The influence of Fingerprint Image Degradations on the Performance of Biometric System and Quality Assessment

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Abstract: One of the main challenges facing biometric technologies is system performance decreasing caused by low quality biometric samples. In fingerprint recognition, the system performance may be negatively affected by fingerprint image degradations, which are introduced by subject characteristic, image acquisition, subject behavior, or environment. Therefore, it is necessary to investigate how different fingerprint image degradations influence biometric system performance. In this paper, we will first study different fingerprint image degradations that affect system performance. Then review state-of-the-art fingerprint sample quality assessment methods and their evaluation approaches. Based on the survey, we select corresponding degradations and apply them to fingerprint samples. The system performance comparison between original and degraded fingerprints will be conducted in order to illustrate the impact of each degradation on biometric system performance. Finally, we use NFIQ fingerprint image quality metric to investigate its performance on selected degradations.

Keywords: Biometric, Fingerprint, Quality Assessment, Degradation, System Performance.

1 Introduction

Biometric recognition is a mature technology used in many government and civilian applications. However, during the past several years, biometric sample quality assessment became a significant issue because of biometric systems' poor performance on degraded samples. Studies and benchmarks have shown that biometric sample quality have a direct influence on the overall performance of a biometric recognition system [AFFOG12, GT07]. Indeed, using a poor quality biometric sample in the enrollment phase of the subject, the recognition of the person cannot be ensured with a high level of accuracy. For example, a blurry sample image at enrollment may require an extra processing step to be able to identify the sample in the system. This operationally important study has nevertheless received little research compared to the primary feature-extraction and pattern-recognition tasks.

Based on biometric sample quality standards [Be, ISb], we introduce the most common degradations, which affect fingerprint sample quality. A fingerprint sample may include degradations because of the following aspects; character of the user; behavior of the user; imaging; or scenery properties. In this paper, the state-of-the-art fingerprint quality assessment methods and their evaluation approaches will be presented in Section 2; the experiment setup is given in Section 3; in Section 4, the experimental results will be illustrated; finally the conclusions and future works will be discussed.

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[3] This research is supported by the Conseil Regional Basse-Normandie Grant 14P02048 and the Research Council of Norway through project number 221073: HyPerCept - Color and Quality in Higher Dimensions.

2 State-of-the-Art

Studies of biometrics noted the significance of sample quality for a comparison algorithm because the performance of the system is mainly dependent on the quality of the sample image [AFFOG12, GT07, Ya16]. Over the last decade, researchers developed plenty of biometric sample quality assessment algorithms and the most important functionality we expect that a quality measurement method can achieve is to predict the sample's utility [ISb]. Utility of a sample refers to the predicted impact of an individual sample to the overall performance of the biometric system. In response to this, samples that have higher image quality result in better recognition or verification performance. Unfortunately, the standardizations and methodologies for biometric sample quality evaluation have recently formalized which means that some of the sample quality assessment approaches have been developed and tested under limited, heterogeneous frameworks [AFFOG12]. Therefore, a review of recent quality assessment for fingerprint is given here.

Yao *et al.* proposed two methods to assess fingerprint quality: the first one used multiple segmentation techniques [Ya15a], and the second one applied blind image quality assessment [Ya15b]. Vatsa *et al.* [Va09] used redundant discrete wavelet transform to compute dominant ridge activity to assess fingerprint quality. Olsen *et al.* [OXB12] proposed a quality evaluation method based on assessing Gabor filter responses of a fingerprint image. The most commonly used fingerprint quality assessment method is the National Institute of Standards and Technology (NIST) Fingerprint Image Quality (NFIQ) [TWW04]. This approach proposed that fingerprint image quality as a classification method. Recently, NFIQ 2.0 [BT11] was introduced with a similar learning-based quality measurement framework in which several new image-based attributes are included. Alonso-Fernandez *et al.* [Al07] presented a comparative study of several fingerprint quality metrics, in which these metrics are divided into global and local algorithms.

3 Experiment setup

According to biometric sample standards [Be, ISb, ISa] and existing research we surveyed [Ma09, Va09, OXB12, TWW04, MKSU07], we select four degradations in this paper: motion blur, JPEG lossy compression artifacts, low contrast, and JPEG 2000 lossy compression artifacts. It has been clearly and widely proved that low contrast between fingerprint ridge and valley, and clarity of fingerprint are two of most common degradations can decrease fingerprint recognition system performance [CJY04, TW05, JFN10, TG15]. Many fingerprint image quality metrics analyze the contrast and clarity as an indicator for image quality. Additionally, due to the dry skin condition of the subjects and too low pressure during acquisition process, low contrast of the fingerprint is anticipated in normal fingerprint processing. In biometric ISO/IEC standard [ISa], JPEG and JPEG 2000 lossy compression are used for fingerprint image data coding. So it is also necessary to investigate the impact of JPEG and JPEG 2000 compression artifacts. The four above mentioned degradations are considered in this paper.

Thus, for each trial degradation, each fingerprint sample is degraded into five levels (from little degraded to significantly degraded fingerprint image). The implementation of each level for each investigated degradation is described as follow:

- Motion blur to original fingerprint images is generated using the $h = fspecial('motion', len)$ Matlab funtion. The len is defined as $3, 6, 9, 12, 15$ for level 1 to level 5, which corresponds to a horizontal motion of 3, 6, 9, 12, 15 pixels;
- Compression ratio for JPEG lossy compression are 0.95, 0.75, 0.55, 0.35, and 0.15 for level 1 to level 5;
- Low contrast fingerprint is simulated applying the $J = imadjust(I, [low_{in}; high_{in}], [low_{out}; high_{out}])$ Matlab function on original fingerprint. The low_{out} value is defined as $15, 30, 45, 60, 75$ for level 1 to level 5;
- Compression ratio for JPEG 2000 compression are $\frac{1}{2}$, $\frac{1}{3}$, $\frac{1}{5}$, $\frac{1}{7}$, $\frac{1}{9}$ for level 1 to 5.

All image processing are carried out using Matlab R2015b. Some examples of original fingerprints compare to degraded images are shown in Figure 1. We can see that, for degradation type blur and low contrast, the differences between each level are visually distinguishable. On the other hand, the differences between each level in JPEG lossy compression and JPEG 2000 lossy compression artifacts are not obvious. However, this does not mean these degradations influence fingerprint recognition system in the same way.

Fig. 1: Fingerprint degradations in five levels. All samples are from FVC 2002 DB1 dataset [Ma02].

In order to investigate how these degradations influence fingerprint recognition performance, we use NIST Biometric Image Software (NBIS) [Bi]. From NBIS, three core applications will be used in this paper: MINDTCT, a minutiae detector; BOZORTH3, a comparison algorithm; and NFIQ, a fingerprint quality metric. The fingerprints used for fingerprint image degradation generation and fingerprint recognition in this paper is part of the FVC 2002 DB1 [Ma02]. The database contains 50 fingers (number 1 to 50 from FVC2001 DB1) and 4 samples (number 1 to 4 from FVC2001 DB1) per finger. Totally, 200 fingerprints are obtained from the database.

4 Experimental results

Two types of fingerprint comparison scores are generated in this paper: the comparison between degraded fingerprints and original fingerprints (we call it D2O); and the comparison between degraded fingerprints and degraded fingerprints (D2D). The genuine comparisons are done between the original image and the degraded images, which are generated from this original image. However, the difference between two types of comparison is not significant enough to affect experimental results. Therefore, we will only illustrate the results from D2O in this paper.

4.1 Distributive tendency of comparison score

We first plot the distribution of the comparison scores for degraded fingerprints versus the genuine comparison scores for original fingerprints. The distributive tendency plots makes it easier for us to see the tendency of the scores change due to the effect of the degradation in different levels. The D2O distribution plots is illustrated in Figure 2. The x axis represents the degraded genuine score and the y axis represents the original genuine score. The reference line is $y = x$.The area below the reference line indicates that the original genuine score from a given fingerprint sample is lower than the degraded genuine score from the same fingerprint sample. The area above the reference line indicates that the original genuine score from a given fingerprint sample is higher than the degraded genuine score from the same fingerprint sample.

From Figure 2 we can see that, after fingerprints become more blurred, more and more score points move to the area above the reference line and very close to the y axis. This shows that blur degradation on fingerprint samples has a high negative impact on the NBIS fingerprint recognition system performance. For JPEG lossy compression artifacts, there is no significant scores change tendency that can be observed. However, when the compression ratio increasing, more score points move away from the reference line but to both lower and upper direction. Similar tendency can be found for both low contrast and JPEG 2000 lossy compression artifacts. This means that these three degradations slightly affect NBIS fingerprint recognition performance but no strong trend.

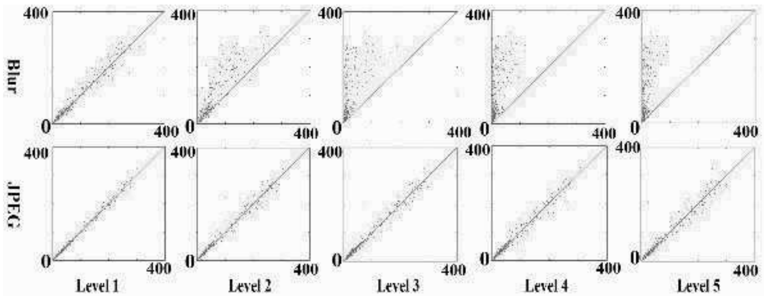

Fig. 2: The D2O distributive tendency plots for blur and JPEG degradations in five levels.

4.2 Detection Error Trade-off (DET) curve

Here, we use Detection Error Trade-off (DET) curve (see Figure 3) to illustrate the influence of different degradations on NBIS fingerprint recognition system performance. From DET curves we can see that the influence of blur degradation is higher than the JPEG degradation (the DET curve for the other two degradations are very similar to JPEG), which is very similar to what we observed before. Moreover, system performance has a dramatic decrease between level 2 and level 3 (between the green curve and the blue curve) in blur degradation. This phenomenon can be observed only from DET curves, but not from the distributive tendency plots.

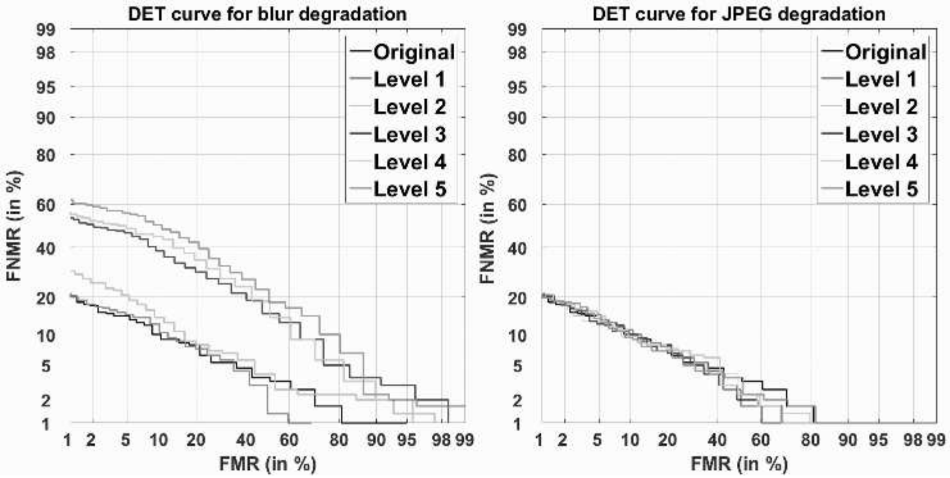

Fig. 3: DET curve for blur and JPEG degradations in five levels of the NBIS system (D2O).

4.3 Fingerprint image quality assessment and its evaluation

Furthermore, we will use one fingerprint image quality assessment method, NIST NFIQ 1.0 [TWW04], to measure the quality of original and degraded fingerprints. Then compare the quality assessment results with the comparison scores to evaluate the performance of NFIQ on selected degradations in five levels.

If we look at Figures 4, 5 and 6 together, we can see that when blur level increases, the comparison scores decrease while more and more fingerprints get higher NFIQ fingerprint quality values (higher NFIQ value indicates lower fingerprint quality). For the other degradations, neither comparison scores nor the NFIQ assessment results have significant variation. These are the same as what we observed from previous results. It means that there is a correlation between NFIQ measurement results and the system performance.

In addition, we compute the Spearmans rank correlation coefficient p as a quantitative method to analyze how well the NFIQ quality assessment results and NBIS system performance are correlated. The result is given in Table 1 with four degradations in five levels for generating the normalized comparison scores. The results show that the Spearmans rank correlation coefficients are about 0.5 in all degradations and levels assuming the normalized comparison score for each sample as the ground truth of sample quality.

5 Conclusions and future works

In this paper, we selected four types of degradation: blur, JPEG lossy compression artifacts, low contrast, and JPEG 2000 lossy compression artifacts to investigate how fingerprint image degradations influence the performance of recognition system. Each degradation has

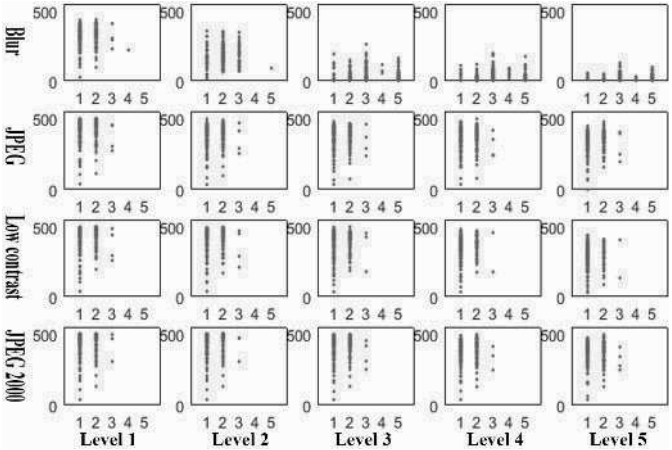

Fig. 4: The scatter plots of the NFIQ quality measurement values (x axis) versus the comparison scores (y axis) for 4 degradations in 5 levels.

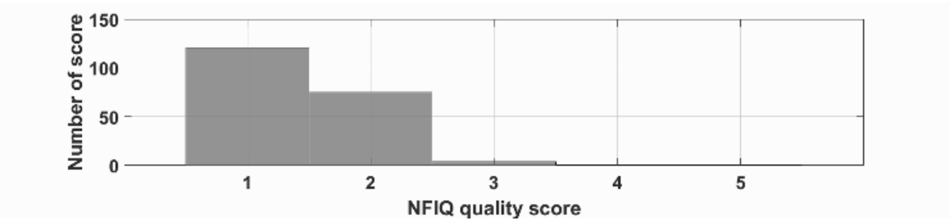

Fig. 5: The histogram of the NFIQ quality assessment results for original fingerprints.

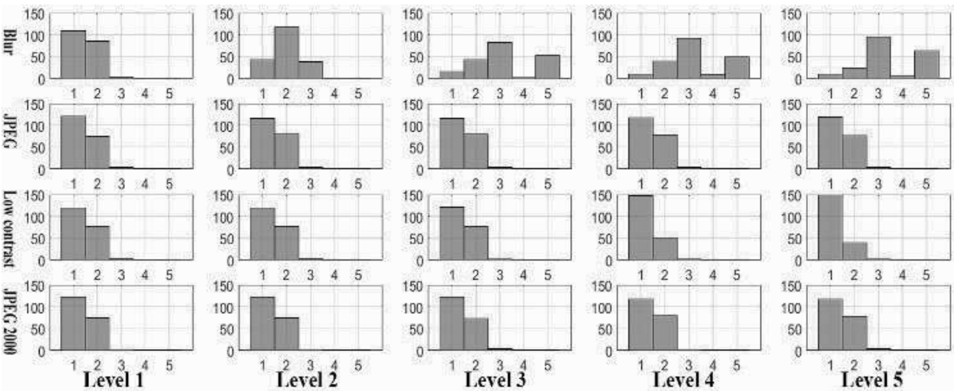

Fig. 6: The histogram of the NFIQ quality assessment results for 4 degradations in 5 levels.

been applied to fingerprint samples from part of the FVC 2002 DB1 database in five levels. The fingerprint recognition system we used is two applications from NBIS: a minutiae detector MINDTCT and a fingerprint comparison algorithm BOZORTH3.

Tab. 1: Spearman's rank correlation coefficients p under four degradations in five levels using the normalized comparison scores as ground truth for NFIQ quality values.

p	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Blur	0.5192	0.5187	0.4868	0.5110	0.5326
JPEG	0.5246	0.5281	0.5286	0.5059	0.5486
Low contrast	0.5386	0.5286	0.5431	0.5530	0.4937
JPEG 2000	0.5264	0.5406	0.5055	0.5222	0.5090

According to the distributive tendency plots, DET curves generated from experimental results, we see that blur degradation significant negatively affect NBIS fingerprint recognition system performance based on certain steps between degradation levels. The performance of the NBIS fingerprint recognition system is not apparently affected by the other degradations. There is no big difference between D2O and D2D results. We also employed NFIQ to evaluate the quality of original and degraded fingerprint samples. We generated the scatter plots of the NFIQ quality measurement values versus the comparison scores, the histogram of the NFIQ quality assessment results, and Spearman's rank correlation coefficients using the normalized comparison scores as ground truth for NFIQ quality values. The results show that the NFIQ fingerprint quality assessment is accurate to assess the samples quality in all degradations and levels assuming the normalized comparison score for each sample as the ground truth of sample quality.

One of the future works is to select more types of degradation and apply them to different databases by using additional fingerprint recognition systems. In addition to NFIQ, other existing fingerprint image quality metrics can also be used for the evaluation of their performance. Since contactless fingerprint technology develops fast in recent years, we can apply the same protocol used in this paper to contactless fingerprint samples and recognition system to investigate how different degradations influence the performance of contactless fingerprint recognition system.

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