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Comparison of fingerprint quality measures using an optical and a capacitive sensor

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Abstract—Although several image quality measures have been proposed for fingerprints, no work has taken into account the differences among capture devices, and how these differences impact on the image quality. In this paper, several representative measures for assessing the quality fingerprint images are compared using an optical and a capacitive sensor. The capability to discriminate between images of different quality and its relationship with the verification performance is studied. We report differences depending on the sensor, and interesting relationships between sensor technology and features used for quality assessment are also pointed out.

I. INTRODUCTION

Fingerprints are commonly used to verify the identity of a person with high accuracy [1]. Recent experimental results pointed out that the verification performance is affected by the quality of the image provided by the electronic sensor [2], [3]. Quality in biometric systems is a current research challenge [4] and even the best fingerprint verification systems worldwide struggle in the presence of noisy images, as demonstrated in the FVC2004 benchmark [5]. A significant drop of performance was observed in FVC2004 with respect to the previous edition in 2002 [6] due to deliberate quality corruption of the databases introduced during the acquisition. In the last FVC2006 edition [7], no deliberate difficulties were introduced in the acquisition, but the population is more heterogeneous, including manual workers and elderly people. Also, no constraints were enforced to guarantee a minimum quality in the acquired images and the final datasets were selected from a larger database by choosing the most difficult fingers according to a quality index, to make the benchmark sufficiently difficult for an evaluation.

So far, several capture devices have been proposed for acquiring fingerprint images [1]. Among the others, optical and capacitive sensors are the most widely used. They are based on different physical principles: the first ones produce the image by evaluating the reflection properties of the skin, whilst the second ones use the electrical properties of the skin as the second armature of the capacitor formed against the silicon acquisition surface. Due to their different physical principles, the conditions affecting the quality of the acquired

images are expected to be different for optical and capacitive sensors. For example, the effect of the pressure on the sensor and the dryness of the skin are expected to impact differently during the fingerprint acquisition. Therefore, it can be hypothesized that the two sensors provide image of different quality in many cases. In addition, one can think that the degradation of the verification performance with the quality can be different for the two sensors. Various quality measures for fingerprint images acquired from electronic sensors have been proposed in the literature [8]. However, no previous work has taken into account the differences among fingerprint capture devices, and how these differences impact on the quality measure computation. In our opinion, some measures could be suitable for the optical sensor and not for the capacitive one, and vice-versa.

Accordingly, the main goal of this paper is to compare by experiments some representative state-of-the-art measures for assessing the quality of fingerprint images, in order to provide indications on which of them are best suited for a certain capture device. An optical and a capacitive sensor are used in our experiments. We evaluate a set of quality measures in terms of their capability to discriminate among images of different quality and their relationship with the verification performance. Reported results show differences depending on the sensor, and relationships between sensor technology and features used for quality assessment are also pointed out. The scope of our conclusions is obviously limited by the fact that we adopt a particular commercial sensor for each family (optical and capacitive). However, it should be noted that the basis acquisition physical principle is the same for all optical and capacitive sensors, so it is possible that reported results could be confirmed in a next and larger experimental stage with other commercial sensors based on optical and capacitive acquisition principles.

The rest of the paper is organized as follows. Section II describes the quality measures used in our study. In Section III, we describe our experiments and results, and conclusions are finally drawn in Section IV.

II. QUALITY MEASURES FOR OPTICAL AND CAPACITIVE FINGERPRINT IMAGES

A number of approaches for fingerprint image quality computation have been described in the literature. A taxonomy is given in [8], see Fig. 1. Image quality is assessed by measuring one of the following properties: ridge strength or directionality, ridge continuity, ridge clarity, integrity of the ridge-valley structure, or estimated verification performance when using the image at hand. A number of sources are used

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Fingerprint Image Quality Estimation Methods

Fig. 1. Taxonomy of existing fingerprint image quality estimation methods.

to compute the features used for image quality assessment: *i*) angle information provided by the orientation field, *ii*) Gabor filters, which represent another implementation of the orientation angle [9], *iii*) pixel intensity of the gray-scale image, *iv*) power spectrum, and *v*) Neural Networks. Fingerprint quality can be assessed either analyzing the image in a holistic manner, or combining the quality from local non-overlapped blocks of the image.

In the following, we give some details about the quality measures used in this paper. Different measures have been selected from the literature in order to have a representative set. We have implemented at least one measure that make use of the above mentioned properties for quality assessment, see Table I. For additional details of the selected measures, we refer the reader to [8] and the references therein.

- **Orientation Certainty Level (Q_{OCL})** [10], which measures the energy concentration along the dominant direction of ridges using the intensity gradient. A relative weight is given to each region of the image based on its distance from the centroid, since regions near the centroid are supposed to provide more reliable information [13].
- **Ridge frequency (Q_{FREC})** [10]. Ridges and valleys are modeled as a sinusoidal-shaped wave along the direction normal to the local ridge orientation (e.g. see [11]). Ridge frequency is computed for each image block. A valid range is defined for the ridge frequency, and blocks whose measure fall outside of the range are marked as “bad” blocks.
- **Local Clarity Score (Q_{LCS})** [12]. The sinusoidal-shaped wave that models ridges and valleys (e.g. see [11]) is used to segment ridge and valley regions. The clarity is then defined as the overlapping area of the gray level distributions of segmented ridges and valleys. For ridges/valleys with good clarity, both distributions should have a very small overlapping area.
- **Local Orientation Quality (Q_{LOQ})** [12], which is computed as the average absolute difference of orientation angle with the surrounding image blocks, providing information about how smoothly orientation angle changes from block to block.
- **Energy concentration in the power spectrum (Q_{ENERGY})** [13], which is computed using ring-shaped bands. For a fingerprint image, the ridge frequency value lies within a certain range and it is expected that as fingerprint image quality increases, the

Quality measure	Property measured	Source
Q_{OCL}	Ridge strength	Local angle
Q_{FREC}	Ridge integrity	Local angle
Q_{LCS}	Ridge clarity	Pixel intensity
Q_{LOQ}	Ridge continuity	Local angle
Q_{ENERGY}	Ridge strength	Power spectrum
Q_{NFIS}	Matcher performance	Neural Networks

TABLE I
SUMMARY OF THE QUALITY MEASURES SELECTED FOR THE
EXPERIMENTS OF THIS PAPER.

Impr.	Press.	Humid.	Impr.	Press.	Humid.
1	Normal	Normal	6	High	Dry
2	Normal	Normal	7	Low	Dry
3	High	Normal	8	Normal	Wet
4	Low	Normal	9	High	Wet
5	Normal	Dry	10	Low	Wet

TABLE II
CONDITIONS OF PRESSURE AND HUMIDITY UNDER WHICH THE
EXTREME DATA SET WAS ACQUIRED.

energy will be more concentrated in ring patterns within the spectrum.

- **Matcher performance (Q_{NFIS})**. One popular method based on classifiers [14], [15] defines the quality measure as the degree of separation between the match and non-match distributions of a given fingerprint, which is computed using Neural Networks. This quality assessment algorithm is included in the publicly available NIST software [16].

III. EXPERIMENTAL RESULTS

A. Database description

Similarly to the FVC2004 benchmark [5], we created a database containing 1680 images in which image quality has been artificially corrupted by using an acquisition procedure with variable contact pressure, artificial dryness and moistness. The index, middle and ring fingers of both hands from seven volunteers were acquired using an optical and a capacitive sensor (six classes per person, therefore having a total number of $6 \times 7 = 42$ classes per sensor). We used the Biometrika FX2000 (312×372 pixels images at 569 dpi) and the Precise Biometrics MC100 (300×300 pixels images at 500 dpi) as optical and capacitive sensor, respectively.

First, ten impressions of each finger were acquired in *normal* conditions, i.e. asking users to press against the sensor in a natural way. This results in 420 multi-sensor fingerprint images, being referred from now on as the *DIEEE* dataset. Next, another ten impressions of each finger were acquired under *corrupted* quality conditions. Across the ten

Fig. 2. Fingerprint examples from the three subsets of low, medium and high quality. Fingerprint images are plotted at the same scale for: *i*) both optical (left subplot) and capacitive sensor; and *ii*) variable quality (from top to bottom): low, medium, high.

acquisitions, users were asked to apply low and high pressure against the sensor surface, and simulate dryness and moisture conditions. Table II show the conditions imposed to each of the ten impressions. This results in a second subset of 420 multi-sensor fingerprint images, being referred from now on as the *EXTREME* dataset.

At the end of the data collection, we gathered two multi-sensor datasets from the same volunteers, one acquired in a natural way and the second having a number of sources of difficulty: artifacts due to wet fingers, poor contrast due to skin dryness or low contact pressure, distortion due to high contact pressure, etc. Examples are shown in Fig. 2.

B. Separation capabilities of quality measures

We first compare the capability of the selected quality measures to discriminate between good and bad quality images acquired with each sensor. For this purpose, three subsets were extracted for each sensor from the *EXTREME*

dataset by visual inspection of their image qualities, one subset with 62 images of low quality, one subset with 62 images of medium quality, and one subset with 62 images of good quality. Images for each subset have been selected in order to have clearly different quality images. The following factors have been taking into account to assess the quality of fingerprint images: incomplete fingerprint (low pressure), smudged ridges in different zones of the image (high pressure or moisture), nonuniform contrast of the ridges (low pressure or dryness), background noise in the image or latent fingerprints from previous acquisitions (moisture), weak impression of the ridge structure (low pressure or dryness), and significant breaks in the ridge structure or artifacts between ridges (high pressure or moisture). These characteristics are quantified by visual inspection and only images undoubtedly classified as bad, medium or good quality are considered. Examples are shown in Fig. 2.

As evaluation criterion, the Fisher distance (FD) has been

CAPACITIVE SENSOR

OPTICAL SENSOR

Fig. 3. Quality distributions of the three subsets of images with different quality. Quality values are normalized to lie into the $[0, 1]$ range, with 0 being the lowest quality and 1 being the highest quality.

used, which is a measure of statistical separation among bad, medium and good quality classes. The FD expression for two classes A and B is as follows:

$$FD = \frac{(\mu_A - \mu_B)^2}{\sigma_A^2 + \sigma_B^2}$$

where μ_A and σ_A (μ_B and σ_B) are the mean and variance of class A (class B).

The quality of all images from the three subsets is computed and normalized to lie into the $[0, 1]$ range, with 0 being the lowest quality and 1 being the highest quality. Then, the mean quality value and standard deviation value of each subset are computed. Next, the FD between the three subsets is extracted. We extracted two FD values: between subsets of low and medium quality images (FD1), and between subsets of medium and high quality images (FD2). The quality assessment algorithms are tuned so as to maximize these two FD values.

In Table III it is shown the results of this experimental evaluation procedure. The quality measures are ranked on the basis of the FD1 value. Also, Fig. 3 depicts quality distributions of the three subsets for all the quality algorithms tested. It can be observed from Table III that FD values between subsets of low and medium quality images (FD1) are higher than FD values between subsets of medium and high quality images (FD2) in most cases. This suggests that the

CAPACITIVE SENSOR

OPTICAL SENSOR

Measure	FD		Measure	FD	
	FD1	FD2		FD1	FD2
Q_{OCL}	4,44	3,21	Q_{FREC}	2,16	0,16
Q_{LOQ}	4,11	0,49	Q_{LCS}	2,09	0,49
Q_{FREC}	3,23	0,33	Q_{NFIS}	1,52	0,18
Q_{LCS}	2,21	0,89	Q_{ENERGY}	0,93	0,14
Q_{NFIS}	2,05	0,25	Q_{LOQ}	0,73	0,16
Q_{ENERGY}	1,82	0,80	Q_{OCL}	0,73	1,68

TABLE III

STATISTICAL MEASURES OF THE THREE SUBSETS OF IMAGES WITH DIFFERENT QUALITY FROM THE *EXTREME* DATA SET. FD1 (FD2) IS THE FISHER DISTANCE BETWEEN SUBSETS OF LOW AND MEDIUM QUALITY IMAGES (MEDIUM AND HIGH QUALITY IMAGES). QUALITY MEASURES ARE RANKED BY FD1 VALUE.

tested quality algorithms are specially good at discriminating images of bad quality from the rest of images. However when image quality increases, discrimination capability between quality groups decreases for both sensors. This can also be observed in Fig. 3, where distributions of the medium and high quality subsets are highly overlapped, specially for the optical sensor.

It can also be seen from Table III that all quality algorithms result in higher Fisher distances for the capacitive sensor

Fig. 4. Experiment discarding scores with the lowest quality (x -axis of the different plots). The quality of a score is defined as $\sqrt{Q_{k_e} \cdot Q_{k_t}}$, where Q_{k_e} and Q_{k_t} are the image qualities of the enrolled and input fingerprints respectively corresponding to the matching.

(i.e., better discrimination between quality groups). There are a number of quality estimation algorithms for the optical sensor that result in high separation between subsets of low and medium quality images (FD1), but most of the algorithms result in low separation between subsets of medium and high quality (FD2). We observe from our experiments that, in general, the discrimination capability is lower for the optical sensor than for the capacitive one.

By looking at Table III, we found interesting relationships between sensor technology and features used for image quality assessment. For instance, the quality measure relying on pixel intensity (Q_{LCS}) is ranked first for the optical sensor and, on the contrary, it is ranked last for the capacitive one. The opposite happens with the measure relying on ridge strength (Q_{OCL}) or ridge continuity (Q_{LOQ}). In particular, the quality measure relying on integrity of the ridge-valley structure (Q_{FREC}) works reasonably well for both sensors. It is worthy to remark that optical sensors are based on light reflection properties [1] which strictly impact on the related grey level values, and that the grey level features-based quality measure ranks first for the optical sensor. Therefore, there seems to be a close relationship between the physical properties of the optical sensor and the quality measures that better work with this sensor.

C. Verification performance improvement

We now compare the capability of quality measures to improve the verification performance as images scored with bad quality are discarded. We use the publicly available fingerprint matcher included in the NIST Fingerprint Image Software 2 (NFIS2) [16]. This matcher employs minutiae to represent and match fingerprints. Minutiae matching is the most well-known and widely used method for fingerprint matching, thanks to its analogy with the way forensic experts compare fingerprints and its acceptance as a proof of identity

in the courts of law [1]. It has been found in previous studies [3], [13], [17] that the performance of minutiae-based systems depends on the quality of fingerprint images, although no studies have taken into account differences between sensors of different technology. For our evaluation and tests with NFIS2, we have used the following packages: *i*) MINDTCT for minutiae extraction; and *ii*) BOZORTH3 for fingerprint matching. MINDTCT takes a fingerprint image and locates all minutiae in the image, assigning to each minutia point its location, orientation, type, and quality. The BOZORTH3 matching algorithm computes a match score between the minutiae from a template and a test fingerprint. For detailed information of MINDTCT and BOZORTH3, we refer the reader to [16].

We consider the 10 impressions from the same finger of the *DIIEEE* data set as enrolment templates. Genuine matchings are obtained comparing the templates to the 10 corresponding impressions from the same finger of the *EXTREME* data set. Impostor matchings are obtained by comparing one template to the 10 impression of the *EXTREME* data set from all the other fingers. The total number of genuine and impostor matchings are therefore $42 \times 10 \times 10 = 4,200$ and $42 \times 41 \times 10 = 17,220$, respectively, per sensor. We further assign a quality value to each score. The quality of a score is defined as $\sqrt{Q_{k_e} \cdot Q_{k_t}}$, where Q_{k_e} and Q_{k_t} are the image qualities of the enrolled and input fingerprints respectively corresponding to the matching. A quality ranking of the scores is carried out and the EER value is then computed discarding scores with the lowest quality value. Results of this procedure are shown in Fig. 4. Score quality values are normalized to lie into the $[0, 1]$ range for better comparison between quality measures.

Based on the results of Fig. 4, we find close relationship between verification performance improvement and the discrimination capability reported in Sect. III-B. For the

capacitive sensor, we observed high discrimination capability between images of different quality. As a result, it can be seen in Fig. 4 that the verification performance is improved for all the quality measures tested. On the other hand, there are a number of algorithms that resulted in low discrimination capability for the optical sensor (Q_{OCL} , Q_{LOQ} , Q_{ENERGY}). We observe in Fig. 4 that these algorithms result in the lowest improvement of performance. Contrarily, the algorithms ranked first for the optical sensor (Q_{FREC} , Q_{LCS}) result in the highest performance improvement.

Taking the relative EER improvement into account, however, we observe from Fig. 4 that higher improvement is obtained with the optical sensor (around 13% and 47% for the capacitive and the optical, respectively, in the best cases). This can be due to the smaller acquisition surface of the capacitive one. It is well known that acquisition surface of fingerprint sensors has impact on the performance due to the amount of discriminative information contained in the acquired biometric data [1]. As a result, increasing image quality results in smaller improvement for the capacitive sensor due to this inherent limitation. Or, in other words, degrading image quality has more impact on the performance of the optical sensor, since higher amount of discriminative information is degraded.

IV. CONCLUSIONS

In this paper, several representative measures for assessing the quality of fingerprint images have been compared, and their differences in behavior when using an optical and a capacitive sensor have been pointed out.

In particular, all quality algorithms have been capable of rejecting images of bad quality for both sensors. However, when image quality is increased, discrimination capability decreases. In general, the discrimination capability is lower for the optical sensor than for the capacitive one. We also pointed out interesting relationships between sensor technology and features used for image quality assessment. The most discriminative measures with one sensor have been the least discriminative ones with the other sensor, and vice-versa. In particular, measures relying on grey level features have been the most discriminative with the optical sensor. We have also compared the performance improvement obtained with each sensor as images with the worst quality are discarded, finding a close relationship between performance improvement and reported discrimination capability.

Future work includes extending this study to a larger set of commercial sensors and also including sensors with other acquisition technology (e.g. thermal ones). Separately considering the impact of specific bad quality sources (e.g. broken ridges, cuts, bruises, non-uniform contrast, etc.) in the different quality measures will also be studied.

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REFERENCES

- [1] D. Maltoni, D. Maio, A. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*. New York: Springer, 2003.
- [2] D. Simon-Zorita, J. Ortega-Garcia, J. Fierrez-Aguilar, and J. Gonzalez-Rodriguez, "Image quality and position variability assessment in minutiae-based fingerprint verification," *IEEE Proceedings - Vis. Image Signal Process.*, vol. 150, no. 6, pp. 402–408, December 2003.
- [3] J. Fierrez-Aguilar, Y. Chen, J. Ortega-Garcia, and A. Jain, "Incorporating image quality in multi-algorithm fingerprint verification," *Proc. Intl. Conference on Biometrics, ICB*, Springer LNCS-3832, pp. 213–220, 2006.
- [4] "NIST biometric quality workshop, Gaithersburg, MD, USA, March 2006 (<http://www.itl.nist.gov/iad/894.03/quality/workshop/index.html>)."
- [5] R. Cappelli, D. Maio, D. Maltoni, J. L. Wayman, and A. K. Jain, "Performance evaluation of fingerprint verification systems," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 28, no. 1, pp. 3–18, Jan 2006.
- [6] D. Maio, D. Maltoni, R. Capelli, J. Wayman, and A. Jain, "FVC2002: Second fingerprint verification competition," *Proc. Intl. Conference on Pattern Recognition, ICPR*, vol. 3, pp. 811–814, 2002.
- [7] "FVC2006 - Fingerprint Verification Competition (<http://bias.csr.unibo.it/fvc2006/default.asp>)."
- [8] F. Alonso-Fernandez, J. Fierrez, J. Ortega-Garcia, J. Gonzalez-Rodriguez, H. Fronthaler, K. Kollreider, and J. Bigun, "A review of fingerprint image quality estimation methods," *IEEE Trans. on Information Forensics and Security, Special Issue on Human Detection and Recognition (to appear)*, 2007.
- [9] J. Bigun, *Vision with Direction*. Springer, 2006.
- [10] E. Lim, X. Jiang, and W. Yau, "Fingerprint quality and validity analysis," *IEEE Proc. Intl. Conference on Image Processing, ICIP*, pp. 469–472, 2002.
- [11] L. Hong, Y. Wan, and A. Jain, "Fingerprint image enhancement: Algorithm and performance evaluation," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, August 1998.
- [12] T. Chen, X. Jiang, and W. Yau, "Fingerprint image quality analysis," *IEEE Proc. Intl. Conference on Image Processing, ICIP*, pp. 1253–1256, 2004.
- [13] Y. Chen, S. Dass, and A. Jain, "Fingerprint quality indices for predicting authentication performance," *Proc. Intl. Conf. on Audio- and Video-Based Biometric Person Authentication, AVBPA*, Springer LNCS-3546, pp. 160–170, 2005.
- [14] E. Tabassi, C. Wilson, and C. Watson, "Fingerprint image quality," *NIST research report NISTIR7151*, August 2004.
- [15] E. Tabassi and C. Wilson, "A novel approach to fingerprint image quality," *IEEE Proc. Intl. Conference on Image Processing, ICIP*, vol. 2, pp. 37–40, 2005.
- [16] C. Watson, M. Garriss, E. Tabassi, C. Wilson, R. McCabe, and S. Janet, *User's Guide to Fingerprint Image Software 2 - NFIS2* (<http://fingerprint.nist.gov/NFIS>), NIST, Ed. NIST, 2004.
- [17] J. Fierrez-Aguilar, L. Munoz-Serrano, F. Alonso-Fernandez, and J. Ortega-Garcia, "On the effects of image quality degradation on minutiae- and ridge-based automatic fingerprint recognition," *IEEE Proc. Intl. Carnahan Conference on Security Technology, ICCST*, pp. 79–82, 2005.