TECHNICAL REPORT

ISO/IEC TR 29794-4

First edition
2010-04-01

Information technology — Biometric sample quality —

Part 4: Finger image data

Technologies de l'information — Qualité d'échantillon biométrique —

Partie 4: Données d'image de doigt

Reference number
ISO/IEC TR 29794-4:2010(E)

ISO copyright office
Case postale 56 • CH-1211 Geneva 20
Tel. + 41 22 749 01 11
Fax + 41 22 749 09 47
E-mail copyright@iso.org
Web www.iso.org

Published in Switzerland

Contents

Page

Foreword

ISO (the International Organization for Standardization) and IEC (the International Electrotechnical Commission) form the specialized system for worldwide standardization. National bodies that are members of ISO or IEC participate in the development of International Standards through technical committees established by the respective organization to deal with particular fields of technical activity. ISO and IEC technical committees collaborate in fields of mutual interest. Other international organizations, governmental and non-governmental, in liaison with ISO and IEC, also take part in the work. In the field of information technology, ISO and IEC have established a joint technical committee, ISO/IEC JTC 1.

International Standards are drafted in accordance with the rules given in the ISO/IEC Directives, Part 2.

The main task of the joint technical committee is to prepare International Standards. Draft International Standards adopted by the joint technical committee are circulated to national bodies for voting. Publication as an International Standard requires approval by at least 75 % of the national bodies casting a vote.

In exceptional circumstances, the joint technical committee may propose the publication of a Technical Report of one of the following types:

— type 1, when the required support cannot be obtained for the publication of an International Standard, despite repeated efforts;

— type 2, when the subject is still under technical development or where for any other reason there is the future but not immediate possibility of an agreement on an International Standard;

— type 3, when the joint technical committee has collected data of a different kind from that which is normally published as an International Standard (“state of the art”, for example).

Technical Reports of types 1 and 2 are subject to review within three years of publication, to decide whether they can be transformed into International Standards. Technical Reports of type 3 do not necessarily have to be reviewed until the data they provide are considered to be no longer valid or useful.

Attention is drawn to the possibility that some of the elements of this document may be the subject of patent rights. ISO and IEC shall not be held responsible for identifying any or all such patent rights.

ISO/IEC TR 29794-4, which is a Technical Report of type 2, was prepared by Joint Technical Committee ISO/IEC JTC 1, *Information technology*, Subcommittee SC 37, *Biometrics*.

ISO/IEC 29794 consists of the following parts, under the general title *Information technology — Biometric sample quality*:

— *Part 1: Framework*

— *Part 4: Finger image data* [Technical Report]

— *Part 5: Face image data* [Technical Report]

Introduction

The quality of finger image data is defined to be the predicted behavior of the image in a matching environment. Thus, the quality information is useful in many applications. ISO/IEC 19784-1 and ISO/IEC 19785-1 do allocate a quality field and specify the allowable range for the scores, with the recommendation that the score be divided into four categories with a qualitative interpretation for each category. Image quality fields are also provided in the fingerprint data interchange formats standardized in ISO/IEC 19794-2, ISO/IEC 19794-3, ISO/IEC 19794-4, and ISO/IEC 19794-8. However, there is no standard way to interpret the quality score that facilitates the interpretation and interchange of the finger image quality scores.

The purpose of this part of ISO/IEC 29794 is to provide an informative technical report on methodologies for objective, quantitative quality score expression and interpretation for finger images. It will complement ISO/IEC 29794-1 in developing a reference finger image corpus. Such a reference corpus can be built upon the availability of public finger images, which should then be used for quality score normalization.

Information technology — Biometric sample quality —

Part 4:
Finger image data

1 Scope

For aspects of quality specific to the finger image modality, this part of ISO/IEC 29794:

- specifies terms and definitions that are useful in the specification, use, and test of finger image quality metrics;
- defines the interpretation of finger image quality scores;
- identifies or defines finger image corpora for the purpose of serving as information for algorithm developers and users;
- develops statistical methodologies specific to finger image corpora for characterizing quality metrics to facilitate interpretation of scores and their relation to matching performance.

Performance assessment of quality algorithms and standardization of quality algorithms are outside the scope of this part of ISO/IEC 29794.

2 Normative references

The following referenced documents are indispensable for the application of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

ISO/IEC 29794-1, *Information technology — Biometric sample quality — Part 1: Framework*

3 Terms and definitions

For the purposes of this document, the terms and definitions given in ISO/IEC 29794-1 and the following apply.

3.1
foreground region
region of a finger image that contains valid finger image patterns

NOTE The most evident structural characteristic of a valid finger image is a pattern of interleaved ridges and valleys.

3.2
local region
block of *m* x *n* pixels of the foreground of a finger image, where m and n are smaller than the width and the height of the finger image

3.3
finger image quality assessment algorithm
algorithm that reports a quality score for a given finger image sample

3.4
finger image corpus
collection of finger image samples

3.5
finger image quality category
common attribute or property of a group of finger images that causes them to perform or behave similarly for a class of fingerprint matchers

4 Symbols and abbreviated terms

FQAA finger image quality assessment algorithm

DFT discrete Fourier Transform

QSN quality score normalization

QAID quality algorithm identification

ppi pixel per inch, which is analogous to dot per inch (dpi).

5 Finger Image Quality

5.1 Defect factors of finger image

A finger image obtained from a scanner is not always perfect. It may contain defects caused by the user character (e.g user's skin condition), user behavior (e.g. improper finger placement), imaging (e.g scanner limitation or imperfection), or environment (e.g. impurities on the scanner surface). Some of the defects and their factors can be listed as follows:

1. Defect caused by user character
   A. Extreme skin conditions such as very wet, very dry, etc.
   B. Scars
   C. Wrinkles
   D. Blisters
   E. Eczema
   F. Impurities such as dirt, latent print, etc.
2. Defect caused by imaging
   A. Sampling error
   B. Low contrast or signal-to-noise ratio
   C. Distortion
   D. Erroneous or streak lines
   E. Uneven background
   F. Insufficient dynamic range
   G. Non-linear or non-uniform grayscale output
   H. Pixels not available due to hardware failure
   I. Aliasing problems
3. Defect caused by user behavior
   A. Elastic deformation
   B. Improper finger placement such as too low, rotated, etc.
   C. Insufficient area of finger image
4. Defect caused by environment
   A. Humidity
   B. Light
   C. Impurities on the scanner surface

The performance of an automated fingerprint recognition system will be affected by the amount of defects or the degree of imperfection present in the finger image. Therefore, it is necessary to compute the quality score of the finger image produced. Section 6 suggests several possible approaches to compute the finger image quality. The quality score shall be predictive of the performance of an automatic fingerprint recognition system. Furthermore, the quality score should preferably be scanner-independent and source-independent.

5.2 Standardization approaches for exchange of finger image quality

As the finger image quality affects the performance of the fingerprint recognition system, the knowledge of quality can and is currently being used to process finger images differently, by for example, invoking some image enhancement methods prior to feature extraction, invoking different matchers based on quality or simply changing the threshold of the system. In fact, the use of finger image quality to enhance the overall performance of the system is increasingly growing. Therefore, there is a need to standardize the quantitative quality score expression and interpretation so that a common interpretation of the quality scores is achieved. This can be done, as suggested in ISO/IEC 29794-1, by either Quality Algorithm Identification (QAID), or Quality Percentile Rank upon standardization of a Quality Score Normalization (QSN) corpus.

6 Finger Image Quality Analysis

6.1 Introduction

A complete finger image quality analysis should examine both the local and global structures of the finger image. Fingerprint local structure constitutes the main texture-like pattern of ridges and valleys within a local region while valid global structure puts the ridges and valleys into a smooth flow for the entire fingerprint. The quality of a finger image is determined by both its local and global structures. This section describes the current most significant features and characteristics of finger images at both local and global structures that are related to performance of fingerprint recognition systems. Some of these algorithms are described in 6.2 and 6.3 and can also be found in [5-8,10,11].

The finger image is assumed to have resolution of 500 ppi. For other resolutions, the resolution dependent parameters should be scaled accordingly. Possible initial finger image corpuses are the publicly available Fingerprint Verification Competition (FVC) 2000, 2002, 2004, and 2006 [4] corpuses.

6.2 Local Analysis

6.2.1 Constituent of Local Analysis

A finger image is partitioned into blocks such that each block contains sufficient ridge-valley information, preferably having at least 2 clear ridges, while not overly constraining the high curvature ridges. For images with a resolution of 500 ppi, the ridge separation usually varies between 8 to 12 pixels [2]. A ridge separation comprises a ridge and a valley. In order to cover two clear ridges, the block size has to be bigger than 24 pixels. Thus the suggested size for each block is 32 x 32 pixels, which is sufficient to cover 2 clear ridges. Nevertheless, other sizes could also be used. Instead of Cartesian coordinate, curvilinear coordinate along the ridge can also be used. This is followed by a segmentation process where each block is tagged as background or foreground. There are several segmentation approaches, such as using the average magnitude of the gradient in each block etc [2]. Local quality analysis is performed on the foreground blocks with a local quality metric computed for each of them.

6.2.2 Approaches to Local Analysis of Finger Image

This section reviews some of the existing approaches for determining aspects of local quality of the finger image.

6.2.2.1 Orientation Certainty Level

The finger image within a small block (as shown in Figure 1) generally consists of dark ridge lines separated by white valley lines along the same orientation. The consistent ridge orientation and the appropriate ridge and valley structure are distinguishable local characteristics of the fingerprint block.

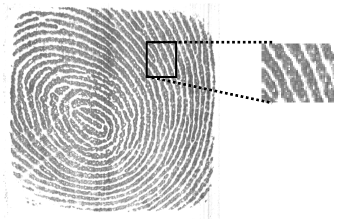


Figure 1 — A typical texture-like ridge block

The grey level gradient (*dx*, *dy*) at a pixel describes the orientation and its strength at the pixel level. As an example, [7] describes a method of measuring orientation certainty level. By performing Principal Component Analysis on the image gradients in an image block, an orthogonal basis for an image block can be formed by finding its eigenvalues and eigenvectors. Principal Components Analysis is a multivariate procedure which rotates the data such that maximum variability is projected onto orthogonal axes. The resultant first principal component contains the largest variance contributed by the maximum total gradient change in the direction orthogonal to ridge orientation. The direction is given by the first eigenvector and the value of the variance corresponds to the first eigenvalue, $\lambda_{\max}$. On the other hand, the resultant second principal component has the minimum change of gradient in the direction of ridge flow which corresponds to the second eigenvalue, $\lambda_{\min}$. The ratio between the two eigenvalues thus gives an indication of how strong the energy is concentrated along the dominant direction with two vectors pointing to the normal and tangential direction of the average ridge flow respectively. The covariance matrix *C* of the gradient vector for an *N* points image block is given by

$$C = \frac{1}{N}\sum_{N}\left(\begin{bmatrix} dx \\ dy \end{bmatrix}\begin{bmatrix} dx & dy \end{bmatrix}\right) = \begin{bmatrix} a & c \\ c & b \end{bmatrix}. \qquad (1)$$

For the covariance matrix in (1), eigenvalues λ are given by:

$$\lambda_{\max} = \frac{(a+b)+\sqrt{(a-b)^2+4c^2}}{2} \qquad (2)$$

$$\lambda_{\min} = \frac{(a+b)-\sqrt{(a-b)^2+4c^2}}{2} \qquad (3)$$

For a finger image block, orientation certainty level (*ocl*), or the ratio between $\lambda_{\min}$ and $\lambda_{\max}$ is then:

$$ocl = \frac{\lambda_{\min}}{\lambda_{\max}} = \frac{(a+b)-\sqrt{(a-b)^2+4c^2}}{(a+b)+\sqrt{(a-b)^2+4c^2}} \qquad (4)$$

The range of the *ocl* value is between 0 and 1 as *a*,*b*>0. It gives an indication of how strong the energy is concentrated along the ridge-valley orientation. The lower the value the stronger it is. The value of *ocl* can then be used to indicate the quality of the finger image block. The orientation certainty level fails to predict match-ability when there exist some marks or residual in the samples that have strong orientation strength, such as those exhibited by latent prints left by the previous user.

6.2.2.2 Ridge-valley Structure

Good quality fingerprints exhibit clear ridge-valley structure. Thus the measure of the ridge-valley structure clarity is a useful indicator of the quality of a fingerprint.

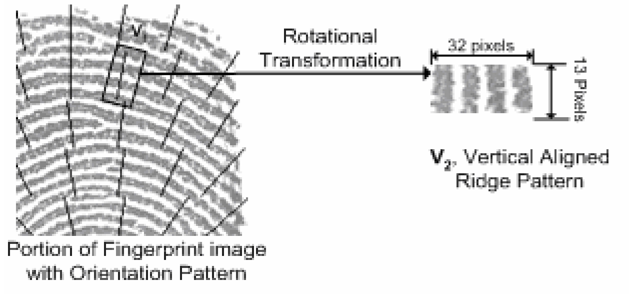


Figure 2 — Extraction of a local region and transformation to vertical aligned ridge pattern

6.2.2.2.1 Ridge-valley Structure Analysis

An example of methods assessing clarity of ridge and valleys is explained in [7]. To perform ridge-valley structure analysis, the finger image is quantized into blocks, preferably of size 32 × 32 pixels. Inside each block, an orientation line, which is perpendicular to the ridge direction, is computed. At the centre of the block along the ridge direction, a 2-D vector V_1 (slanted square in Figure 2) of smaller size than the block size, such as with size 32 × 16 pixels is extracted and transformed to a vertical aligned 2-D Vector V_2. By using equation (5), a 1-D Vector V_3, that is the average profile of V_2, can be calculated.

$$V_3(i) = \frac{\sum_{j=1}^{m} V_2(i,j)}{m}, \; i = 1..32 \tag{5}$$

where m is the block height (16 pixels) and i is the horizontal index.

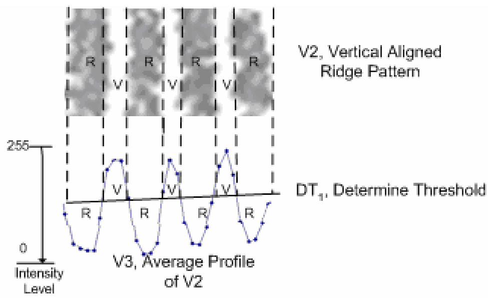


Figure 3 — Region Segmentation of Vector V_2

Once V_3 has been calculated, linear regression (or least square fitting) is then applied to V_3 to find the parameter, called Determine Threshold (DT_1). DT_1 is the line positioned at the centre of the Vector V_3, and is used to segment the image block into the ridge or valley region. Regions with grey level intensity lower than DT_1 are classified as ridges; else they are classified as valleys. The process of segmenting the fingerprint region into ridge and valley using DT_1 is shown in Figure 3. The top portion of Figure 3 shows the ridge pattern. The gray scale distribution of the ridge pattern projected as a one dimensional cumulative intensity profile is shown at the lower portion. The Y-axis is the intensity level, while the x-axis the cross section of the ridge pattern. Each local block will have its own DT_1.

From the one-dimensional signal in Figure 3, several useful parameters are computed, such as valley thickness and ridge thickness. Since good finger images cannot have ridges that are too close or too far apart, thus the nominal ridge and valley thickness can be used as a measure of the quality of the finger image captured. Similarly, ridges that are unreasonably thick or thin indicate that the finger image may not be captured properly, such as pressing too hard or too soft, or the image is a residual sample. Thus, the finger image quality can be determined by comparing the ridge and valley thickness to each of their nominal range of values. Any value out of the nominal range may imply a bad quality ridge pattern. The ridge and valley thickness values are dependent on the resolution of the fingerprint scanner. To normalize these values, a factor is computed by dividing the scanner resolution with 125 ppi which is the minimum resolution permitted in ISO/IEC 19794-4. To normalize the range of the thickness values, a pre-set maximum thickness is used.

With a scanner resolution of 500 ppi, the maximum ridge or valley thickness (W_{max}) for a good finger image is estimated at 20 pixels or 5 pixels for a 125 ppi scanner in the normalized case. The pre-set value of 20 pixel for a 500 ppi scanner resolution is obtained from the median of the typical ridge separation of 8 to 12 pixels [2], and assuming that any ridge separation will not exceed twice of the median value. This will ensure that the pre-set value is indeed the maximum to limit the value of the normalized ridge and valley thickness between 0 and 1. The ridge thickness (W_r) and valley thickness (W_v) are then normalized as follows:

$$NW_r = W_r / ((Sc/125) * W_{\max}) \text{ ; where } W_{max} = 5 \quad (6)$$

$$NW_v = W_v / ((Sc/125) * W_{\max}) \text{ ; where } W_{max} = 5 \quad (7)$$

where NW_r and NW_v are the normalized ridge and valley thickness respectively and Sc the scanner resolution.

With the ridge and valley separated as above, a clarity test can be performed in each segmented rectangular 2-D region. Figure 4 shows a sample grey level distribution of the segmented ridge and valley. The overlapping area is the region of potential misclassification since in this region, whether a pixel belongs to ridge or valley cannot be accurately determined using DT_1. Hence, the area of the overlapping region can be an indicator of the clarity of ridge and valley, subject to the ridge and valley thicknesses being within the acceptable range.

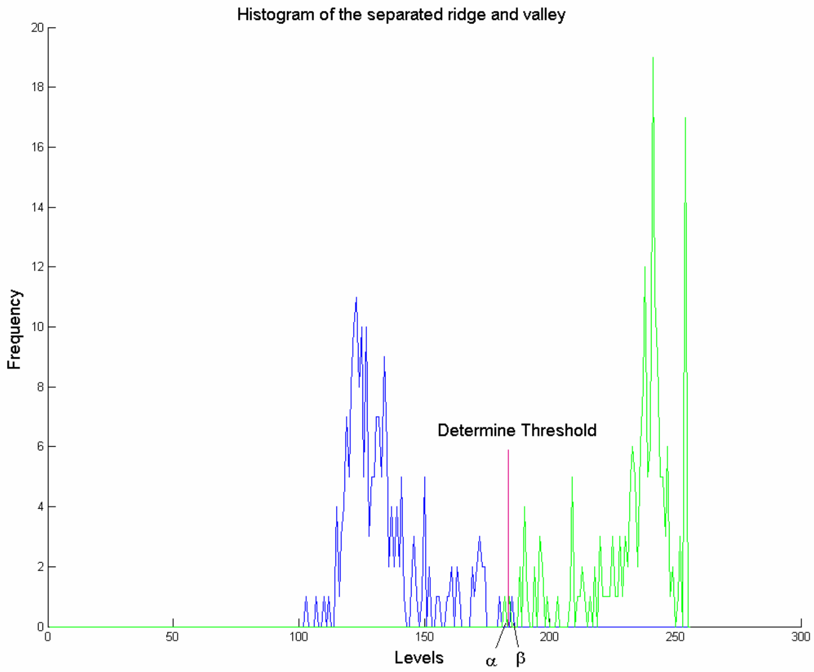


Figure 4 — Distribution of Ridge and Valley

The following equations describe the calculation of the clarity score, where υ_B is the number of pixels in the valley with intensity lower than DT_1 (also known as "bad pixel" for valley), υ_T is the total number of pixels in the valley region, $\Re_B$ is the number of pixels in the ridge with intensity higher than DT_1 (also known as "bad pixel" for ridge), $\Re_T$ is the total number of pixels in the ridge region.

$$\alpha = \upsilon_B / \upsilon_T \quad (8)$$

$$\beta = \Re_B / \Re_T \quad (9)$$

$$LCS = \begin{cases} (\alpha+\beta)/2 & \text{if } ((NW_{v\min} < NW_v < NW_{v\max}) \wedge (NW_{r\min} < NW_r < NW_{r\max})) \\ 1 & \text{otherwise} \end{cases} \quad (10)$$

where $\wedge$ is the logical AND operator; α and β are the portion of bad pixels while (NW_{rmin}, NW_{rmax}) and (NW_{vmin}, NW_{vmax}) are the minimum and maximum values for the normalized ridge (NW_r) and valley (NW_v) respectively. Hence, the Local Clarity Score (*LCS*) is the constrained average value of α and β with a range between 0 and 1.

For ridges with good clarity, both distributions should have a very small overlapping area and thus *LCS* is small. The following factors affect the size of the total overlapping area:

a. Noise on ridge and valley
b. Water patches on the image due to wet finger
c. Incorrect orientation angle due to the effect of directional noise
d. Scar across the ridge pattern
e. Highly curved ridges
f. Ridge endings, bifurcations, delta and core points.
g. Incipient ridges, sweat pores and dots

Factors (a) to (c) are physical noise found in the image. Factors (d) to (g) are actual physical characteristics of the fingerprint. Therefore, a small window, such as with size 32 × 16, is chosen to minimize the chance of encountering too many distinct features in the same location.

6.2.2.2.2 Directional Contrast

[8] describes a method for measuring clarity of ridge-valley structure by measuring directional contrast. The value for directional contrast, *D*, is obtained by measuring the contrast between the gray values in the ridges and the valleys along the orientation of the ridge flow [8]. The underlying idea is that the region of good quality shows high directional contrast, which means that the ridges and the valleys in a given finger image are well separated with regard to gray values. The overall process to calculate *D* is described in reference [8], and the equation is simplified as follows. In Equation (11), $\Sigma_k(i, j)$ is the sum of the pixels that follow the same orientation, θ, and (i, j) represent the pixel indices in a block of size *N*x*N* of a finger image.

$$D = |\theta_{\max} - \theta_{ortho}| \quad (11)$$

where $\theta_{\max} = \max\{\theta_k = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_k(i,j), k = 1,\ldots 8\}$, and $\theta_{ortho} \perp \theta_{\max}$

k = orientation index

6.2.2.3 Frequency Domain Analysis

The signature of a high quality sample is a periodic signal, which can be approximated either by a square wave or a sinusoidal wave. In the frequency domain, an ideal square wave should exhibit a dominant frequency with sideband frequency components (sinc function). A sinusoidal wave consists of one dominant frequency and minimum components at other non-dominant frequencies. Thus, we are able to make use of such information in identifying good or bad quality blocks. The existences of one dominant frequency as well as the frequency of such dominant components are two main elements that are useful in quality determination.

For each block a signature along the ridge-valley (*x*) direction, centered at the centre of each block as shown below can be computed. The signature will pass through the centre of the image block in the direction of *x* as shown in Figure 5.

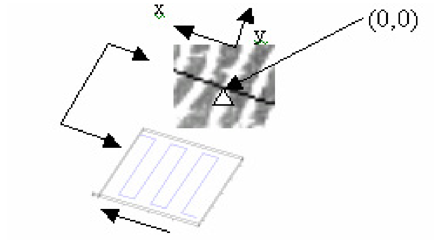
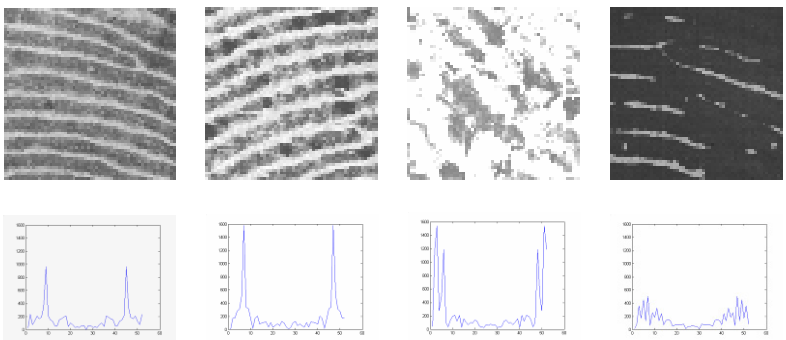


Figure 5 — Signature along *x* direction

In the coordinate system of *(x, y)* as shown above, the signature is computed as :

$$T(x) = \frac{1}{2r+1} \sum_{k=-r}^{r} I(x,k) \tag{12}$$

where *I(x, y)* is the grey level at point *(x, y)*; *x* is the index along *x* axis and the range $-25 \le x \le 26$ is usually sufficient to cover two ridge separations [2] (Note that the exact value is not critical so long as it can cover at least one periodic cycle completely); *r* is the width along the *y* axis that the signature is computed from and a typical range used is $-10 < r < 10$ to obtain sufficient average grey level representation along the *y* axis. The exact value is not critical but should not be too high to ensure that the direction of the ridges in the block is consistent or too low which may not provide sufficient robustness against noise.



(a) Good Quality (b) Good Quality (c) Bad Quality (d) Bad Quality

Figure 6 — Image blocks with their respective DFTs of the signatures along the ridge direction.

Figure 6 above shows four finger image blocks with varying quality and their Discrete Fourier Transform (DFT) of the signatures derived. The vertical axis of the plot is the DFT value of *T(x)* and the horizontal axis is the index of the *x*-axis. Bad quality image (c) can be easily identified by the existence of dominant frequency at very low frequency (<5), which is out of the normal ridge frequency range. On the other hand, figure (d) does not possess obvious dominant frequency, which suggests that the image is highly contaminated.

The final output of this analysis is an image quality measure (*IQM*) computed by:

$$IQM = \frac{A(F_{\max}) + 0.3[A(F_{\max} - 1) + A(F_{\max} + 1)]}{\sum_{F=1}^{NF/2} A(F)} \tag{13}$$

where *A (x)* is the amplitude at frequency index *x*. *F* is the DFT frequency index ranging from 1 to *NF*/2 with *NF* the number of points used in the DFT (*NF* = 52 is recommended) and F_{max} is the frequency index when the amplitude is maximum.

The Frequency Domain analysis described in this sub-section computes the one-dimensional signatures by performing averaging along the ridge flow direction. The averaging process filters off noises along the ridges and valleys flow and provides a better modeling of smooth changing signal in a direction perpendicular to ridge flow. However, the effect of pixel level noise along the ridges and valleys is also neglected due to the averaging process. Random variations in grey levels of the ridges and valleys are another symptom of low quality sample, but these are not considered here as it is measured by the ridge-valley structure analysis and the uniformity measure as explained in Section 6.2.2.2 and Section 6.2.2.4 respectively.

6.2.2.4 Uniformity

Uniformity is the measure of consistency in ridge and valley's grey level. Four samples of fingerprint blocks with good to bad uniformity are shown in Figure 7.

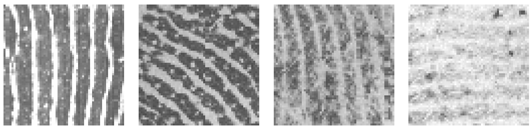


Figure 7 — Four Fingerprint Blocks. Uniformity ranged from the highest (leftmost) to the lowest (rightmost)

The first block on the left carries a fairly constant grey level for the ridge-valley regions while the rightmost has no obvious ridge-valley regions that are uniform and easily distinguished. The Clustering Factor is defined as the degree to which similar grey level pixels cluster together in the nearby region. The more the clustering of "black" or "white" pixels, the higher the confidence level of such structure being a useful signal and hence giving higher sample quality. To produce a binary image before the Clustering Factor is computed, the Otsu method [9] is first applied to obtain the optimum threshold values that can be used to binarize the image block.

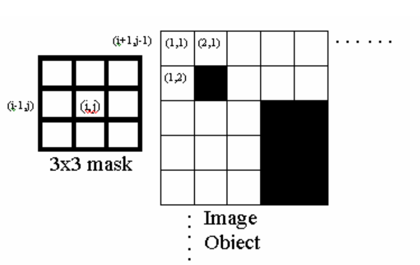


Figure 8 — Uniformity computation

Figure 8 shows the Image Object (32 x 32 finger image block in the example above) as well as a 3 x 3 mask used to compute the Clustering Factor. The mask is centered at (*i,j*) and overlaid on the image object. The centre of the mask moves from the top – left corner to the bottom – right corner, computing accumulative results for the clustering factor. For the mask centered at a black pixel, the region covered under the masking area is examined for its pixel value. If more than 4 out of 9 pixels are black pixels, a 1 is returned, else a pro-rated value, (*n* x *0.2)*, is returned, where *n* is the number of black pixels including the middle pixel in the 3 x 3 mask. The returned value is accumulated for the whole mask-shifting process with the mask centered at black pixels. A higher Clustering Factor indicates a higher confidence level of the structure and hence higher quality.

6.3 Global Analysis

6.3.1 Constituent of Global Analysis

Continuity and ridge-valley uniformity are general characteristics of finger images. Continuity is found along the orientation change while uniformity is observed all over the sample for its ridge and valley structure. Each of these characteristics contributes to a standalone global metric that could be combined with the local analysis metric to obtain the final quality score.

6.3.2 Approaches to Global Analysis of Finger Image

This section reviews some of the existing approaches for determining aspects of global quality of the finger image.

6.3.2.1 Orientation Flow Analysis

Orientation flow is the first indicator to describe the quality of good fingerprint pattern because, in general, the flow of the ridge direction changes gradually, except when a delta or core point is encountered.

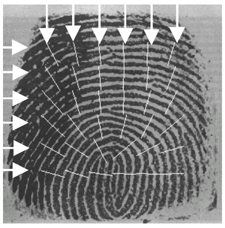


Figure 9 — Ridge-valley direction in smooth trend

Figure 9 illustrates the normal of the orientation flow of a finger image. A 2D array, V_4, is defined to hold all orientation angles from the fingerprint. To analyze the orientation flow in $V_4(i,j)$, the absolute difference of the orientation angle with its surrounding blocks is used. If the 8-neighbouring blocks are considered, this measure, called the Local Orientation Quality (*LOQ*), can be computed using equation (14).

$$LOQ(i,j) = \frac{\sum_{m=-1}^{1} \sum_{n=-1}^{1} \left| V_4(i,j) - V_4(i-m, j-n) \right|}{8} \tag{14}$$

On average, a tolerance to 8° of angular change is expected. The average difference should not be zero because the orientation flow is constantly changing gradually. Therefore, the Local Orientation Quality Metric (*LOQS*) is defined as follows:

$$LOQS(i,j) = \begin{cases} 0 \, , LOQ(i,j) \leq 8^\circ \\ \dfrac{LOQ(i,j) - 8^\circ}{90^\circ - 8^\circ} \, , LOQ(i,j) > 8^\circ \end{cases} \tag{15}$$

The Global Orientation Quality Metric (*GOQS*) is obtained by averaging all the *LOQS* values. Therefore, *GOQS* can be computed by the following equation.

$$GOQS = LOQS(i,j) / N \tag{16}$$

where *N* is the number of blocks in V_4. Hence, the *GOQS* provides information about the degree of smoothness of the change in orientation angles from block to block.

6.3.2.2 Ridge-valley Uniformity

Referring to finger images in Figure 10(a), (b) and (c), visual inspection concludes that Figure 10(a) has the poorest quality among them, while Figure 10(c) has the best. Such judgment relies on the consistently clear separation between the ridges and the valleys. A method to measure such an observation is to use the ratio of ridge thickness to valley thickness, *GRU*. This ratio should be fairly constant throughout the whole image for a good quality finger image. Thus, the standard deviation of such ratio throughout the whole sample gives an indication of the quality of the finger image. Large deviation from the mean ratio value could indicate a bad quality sample as the sample could be more randomly structured.

(a) (b) (c)

Figure 10 — Three finger images with different ridge-valley uniformity

6.3.2.3 Radial Power Spectrum

The maximum value of the Fourier spectrum is defined as stable in that ridge direction. Since the ridges of a finger image can be locally approximated by one sine wave, large value of sine wave energy can represent the strong ridges. The robustness of the ridge structure can be used to measure the finger image quality, and this is shown in Equation 17. *f(p,q)* is the results of a 2-dimensional Fourier transform, and *Re(p,q)* and *Im(p,q)* represent the real part and the imaginary part of *f(p,q)* respectively. *F* is decided as the maximum Radial Fourier spectrum value within the reasonable Fourier domain. The reasonable Fourier domain refers to the region of neither the highest nor the lowest frequency. Samples of results using this measure as a global measure are shown in Figure 12. The higher the value of F, the better is the finger image quality.

$$F = \max_{\substack{\text{Reasonable} \\ \text{Fourier domain}}} \left(\left| J(r) \right| \right) \tag{17}$$

The Radial Fourier spectrum, *J(r)*,is determined as:

$$J(r) = \frac{1}{\sum_{\alpha=0}^{\pi} \sum_{r_{\min}}^{r_{\max}} \left| f(\alpha, r) \right|} \sum_{\alpha=0}^{\pi} \sum_{r}^{r+\Delta r} \left| f(\alpha, r) \right| \tag{18}$$

where *f(α,r)* is the Spectrum *f(p,q)* representation in polar coordinate system *(α,r)*, see Figure 11;
r_{min} ,r_{max} is the lowest and highest frequency in the reasonable Fourier domain;
Δr is the sampling step;

$$f(p,q) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} e^{-2\pi \left[\frac{p.x}{M} + \frac{p.y}{N} \right]} p(x,y) = \mathrm{Re}(p,q) + i\,\mathrm{Im}(p,q)$$

and $\left| f(p,q) \right| = \sqrt{\mathrm{Re}(p,q)^2 + \mathrm{Im}(p,q)^2}$

Samples of Fourier spectrum are shown in Fig. 12 while samples of Radial spectrum are shown in Fig. 13.

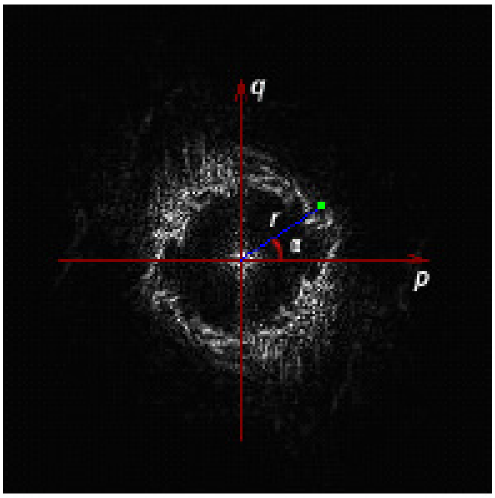
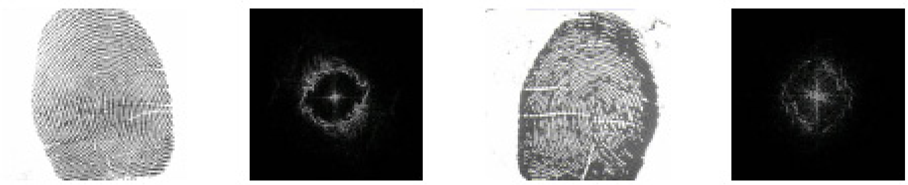


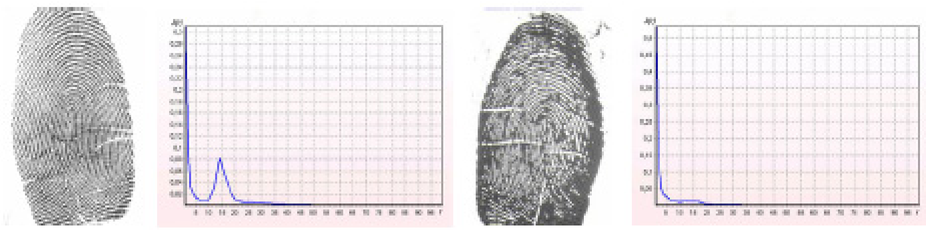
Figure 11 — Fourier spectrum in polar coordinate system *(α,r)*



a) 'Excellent' or 'Adequate'

b) 'Marginal' or 'Unacceptable'

Figure 12 — Samples of Fourier spectrum



a) 'Excellent' or 'Adequate'

b) 'Marginal' or 'Unacceptable'

Figure 13 — Samples of Radial Fourier spectrum

6.4 Unified Quality Score

6.4.1 Methodology for Combining Quality Metrics

In order to obtain a single or unified output from several or all the quality metrics described in the earlier sections, it is necessary to combine the values of the quality metrics described above and produce a single scalar quality score as required in the quality field. Each of the quality score is normalized to the range between 0 and 1 prior to combining them. Combining quality metrics shall be done such that the overall quality score is predictive of performance. There are various methods that can be used to combine all the quality metrics, e.g. weighted averaging, the use of pattern classifiers and other nonlinear computations. The signal fidelity measures to be used include, but not limited to, those mentioned in clauses 6.2 and 6.3.

6.4.2 Weighted Average

A simple approach to combine all the values computed using the algorithms described in Section 6.2 and Section 6.3 is to compute their weighted average. The unified quality score, *QS*, (0 ≤ *QS* ≤ 1) can then be computed using weighted average as follows:

$$QS = \alpha_1(\sigma_1 MOCL + \sigma_2 MLCS + \sigma_3 MIQM + \sigma_4 MU + \sigma_5 MD) + \alpha_2(\beta_1 GOQS + \beta_2 GRU + \beta_3 F) \quad (19)$$

where

$$\alpha_1 + \alpha_2 = 1,\ \beta_1 + \beta_2 + \beta_3 = 1 \text{ and } \sum_{i=1}^{5} \sigma_i = 1$$

σ_i, α_i and β_i are the weights and *MOCL*, *MLCS*, *MIQM, MU* and *MD* are the average of the block-based orientation certainty level, *LCS*, *IQM*, uniformity metric and directional contrast respectively. *GOQS, GRU* and *F* are global orientation quality metric, global ridge-valley uniformity metric and radial power spectrum respectively.

For each of the local quality metrics, the metric for the overall sample can be computed by taking the average of all the scores of the local quality metrics in the sample. The values for the weights σ_i, α_i and β_i should be selected such that the overall quality score is indicative of performance of the sample in a matching environment. Weights could be determined in the least square sense from a corpus of finger images (such as from the QSN corpus) or using outputs of one or many matching algorithms. Other combination rules such as product or minimum can also be used instead of the average rule.

6.4.3 Pattern Classifier

Pattern classifiers are mathematical models that can intelligently learn a concept and predict an output when presented with new and even unseen samples. To apply pattern classification to combine the finger image quality analysis metrics, it is necessary to train the pattern classifier by providing finger images with the values for all the quality metrics computed and the overall quality scores for each sample. Once the pattern classifier is well-trained, given the values of the quality metrics, it will be able to provide an overall quality score for the finger image.

For each local quality metric, the score for the overall finger image can be computed from the average of all the values of the local metrics in the finger image. Together with the global quality metrics, they form a feature vector, *f*. Equation 20 is an example of what a quality feature vector could look like when all the quality metrics described in 6.2 and 6.3 are used.

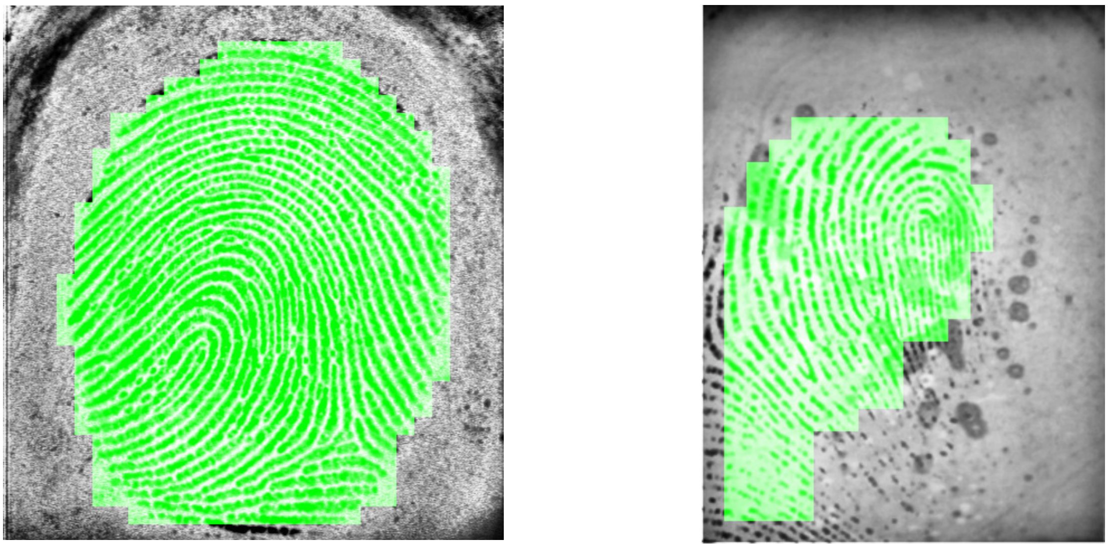
$$f = (MOCL, MLCS, MIQM, MU, MD, GOQS, GRU, F)^T \quad (20)$$

where *MOCL*, *MLCS*, *MIQM, MU* and *MD are* the overall average scores of the block-based orientation certainty level, *LCS*, *IQM,* uniformity metric and directional contrast respectively and *GOQS, GRU* and *F* are the global orientation flow, ridge-valley uniformity and radial power spectrum metrics respectively.

This feature vector, *f*, will be the input to the pattern classifier. Training the pattern classifier could be performed using a corpus of finger images with pre-assigned quality categories or scores such as the QSN corpus, on the output of one or many quality algorithms. Detailed approach to establish the QSN database and the minimum number of samples required can be found in ISO/IEC 29794-1. For all the samples in the corpus, the feature vectors are computed. They are then paired with the quality category or score and fed into the pattern classifier for training. Once the pattern classifier is successfully trained, given a feature vector of a finger image, the pattern classifier will be able to produce the resultant overall quality score, *QS*, or the quality category. An example of using pattern classifier to combine components of feature vector into a scalar is given in [5,6].

6.4.4 Area Consideration

Even though area alone should not be used as an indicator of quality, the area in the image containing valid fingerprint pattern will affect the performance of matcher and thus, the quality of the image. If the valid area is too small, then the finger image should be considered poor. The local analysis operates on a block basis while the global analysis operates on the entire image without consideration for the actual area occupied by the ridge-valley structure. In the global analysis, there is a possibility that a small but very good quality region may produce sufficient overall score to give the entire image an acceptable quality. Therefore, an explicit area measure is needed. The finger area is calculated based on the number of blocks occupied by the valid ridge-valley structure (the foreground) of a finger image. Figure 14 (taken from the FVC database [4]) shows the example of valid ridge-valley structure. The background region, sweat or other impurities present in the image but not located within the valid ridge-valley structure of the finger image shall be excluded from the calculation of the finger area. The border region of the image may also be excluded.



a) Valid ridge-valley region

b) Valid ridge-valley region excluding the image border and impurities

Figure 14 — Example of valid ridge-valley structure

The process of automatically classifying the image into foreground region which contains valid ridge-valley structure and the remaining region as background is known as fingerprint segmentation. One of the segmentation approaches is to compute the strength of the orientation in each block [2]. From the segmentation process, the number of blocks, or in general, the area in the foreground and background of the fingerprint can be known, thus providing a possible area consideration in the overall quality of the image.

Bibliography

[1] ISO/IEC JTC 1/SC 37 Standing Document 2, Version 9, *Harmonized Biometric Vocabulary*

[2] D. Maltoni, D. Maio, A.K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*, Springer, 2003

[3] J.F. Mainguet, W. Gong, A. Wang, "Reducing Silicon Fingerprint Sensor Area", *Lecture Notes in Computer Science,* vol 3072, 2004, pp 301-308

[4] Biometric System Laboratory, University of Bologna, Italy website http://biolab.csr.unibo.it

[5] E. Tabassi, C. L. Wilson, "A Novel Approach to Fingerprint Image Quality", *Proc. IEEE International Conference on Image Processing,* 2005

[6] E. Tabassi, C. L. Wilson and C. I. Watson. *Fingerprint Image Quality, NFIQ.* National Institute of Standards and Technology, NISTIR 7151, 2004

[7] E. Lim, X. Jiang and W.-Y. Yau, "Fingerprint Image Quality Analysis", *Proc. Int. Conf. On Image Processing (ICIP 02)*, Sep. 2002, vol. 1, pp. 469 -472

[8] S. Joun, H. Kim, Y. Chung and D. Ahn, "An Experimental Study on Measuring Image Quality of Infant Fingerprints," LNCS 2774, pp.1261-1269, 2003

[9] N. Otsu, "A threshold selection method from gray-level histograms", *IEEE Trans. Syst., Man, Cybern.*, vol. 9, no. 1, pp.62-66,1979

[10] N. K. Ratha and R. M. Bolle. "Fingerprint image quality estimation". IBM computer science research report RC21622, 1999

[11] L. L. Shen, A. Kot and W. M. Koo. "Quality measures of fingerprint images". *Proc. of the Third AVBPA 2001*, p182-271, June 2001

[12] ISO/IEC 19794-4, *Information technology — Biometric data interchange formats — Part 4: Finger image data*

ICS 35.040

Price based on 15 pages