Comparative Test of Smartphone Finger Photo vs. Touch-based Cross-sensor Fingerprint Recognition

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***Abstract*—Today's smart-phone cameras enable touch-less biometric fingerprint capture for practical use. This is inexpensive, comfortable and now fast enough for practical use. This paper deals with the question of how reliably two fingerprints can be compared, when one of them is captured by a smart-phone and the other by a dedicated fingerprint scanner. A multi-sensor database with 4310 fingerprint images from 108 users was collected. Three touch-based sensors and two touch-less finger photo sensors were used. Latest quality estimations using NFIQ 2.0 and vendor-specific quality metrics complete the study on professional capabilities of finger photo recognition. As side-result of the study, a new touch-less fingerprint processing chain is presented, which reduces the error rates to 1% EER for touch-less-to-touch comparison. This value is comparable to that for touch-to-touch applications.**

***Index Terms*—fingerprint recognition, inter-operability test, touch-less vs. touch-based.**

I. Introduction

According to a user acceptance study by Labati et al. [10] 96.7% of users prefer touch-less sensing of fingerprints over touch sensors for biometric recognition. Advantages compared to classical touch-based acquisition are manifold: no skin distortions in free acquisition (projection); almost no skin condition impact because frustrated total internal reflection (FTIR) setup is avoided; better hygienic conditions as no surface is touched; and safer application without latent fingerprints left on the sensor. Consequently, the last decade has seen a series of developments towards new acquisition methods at-a-distance [9].

An example of a new touch-less sensing device is Morpho's 2014 'Finger On the Fly' fingerprint sensor, but also webcams and smart-phones are already in use. Under lab conditions EERs as low as 0.22% were achieved with pre-processing of the photos captured [10]. Under less restrictive conditions, however, the error rates for finger photos can easily be over 20% and even higher [22]. The lack of resolution information, the different depth of field and quality assurance are challenges that the research groups address, especially in manual smart-phone acquisition. Figure 1 shows a typical set-up where a database fingerprint from a touch-based sensor is compared to a fingerprint from a touch-less sensor.

A prominent representative of Automated Fingerprint Identification Systems (AFIS) benefiting from the new non-contact technology is access control. The cooperation of contact-less and touch-based systems seems to become necessary soon.

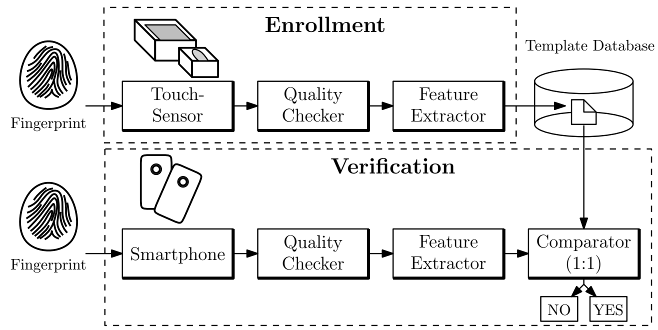


Fig. 1: Touch-based to touch-less fingerprint comparison setup.

Up to now, studies on touch-less fingerprint scanning have dealt little with the interaction with touch-based scanners. The topic was addressed by e. g. [10], [20], but deserves further attention to identify limitations and propose new solutions. The detection of counterfeits has also attracted a great deal of attention. Stein et al. [21] developed anti-spoofing algorithms to detect spoof attempts with fingerprint patterns recorded with an integrated smart-phone camera. The Fingerprint Liveness Detection Competition (LivDet) compares various fingerprint recognition methods [13]. This paper investigates cross-sensor inter-operability issues in touch-less (finger photo) vs. touch-based fingerprint recognition. It comes with contributions in inter-operability and novel finger segmentation and image enhancement methods. First, regarding inter-operability the paper adds compared to previous work [10], [20], [12]: (a) the first cross-sensor inter-operability test involving multiple reference touch sensors (4-finger optical, 2-finger optical and 1-finger capacitive) and smart-phones (LG Flex 2 with standard illumination and fixed focus, Samsung Note 4 with autofocus and dedicated ring light) on a database of 4310 samples coming from 108 users; and (b) a quality evaluation based on latest quality measurement tools (NFIQ 2.0) highlighting the usability of quality metrics on touch-less, enhanced fingerprint images. Second, with regards to new touch-less fingerprint processing methods, the paper adds a new segmentation technique designed for simultaneous 4-finger-capture, in contrast to previous techniques focusing on single-finger acquisition. It is shown that touch-less fingerprint capture with modern smart-phones can achieve a recognition rate similar to that of traditional touch-based scanners. This paper is structured as follows: An introduction to related work is given in Section II.

The novel 4-finger preprocessing method is presented in Section III. The collected database and exhaustive experiments on multiple sensors are presented in Section IV. Section V summarises the results of the study and concludes with an outlook on future work.

II. Related Work

Recent studies have shown that fingerprint recognition from smart-phones is possible [11], however accuracy largely depends on the image enhancement and quality restrictions of the underlying acquisition process. Under laboratory conditions and with fixed finger distance to the smart-phone, less than 5% EER were achieved [1], [5]. But with varying finger distances and less restrictive image quality, considerable degradations (more than 20% EER) were observed [22]. Besides smart-phones as finger photo sensors, also webcams [19], digital cameras [3], or dedicated sensing devices [5] have been employed. Sensing may be based on single images or video, use specific illumination to improve ridge contrast, and may or may not use placement guides to overcome the problem of segmentation and/or estimating the correct resolution [10]. Images traditionally need enhancement, such as contrast improvement [3], noise reduction, and unrolling [25] in order to provide reasonable accuracy. Besides 2D also 3D sensing technology has been investigated for finger photo recognition: structured light [24] and photometric stereo [8] have been successfully used for it. These two methods directly estimate ridge shape from the sensed data. Kumar and Kwong [8] reported 1.17% EER for combining 2D and 3D and Labati et al. [10] recently presented a depth from stereo approach with EERs as low as 0.22% outperforming previous solutions. 3D information can also be used to improve distortion correction. Here, finger shape instead of surface details are taken into account to unroll the 3D fingerprint surface details into 2D [25]. This leads to better minutiae pairing at the comparison stage. In addition to classical high-resolution features, inferior (50 dpi) fingerprint solutions [7] that concentrate on textural properties or Level 1 features were also investigated. In the last decade finger photo recognition research has largely introduced specific systems focusing on advancements in the processing chain: new preprocessing methods, features and comparators supporting the larger variability in scale (Table I). New processing chains for smart-phones (especially segmentation and preprocessing techniques) have been suggested [11], [1], [22], [23], [20]. Khalil and Wan [6] review image quality assessment, alignment and segmentation for finger photo recognition for mobile phones, but without a quantitative assessment of methods. While smart-phones come with a series of advantages in biometric sensing, especially availability and market penetration, there are only very few studies including questions on inter-operability between touchless and touch-based systems. Recently, this topic receives further attention: Labati et al. [10] investigate inter-operability comparing their high-end dedicated machine vision touchless 3D finger acquisition system with touch-based technology (Crossmatch Verifier 300) revealing 4.62% EER in inter-device mode compared to 0.17% on the same database (single-image enrolment) as a side aspect of their proposed system. Sankaran et al. [20] evaluate finger-photo-to-fingerprint in their work, but just a single touch-sensor (Lumidigm Venus IP65) is used and EERs are rather high and scattered (5.53-49.51% EER for inter-sensor vs. 3.65-37.25% EER for finger photo only) due to non-optimised algorithms. A good overview on finger photo recognition methods can be found in the recent work of Labati et al. [9]. Current paper suggests a new segmentation procedure, investigates quality filtering impacts on recognition accuracy, and highlights state-of-the-art recognition performance in true inter-sensor-type configurations.

III. Segmentation & Image Enhancement

Current smart-phones are normally equipped with 12 (or higher) megapixel (MP) cameras, such as the LG Flex 2 (4160×3120 pixels, hereafter Flex 2) or the Samsung Note 4 (5312×2988 pixels, hereafter Note 4). Table II shows the resulting resolution in dpi for the Note 4 for different image formats and distances. The image resolution at a distance of 8±2 cm is more than sufficient for Level-2 fingerprint details. A key feature is the fast image segmentation that extracts up to $n = 4$ upright oriented finger areas $F_1, \ldots, F_n$ from an input image I. Since the high resolution does not contribute much for this purpose, the images are reduced in size. This speeds up the segmentation procedure which is an intensive computing process. The segmentation is based on combined skin colour masks in the HLS and RGB colour spaces. Individual fingers (often touching fingers) are separated by using the dark finger borders that are obscured by shadows and the local contrast which is higher there. Generally, this does not work to separate fingers from the possible visible palm of the hand. For this reason, an outline tracing separates significant peaks (fingers) from the torso (palm of the hand). The segmentation results are then used to cut out the fingerprints individually. Monochrome images using full resolution are obtained. The image enhancement processes are essentially noise reduction and contrast enhancement. Since the exact distance between fingers and camera is not known, the image resolution is estimated based on the average ridge distance. This reduces variability and allows a reasonable scaling for the comparison algorithm.

A. Skin-Mask Finger Segmentation

For the segmentation, the image resolution is reduced to 400 pixels in width while maintaining the aspect ratio. This reduced RGB image is then smoothed with a Gaussian filter ($\sigma = 1.5$) and converted to HLS. Separate masks for H, L and S of the HLS colour space are created. For each mask, a valid range of values (minimum and maximum) for skin colour is defined separately, relative to the corresponding values of a reference HLS triplet. The reference HLS triplet is calculated from the reference RGB triplet. The default reference RGB triplet is $(r_\mathrm{R}, r_\mathrm{G}, r_\mathrm{B}) = (200, 140, 120)$. Alternatively, manually selected finger pixels from the RGB image can be used. This approach is recommended as it supports different skin

$$\mathrm{NCC}^{\circ 2} = \frac{(w_\mathrm{R} * r_\mathrm{R} * I_\mathrm{R} + w_\mathrm{G} * r_\mathrm{G} * I_\mathrm{G} + w_\mathrm{B} * r_\mathrm{B} * I_\mathrm{B})^{\circ 2}}{(w_\mathrm{R} * r_\mathrm{R}^2 + w_\mathrm{G} * r_\mathrm{G}^2 + w_\mathrm{B} * r_\mathrm{B}^2) * (w_\mathrm{R} * {I_\mathrm{R}}^{\circ 2} + w_\mathrm{G} * {I_\mathrm{G}}^{\circ 2} + w_\mathrm{B} * {I_\mathrm{B}}^{\circ 2})} \tag{1}$$

TABLE I: Some finger photo recognition systems in the literature. FAR = False Acceptance Rate, FRR = False Rejection Rate, EER = Equal Error Rate, GAR = Genuine Acceptance Rate. sa = samples, us. = users, cl = classes, n.s. = not specified.

Reference	**Sensing**	**Contribution**	**Test Database (sa., us., cl.)**	**Reported Accuracy (best)**
Labati et al. [10]	3D touch-less	new setup (depth from stereo) & (multi-template) matching	(2368, n.s., n.s.)	0.22% EER
Jonietz et al. [5]	2D touch-less	novel portable device & segmentation comparison	(96, n.s., n.s.)	2% FRR at 0.1% FAR
Sankaran et al. [20]	smart-phone	open database (iPhone 5), segmentation & feature (ScatNet)	(5100, 64, n.s.)	3.65% EER
Tiwari and Gupta [23]	smart-phone	new (scale-invariant) features & segmentation	(n.a., 50, n.s.)	3.33% EER
Kumar and Kwong [8]	3D touch-less	3D sensing (shape from shading) & finger surface code	(1440, 240, n.s.)	1.17% EER (3D+2D)
Ravi and Sivanath [19]	webcam	new 1-finger processing chain (segment, extract, compare)	(120, 20, n.s.)	93.6% acc.
Stein et al. [22]	smart-phone	processing chain (quality, segmentation) for freeform 1-finger	(n.a., 41, n.s.)	$<$ 20% EER
Derawi et al. [1]	smart-phone	comparison of fingerphoto capability (Nokia N95, HTC desire) with standard software	(1320, 22, n.s.)	4.5% EER
Kumar and Zhou [7]	2D touch-less	novel low-resolution (50 dpi) feature; new 2-session database	(1566, 156, n.s.)	3.95% EER
Zhao et al. [25]	3D touch-less	comparison of 3D-2D unrolling methods & new approach	(n.s., n.s., 24)	17 avg. mated minutiae
Hiew et al. [4]	2D touch-less	new preprocessing & Multiple Random Projections-Support Vector Machine method	(1938, n.s., 103)	1.23% EER
Hiew et al. [3]	2D touch-less	novel normalisation, segmentation, enhancement (STFT)	(1938, n.s., 103)	95.44% acc. core points
Lee et al. [11]	smart-phone	new acquisition method & processing chain	(840, n.s., 168)	85% GAR at 0.1% FAR

TABLE II: Image resolution in dpi when capturing fingerprints with a Note 4 at 5K, 4K (UHD) and 1080p (HD) sensor resolution, for different shooting distances.

	6 cm	**7 cm**	**8 cm**	**9 cm**	**10 cm**
5K	1955	1687	1467	1297	1163
UHD	1414	1219	1060	938	841
HD	707	610	530	469	420

colours and other influencing parameters, like white-balance. By applying the value ranges, the three binary masks H, L and S are created which are linked with a logical *'and'*. In addition, the left and right edge areas are blanked out in this combined HLS mask to avoid background pixels with skin-like tones. A practical example of this is a red brick wall that appeared in one of our outdoor test shots. A weighted normalised cross correlation (NCC) with the reference RGB triplet is performed for each RGB pixel (equation 1). The weights for red, green and blue are $w_\mathrm{R} = 1.0$, $w_\mathrm{G} = 0.7$ and $w_\mathrm{B} = 0.3$ and the operator $^{\circ 2}$ denotes element-wise power. The combined HLS mask is applied to the image $\mathrm{NCC}^{\circ 2}$ with the squared correlation values (the correlation values themselves are not computed for calculation speed reasons). Then an RGB mask is created to select the pixels with the highest correlation values, but not more than 10% of all pixels. Morphological operations are used to fill small holes and remove small pixel groups in this mask. This limited pixel selection is assumed to belong to the fingers, but do not necessarily include all finger pixels. From this pixel selection a new reference RGB triplet is generated by averaging the selected pixels and the whole process is repeated, although the size restrictions (left and right margin blanked out, not more than 10% of the pixels) are now omitted. In addition, the RGB image is vertically smoothed, converted to grey values and the local

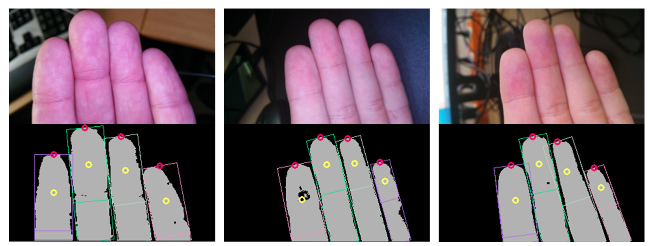


Fig. 2: Segmentation examples for 4 touching fingers. Top row: input images, bottom row: segmentation results. The yellow rings mark the centres of the rectangles that will be cut-out. The red rings mark the mid of the upper rectangle edge (indicates that the found fingers are pointing upwards).

variance is calculated for each pixel. Dark pixels with high local variance are considered as potential boundaries between touching fingers and masked out with a threshold applied to the ratio between the local variance and the brightness of the pixels. The contour silhouettes of the fingers are retrieved by following the boundaries of segmented objects. For the case that fingers are connected via the potentially visible ball of the thumb, fingers are separated by evaluating significant local minima and maxima in the contours. Individual finger contour point sets are then enclosed with minimum rotated rectangles. Based on these oriented rectangles, which are scaled back onto original size, the individual finger images are extracted.

B. Finger Image Enhancement

While colour is very useful for segmentation, it has little impact on the quality of the fingerprint. Therefore, the image enhancement works monochrome (Image I_m). We invert our fingerprint images in brightness and mirror them so that they can be compared with classical fingerprint images, in which the fingerprint is recorded and not the finger itself. To enhance the fingerprint images, following operations are applied:

$$N = g(\mathrm{boxblur}(I_\mathrm{m}, s) - I_\mathrm{m}, \sigma) \quad (2)$$

$$E = \mathrm{dilate}(\mathrm{erode}(\mathrm{dilate}(N))) \quad (3)$$

$$C = \sqrt{\mathrm{boxblur}(N^{\circ 2}, s)} \quad (4)$$

$$C_\mathrm{n} = E/C \quad (5)$$

where $\mathrm{boxblur}(., s)$ is a box blur filter with size s, $g(., \sigma)$ refers to Gaussian blurring with sigma σ and image N is locally brightness normalised (i.e. local brightness is zero), brightness inverted and smoothed. Note that these calculations work with floating point and that N and E also have negative pixels. The morphological operations dilate and erode for image E are *not* binary. They work with local minima and maxima functions and help to reduce noise. Image C contains local standard deviations (as a measure of contrast). Image C_n has normalised local standard deviations (i.e. local standard deviation is 1.0). The image C_n is then mirrored and converted to a non-negative value range (e.g. 0 to 255). This is done by multiplying the image values with a gain factor, adding an offset and truncating the obtained values. Background pixels (determined by the finger segmentation) and pixels with very low contrast values (in C) are masked out (i.e. set to white) in C_n. Finger borders are blurred to avoid that sharp edges interfere with fingerprint comparison.

C. Resolution Estimation

Within the final processing stage, the fingerprint region of interest is re-scaled based on an estimation of the ridge frequency. According to [18] the mean distance between fingerprint ridges in 500 dpi impressions is 7.71 pixels, while standard deviation is as low as 1.01 pixels. This is quite promising to serve as an initial estimate for fingerprint scale estimation. To estimate ridge frequency, for each finger region $F_1, \ldots, F_n$ the image is transformed into Fourier domain using the maximum inscribed square with optimal size for fast DFT. The mean values of the most pronounced frequencies are averaged over all visible finger regions. This serves as a basis for scaling the fingerprints to approximately 500 dpi. Although this measurement is not accurate, it does offer a useful approach for consider the limited scale invariance of current fingerprint comparison algorithms.

IV. Experimental Study

Experiments were conducted to: (a) investigate touch-less smart-phone fingerprint recognition performance when compared against touch-based systems, (b) validate the usefulness of the presented fast multi-finger segmentation chain, and (c) verify the compatibility of different fingerprint quality estimation algorithms (including the recently released NFIQ 2.0 [16]) for fingerprints of touch-less systems.

A. Fingerprint Quality Estimation

The image quality of fingerprints is influenced by a number of different variables. Dry skin causes eroded ridges and wet skin leads to dilated ridges. Besides, variable contact pressure, high displacement, rotation, and non-linear distortions between 3D surface and 2D touch-based sensing make fingerprint acquisition and comparison a non-trivial task. Algorithms for evaluating fingerprint quality, such as NFIQ 1.0 or NFIQ 2.0, map each fingerprint image to a discrete quality value. This value estimates the likelihood that an image will lead to a successful inter-personnel comparison. Although none of the algorithms have been designed for application to finger-photo data, NFIQ 2.0 delivered good results in our experiments. High quality is desirable to keep system error rates low, but in the past it was shown that some algorithms for quality assessment, such as the neural network based NFIQ 1.0, have certain weaknesses [17]. When comparing touch-based with touch-less fingerprint images, the resulting images may suffer from different influences (e.g. blurred images are a common source of error in touch-less systems, while touch-based systems can easily control focus).

B. Database

For the current study we have collected a database with 4310 fingerprints of 108 users. For each user 8 fingerprints were taken with 5 different sensors, although it was not always possible to capture all fingers (e.g. presence of adhesive bandages or cut fingers). The following three touch-based (TB) systems and two touch-less (TL) smart-phones were used:

- **TB Opt4**: **Opt**ical **4**-finger sensor ARH AFS510. This is an FBI IAFIS Appendix F-certified device (500 ppi capture device, 3.58×3.07 inch sensor plate).
- **TB Opt2**: **Opt**ical **2**-finger sensor Crossmatch EF200. This is an FBI IAFIS Appendix F-certified device (500 ppi capture device, 1.60×1.50 inch sensor plate).
- **TB Cap1**: **Cap**acitative **1**-finger sensor SMUFS Bluetooth. This system offers wireless mobile 508 ppi fingerprint scanning, but is not certified according to FBI IAFIS Appendix F [2].
- **TL PhoneA**: Smart-**phone** Samsung Note 4 with **a**utofocus. Fingerprint capture with additional ring-light support (9 white LEDs attached to the phone's case, surrounding the 16 MP rear camera).
- **TL PhoneF**: Smart-**phone** LG Flex 2 with **f**ixed focus. With this innovative fingerprint capture, multiple shots are taken at different distances with fixed focus and the best (sharpest) is selected.

C. Algorithms

For each touch-based device, the manufacturer-specific APIs were used to perform fingerprint capture (Opt4 and Opt2 with internal quality controls, a series of attempts before a result is delivered). In case of touch-less devices, while PhoneA works with autofocus, PhoneF acquires images with fixed focus. To do this, a number of shots are taken in continuous shooting mode, varying the distance between the PhoneF and the fingers. The best-shot selection was then made by estimating the sharpness of the images using a square gradient approach. After applying the finger segmentation and enhancement of Section III-A the NIST's most recent release of Biometric Image Software [15] (open source reference system), and the Verifinger SDK Neurotechnology's fingerprint matcher [14] (state-of-the-art commercial reference system) were employed for assessment.

In case of touch-based systems, the image resolution is known which is why the two aforementioned methods are not robust against scaling errors. Since the resolution (in dpi) of the smart-phone images can only be estimated, we improve the recognition accuracy by up-scaling and down-scaling the fingerprint images based on the resolution estimation in the range of -25% to $+25\%$ in 5% steps. The highest resulting score for the fingerprint recognition is then regarded as the correct one. This method is a bit time-consuming, yet simple. In the future, there may be fingerprint comparison methods that are insensitive to fluctuations in scaling.

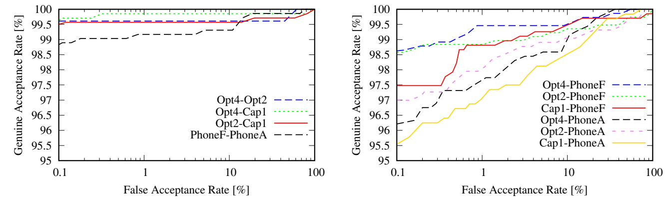
D. Evaluation Procedure

To assess fingerprint recognition performance in inter-sensor-type versus cross-sensor-type configurations we employ latest ISO/IEC 19795-6 metrics (FAR, FRR, FTA and GAR) and quality measures (NFIQ-1, NFIQ-2 and VF) for operational testing of biometric systems:

- **FAR**: False Accept Rate - proportion of incorrectly authenticated impostors.
- **FRR**: False Reject Rate - proportion of falsely denied authentic users.
- **FTA**: Failure To Acquire - proportion of attempts for which the system fails to capture a sample.
- **GAR**: Genuine Acceptance Rate - proportion of correctly accepted authentic (genuine) users. GAR $= 100\% - \text{FRR}$.
- **NFIQ-1**: Quality metric from NFIQ release 1.0. Quality levels 1 to 5, 1 is best.
- **NFIQ-2**: Quality metric from NFIQ release 2.0. Quality levels 0 to 100, 100 is best.
- **VF**: Quality metric from the commercial Verifinger SDK. Quality levels 0 to 100, 100 is best.

E. Distribution of Quality Values

In a first experiment, the collected database was used to investigate the distribution of the quality values depending on the quality metrics and sensors. The graphs on the left column of Fig. 4 show that in general the quality metrics 'NFIQ-1' and 'VF' assign significantly lower quality values to the images of the touch-less sensors ('PhoneA' and 'PhoneF') than those of the touch-based sensors. This can be seen in the higher curves. This is because even at low thresholds many samples are already covered, so there are fewer samples with a better level and the curve is higher. But the curves for the quality metrics NFIQ-2 (Fig. 4c) suggest that the sensors have a similar quality and only the images from the touch-based sensor 'Cap1' are evaluated worse. These different classifications of the quality metrics show their limited usability. It should still be noted that all 3 metrics show a slightly better quality for 'PhoneF' images (fixed focus) compared to 'PhoneA' images (autofocus).



(a) Inter-sensor-type ROC. (b) Cross-sensor-type ROC.

Fig. 3: ROCs comparing sensor performance at NFIQ-2 quality threshold level 30. Inter-sensor-type ROC compares TL with TL and TB; cross-sensor-type ROC compares TL with TB. TL=touch-less, TB=touch-based.

F. Inter- vs. Cross-sensor-type Performance

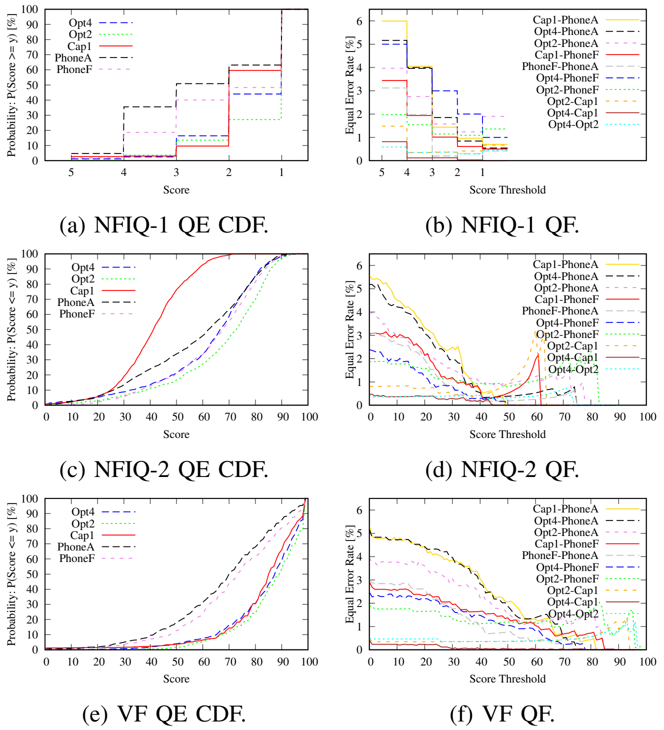
Our investigations focus on the cross-sensor-type performance of fingerprint acquisition sensors. Since the images of all touch-based systems undergo a vendor-specific quality check, we have adopted this behaviour for smart-phones and defined a common minimum quality threshold. We use NFIQ-2, which seems to have the best quality assessment and we use level 30 as quality threshold which even in the worst case (see 'Cap1' in Fig. 4c) excludes not more than 20% of the images. Figure 3 shows the Receiver Operating Characteristics (ROCs) for the inter-sensor-type (a) and cross-sensor type (b) comparisons. Touch-based inter-sensor-type systems (optical and capacitive) come to 99.5% GAR at only 0.1% FAR. The touch-less inter-sensor-type system (PhoneA and PhoneF image matches) still comes close to 99% GAR at 0.1% FAR. In the cross sensor type configurations (Fig. 3b), the fixed focus smart-phone ('PhoneF') achieves better values, with GARs from 97.5% to 98.6% at 0.1% FAR. 'PhoneA' scores only 95.5% to 97% GAR at 0.1% FAR. For both smart-phones, the fingerprint comparisons with the capacitive sensor ('Cap1') show the weakest detection accuracy. By restricting comparisons to Appendix F-certified touch sensors ('Opt4' and 'Opt2') and 'PhoneF', the recognition accuracy is only slightly worse than that of the inter-phone configurations.

G. Threshold for Fingerprint Quality Estimation

The right column of Fig. 4 shows for each quality measure how EER depends on the choice of the quality threshold. Filtering based on 'NFIQ-2' tends to decrease EER at significantly lower quality values than 'VF'. Therefore, even at comparatively low thresholds, small EER values are achieved. The spikes at the end of the curves (Fig. 4d and 4f) come about because the sample quantities become too small with high thresholds and the statistical power is lost. We also examined the dependence of EER (as a measure for classification accuracy) on FTE (images that are not approved for fingerprint comparison due to poor quality) and we observed that the quality assessment by 'NFIQ-2' criterion seems to be most suitable for smart-phones.

V. Conclusion and Future Work

In this paper we examined the performance of touch-less fingerprint capture with smart-phones. Designated fingerprint



(a) NFIQ-1 QE CDF. (b) NFIQ-1 QF.

(c) NFIQ-2 QE CDF. (d) NFIQ-2 QF.

(e) VF QE CDF. (f) VF QF.

Fig. 4: Left column: Cumulative Distribution Functions (CDFs) of the quality estimation (QE) techniques. The curves show for each score the relative frequency of the samples in our database, whose score is no better. Right column: Equal Error Rate (EER) performance obtained by filtering according to quality threshold (rejecting all images with lower quality). QF means Quality Filtering.

scanners have qualitative advantages because of their controlled recording conditions (e.g. constant scanning distance), but smart-phones are nowadays widely used devices and therefore in application scenarios where mobility is important a highly attractive alternative. We have presented a new approach to segmenting the fingers in the images, which also works well when the fingers touch each other and therefore do not need to be clearly spread. The algorithm is based, among other features, on the correlation of the pixel RGB triplets with a skin-coloured reference RGB triple and the evaluation of local brightness and contrast (for finger segmentation). With a fixed focus and a threshold of level 30 ($<$20% FTE) of the recently released NFIQ 2.0 quality metrics, a smart-phone in combination with FBI IAFIS Appendix F certified fingerprint scanners achieved 98.5% GAR at 0.1% FAR. Alternatively, an EER of 1% can be achieved (99% GAR at 1% FAR). In the future we will try to improve the algorithms. Instead of selecting only the best (sharpest) from a stack of images, we want to try to use the information from the other stack images as well. Future smart-phones will probably have even better sensors and capabilities offering new possibilities such as better estimation of the distance and resolution, which would help both processes segmentation and fingerprint comparison.

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