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# Pixel Pruning for Fingerprint Quality Assessment

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## I. INTRODUCTION

Fingerprint quality assessment (FQA) works as a toll-gate to ensure that poor quality samples are rejected before sending them to next stage. This is very important to guarantee the performance of a biometric system [1], especially during the enrollment step. Therefore, this problem has attracted attentions from both academic and industrial areas, and a lot of studies had been made. Prior studies in estimating fingerprint quality could be classified into several categories:

- 1) Assessment approaches that rely on segmentation tasks, which could be either implemented by dividing the foreground area into several classes [2], [3], [4] or carried out via an approximation of the informative regions by using minutiae template only [5],
- 2) Quality indexes represented by a single feature [4], [6], which can be indicated by either the feature itself or an observed regularity of the employed feature [7],
- 3) Solutions carried out by using multi-feature fusion, which can be achieved via a linear fusion or classification and both of them might involve in a prior-knowledge of matching performance [8], [9].

In addition, studies proposed in recent years have made attempt by learning [10] a multi-layer neural network. The quality feature in [10] is also indicated by a regularity of a histogram obtained from the best-matching unit assigned to fingerprint block. Likewise, the quality index is also involved in a classification that relies on a prior-knowledge of genuine matching scores. In this paper, we propose a new metric based on pixel pruning. We show its benefit using the Enrollment Selection (ES) approach on different databases.

## II. QUALITY ASSESSMENT FRAMEWORK

As the specialty of the biometric application, fingerprint quality is not only a problem of image distortion determination. The purpose of FQA is to guarantee the reliability of the feature extracted from the image and hence benefits the matching performance. In this case, segmentation is initially a choice to determine the useful and reliable area of the ridge-valley pattern, which somehow indicates fingerprint's availability in a quantitative manner [5].

### A. Feature given by Morphology Segmentation

The first step of the proposed framework is to obtain a measure of fingerprint foreground area as we have just mentioned before. To do this, a coarse segmentation is adopted

in this study, which is achieved via morphological processing of images. Such a processing mainly consists of two tasks: dilation and erosion. Fingerprint image is composed by parallel run ridge-valley pattern with relatively stable frequency. With this property, it is able to connect the edges formed by the ridge-valley pattern (see Figure 1). Four images in Figure 1

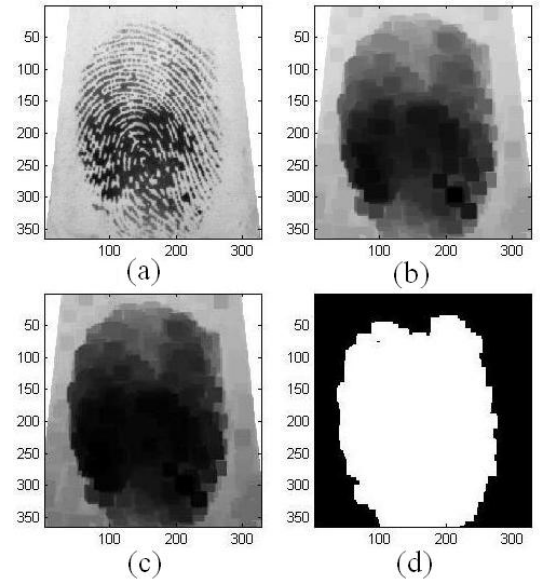


Fig. 1. Example of segmentation with morphology operation.

illustrate a morphology processing of a fingerprint image with several iterations, where image 1(a) is the original fingerprint pattern, 1(b) is the image after erosion processing(s), 1(c) is the enhanced version of image 1(b), and 1(d) is the segmented mask. In this study, we use the approach in [11] to perform the first coarse segmentation. The first feature for indicating fingerprint quality is hence a pixel ratio of the foreground area to the entire image.

### B. Pixel-pruning based on Coherence

In this task, we propose a pixel-pruning approach by using an existing feature of oriented pattern namely coherence [12]. The coherence is initially applied onto directional field estimation of oriented patterns and has been used as one of the features [12] for classification-based fingerprint segmentation approaches. The feature is to indicate the uniformity of the foreground gradients. In our experiments, we found that this feature is sensitive to the variation of the ridge-valley direction in a local area. Because of this, in this study, we customize

an approach by using this feature to extensively remove foreground pixels in a local region where the directional information of the ridge-valley pattern changes abruptly. The definition of the coherence is given by gradient measures of pixel intensity. In a local window  $W$ , it is defined by:

$$Coh = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}} \quad (1)$$

where  $G_{xx} = \sum_W G_x^2$ ,  $G_{yy} = \sum_W G_y^2$ ,  $G_{xy} = \sum_W G_x G_y$  and  $(G_x, G_y)$  is the local gradient. Figure 2 illustrates an example of the pixel-pruning result of a fingerprint image.

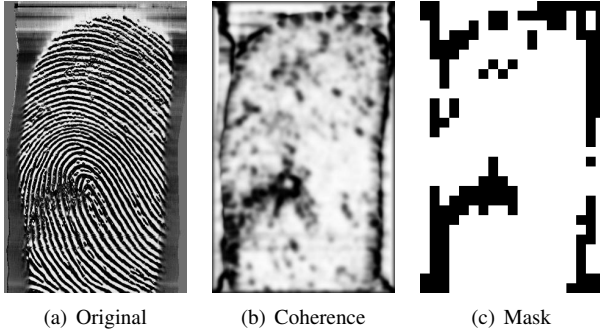


Fig. 2. Example of segmentation with Coherence.

In Figure 2, image 2(b) is the coherence image calculated from the original fingerprint illustrate by 2(a), while image 2(c) is the region mask obtained by using our pixel-pruning method which is carried out via a thresholding operation to the coherence image.

In our study, the coherence image is first normalized into  $[0,1]$ , and then divided into non-overlapped blocks which is followed by thresholding operations with a baseline value of 0.5. The block size is 16 in this study, and both the block size and the threshold are all empirical values in our study. Finally, the quality feature is also a ratio of the light pixels number to the pixel number of the entire image.

### C. Metric Generation

The proposed framework of fingerprint quality assessment is essentially implemented by fusing two (or more) features in the segmentation phase, *i.e.* the binary images of mask obtained in the segmentation stage and pixel-pruning session would be combined together. Considering score-based fusion in biometrics [13], one can observe that there are several ways to achieve fusion task such as 'min' and 'max' rules. In the proposed framework, we simply use the logical 'and' rule to fuse two binary mask images, which is actually equivalent to fusing two features (obtained by two steps) in terms of the 'add' rule. An example of such a fusion is given in Figure 3.

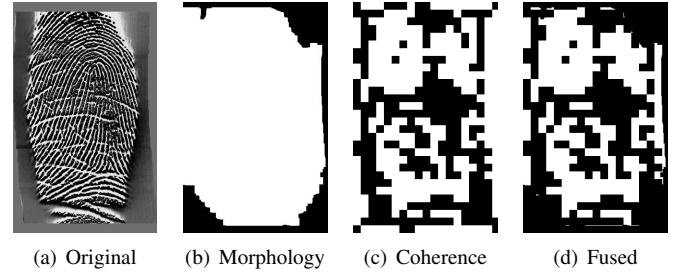


Fig. 3. Example of segmentation with Coherence

In Figure 3, one can note that the morphology approach is to coarsely generate an entire foreground area, where the pixel-pruning approach is used for removing pixels in terms of the mean value of coherence at block-wise. The pruning task is particularly effective for bad quality images that contain some abrupt changes of the direction of the ridge-valley flow.

### III. EVALUATION

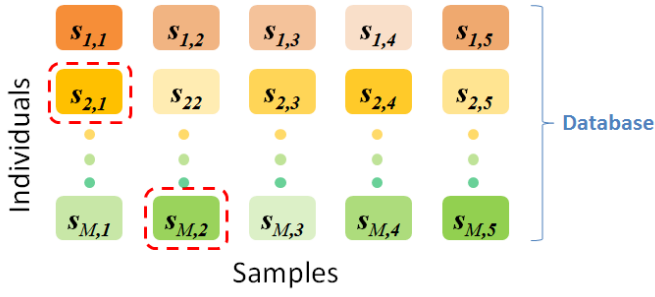
The validation approach adopted in this study is based on the Enrollment Selection (ES) approach defined in [14], [15]. The ES measures a quality metric via a statistically computed global EER value, indicating the contribution of the quality metric in reducing the overall error rate. Figure 4(a) shows a typical dataset with different samples for many individuals. In order to quantify the performance of biometric system, we have to choose the sample to be used as reference. For each individual, this choice can be done by taking account the worst sample (associated to the lowest performance), the best sample (minimizing the global EER). Given a FQA metric, one can make the choice of the reference sample. We can plot the ROC curve by making all the choices for the reference samples. Figure 4(b) presents a typical result where in this case, the Metric 1 outperforms Metric 2 as it allows a global better performance. We used this validation approach with NFIQ as reference FQA metric.

In the experiments, we use several different datasets to perform the evaluation of the proposed FQA metric. Five of Fingerprint Verification Competition (FVC) [16] database (Set A) are adopted, including FVC2000DB2, FVC2002DB2, and three of FVC2004 datasets. Each of the FVC datasets includes 100 individuals and 8 samples per individual, 800 images in total. The detail of each dataset is given in table I.

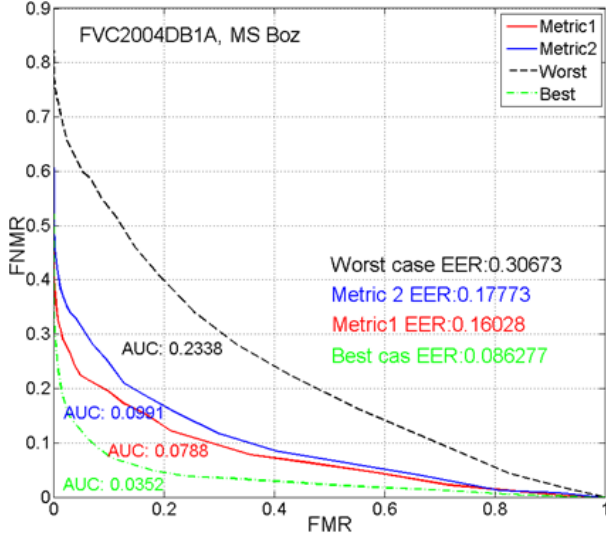
TABLE I  
DATASET SPECIFICATION.

DB	Sensor	Dim.	Resolution
00DB2A	Low-cost Capacitive	256×364	500dpi
02DB2A	Optical	296×560	569dpi
04DB1A	Optical	640×480	500dpi
04DB2A	Optical	328×364	500dpi
04DB3A	Thermal	300×480	512dpi

The image size of each dataset is different from one another and the resolution is over 500-dpi. A glance of the datasets are given by several samples in Figure 5.



(a) Selection of the reference template



(b) Metrics validation

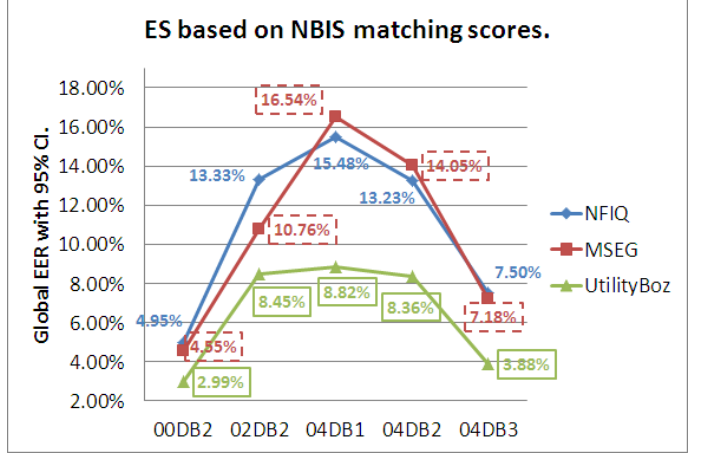
Fig. 4. Explanation of the ES validation approach



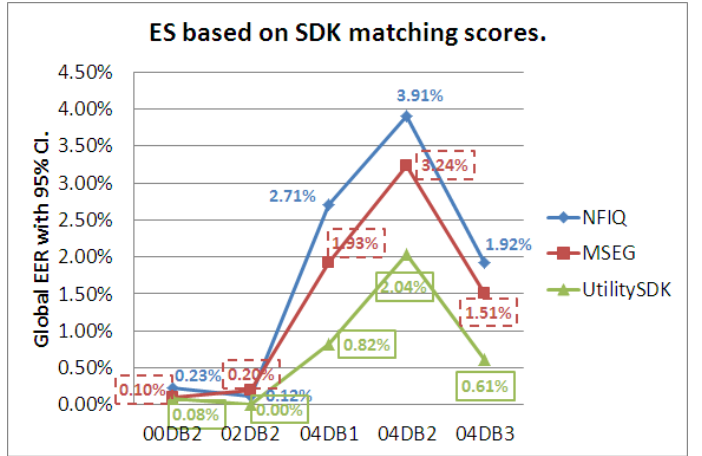
Fig. 5. Illustration of dataset samples.

The experiment results are indicated by a set of global EER values and their 95% confidence interval (CI) obtained from each dataset by substituting the associated **sample utility**

and quality values to the ES, respectively. Figure 6 plots the global EERs of the FVC datasets, where Figure 6 (a) is the result calculated from the NBIS matching scores and Figure 6 (b) shows the result obtained by using the matching scores of the SDK.



(a) Results based on NBIS software.



(b) Results based on SDK.

Fig. 6. Global EER plots. UtilityBoz and UtilitySDK in (a) and (b): global EER obtained with NBIS-based sample utility and SDK-based sample utility. Lower EER means better result.

In Figure 6 (a), when NBIS matcher is involved, MSEG (red plot) respectively generates 16.54% and 14.05% on 04DB1 and 04DB2 which are relatively bad results in comparison with the reference metric (blue plot), while MSEG shows better results on the other 3 datasets. On the other hand, MSEG (Figure 6 (b)) performs relative bad on 02DB2 only and better on the other 4 datasets when a vendor-free matcher (SDK) is used. This is due to the difference of the matching performance between the two algorithms. In addition, the NFIQ is involved in a prior-knowledge of matching performance, which could more probably result in a different evaluation result. The global EERs of MSEG and NFIQ obtained from 02DB2 are 0.2% and 0.12%, respectively. The global EERs obtained by sample utility

[14] are plotted via green points in each figure. The sample utility is simply an approximation of the groundtruth (with respect to the employed matcher) of the original sample. The utility-based global EERs are illustrated as a reference, indicating how much the quality metric is close to the best case that one matching algorithm can obtain from a trial dataset.

TABLE II  
THE 95% CI OF THE GLOBAL EER OF EACH METRIC.

DB \ QM	NFIQ	MSEG
00DB2A (NBIS)	[0.0490 0.0500]	[0.0450 0.0461]
02DB2A (NBIS)	[0.1326 0.1340]	[0.1068 0.1084]
04DB1A (NBIS)	[0.1540 0.1557]	[0.1645 0.1662]
04DB2A (NBIS)	[0.1312 0.1334]	[0.1396 0.1413]
04DB3A (NBIS)	[0.0745 0.0756]	[0.0712 0.0723]
00DB2A (SDK)	[0.0022 0.0024]	[0.0009 0.0011]
02DB2A (SDK)	[0.0011 0.0013]	[0.0019 0.0021]
04DB1A (SDK)	[0.0266 0.0275]	[0.0189 0.0196]
04DB2A (SDK)	[0.0384 0.0397]	[0.0319 0.0328]
04DB3A (SDK)	[0.0189 0.0195]	[0.0148 0.0153]

The CIs given in table II are also consistent with these global EERs, indicating the validity of the proposed MSEG. Meanwhile, the experimental result also shows that the MSEG is commonly available for multiple image specifications, at least the employed image types.

#### IV. CONCLUSION

We presented a new FQA metric based on pixel pruning. We used the ES validation approach as objective and operational approach. The proposed metric shows a good behavior when compared to NFIQ.

#### REFERENCES

- [1] P. Grother and E. Tabassi, "Performance of biometric quality measures," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 29, no. 4, pp. 531–543, 2007.
- [2] R. M. Bolle, S. U. Pankanti, and Y. Yao, "System and method for determining the quality of fingerprint images," Oct. 5 1999, uS Patent 5,963,656.
- [3] L. Shen, A. Kot, and W. Koo, "Quality measures of fingerprint images," in *IN: PROC. AVBPA, SPRINGER LNCS-2091*, 2001, pp. 266–271.
- [4] B. Lee, J. Moon, and H. Kim, "A novel measure of fingerprint image quality using the Fourier spectrum," in *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, ser. Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series, A. K. Jain and N. K. Ratha, Eds., vol. 5779, Mar. 2005, pp. 105–112.
- [5] Z. Yao, J.-M. LeBars, C. Charrier, and C. Rosenberger, "Quality assessment of fingerprints with minutiae delaunay triangulation," in *International Conference on Information Systems Security and Privacy*, Feb. 2015.
- [6] Y. Chen, S. C. Dass, and A. K. Jain, "Fingerprint quality indices for predicting authentication performance," in *Audio-and Video-Based Biometric Person Authentication*. Springer, 2005, pp. 160–170.
- [7] S. Lee, H. Choi, K. Choi, and J. Kim, "Fingerprint-quality index using gradient components," *Information Forensics and Security, IEEE Transactions on*, vol. 3, no. 4, pp. 792–800, 2008.
- [8] M. El Abed, A. Ninassi, C. Charrier, and C. Rosenberger, "Fingerprint quality assessment using a no-reference image quality metric," in *European Signal Processing Conference (EUSIPCO)*, 2013, p. 6.
- [9] E. Tabassi, C. Wilson, and C. Watson, "NIST fingerprint image quality," *NIST Res. Rep. NISTIR7151*, 2004.

- [10] M. Olsen, H. Xu, and C. Busch, "Gabor filters as candidate quality measure for NFIQ 2.0," in *Biometrics (ICB), 2012 5th IAPR International Conference on*, 2012, pp. 158–163.
- [11] "Fingerprint enhancement using STFT analysis," *Pattern Recognition*, vol. 40, no. 1, pp. 198 – 211, 2007.
- [12] A. M. Bazen and S. H. Gerez, "Systematic methods for the computation of the directional fields and singular points of fingerprints," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 24, no. 7, pp. 905–919, 2002.
- [13] A. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," *Pattern recognition*, vol. 38, no. 12, pp. 2270–2285, 2005.
- [14] Z. Yao, C. Charrier, and C. Rosenberger, "Utility validation of a new fingerprint quality metric," in *International Biometric Performance Conference 2014*. National Institute of Standard and Technology (NIST), April 2014.
- [15] Z. Yao, J. L. Bars, C. Charrier, and C. Rosenberger, "A literature review of fingerprint quality assessment and its evaluation," *IET journal on Biometrics*, 2016.
- [16] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. J., "Fvc2004: Third fingerprint verification competition," in *Biometric Authentication*. Springer, 2004, pp. 1–7.