A Comparative Study of Fingerprint Quality on High-Resolution Images

Adão Henrique Oliveira, Valfride Wallace do Nascimento, Gabriel Róson da Silva, Jirlon Oliveira, and Raoni F. S. Teixeira
School of Engineering of Várzea Grande
UFMT - Federal University of Mato Grosso
Várzea Grande, Brazil
Email: adaohenrique48@gmail.com, raoni@ufmt.br

***Abstract*—The quality assessment of sets of features extracted from patterns of epidermal ridges on our fingers is a biometric challenge problem with implications on questions concerning security, privacy and identity fraud. In this work, we compare eight quality indexes by using error reject curves. Experimental results show that the indexes based on ridge orientation (namely OCL and Coherence Sum index) have proved to be effective as a performance predictor and as a filter excluding low-quality features in a recognition process**

I. Introduction

Automated Fingerprint Identification System (AFIS) is a popular identification methodology that uses digital imaging technology to obtain, store, and analyze fingerprint data. To verify if two fingerprints are in agreement, instead of compare the images directly, an AFIS extracts sets of features from each image and produces a real-valued similarity score based on feature correspondence. Unlike traditional image processing approach, the term feature here is related to specific details of the fingerprint pattern. Roughly specking, the extracted features can be categorized in 3 levels. Level 1 refers to global patterns of the friction ridges flow represented mainly by loop, delta, arch and whorl. Level 2 is commonly related to the local ridges discontinuities named minutia and level 3 is represented by fine intra-ridge details such as fingertip sweat pores. Although most of the existing system are based on level-1 and level-2 features, with the availability of high resolution sensors ($\geq$ 1000 dpi) the use of more distinguishable level-3 features is becoming more and more common [1]–[6].

AFIS operates under different non-controlled conditions due to the potential number of users and the inappropriate handling of the attached sensor. The image quality can be affected for example by skin injuries, inconsistent contact and unwanted residues on sensor surface. Depending on image quality, some operations can be then taken to improve the overall system efficiency. The quality index can be used for example to assist on the feature extraction or provide a quality feedback about the image acquisition process. Moreover, the quality information can assign confidence levels to the extracted features during a matching phase or be used in conjunction with other biometric features [7], [8]. Fig.1 shows a good and a poor quality image where the red circles indicate the extracted pores by using state-of-art algorithm. As we can see in the image depicted in Fig.1b, features on poor quality images are difficult to precisely detect, even for a state-of-art algorithm.

Although great progress has been made (see Ref. [9], for a brief review), prior works on fingerprint quality are generally limited in the sense that they are based mainly on conventional low-resolution images (i.e., 500 dpi). That is the question we address here: *can we apply the quality methods developed for conventional images on high-resolution ones?* To the best of our knowledge, the work by Zhao et. al [10] is the only one that partly addressed this question by studying just three quality indexes. To extend the Zhao's study, we considered here eight top quality assessment methods proposed in literature [11]. Since the practical value of a given system depends on its capacity to correctly accept or reject the identity of an individual, all experiments in this paper evaluate how the nine conventional image-based quality indexes can be used to improve the identification accuracy of a well-known pore-based AFIS [4], [6].

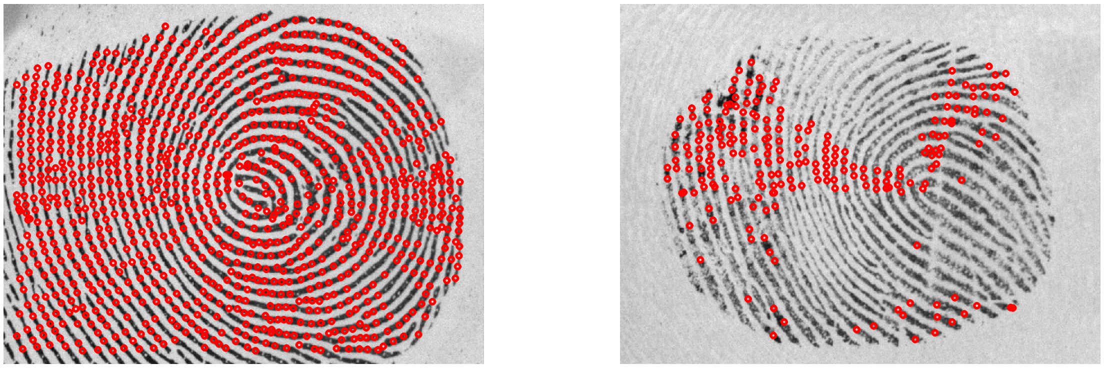
The rest of this paper is organized as follows. Section 2 examines the literature for quality assessment methods. The experimental results are reported in Section 3, while some conclusions are drawn in Section 4.

II. Image-Quality Assessment Methods

In general, a quality assessment algorithm takes a gray-scale fingerprint image and defines a quality map for blocks (or individual pixels) of the input image, at a given position. The quality measure defined considers some fingerprint photometric information about the clarity of the ridges and valleys and the corresponding extractability of the considered features In this study, we consider eight fingerprint quality measures from literature by following the criteria recently proposed by the National Institute of Standards and Technology (NIST) [11]. Next, we describe the considered methods (see Table I for a summary).

A. OCL

A typical local feature based fingerprint image quality index is the orientation certainly level (OCL) [12]. The OCL measures the energy concentration along the dominant orientation of ridges on a local block. It can be calculated as the ratio between the two eigenvalues of the covariance



(a) Good quality image (b) Poor quality image

Fig. 1. Feature extraction on good and poor images.

TABLE I
SUMMARY OF CONSIDERED FINGERPRINT QUALITY MEASURES.

Local Clarity Score Ridge and valley clarity analysis shows the capacity to distinguish the ridge and valley along the ridge orientation.
Orientation Certainty Level Force Orientation measure calculated from the grayscale image gradient
Orientation Flow The ridge flow continuity can be measure by the Orientation Flow
Ridge Valley Uniformity Ridge Valley Uniformity is a measure of the consistency of the ridge and valley widths.
MU Quality feature is the arithmetic mean of the gray scale input image.
MMB Feature is the arithmetic mean of per block computed arithmetic mean in the gray scale input image.
ROI Area Mean Calculates the quality value as the average of the gray scale intensity value of pixels of all these ROI blocks.
ROI Orientation Map Coherence Sum Determines the sum of coherence values over all image blocks in the region of interest.
ROI Relative Orientation Map Coherence Sum Determines the arithmetic mean of the coherence values over all image blocks in the ROI.

matrix obtained by considering the two gradient vectors. This indicator measures the abrupt changes occurring along the adjacent blocks of the directional field and is based on the observation that the ridge direction changes smoothly in high-quality images.

B. Local Clarity Score

Local clarity score [13] is a measure of clarity of the ridges and valleys and the corresponding extractability of the considered features (e.g. minutiae and pores). The rationale behind this approach is that low-quality samples rely on image regions where the ridges are not distinguishable. LCS calculates the block-wise clarity of ridge and valleys by using a linear regression to set a gray-level threshold that is then used to classify pixels as ridge or valley.

C. Ridge Valley Uniformity

Ridge Valley Uniformity [13] is a measure of the consistency of the ridge and valley widths. The ratio between ridge and valley widths remains fairly constant for a fingerprint image with clear ridge and valley division and consequently the standard deviation of ratios is used as an indication of the sample quality.

D. Orientation Flow

The Orientation Flow [7] is a frequency domain algorithm based on the concentration of energy in a ring-shaped region of the spectrum. The approach explore the fact that the frequency values of the ridges in a fingerprint image lie within a certain range. It is also expected that low-quality images have a diffuse distribution of energy while high-quality ones exhibit a concentration of energy in a few bands only. A set of bandpass filters computes the energy at each frequency and the entropy is used to evaluate the energy concentration.

E. ROI Area Mean

The index ROI Area Mean uses ROI determination algorithm to identify the ROI (Region of Interest). This indicator determines the ROI blocks as image blocks with at least one pixel in the ROI and calculates the quality value as the average of the gray scale intensity value of pixels of all these ROI blocks.

F. ROI Orientation Map Coherence Sum

The indicator ROI Orientation Map Coherence Sum [13] determines the coherence map of the orientation field estimation and returns the sum of coherence values over all image blocks in the region of interest.

G. ROI Relative Orientation Map Coherence Sum

The quality index ROI Relative Orientation Map Coherence Sum [13] computes the coherence map of orientation field estimation and determines the arithmetic mean of the coherence values over all image blocks in the ROI.

H. MU and MMB

The MU and MMB correspond respectively to the arithmetic mean and the block-wise arithmetic mean of the gray scale input image.

III. Experiments

The aim of this paper is to study the impact of the conventional image-quality measures on identification performance of a pore-based AFIS. To this end, we considered in the experiments the state-of-the-art pore extraction algorithm in [6], the pore-based comparator in [4], and the entire PolyU HRF dataset, including a total of $1,480$ images. Following our advisor' previous work [14], the error versus reject curves introduced in [15] were used to objectively indicate how rejection of low-quality samples improves the recognition performance. These curves show the behavior of quality indexes over the range of quality values in relation to the false non-match rate (FNMR). Ideally, when the quality values are monotonically correlated with genuine comparison scores, the FNMR decreases quickly with the fraction of comparisons rejected. This models the operational case in which quality is maintained by reacquisition after low-quality samples are detected [15].

In the experiment, we adopt the same strategy in [14]. Once again, all images from the PolyU HRF second session were compared against the images of the first session, resulting in a total of $3,700$ genuine comparison scores (i.e., 740 images from the second session $\times 5$ images of the same finger in the first session). To combine the quality of the two samples involved in a comparison, we use the *min* function and we set the threshold of the error versus reject curves to give a false non-match rate of 2.5%.

Fig. 2 shows the error versus reject behavior for the OCL, Mu, LCS, and OF quality indexes obtained by considering Zhaos pore extraction approach [6]. The black and red solid lines in Fig. 2 indicate, respectively, the OCL and Mu indexes. The black dashed and blue solid lines indicate the response of the OF and LCS quality indexes. Since the false non-match rate improves as more quality samples are rejected, only the OCL curve trend in the correct direction. This confirms the main conclusion of Zhao's previous study [10]. The explanation of this is that the "indexes based on ridge orientation are more effective for high resolution fingerprint recognition systems".

Fig. 3 depicts the error versus reject behavior for the RVU, MMB, Coherence Sum, and Relative Coherence Sum quality indexes obtained by considering Zhao's pore extraction approach [6]. The black, red and blue solid lines in Fig. 3 indicate, respectively, the RVU, MMB and Coherence Sum indexes. The black dashed and blue solid lines indicate the response of the Relative Coherence Sum index. Since the false non-match rate improves as more quality samples are rejected, only the Coherence Sum Index curve trend in the correct direction. This is a new result in the literature and the reason is that the ridge orientation field plays an important role in the extraction pores.

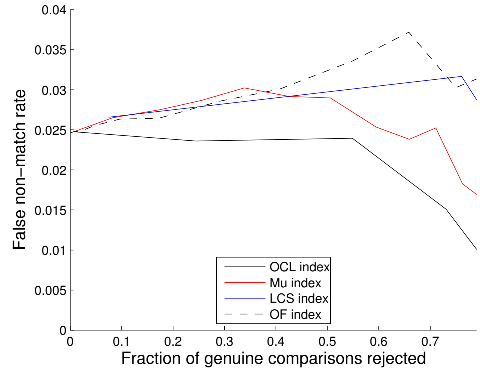


Fig. 2. Error versus reject curves for Zhaos approach [10]. The threshold is set to give an initial false non-match rate of 2.5%. The black, red and blue solid lines indicate, respectively, the OCL, Mu, and LCS quality indexes, while the black dashed line indicates the response of the OF quality index.

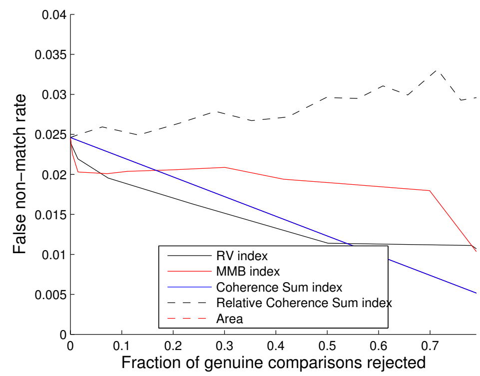


Fig. 3. Error versus reject curves for Zhaos approach [10]. The threshold is set to give an initial false non-match rate of 2.5%. The black, red and blue solid lines indicate, respectively, the RV, MMB, and Coherence Sum quality indexes, while the black dashed line indicates the response of the Relative Coherence Sum quality index.

IV. Conclusion

In this paper, we present a comparative study for quality evaluation of high resolution digital images. The results showed that only image quality indexes based on directional information are more efficient for high resolution fingerprint images when pores are used in recognition. In the future, we will conduct other experiments and evaluate these indicators in other databases.

References

[1] A. K. Jain, Y. Chen, and M. Demirkus, "Pores and ridges: High-resolution fingerprint matching using level 3 features," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 1, pp. 15–27, Jan 2007.

[2] S. Jirachaweng, Z. Hou, W.-Y. Yau, and V. Areekul, "Residual orientation modeling for fingerprint enhancement and singular point detection," *Pattern Recognition*, vol. 44, no. 2, pp. 431 – 442, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S003132031000405X

[3] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*, 2nd ed. Springer Publishing Company, Incorporated, 2009.

[4] Q. Zhao, L. Zhang, D. Zhang, and N. Luo, *Direct Pore Matching for Fingerprint Recognition*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 597–606. [Online]. Available: https://doi.org/10.1007/978-3-642-01793-3_61

[5] R. F. S. Teixeira and N. J. Leite, "Improving pore extraction in high resolution fingerprint images using spatial analysis," in *2014 IEEE International Conference on Image Processing (ICIP)*, Oct 2014, pp. 4962–4966.

[6] Q. Zhao, D. Zhang, L. Zhang, and N. Luo, "Adaptive fingerprint pore modeling and extraction," *Pattern Recognition*, vol. 43, no. 8, pp. 2833 – 2844, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320310000944

[7] Y. Chen, S. C. Dass, and A. K. Jain, *Fingerprint Quality Indices for Predicting Authentication Performance*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 160–170. [Online]. Available: https://doi.org/10.1007/11527923_17

[8] L. Hong, Y. Wan, and A. Jain, "Fingerprint image enhancement: algorithm and performance evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, Aug 1998.

[9] F. Alonso-Fernandez, J. Fierrez, J. Ortega-Garcia, J. Gonzalez-Rodriguez, H. Fronthaler, K. Kollreider, and J. Bigun, "A comparative study of fingerprint image-quality estimation methods," *IEEE Transactions on Information Forensics and Security*, vol. 2, no. 4, pp. 734–743, Dec 2007.

[10] Q. Zhao, F. Liu, L. Zhang, and D. Zhang, "A comparative study on quality assessment of high resolution fingerprint images," in *Proceedings of the International Conference on Image Processing, ICIP 2010, September 26-29, Hong Kong, China*, 2010, pp. 3089–3092. [Online]. Available: https://doi.org/10.1109/ICIP.2010.5648800

[11] N. I. of Standards an Technology. (2011) Development of nfiq 2.0. [Online]. Available: https://www.nist.gov/services-resources/software/development-nfiq-20

[12] E. Lim, X. Jiang, and W. Yau, "Fingerprint quality and validity analysis," in *Proceedings. International Conference on Image Processing*, vol. 1, 2002, pp. I–469–I–472 vol.1.

[13] E. Tabassi and C. Wilson, "A novel approach to fingerprint image quality," in *Image Processing, 2005. ICIP 2005. IEEE International Conference on*, vol. 2, Sept 2005, pp. II–37–40.

[14] R. Teixeira and N. Leite, "A new framework for quality assessment of high-resolution fingerprint images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PP, no. 99, pp. 1–1, 2017.

[15] E. Tabassi and C. L. Wilson, "A novel approach to fingerprint image quality," in *IEEE International Conference on Image Processing 2005*, vol. 2, Sept 2005, pp. II–37–40.