Fingerprint Image Quality Assessment Based on Oriented Pattern Analysis

Raimundo Claudio da Silva Vasconcelos[1,2](✉) and Helio Pedrini[2](✉)

[1] Federal Institute of Brasília, Taguatinga, DF 72146-050, Brazil
[2] Institute of Computing, University of Campinas, Campinas, SP 13083-852, Brazil
r.claudio@gmail.com, helio@ic.unicamp.br

Abstract. Decision based on fingerprint image quality is crucial for automatic fingerprint classification and recognition tasks. Quality is challenging due to a variety of noise types that may exist in an image. Researches have been conducted to propose suitable combination of techniques for assessing fingerprint quality, however, it is difficult to achieve a generic solution for different data sets. This work proposes a fingerprint image quality indicator based on directional information inherent in fingerprint ridges and evaluates a metric for quality assessment. Experimental results on Fingerprint Verification Competition (FVC) data sets demonstrate the usability of the proposed index.

Keywords: Fingerprint images · Quality · Directional information

1 Introduction

Identification systems based on fingerprints became the most used among all biometric systems due to certain characteristics [12,18]: (i) fingerprint patterns are stable and invariant, satisfying the requirement of uniqueness; (ii) the use of fingerprint is more acceptable to people in comparison to other kinds of biometric modalities.

Fingerprints are oriented texture patterns created by interleaved *ridge* and *valley* information present on the fingertip surface. There are different possible ways to obtain an image representation from these patterns. The traditional technique consists in rolling an inked finger surface on a paper and then scanning the produced impression. Nowadays, due to the advances in sensor technology, a variety of fingerprint sensors can also be used on online acquisition [12,18]. Figure 1 illustrates some images acquired with different techniques.

Automatic recognition depends on accurate extraction of features derived from a fingerprint pattern. These features are roughly categorized in the literature into three levels [5,12]. Level 1 refers to *singular points*, where the ridge orientation is discontinuous or changes abruptly [21]. Level 2 corresponds to local

This work was partially supported by CAPES, FAPESP (17/12646-3) and CNPq (305169/2015-7).

© Springer Nature Switzerland AG 2019
R. Vera-Rodriguez et al. (Eds.): CIARP 2018, LNCS 11401, pp. 637–644, 2019.
https://doi.org/10.1007/978-3-030-13469-3_74

Fig. 1. Visual differences among fingerprint acquisition techniques.

discontinuities in the ridges, known as *minutiae* [5,17]. Level 3 corresponds to fine intra-ridge details, such as fingertip *pores* [7].

The performance of fingerprint systems depends substantially on the reliability of features extracted from the sensed fingerprint image. Thus, depending on this quality information, a significant number of spurious features may be created and a percentage of genuine ones may be ignored [2]. Some approaches attempt to improve the reliability of the detected features via postprocessing [17] or to improve the quality of fingerprint images through enhancement or other preprocessing approaches.

Fingerprint quality is usually defined as the ease in extracting relevant characteristics for identification, such as minutiae, nucleus and deltas. It can also be considered as a measure for ridge and valley clarity. Therefore, it is desirable that ridges and valleys are well characterized and have well-defined guidelines [1,20]. More generally, we can define quality using extrinsic and intrinsic fingerprint factors [9]. Intrinsic factor refers to quality degradation caused by inaccurate parameter estimation during the image processing, whereas extrinsic factor is related to the fingerprint acquisition process, which is affected by physical skin injuries, inconsistent contact, residues on sensor surface, among others.

This work presents a novel image quality index to assist Automated Fingerprint Identification Systems (AFIS) in the decision-making process when a fingerprint image sample must be discarded and a new one is required. Our index, referred here as neighborhood strengthness homogeneity (NSH), can be computed by considering a multiscale directional operator.

In terms of directional field estimation, the proposed operator is less noise sensitive than some classical gradient approaches. Such performance analysis should not only evaluate extrinsic, but also intrinsic factors and can be used to assess the estimated ridge orientation. In addition, despite the emphasis on the fingerprint domain, the quality index is fairly general and can be used to measure the significance of many other methods related to directional information.

The remainder of this paper is organized as follows. Section 2 introduces our operator for extracting anisotropic quality information from fingerprint images. Experimental results are presented in Sect. 3, as well as the fingerprint database, Griaule AFIS used for fingerprint matching, and a result discussion. Concluding remarks are provided in Sect. 4.

2 Directional Information Operator

In this work, we are particularly interested in a measure of the distance between ridge and valley information in fingerprint images. A systematic way to compute such distance is initially considered within a given neighborhood. Then, we define a specific fingerprint quality index.

Consider Γ as a sliding window of size $M \times N$ (usually, $M = N = (2l+1), l \in \mathbb{Z}$) of an image $f(x,y), f : (x,y) \in \mathcal{D}_f \subset \mathbb{Z}^2 \mapsto \mathbb{Z}$. Let D be the number of considered directions in Γ, and n the corresponding number of pixels in a given direction. In order to represent all D directions in a two-dimensional grid, n has a minimum bound, that is, it can be defined up to $(2n-2)$ directions, for any $n \geq 2$. Thus, coordinates (x,y) of the n points, in a given direction α, can be computed as: $x = x_{center} + p \cdot \cos(\alpha)$ and $y = y_{center} - p \cdot \sin(\alpha)$, for all p such that $-n/2 \leq p \leq n/2$. x_{center} and y_{center} are the coordinates of the point containing the sliding window Γ centered in this location.

Finally, this neighborhood can be defined as a set S_i^n of D test points with length n and discrete direction i, which can easily be computed by repeating the above procedure for all D directions ($i \in \{0, 1, ...D-1\}$), by respectively changing the value of α accordingly ($\alpha = 0,\ 1 \cdot 180/D,\ 2 \cdot 180/D, ..., (D-1) \cdot 180/D$).

In this approach, it is assumed that, in the aforementioned neighborhood, the physics of the image acquisition imposes certain arrangements on the image gray levels. This is the case, for example, when image points are associated with two distinct regions: one which is parallel and the other perpendicular to the flow orientation contained in an intensity pattern created by some anisotropic process [8].

Algorithm 1. Algorithm for Directional Information Operator

1: Input: fingerprint image I; neighborhood S; the number of directions D
2: Output: quality index R
3: **for all** pixel $(x,y) \in \mathcal{D}_f$ centered in S **do**

1. Compute an information parameter (for instance, mean, standard deviation, moments of higher orders, morphological measures, among others) on $S_i(x,y)$ for each of the D directions. In terms of implementation issues, these data can be stored into an array $A[i]$, where $i \in \{0, 1 \ldots D-1\}$.
2. The information associated with each direction i is compared to the one obtained from another direction j, $i \neq j$. Once perpendicular direction pairs are sufficient to characterize oriented patterns, the value of $A[i]$ is compared to $A[i + \frac{D}{2}]$, where $i \in \{0, 1, \ldots, \frac{D}{2} - 1\}$, and $i + \frac{D}{2}$ is the corresponding perpendicular direction.
3. The pair of directions i and j exhibiting the highest information contrast ($\text{argmax}_i \mid A[i] - A[i + \frac{D}{2}] \mid$), in a given pixel, defines the local orientation image O.
4. Neighborhood strengthness homogeneity (NSH) quality indicator is obtained as an average of this directional information in a given neighborhood and expresses the strength of the estimated anisotropic information in any region R.

For the sake of simplification, this work adapts the formalism presented by Oliveira and Leite [13], whose approach employed oriented information to reconnect broken ridges. Here, it is used to measure quality. Therefore, the abstract idea behind this quality index consists in analyzing samples drawn from these two image regions in order to quantify the difference that makes the anisotropy distinguishable.

A high-level description of our operator is presented in Algorithm 1. Different amounts of test points and directions can be set up in accordance with a certain scale and resolution for a given image. Similarly, several quality and information criteria can be considered to express separability (or contrast), variability, homogeneity, completeness, entropy, among others.

In this work, we consider fingerprint pattern as a regular anisotropic texture, that is, there is a certain regularity on the ridge and valley information. Despite the gradual changes on ridge and valley gray levels, there is a certain homogeneity of the pixels along their parallel orientations. The operator expresses the strength of information along certain oriented pattern. Based on this information, it is possible to extract two types of information: one based on the strength of direction - its absolute value - and another based on the direction of its neighbors. The latter was considered promising and used as an indicator of image quality.

3 Experiments

The main purpose of these experiments is to compare the behavior of quality measures by assessing their utility when, based on them, certain images are rejected. In this study, Griaule AFIS [6] was used to represent and match fingerprints as minutiae. Minutiae matching is certainly the most well-known and widely used method for fingerprint correspondence, as an analogy with the way forensic experts compare fingerprint images and their acceptance as a proof of identity in court [12].

3.1 Fingerprint Database

The Fingerprint Verification Competition (FVC) took place in 2000, 2002, 2004 and 2006, as an initiative to compare fingerprint matching algorithms. This competition was organized by the Biometric System Laboratory of the University of Bologna [16], as well as Pattern Recognition and Image Processing Laboratory of the Michigan State University, Biometric Test Center of San Jose State University and, in the last year, Biometrics Research Laboratory of the Universidad Autonoma de Madrid. In this work, 2004 and 2006 data sets were used in our experiments to validate the proposed directional information operator.

3.2 Griaule AFIS

The Griaule fingerprint recognition framework [6] won the Open Category, section "average results over all databases" of the Fingerprint Verification Contest 2006 [16], achieving the best average equal error rate (EER).

Regarding the fingerprint matching algorithm, we can highlight: (i) fingerprint images are acquired by a fingerprint scanner; (ii) images are enhanced through better contrast and distinctness; (iii) noise and defects are eliminated; (iv) fingerprint features are detected and analyzed; and (v) minutiae are identified.

Fingerprint search on the database is made based on some measures, for instance, polygons are determined by connecting three minutiae. Thus, internal angles, sides and each minutiae angle are computed. These measures are invariant to rotation and translation. This method allows that a desired fingerprint can be localized on the database even with position variation (displacement and rotation) in relation to the found fingerprint.

3.3 Experiment Design

In our experiments, we compare the performance of the verification process before and after the removal of the worse quality fingerprints based on the proposed index. The protocols employed in the comparison are the same as those used for the performance of FVC 2004/2006 verification algorithms. Griaule AFIS was used to compare all of the images to each other, following the protocol described in the FCV competition.

This work compared our quality indicator with eight of the others available in the literature:

- OCL (Orientation Certainty Level) [10]: is a measure of the energy concentration strength along the dominant ridge flow orientation. The feature operates in a block-wise manner.
- LCS (Local Clarity Score) [3]: computes the block-wise clarity of ridge and valleys by applying linear regression to determine a gray-level threshold, classifying pixels as ridge or valley. A ratio of misclassified pixels is determined by comparing with the normalized ridge and valley width of that block.
- OFL (Orientation Flow) [3]: is a measure of ridge flow continuity based on the absolute orientation difference between a block and its neighboring blocks.
- RPS (Radial Power Spectrum) [4]: is a measure of maximal signal power in a defined frequency band of the global radial Fourier spectrum. Ridges can be locally approximated by means of a single sine wave, hence high energy concentration in a narrow frequency band corresponds to consistent ridge structures.
- FDA (Frequency Domain Analysis) [11]: operates in a block-wise manner. A one-dimensional signature of the ridge-valley structure is extracted and a discrete Fourier transform is computed on the signature to determine the frequency of the sinusoid following the ridge-valley structure.
- RVU (Ridge Valley Uniformity) [10]: is a measure of the consistency of the ridge and valley widths. The expectation for a finger image with clear ridge and valley separation is that the ratio between ridge and valley widths remains fairly constant and thus the standard deviation of ratios is used as an indication of the sample quality.

– GAB (Gabor Quality Feature) [14]: operates on a per-pixel basis by calculating the standard deviation of the Gabor filter bank responses.
– GSH (Gabor Shen) [19]: is a Gabor-based feature to separate blocks into two classes: good and bad. The scalar quality is the ratio between number of foreground blocks and number of foreground blocks marked as poor.

In this work, we used an implementation of these measures provided by Olsen [15], which were compared to our quality operator.

3.4 Discussion

Each FVC data set has its own features: distinct dimensions, different sensors were used to capture (thermal, optical, electric) in such way that noise types and other eventual injuries are also distinct. Criteria for evaluation and weighting should also be distinct, reflecting the ridge and valley patterns.

Furthermore, other issues should be taken into account when defining the weighting: (i) absolute position (first, second and third position) achieved by the index when compared to the others; and (ii) experiments consisted in removing the worst quality fingerprint images according to the index. In each experiment, a distinct percentage of images is removed (1, 5, 10, 15 and 20%).

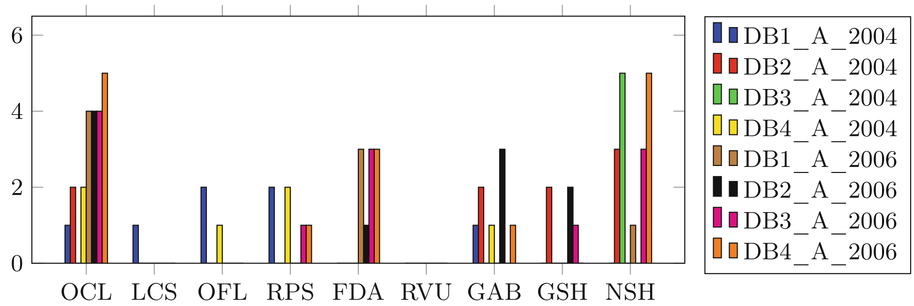

Fig. 2. Average number of times in which the indices were ranked among the top-3 according to AUC value.

Twelve different combinations of weights related to the image removal were performed in each dataset. Experiments were summarized and counted how many times each indicator occurred in the first three positions, considered here as a simple average. The evaluations were based on the calculation of area under the curve (AUC) and equal error rate (EER).

Our approach requires the configuration of several parameters: percentage of samples to be removed, weights relative to such removal, weights related to the absolute position in the precision. It can be observed from Fig. 2 that our indicator (NSH) has a suitable response on DB2_A_2004, DB3_A_2004, DB3_A_2006 and DB4_A_2006 data sets with respect to AUC. Considering EER (Fig. 3), our proposal also has satisfactory results on DB2_A_2004, DB3_A_2004 and DB4_A_2006 data sets.

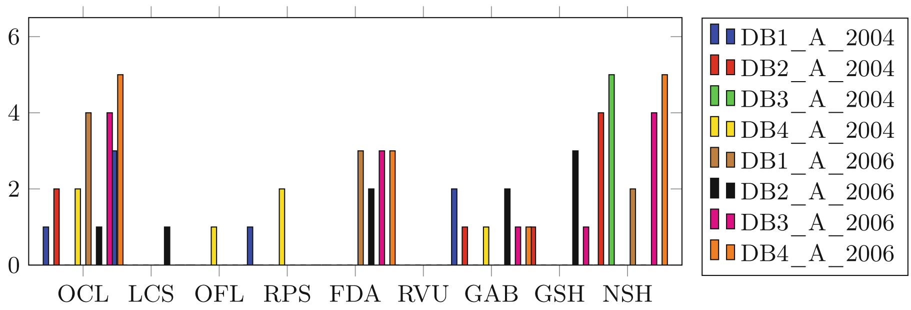

Fig. 3. Average number of times in which the indices were ranked among the top-3 according to EER value.

4 Conclusions and Future Work

Fingerprint image quality plays an important role in biometric systems. For quality evaluation, it is necessary to use specific metrics for each data set due to their inherent characteristics. This makes the task of selecting a subset of features and their weights more challenging, however, more suitable for a combined quality metric.

In this work, we presented a fingerprint quality index based on directional information through a multiscale directional operator. This operator demonstrate to be less noise sensitive than classical gradient approaches. Despite its application in the fingerprint domain, our quality index could be used to assess the significance of many other methods related to directional information.

As directions for future research, we intend to combine different quality features in a way that minimizes the dependence on individual features while maintaining a sufficient predictive behavior with respect to the biometric performance. We also plan to develop an adaptive system that takes into account the characteristics of the sensor to determine the quality of the acquired images.

References

1. Alonso-Fernandez, F., et al.: A comparative study of fingerprint image-quality estimation methods. IEEE Trans. Inf. Forensics Secur. **2**(4), 734–743 (2007)
2. Bazen, A.M., Gerez, S.H.: Systematic methods for the computation of the directional fields and singular points of fingerprints. IEEE Trans. Pattern Anal. Mach. Intell. **24**(7), 905–919 (2002)
3. Chen, T., Jiang, X., Yau, W.: Fingerprint image quality analysis. In: IEEE International Conference on Image Processing, pp. 1253–1256 (2004)
4. Chen, Y., Dass, S., Jain, A.: Fingerprint quality indices for predicting authentication performance. In: International Conference on Audio-and Video-Based Biometric Person Authentication, pp. 160–170 (2005)
5. Feng, J., Jain, A.K.: Fingerprint reconstruction: from minutiae to phase. IEEE Trans. Pattern Anal. Mach. Intell. **33**, 209–223 (2011)

6. Griaule Biometrics. Griaule Big Data Biometrics (2018). http://www.griaulebiometrics.com/new/
7. Jain, A.K., Chen, Y., Demirkus, M.: Pores and ridges: fingerprint matching using level 3 features. IEEE Trans. Pattern Anal. Mach. Intell. **29**, 15–27 (2007)
8. Kass, M., Witkin, A.: Analyzing oriented patterns. Comput. Vis. Graphics Image Process. **37**(3), 362–385 (1987)
9. Lee, S., Choi, H., Choi, K., Kim, J.: Fingerprint-quality index using gradient components. IEEE Trans. Inf. Forensics Secur. **3**(4), 792–800 (2008)
10. Lim, E., Jiang, X., Yau, W.: Fingerprint quality and validity analysis. In: IEEE International Conference on Image Processing, vol. 1, 469–472 (2002)
11. Lim, E., Toh, K.-A., Suganthan, P., Jiang, X., Yau, W.-Y.: Fingerprint image quality analysis. In: IEEE International Conference on Image Processing, pp. 1241–1244 (2004)
12. Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S.: Handbook of Fingerprint Recognition, 2nd edn. Springer, London (2009). https://doi.org/10.1007/978-1-84882-254-2
13. Oliveira, M.A., Leite, N.J.: A multiscale directional operator and morphological tools for reconnecting broken ridges in fingerprint images. Pattern Recogn. **41**(1), 367–377 (2008)
14. Olsen, M., Xu, H., Busch, C.: Gabor filters as candidate quality measure for NFIQ 2.0. In: 5th IAPR International Conference on Biometrics, pp. 158–163 (2012)
15. Olsen, M.A., Smida, V., Busch, C.: Fingerprint Quality Assessment Algorithms (2015). http://www.nislab.no, https://www.dasec.h-da.de
16. Cappelli, A.F.R., Ferrara, M., Maltoni, D.: Fingerprint verification competition 2006. Biometric Technol. Today **15**(7–8), 7–9 (2007)
17. Ratha, N.K., Chen, S., Jain, A.K.: Adaptive flow orientation based feature extraction in fingerprint images. Pattern Recogn. **28**, 1657–1672 (1995)
18. Ross, A., Nadgir, R.: A thin-plate spline calibration model for fingerprint sensor interoperability. IEEE Trans. Knowl. Data Eng. **20**, 1097–1110 (2008)
19. Shen, L., Kot, A.C., Koo, W.M.: Quality measures of fingerprint images. In: 3rd International Conference on Audio- and Video-Based Biometric Person Authentication, pp. 266–271 (2001)
20. Yun, E.-K., Cho, S.-B.: Adaptive fingerprint enhancement with fingerprint image quality analysis. Image Vis. Comput. **24**, 101–110 (2006)
21. Zhou, J., Chen, F., Gu, J.: A novel algorithm for detecting singular points from fingerprint images. IEEE Trans. Pattern Anal. Mach. Intell. **31**, 1239–1250 (2009)