A New Ridge-Features-Based Method for Fingerprint Image Quality Assessment

Katy Castillo-Rosado(✉) and José Hernández-Palancar

Advanced Technologies Application Center (CENATAV),
7ma A #21406 e/ 214 Y 216, Rpto. Siboney, Playa, 12200 La Habana, Cuba
{krosado,jpalancar}@cenatav.co.cu

Abstract. Fingerprint is the most widely used biometric trait. Many factors may cause the quality degradation of fingerprint impressions: users, sensors and environmental facts. Most of the fingerprint-based biometric systems need an accurate prediction of fingerprint quality. A fingerprint quality measure can be used in enrollment or recognition stages, for improving the AFIS performances. In this work, a new fingerprint image quality estimation method guided by how experts classify fingerprint images quality is presented. By using six features, a continuous quality value is calculated. Experiments were performed in a well-known database. The proposed approach performance was evaluated by measuring its impact on the recognition stage and comparing it with the NFIQ quality algorithm. The Verifinger 4.2 was used as matching algorithm. The results shown that the proposed approach has a very good performance.

Keywords: Fingerprint · Quality estimation · Orientation map · Coherence value · Ridge frequency

1 Introduction

Biometrics is the study of measurable biological characteristics for automatic authentication purposes. Some of these human characteristics are fingerprints, palms, facial patterns, eye retinas and irises, voice patterns, hands, gait, etc. Currently, fingerprints are one of the most used biometric trait, in both, civilian and forensic applications. Fingerprints can be classified into three types depending on the acquisition methodology: rolled, plain and latent impressions. Rolled and plain fingerprint impressions are acquired with the supervision of an expert. Rolled impressions are obtained by rolling the finger from one side to the other to obtain the entire fingerprint pattern, while plain impressions are captured by pressing down the finger on a flat surface, without rolling it [7]. It is expected that these two kind of impressions have good quality due to their acquisition way. This is different for latent fingerprints, that are lifted from surfaces of objects touched by a person in a crime scene. Normally, latent impressions are partial fingerprints and have poor quality.

A. Pardo and J. Kittler (Eds.): CIARP 2015, LNCS 9423, pp. 208–215, 2015.
DOI: 10.1007/978-3-319-25751-8_26

Automatic Fingerprint Identification Systems (AFIS) can be used in criminal investigations, attendance system, access control and others. Its performances are highly influenced by the quality of the enrolled fingerprints in the database and also by the quality of the query fingerprint. Experts must be involved in the process of acquiring reference fingerprints (database), for recapturing fingerprints in cases where poor quality is noted [3]. But, this process still needs automatic improvements, either to not storing corrupt information in databases or for knowing how reliable the features extracted from fingerprints can be. That is why, an algorithm that correctly estimate a quality value from fingerprint non-latent images is needed.

In this work, a new method for estimating a fingerprint quality value is presented. In section 2 a review of features used in other works of fingerprint quality assessment is given. In section 3, features and a general background of the proposed method are discussed. The new method performance is evaluated and its results are compared with another fingerprint quality algorithm in section 4. Finally, conclusions and future works are presented.

2 Related Work

A lot of approaches have been proposed in order to obtain a fingerprint image quality value. This value can be used in both enrollment and recognition/identification stages depending on user needs. A comparative study of some of the more important works is presented by Alonso-Fernandez et al. [1]. Most of the algorithms found on the literature are based on the extraction of local or global features. An overall quality value is calculated using a combination of these features. Other works address the quality assessment task as a classification problem.

Some features used for quality assessment are based on pixel intensities like Local Clarity Score (LCS) [4], low contrast map [10], gray intensity mean, gray intensity standard deviation [2][8][12], uniformity, smoothness, inhomogenity [2][12] and texture features [13]. Other features are extracted from the spectral domain like power spectrum and the response of Butterworth band-pass filters using Fast Fourier Transform [8], or global spectrum and relative spectral density [9]. Also, features characterizing the wavelength and amplitude are extracted from the wave representation of the ridges [2]. On the other hand, features based on the orientation field are also used. Examples of this are orientation certainty level (OCL) [6], Local Orientation Quality Score (LOQS) [4], direction map, low flow map, high curve map [10], orientation coherence [12], relative spectral orientation continuity [9], orientation certainty and consistency [2] and ridge-line smoothness [11]. Also, penalty due to the backgrounds noise and the quality of the core point position are features used [12]. Recently, minutiae features have been used to obtain a quality measure. Examples of them are the minutiae extractability [11], the number of total minutiae found and a quality minutia histogram [10]. Eight other features based on minutiae number and DFT of their three components have been previously used [13]. Another approach, computes a quality value based on unreasonable minutiae structures detected from the minutiae Delaunay triangulation [14].

Some approaches compute a quality value for each analysed block [2][6][8][10] and in a final step an overall quality value is obtained by combining the blocks classification results. In other cases a combination of the features values is used to estimate the final quality measure [12].

There are cases in which classifiers are used to generate a quality class. In a previous work, a neural network was used to classify a 11-dimensional feature vector extracted, into one of the quality levels defined (poor (5), fair (4), good (3), very good (2), and excellent (1)) [10]. In another proposal, a hierarchical k-means clustering algorithm was utilized to classify the fingerprint image in one of four classes (good, dry, normal or wet) [8]. Also, a genetic algorithm was proposed in another work to computed the quality image metric [13].

3 Proposed Fingerprint Quality Features

The fingerprint quality must be a measure of its efficiency in aiding recognition to a person [3]. In order to obtain a reliable quality value for fingerprint images, both, local and global characteristics of the biometric sample should be examined. The proposed quality estimation is inspired by how experts work. They take into account two principal features to classify the fingerprint quality: completeness of the three ridges systems (marginal, nuclear and basilar) and consistency (clarity) of the ridges pattern. A fingerprint impression has high quality when it has a clear ridge pattern and their three ridges systems are complete. To automatically describe these two characteristics, six features describing them are extracted. First, the region of interest (ROI) is detected using a segmentation method implemented by our investigation group, and a mask is obtained. Then, the minimum rectangle containing the ROI is located. A preprocessing step is applied to the image where a median filter and a normalization are performed to remove small noises in the ROI. The orientation map from the ROI is calculated with the gradients of the fingerprint image [5]. Using the fingerprint image, its ROI mask, and the orientation map, features that characterize the ridges systems completeness and the ridges pattern clarity are extracted. These features are invariant to the image texture, due to the high relation of texture with the enrollment step. Finally, an overall fingerprint image quality is estimated.

3.1 Ridges Pattern Clarity Features

One of the main features extracted from fingerprints is the orientation map. It describes the general flow direction of fingerprint ridges. The orientation map Φ is a matrix where each element Φ_{ij} denotes the average orientation of the ridges in a neighbourhood of pixel (i, j) [7]. A very common way for calculating the ridge orientation is the computation of the square gradients $G_{xx}(i,j)$, $G_{yy}(i,j)$, $G_{xy}(i,j)$ for pixel (i, j) [5].

A measure defined for indicating the behaviour of the local strength of the directional field is the coherence of its orientation vectors Ω_{Φ} defined in the equation 1 [5].

$$\Omega_{\Phi}(i,j) = \frac{\sqrt{(G_{xx}(i,j) - G_{yy}(i,j))^2 + 4G_{xy}(i,j)^2}}{G_{xx}(i,j) + G_{yy}()i,j}. \tag{1}$$

This is why, the coherence is used for separating orientation in good or bad. A binary coherence map $G_{\Omega_{\Phi}}$ is computed, where $G_{\Omega_{\Phi}}(i,j)$ takes value 1 (good coherence) if the coherence of the pixel $(i,\ j)$ is equal or higher than a threshold ξ and 0 (bad coherence) otherwise, as follow:

$$G_{\Omega_{\Phi}}(i,j) = \begin{cases} 1 \text{ if } \Omega_{\Phi}(i,j) \geq \xi, \\ 0 \text{ otherwise.} \end{cases} \tag{2}$$

Using this, three features are defined in order to describe the ridges pattern in the fingerprint:

Orientation Strength. Because of the shape of fingerprint ridges, orientation changes must be continuous and smooth. In this work is used the amount of pixels with good coherence for calculating a value between 0 and 1. This value describes the continuity and smoothness of the orientation map of a fingerprint impression, as follow:

$$S_{gos} = \frac{|P_{gos}|}{|P_{ROI}|}, \tag{3}$$

where P_{gos} is the set of pixels $(i,\ j)$ where $G_{\Omega_{\Phi}}(i,j)$ has value 1, P_{ROI} is the set of pixels present in the ROI, $|P_{gos}|$ and $|P_{ROI}|$ are the cardinality of each set. While better is the quality of the fingerprint, closer to 1 is P_{gos}.

Orientation Strength in Center Area. Singular points and fingerprint Henry classification are features commonly used by recognition algorithms. For their reliable extraction the center area of the fingerprint must have very good quality. Therefore, a proportion of pixels with bad orientation strength around the center area is presented:

$$S_{bosc} = \frac{|P_{bosc}|}{(w * 2 + 1)^2}, \tag{4}$$

where w is the block size used for choosing the pixels that will be analysed, P_{bosc} is the set of pixels with bad coherence present in the neighbourhood with window size w around the ROI center and $|P_{bosc}|$ is its cardinality. S_{bosc} moves between 0 and 1 and it is inversely proportional to the fingerprint quality.

Ridge Frequency. The ridge frequency is a popular feature extracted from fingerprints and it has been used for enhancement recognition algorithms. This feature describes the ridge distribution in a block. For describing the ridge distribution in the entire fingerprint, a proportion of blocks with good ridge frequency with respect to all analysed blocks is proposed:

$$S_{grf} = \frac{|P_{grf}|}{T_b}, \tag{5}$$

where $|P_{grf}|$ is the set of blocks where its ridge frequency is between two thresholds f_1 and f_2 experimentally chosen, $|P_{grf}|$ is its cardinality and T_b is the total analysed blocks with an empirically estimated size.

3.2 Ridges Systems Completeness Features

In dactyloscopy, experts separate the fingerprint in three ridge systems: marginal, nuclear and basilar as can be seen in figure 1. In this work, the completeness of these ridges systems is used to classify the fingerprint image quality.

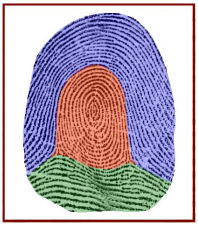

Fig. 1. Example of the three ridge systems of a fingerprint: marginal(blue, upper area), nuclear (red, central area) and basilar (green, bottom area).

The completeness of the ridges systems gives an idea of how much of the fingerprint is captured in the impression. The region of interest is the area that will be analysed, so a set of three features were defined to describe its size:

Region of Interest. The ROI is the region chosen for being processed in later steps of the biometric systems (feature extraction and matching). Its size is highly important for obtaining an accurate performance on these stages. With the aim of describing it, the proportion of the amount of pixels belonging to ROI with respect to the number of pixels present in the minimum rectangle containing this region is calculated:

$$S_{roi} = \frac{|P_{ROI}|}{width * height}, \tag{6}$$

where P_{ROI} is the set of pixels present in the ROI, $|P_{ROI}|$ is its cardinality and $width$ and $height$ are the size of the minimum rectangle containing ROI.

Attempting to represent the amount of information that can be extracted from a fingerprint image, two other features are used:

Horizontal Ridge Count. The number of ridges crossing the horizontal line to the central pixel (S_{hrc}) of ROI, and

Vertical Ridge Count. The ridges count crossing the vertical line to the central pixel (S_{vrc}) of ROI.

3.3 Overall Quality Estimation Function

With the aim of calculating the continuous quality metric proposed, first a Gaussian function (equation 7) is applied to each feature for obtaining a fuzzy value of belonging to a high quality fingerprint,

$$G_f(x) = \begin{cases} 1 & \text{if } \delta_{min} \leqslant x \leqslant \delta_{max}, \\ \alpha_1 e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} & x < \delta_{min}, \\ \alpha_2 e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}} & \text{otherwise}, \end{cases} \tag{7}$$

where α_1, α_2, μ_1, μ_2, σ_1 and σ_2 are the parameters of the Gaussian function.

So as to describe the ridges pattern clarity (Q_{RPC}) and the ridges systems completeness (Q_{RSC}), one dominant feature is chosen for each of these global characteristics by the following equations:

$$Q_{RPC} = min(G_f(S_{gos}), G_f(S_{bosc}), G_f(S_{grf})), \tag{8}$$

$$Q_{RSC} = min(G_f(S_{roi}), G_f(S_{hrc}), G_f(S_{vrc})). \tag{9}$$

Then, the final quality value is calculated by merging Q_{RPC} and Q_{RSC} as shown below:

$$Q_f = Q_{RPC} * Q_{RSC}. \tag{10}$$

4 Experimental Results

The fingerprint quality value is a measure of the biometric sample usability for both, enrollment and recognition stages. An accurate estimation of fingerprint quality is extremely important for improving fingerprint-based biometric systems, because the false non-matches can be reduced. To validate the proposed metric, the experiments measure its impact on the matching stage using the Verifinger 4.2 matching algorithm. Five different matching accuracy measures are used for obtaining the impact of the new fingerprint quality assessment method. Its performance is compared with NFIQ quality method. Experiments were conducted on a well-know public database, FVC2004 DB1-A which contains 100 fingers and 800 images.

In order to perform a comparison with NFIQ algorithm the proposed continuous quality value is quantified in five quality levels: 1, 2, 3, 4, 5, where 1 is the best quality and 5 is the worst quality. The matching accuracy measures are computed by eliminating the comparisons where at least one fingerprint image with bad quality (3, 4, or 5) is involved. A good performance of a quality assessment method should reduce error rates. The methodology used for the matching algorithm is the same proposed by the FVC competitions. Table 1 present a comparison of the three possible scenarios.

In table 1 it is shown that the matching algorithm performance is improved when both quality assessment algorithms are used. It can be clearly seen that the results of the proposed algorithm outperform the results of NFIQ method, even

Table 1. Comparison of the Verifinger algorithm performance, performance of the Verifinger algorithm using NFIQ method and the proposed quality assessment method.

	FVC 2004 db1A		
	Normal	*NFIQ*	Q_f
EER	0.0968	0.0826	0.0782
OP(0.001)	0.1854	0.1633	0.1505
FMR100	0.1504	0.1332	0.1191
FMR10	0.0889	0.0810	0.0782
ZeroFMR	0.2311	0.2003	0.1922

Table 2. Amount of impressions for each quality levels defined by NFIQ and the proposed approach.

Quality Levels	1	2	3	4	5
NFIQ	512	208	70	4	6
Q_f	484	246	39	25	11

Fig. 2. Example of a fingerprint image with NFIQ quality value of 1 (best quality) where the quality value generated by the new proposal is 5 (worst quality).

when the amount of images of higher quality levels is lower with the proposed approach than with NFIQ method as indicated in table 2.

An example of a fingerprint image where NFIQ gives the best posible quality and the proposed approach classifies it in the worst quality level can be seen in figure 2. This occurs because the zone of the fingerprint in the impression presents good quality, and has an acceptable amount of minutiae, but it can be clearly seen that its size is not acceptable for a fingerprint with good quality.

5 Conclusions and Future Work

In this work, a new method for fingerprint image quality assessment based on ridge characteristics, that can perform a continuous classification is presented. Six features that correctly describe the fingerprint quality are proposed. Its performance is evaluated in the recognition stage, using the Verifinger 4.2 matching algorithm. From the experiments carried out it can be concluded that the proposed method can attain accurate quality values for fingerprints and it outperforms the NFIQ results. The function used for obtained the final quality value is quite simple, nevertheless the proposed method achieved very good results. Consequently, a more sophisticated function to calculate the final quality value is being studied. Moreover, some of these features can be used for describing palm impressions quality.

References

1. Alonso-Fernandez, F., Fiérrez-Aguilar, J., Ortega-Garcia, J., Gonzalez-Rodriguez, J., Fronthaler, H., Kollreider, K., Bigün, J.: A comparative study of fingerprint image-quality estimation methods. IEEE Transactions on Information Forensics and Security **2**(4), 734–743 (2007)
2. Awasthi, A., Venkataramani, K., Nandini, A.: Image quality quantification for fingerprints using quality-impairment assessment. In: IEEE Workshop on Applications of Computer Vision, WACV, pp. 296–302 (2013)
3. Bharadwaj, S., Vatsa, M., Singh, R.: Biometric quality: a review of fingerprint, iris, and face. EURASIP Journal on Image and Video Processing **2014**, 34 (2014)
4. Chen, T.P., Jiang, X., Yau, W.Y.: Fingerprint image quality analysis. In: ICIP, pp. 1253–1256 (2004)
5. Kass, M., Witkin, A.P.: Analyzing oriented patterns. Computer Vision, Graphics, and Image Processing **37**(3), 362–385 (1987)
6. Lim, E., Jiang, X., Yau, W.: Fingerprint quality and validity analysis. In: ICIP (1), pp. 469–472 (2002)
7. Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S.: Handbook of fingerprint recognition, 2nd edn. Springer Publishing Company, Incorporated (2009)
8. Munir, M.U., Javed, M.Y., Khan, S.A.: A hierarchical k-means clustering based fingerprint quality classification. Neurocomputing **85**, 62–67 (2012)
9. Phromsuthirak, K., Areekul, V.: Fingerprint quality assessment using frequency and orientation subbands of block-based fourier transform. In: International Conference on Biometrics, ICB, pp. 1–7 (2013)
10. Tabassi, E., Wilson, C.L., Watson, C.I.: Fingerprint image quality. Tech. Rep. NISTIR 7151, National Institute of Standars & Technology, August 2004
11. Tiwari, K., Gupta, P.: No-reference fingerprint image quality assessment. In: Huang, D.-S., Jo, K.-H., Wang, L. (eds.) ICIC 2014. LNCS, vol. 8589, pp. 846–854. Springer, Heidelberg (2014)
12. Wu, M., Yong, A., Zhao, T., Guo, T.: A systematic algorithm for fingerprint image quality assessment. In: Huang, D.-S., Gan, Y., Gupta, P., Gromiha, M.M. (eds.) ICIC 2011. LNCS, vol. 6839, pp. 412–420. Springer, Heidelberg (2012)
13. Yao, Z., Bars, J.L., Charrier, C., Rosenberger, C.: Fingerprint quality assessment combining blind image quality, texture and minutiae features. In: 1st International Conference on Information Systems Security and Privacy, ICISSP, pp. 336–343 (2015)
14. Yao, Z., Bars, J.L., Charrier, C., Rosenberger, C.: Quality assessment of fingerprints with minutiae delaunay triangulation. In: 1st International Conference on Information Systems Security and Privacy, ICISSP, pp. 315–321 (2015)