is applied and the best quality score represents the final one and the corresponding fingerprint sample is used for further processing.

3.2 Biometric Performance Prediction

For evaluating the predictive power of a quality assessment algorithm for a biometric recognition system Grother and Tabassi [GT07] introduced the ERC. This method evaluates whether a rejection of low quality samples results in a reduce false-non-match error rate (FNMR).Each genuine comparison is associated with a similarity score s_{ii} and two quality scores $q_i^{(1)}$ and $q_i^{(2)}$ in order to aggregate the pair of quality scores from a pair of samples to be compared. As combination function H the min function is chosen:

$$q_i = H\left(q_i^{(1)}, q_i^{(2)}\right) = \min\left(q_i^{(1)}, q_i^{(2)}\right) \tag{1}$$

Then a set $R(u)$ is formed containing the pairwise minima which are less than a fixed threshold of acceptable quality u:

$$R(u) = \left\{i : H\left(q_i^{(1)}, q_i^{(2)}\right) < u\right\} \tag{2}$$

Subsequently, $R(u)$ is used to exclude comparison scores and computing the FNMR on the rest. Starting with the lowest of the pairwise minima, comparisons are excluded up to a threshold t which is obtained by using the empirical cumulative distribution function of the comparison scores, which corresponds to a FNMR of interest denoted by f:

$$t = M^{-1}(1 - f) \tag{3}$$

The ERC is then computed by iteratively excluding a portion of samples and recomputing the FNMR on the remaining comparison scores which are below the threshold:

$$\mathrm{FNMR}(t,u) = \frac{\left|\{s_{ii} : s_{ii} \leq t, i \notin R(u)\}\right|}{\left|\{s_{ii} : s_{ii} \leq \infty\}\right|} \tag{4}$$

Due to the effect that a fraction of low quality samples are excluded in every iteration step the FNMR should decrease constantly if the quality measure is a good predictor for the biometric performance.

In order to compare the different ERCs, the area under each curve minus the area under the optimal curve value is computed and denoted as partial area under curve (PAUC). Here the threshold is set to $x = 0.2$ to consider the most relevant part of the curve only.

4 Experimental Results

In experiments, we first estimate the distributions of NFIQ2.0 scores for touch-based and touchless fingerprint data sets applying the proposed evaluation pipeline. Additionally, the biometric performance is evaluated on the used fingerprint databases employing open-source fingerprint recognition systems. The features (minutiae triplets – 2-D location and angle) are extracted using neural-network based approaches. In particular, the feature extraction method of Tang *et al.* [Ta17] is employed for all databases except for touchless fingerprint images of ISPFDv1 for which the algorithm of Nguyen *et al.* [NCJ18] is applied. The latter feature extractor is designed for more challenging scenarios and hence is more suitable for said image subsets. For both feature extractors pre-trained models are made available by the authors. To compare such templates, a minutiae pairing and scoring algorithm of the sourceAFIS system of Važan [Va19] is used[3]. Moreover, we evaluate the predictive power of NFIQ2.0 regarding biometric performance using the ERC method.

4.1 Sample Quality Estimation

The score distributions of NFIQ2.0 quality scores obtained from the considered databases are plotted in Figure 6. Table 2 lists means and standard deviations of said score distributions together with resulting biometric performance in terms of Equal Error Rates (EERs). EERs are estimated by performing all possible genuine and impostor comparisons. A wide range of quality scores is represented in the NFIQ2.0 score distributions of the FVC06 and MCYT database, *c.f.* Figure 6 (a)-(b). Competitive performance rates are obtained on most subsets of theses databases except for the FVC DB3-A, see Table 2.

By incorporating the proposed pre-processing pipeline for touchless fingerprint imagery, similar NFIQ2.0 quality score distributions can be obtained, *e.g.* for the PolyU database,

[3] The original algorithm uses minutiae quadruplets, *i.e.* additionally considers the minutiae type (*e.g.* ridge ending or bifurcation). Since minutiae triplets are extracted by the used minutiae extractors, the algorithm has been modified to ignore the type information.

Tab. 2: Average NFIQ2.0 scores and biometric performance obtained from the considered databases.

DB	Subset	Preproc.	Avg. NFIQ2.0 score	EER (%)	PAUC
FVC06	DB2-A	–	36.07 (±9.07)	0.15	0.01261
	DB3-A	–	40.92 (±12.85)	6.71	0.00883
	DB4-A	–	27.80 (±12.28)	2.90	0.01261
MCYT	dp	–	37.58 (±15.17)	0.48	0.00868
	pb	–	33.02 (±13.99)	1.35	0.00970
PolyU	CB-S1	–	42.64 (±11.96)	0.67	0.00890
	CB-S2	–	40.97 (±13.14)	1.75	0.00893
	CL-S1	proposed	47.71 (±10.86)	3.91	0.00998
	CL-S2	proposed	47.08 (±13.21)	3.17	0.01106
ISPFDv1	LS	–	58.19 (±7.70)	0.51	0.01275
	NI	proposed	9.62 (±7.65)	34.64	0.01205
	NO	proposed	14.70 (±9.39)	28.12	0.01214
	WI	proposed	16.86 (±7.02)	35.67	0.01465
	WO	proposed	18.60 (±9.77)	25.29	0.01246

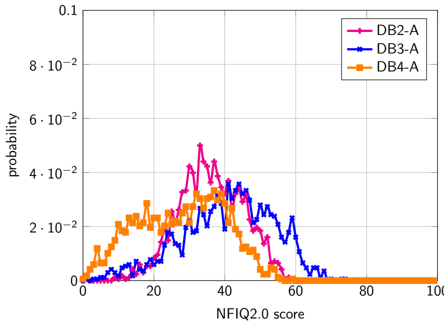
c.f. Figure 6 (c). In contrast, for the ISPFDv1 database two extreme cases can be observed: touch-based fingerprints exhibit very high quality while touchless fingerprint data are of rather very low quality in terms of NFIQ2.0, *c.f.* Figure 6 (d). This can be explained by the fact that the touchless fingerprint data of the ISPFDv1 database was acquired under rather unconstrained conditions, *i.e.* at variable distance, lightning, and focus. This is also reflected by the biometric recognition performance obtained on the subsets of the ISPFDv1 database, see Table 2. In such unconstrained environments dedicated feature extractors are required, as showcased by Sankaran *et al.* [Sa15].

Focusing on the relation of biometric performance and quality score distributions a clear inter-relation between recognition accuracy and quality can be observed from Table 2. However, we also observe that the biometric performance strongly depends on the applied feature extractor. More specifically, lower EERs are obtained for touch-based fingerprint data which has been captured using an optical or capacitive sensor, *e.g.* the MCYT database. In contrast, the fingerprint images of FVC DB3-A and DB4-A, which have been captured with a thermal sensor and generated synthetically, respectively, yield significantly higher EERs albeit exhibiting similar NFIQ2.0 score distributions. This also hold for touchless fingerprint data, as it can be clearly observed from EERs obtained on the PolyU database.

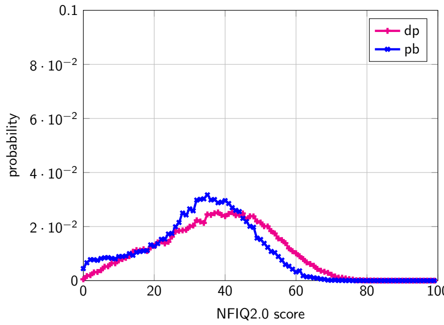
4.2 Biometric Performance Prediction

For the estimation of ERCs a FNMR of 10% is used as starting point for each database as suggested in [OŠB16]. ERCs for the considered databases are depicted in Figure 7. Strongly dropping ERCs indicate high predictive power, *i.e.* the FNMR is effectively reduced by rejecting fingerprint samples which exhibit low quality. Based on the obtained ERCs the following conclusions can be drawn:

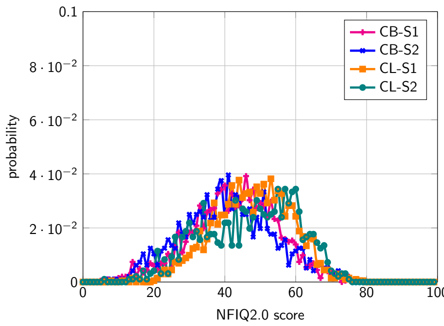
- If no significant biometric performance gains are to be expected, the predictive power in terms of ERC is rather low. This corresponds to the cases were either very



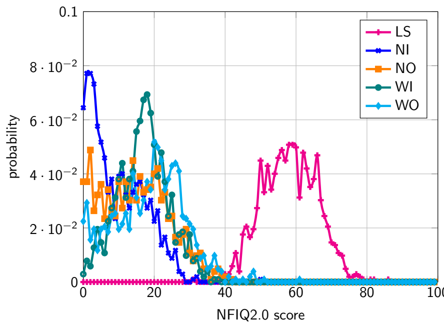
(a) FVC06



(b) MCYT



(c) PolyU



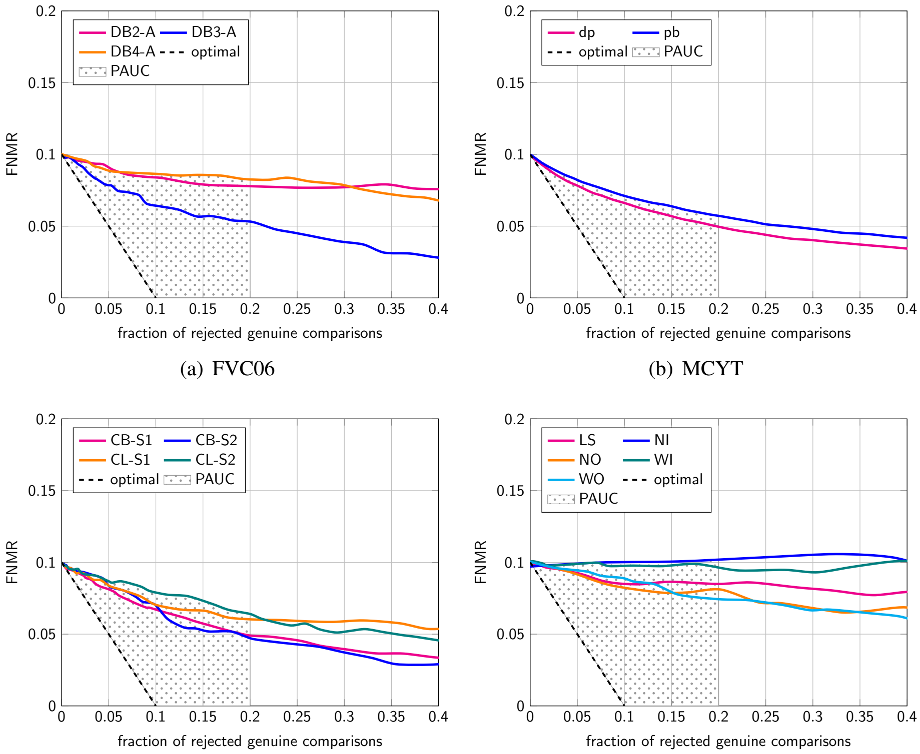
(d) ISPFDv1

Fig. 6: Probability density functions of NFIQ2.0 scores obtained from the considered databases.

high or very low recognition accuracy is obtained and quality scores are distributed in narrow ranges, *c.f.* ERCs, EERs, and NFIQ2.0 score distributions of FVC06 DB2-A (PAUC: 0.01261) and ISPFDv1 (*e.g.* PAUC NO: 0.01214).

- In case rather low recognition accuracy is obtained or NFIQ2.0 quality score distributions exhibit a wider range, the predictive power in terms of ERC is higher. This can be observed from the ERCs, EERs, and NFIQ2.0 score distributions of FVC06 DB3-A (PAUC: 0.00883), MCYT (*e.g.* PAUC dp: 0.00868), and PolyU (*e.g.* PAUC CB-S2: 0.00893).
- Under the aforementioned condition, the predictive power of NFIQ2.0 for touchless fingerprint data is only slightly inferior compared to that of touch-based fingerprint data. That is, ERCs drop less strongly (*e.g.* PAUC FVC06 DB2-A: 0.01261), *c.f.* ERCs obtained for PolyU (*e.g.* PAUC CB-S2: 0.00893).

Further, it might be concluded that NFIQ2.0 has less predictive power on synthetic data compared to real fingerprint data, *c.f.* ERCs for FVC DB4-A (PAUC: 0.00883).



(a) FVC06

(b) MCYT

(c) PolyU

(d) ISPFDv1

Fig. 7: ERCs obtained from the considered databases.

5 Conclusions

This work firstly investigated the applicability and predictive power of NFIQ2.0 for touchless fingerprint data. We conclude that NFIQ2.0 can be a viable tool for quality assessment in touchless fingerprint recognition scenarios in case adequate pre-processing is employed. Finally, it is important to emphasize that more a sophisticated pre-processing might further favour the predictive power of NFIQ2.0 for touchless fingerprint data.

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