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Fingerprint Quality Analysis and Estimation for Fingerprint Matching

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1. Introduction

Due to their permanence and uniqueness, fingerprints are widely used in the personal identification system. In the era of information technology, fingerprint identification is popular and widely used worldwide, not only for anti-criminal, but also as a key technique to deal with personal affairs and information security. Accurate and reliable fingerprint identification is a challenging task and heavily depends on the quality of the fingerprint images. It is well-known that the fingerprint identification systems are very sensitive to the noise or to the quality degradation, since the algorithms' performance in terms of feature extraction and matching generally relies on the quality of fingerprint images. For many application cases, it is preferable to eliminate low-quality images and to replace them with acceptable higher-quality images to achieve better performance, rather than to attempt to enhance the input images firstly. To prevent these errors, it is important to understand the concepts that frequently influence the images' quality from fingerprint acquisition device and individual artifacts. Several factors determine the quality of a fingerprint image: acquisition device conditions (e.g. dirtiness, sensor and time), individual artifacts (e.g. skin environment, age, skin disease, and pressure), etc. Some of these factors cannot be avoided and some of them vary a long time.

Fingerprint quality is usually defined as a measure of the clarity of ridges and valleys and the "extractability" of the features used for identification such as minutiae, core and delta points, etc (Maltoni, et al. 2003). In good quality images, ridges and valleys flow smoothly in a locally constant direction and about 40 to 100 minutiaes are extracted for matching. Poor-quality images mostly result in spurious and missing minutiae that easily degrade the performance of identification systems.

Therefore, it is very important to estimate the quality and validity of the captured fingerprint image in advance for the fingerprint identification system. The existing

fingerprint estimation algorithms (Chen, et al. 2005; Lim, et al. 2004; Maltoni, et al. 2003;Shen, et al.2001; Tabassi, et al. 2004; Tabassi, et al.2005) can be divided into: i) those that use local features of the image; ii) those that use global features of the image; and iii) those that address the problem of quality assessment as a classification problem. The local feature based methods (Maltoni, et al. 2003; Shen, et al. 2001) usually divide the image into non-overlapped square blocks and extract features from each block. Blocks are then classified into groups of different quality. Methods that rely on global features (Chen, et al. 2005; Lim, et al. 2004) analyze the overall image and compute a global measure of quality based on the features extracted. The method that uses classifiers (Tabassi, et al. 2004; Tabassi, et al.2005) defines the quality measure as a degree of separation between the match and non-match distributions of a given fingerprint. The discrimination performance of quality measures, however, can be significantly different depending on the sensors and noise sources. In this chapter, we propose an effective fingerprint quality estimation approach. Our proposed method is not only based on the basic fingerprint properties, but also on the physical properties of the various sensors.

The chapter is organized as follows: in section 2, we firstly discuss about the factors influencing the fingerprint quality from two aspects: physical characteristics of acquisition devices and artifacts from fingers. And then, we present our proposed effective fingerprint quality estimation approach in consideration of feature analysis for fingerprint quality estimation in section 3. Finally, in section 4, we test and compare a selection of the features with a classifier for quality estimation performance evaluation on the public databases. Conclusion and further work are conducted in section 5.

2. Factors influencing the fingerprint quality

In this section, the concepts that frequently influence images' quality from fingerprint acquisition device and individual artifacts are first introduced. The development of fingerprint acquisition devices in common use are reviewed and analyzed with their physical principles of acquiring images, too. Due to different characteristics of capturing devices, the fingerprint quality estimation methods can be specific for each acquisition device. And we also consider various external situations reflecting individual artifacts come from users of devices, such as distortions and noises from the skin condition, the pressure, rotation, etc., which can significantly affect the fingerprint alignment and matching process.

2.1 Fingerprint acquisition devices

The most important part of fingerprint authentication is the fingerprint acquisition devices, which are the components where the fingerprint image is formed. The fingerprint quality would influence the matching results since the entire existed matching algorithm has their limitations. The main characteristics of a fingerprint acquisition device depend on the specific sensor mounted which in turn determines the image features (dpi, area, and dynamic range), cost, size and durability. Other feature should be taken into account when a finger scanner has to chosen for a specification use. Two main problems of fingerprint sensing are as follows: (1) Correct readout of fingerprints is impossible in certain cases, such as with shallow grooves. (2) When the skin conditions of the finger are unstable; for example, in case of a skin disorder, the finger pattern changes from readout to readout.

The principle of the fingerprint acquisition process is based on geometric properties, biological characteristics and the physical properties of ridges and valleys (Maltoni, et al.2009). The different characteristics obtained from ridges and valleys are used to reconstruct fingerprint images for different types of capture sensors.

- Geometry characteristics

The fingerprint geometry is characterized by protuberant ridges and sunken valleys. The intersection, connection and separation of ridges can generate a number of geometric patterns in fingerprints.

- Biological characteristics

The fingerprint biological characteristic means the ridge and valley have different conductivity, different dielectric constant of the air, different temperatures, and so on.

- Physical characteristics

Referring to the physical characteristics of the fingerprints, the ridges and valleys exert different pressures on the contact surface, and they have different pairs of wave impedance when they are focused on the horizontal plane.

According to these characteristics, there are two methods for capturing fingerprints. One type of sensors initially sends a detecting signal to the fingerprint, and then it analyzes the feedback signal to form a fingerprint ridge and valley pattern. Optical collection and Radio Frequency (RF) collection are two typical active collection sensors. Other fingerprint sensors are the passive ones. As the finger is placed on the fingerprint device, due to the physical or biological characteristics of the fingerprint ridges and valleys, the different sensors form different signals, and a sensor signal value is then analyzed to form a fingerprint pattern, such as in the thermal sensors, semiconductor capacitors sensors and semiconductor pressure sensors.

Fig.1. shows the development of fingerprint acquisition devices. The oldest "live-scan" readers use frustrated refraction over a glass prism (when the skin touches the glass, the light is not reflected but absorbed). The finger is illuminated from one side with a LED while the other side transmits the image through a lens to a camera. As optical sensors are based on the light reflection properties (Alonso-Fernandez, et al, 2007), which strictly impact the related gray level values, so that the gray level features-based measure quality, so Local Clarity Score ranks first for optical sensors. Optical sensors only scan the surface of the skin and don't penetrate the deep skin layer. In case that there are some spots left over or the trace from the previous acquisition of fingerprints, the resulting fingerprint may become very noisy resulting in difficulty in determining dominant ridges and orientations. This, in turn, makes the orientation certainty level of the fingerprint lower than that of a normal one. Kinetic Sciences and Cecrop/Sannaedle have proposed sweep optical sensors based on this principle. Casio + Alps Electric use a roller with the sensor inside. TST removed the prism by directly reading the fingerprint, so the finger does not touch anything (but still need a guide to get the right optical distance). Thales (formerly Thomson-CSF) also proposed the same, but with the use of a special powder to put on the finger. The BERC lab from Yonsei University (Korea) also developed a touchless sensor (2004). In 2005, TBS launch a touchless sensor with the "Surround Imaging".

A capacitive sensor uses the capacitance, which exists between any two conductive surfaces within some reasonable proximity, to acquire fingerprint images. The capacitance reflects changes in the distance between the surfaces (Overview, 2004). The orientation certainty ranks first for the capacitive sensor since capacitive sensors are sensitive to the gradient changes of ridges and valleys.



Fig. 1. The development of fingerprint acquisition devices, (a) ink (b) optical rolling devices(c) regular camera for fingerprint scan (d) silicon-capacitive scanner (e) optical touch less scanner (f) ultra sound scanner (g) thermal sensor (h) Piezo-electric material for pressure sensor

A thermal sensor is made of some pyro-electric material that generates current based on temperature differentials between ridges and valleys (Maltoni, et al.2003). The temperature differentials produce an image when the contact occurs since the thermal equilibrium is quickly reached and the pixel temperature is stabilized. However, for the sweeping thermal sensor, the equilibrium is broken as the ridges and valleys touch the sensor alternately. Some parts of the fingerprint look coarse and have poor connectivity properties.
Pressure sensor is one of the oldest ideas, because when you put your finger on something, you apply a pressure. Piezo-electric material has existed for years, but unfortunately, the sensitivity is very low. Moreover, when you add a protective coating, the resulting image is

blurred because the relief of the fingerprint is smoothed. These problems have been solved, and now some devices using pressure sensing are available. Several solutions, depending on the material, have been proposed: Conductive membrane on a CMOS silicon chip; conductive membrane on TFT, Micro-electromechanical switches on silicon chip (BMF,2011).

2.2 Individual artifact

In the processing of fingerprint acquisition, user's skin structure on the fingertip is captured. Some researches are focused on the possible impacts that skin characteristics such as moisture, oiliness, elasticity and temperature could have on the quality of fingerprint images.

2.2.1 Skin structure

For better understand the skin influence of fingerprint quality, we should know basics of our skin structure as in Fig. 2. Skin is a remarkable organ of the body, which is able to perform various vital functions. It can mould to different shapes, stretch and harden, but can also feel a delicate touch, pain, pressure, hot and cold, and is an effective communicator between the outside environment and the brain (Habif, et al.2004) .

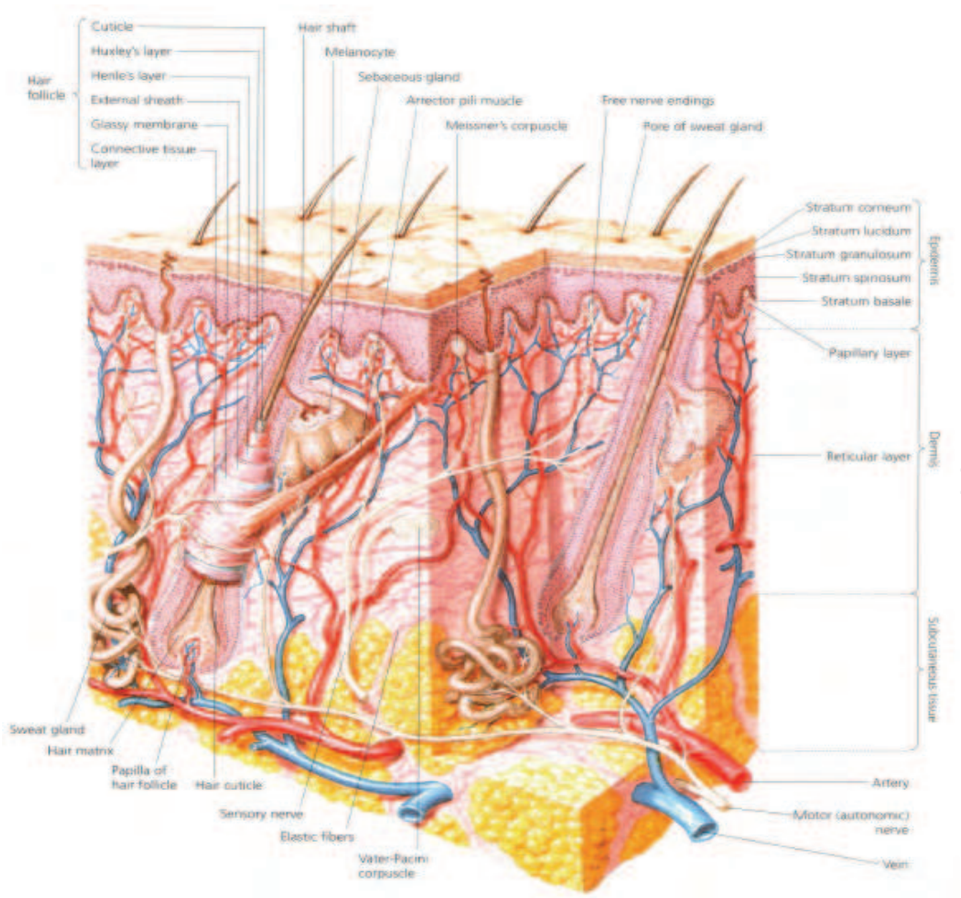


Fig. 2. Skin structure (Habif, et al.2004)

Skin is constantly being regenerated. A skin cell starts its life at the lower layer of the skin (the basal layer of the dermis), which is supplied with blood vessels and nerve endings. The cell migrates upward for about two weeks until it reaches the bottom portion of the epidermis which is the outermost skin layer. The epidermis is not supplied with blood vessels, but has nerve endings. For another 2 weeks, the cell undergoes a series of changes in the epidermis, gradually flattening out and moving toward the surface. Then it dies and is shed (Habif et al. 2004) .

2.2.2 Environmental factors and skin conditions

With fingerprint technology becoming a more widely used application, the effects of environmental factors and skin conditions play an integral role in overall image quality, such as air humidity, air temperature, skin moisture, elasticity, pressure and skin temperature, etc. If the finger is dry, the image includes too many light cells which will be marked for operator visual cue. On the other hand, the wet finger or the high pressure image includes more dark cells. The enrolment system will automatically reject the images that are not formed correctly. Fig.3. shows some examples of images representing three different quality conditions. The rows from top to bottom are captured by an optical sensor, capacitive sensor and thermal sensor. In each row, moving from left to right, the quality is bad, medium and good. Different factors affect diverse capture sensors.

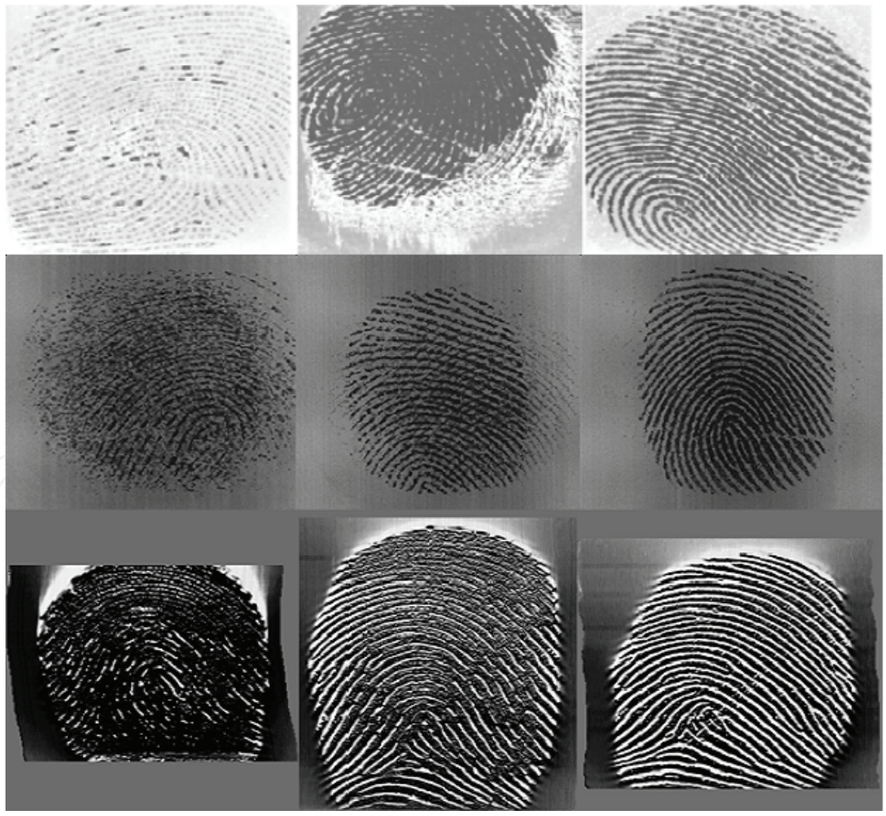


Fig. 3. Fingerprint images from different capture sensors with different environment and skin condition: (a) optical sensor, (b) Capacitive sensor and (c) Thermal sensor. (Xie,et al, 2010b)

Kang et al. (2003) researched 33 habituated cooperative subjects using optical, semi-conductor, tactile and thermal sensors throughout a year in uncontrolled environment. This study evaluates the effects that temperature and moisture have in the success of the fingerprint reader. While evaluating the fingerprints of a variety of subjects, tests determine the role of temperature and moisture in future fingerprints' applications. Each subject uses six fingers (thumb, index, and middle fingers of both hands). For each finger, the fingerprint impression is given at five levels of air temperature, three levels of pressure and skin humidity. The levels of environmental factors and skin conditions used in their experiments are listed in Table 1 (Kang, et al, 2003).

Correlation summary of the performance are conclude, for the optical sensor, it has been observed that the image quality decreases when the temperature goes below zero due to the dryness of the skin. Although all the sensors produce no major image degradation as the temperature changes, they, on the whole, give good quality images above the room temperature. This goes to the same for the air humidity. As far as the pressure is concerned, the image quality is always good with the middle level. For the optical sensor, the foreground image gets smaller for the low pressure while the fingerprint is smeared for the high pressure. The semi-conductor sensor produces good images not only with the middle pressure but also with the high pressure. It is very interesting, however, that the tactile sensor gives better images at the low pressure than at the high pressure. It is also observed that the skin humidity affects to the image quality of all the sensors except the thermal sensor which is a sweeping type. Overall, the quality of fingerprint image is more affected by the human factors such as skin humidity and pressure than the environmental factors such as air temperature and air humidity.

Factor		**State**
Environment Humidity		0~100%
Environment Temp(℃)	Below 0	Winter
	0~10	Beginning of the spring or end of the fall
	10-20	Spring or fall
	20-30	Room Temperature
	Above 30	Summer
User Pressure	High	Strongly pressing
	Middle	Normally pressing
	Low	Softly pressing
Skin Humidity	High	71~100%
	Middle	36~70%
	Low	0~35%

Table 1. Levels of Environmental factors and skin conditions used in experiments (Kang, et al. 2003)



Fig. 4. Samples of high quality fingerprints (top row) and low quality fingerprint (bottom row) with different age ranges (Blomeke, et al, 2008).

2.2.3 Age

The Biometrics assurance group stated that it is hard to obtain good quality fingerprints from people over the age of 75 due to the lack of definition in the ridges on the pads of the fingers. Purdue University has made several inquiries into the image quality of fingerprints and fingerprint recognition sensors involving elderly fingerprints. The study compared the fingerprints of an elderly population, age 62 and older, to a young population, age 18-25 on two different recognition devices: optical and capacitive. The results were affected by the age and moisture for both the image captured by the optical sensor, but age only significantly affects the capacitive sensor. Further studies are continued by (Blomeke, et al. 2008) involving the comparison of the index fingers of 190 individual 80 years old of age and older. Fig.4. demonstrates samples of high quality fingerprints (top row) and low quality fingerprint (bottom row) with different age ranges (Blomeke, et al, 2008).

2.2.4 Skin diseases

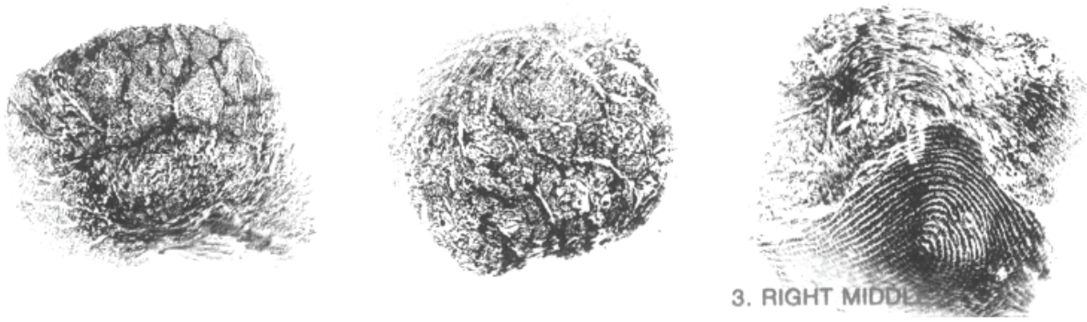
Skin diseases represent a very important, but often neglected factor of the fingerprint acquirement. It is hard to account how many people suffer form skin diseases, but there are many kinds of skin disease (Habif, et al. 2004). When considering whether the fingerprint recognition technology is a perfect solution capable to resolve the security problems, we should take care about these potential skin disease patients with very poor quality fingerprints. The researchers have collected the most common skin diseases, which are psoriais, atopic eczema, verruca vulgaris and pulpitis sicca (Drahansky, et al, 2010).

Fig.5 shows some fingerprint from patients suffering under different skin diseases, either the color of the skin or the ridge lines on the fingertip could be influenced. If only the color of the skin is changed, we can avoid the problem by eliminating the optical sensor. However, the change of skin structure is very significant; the ridge lines are almost damaged. The minutiae are impossible to find for the fingerprint recognition. Even the existed image enhancement methods are helpless to reconstruct the ridge and valley structures, and the image could not be processed further more. The image will be rejected to

the fingerprint acquisition devises and fail for the enrollment since it is really poor quality due to most of the fingerprint quality estimation methodologies. The situation is unfair to the patients; they can not use the fingerprint biometrics system.



(a) Fingerprints with atopic eczema



(b) Fingerprints with psoriasis

Fig. 5. Fingerprints from patients suffering under different skin diseases

For the temporary skin diseases, the users are able to use their fingers for the fingerprint authentication task after they have healed the diseases. However, for some skin disease, the irrecoverable finger damage may leave, such as the new growth of papillary lines which may cause the users can not to use their fingerprints appropriately. The disease fingerprint will be used for quality assessment, not only based on minutiae, but on finger shape, ridge, correlation, etc .Solutions are expected for the skin disease suffering patients.

3. Feature analysis for fingerprint quality estimation

In previous studies (Chen, et al. 2005;Lim, et al. 2004; Maltoni, et al. 2003;Shen, et al.2001; Tabassi, et al. 2004; Tabassi, et al.2005), some fingerprint quality assessments have been performed by measuring features such as ridge strength, ridge continuity, ridge directionality, ridge-valley structure or estimated verification performance. Various types of quality measures have been developed to estimate the quality of fingerprints based on these features. Existing approaches for fingerprint image quality estimation can be divided into: i) based on local features of the image; ii) based on global features of the image; and iii) based on the classifier. The local feature based methods (Maltoni, et al. 2003; Shen, et al.2001) usually divide the image into non-overlapped square blocks and extract features from each block. Methods based on global features (Chen, et al. 2005; Lim, et al. 2004) analyze the overall image and compute a global quality based on the features extracted. The method

that uses classifiers (Tabassi, et al.,2004, Tabassi, et al. 2005) defines the quality measure as a degree of separation between the match and non-match distributions of a given fingerprint.

3.1 Quality estimation measures based on local features

The local feature based quality estimation methods usually divide the image into non-overlapped square blocks and extract features from each block. Blocks are then classified into groups of different qualities. A local measure of quality is generated by the percentage of blocks classified with "good" or "bad" quality. Some methods assign a relative important weight to each block based on its distance from the centroid of the fingerprint image, since blocks near the centroid are supposed to provide more reliable and important information (Maltoni, et al. 2003). The local features which can indicate fingerprints quality are researched, such as orientation certainty, ridge frequency, ridge thickness and ridge to valley thickness ratio, local orientation, consistency, etc.

3.1.1 Orientation Certainty Level (OCL)

The orientation certainty is introduced to describe how well the orientations over a neighborhood are consistent with the dominant orientation. It measures the energy concentration along the dominant direction of ridges. It is computed as the ratio between the two eigenvalues of the covariance matrix of the gradient vector. To estimate the orientation certainty for local quality analysis, the fingerprint image is participated into non-overlapping blocks with the size of 32×32 pixels (Lim, et al.,2004; Xie, et al.,2008; Xie, et al.,2009). A second order geometry derivative, named Hessian matrix, is contributed to estimate the orientation certainty. The Hessian matrix that is constructed by H of the gradient vector for an N points image block can be expressed as in Eq. 1.

$$H = \frac{1}{N}\sum_{N}\left\{\begin{bmatrix} dx \\ dy \end{bmatrix}\begin{bmatrix} dx & dy \end{bmatrix}\right\} = \begin{bmatrix} h_{xx} & h_{xy} \\ h_{yx} & h_{yy} \end{bmatrix} \tag{1}$$

In this equation, dx and dy are the intensity gradient of each pixel calculated by Sobel operator. Two eigenvectors of H indicate the principal directions and also the directions of pure curvature that are denoted λ_a and λ_b . λ_a is the direction of the greatest curvature and λ_b denotes the direction of least curvature.

$$Orientation_certainty = 1 - \frac{\lambda_b}{\lambda_a} \tag{2}$$

The orientation certainty range is from 0 to 1. For a high certainty block, ridges and valleys are very clear with accordant orientation and, as the value decreases, the orientations change irregularly. When the value is 0, ridges and valleys in the block are changing consistently in the same direction. On the other hand, if the certainty value is 1, the ridges and valleys are not consistent at all. These blocks may belong to a background with no ridges and valleys.

3.1.2 Local Orientation Quality (LOQ)

A good quality image displays very clear local orientations. Knowing the curvature of such images with local orientations can be used to determine the core point region and invalid curvatures. Based on local orientations, LOQ is calculated by three steps (Lim, et al. 2004).

Step 1. Partition the sub-block.
Partition each sub-block into four quadrants and compute the absolute orientation differences of these four neighboring quadrants in clockwise direction. The absolute orientation difference is lightly greater than zero since the orientation flow in a block is gradually changed.
Step 2. Calculate the local orientation quality.
When the absolute orientation change is more than a certain value, in this case, 8-degrees, then the block is assumed as the invalid curvature change block. The local orientation quality of the block is determined by the sum of the four quadrants.

$$O_{mn} = \begin{cases} 0 & |ori(m) - ori(n)| \le 8^{\circ} \\ 1 & |ori(m) - ori(n)| > 8^{\circ} \end{cases} \tag{3}$$

$$loq_1(i,j) = O_{12} + O_{23} + O_{34} + O_{41} \tag{4}$$

In the equation, ori(m) denotes the orientation value of quadrant m.
Step 3. Compute the preliminary local orientation quality.
The LOQ value of an image is then computed as an average change of blocks with M×N blocks in Eq. 5.

$$LOQ_1 = \sum_{i=1}^{M}\sum_{j=1}^{N} loq_1(i,j) \tag{5}$$

3.1.3 Ridge frequency

Fingerprint ridge distance is an important intrinsic texture property of fingerprint image and also a basic parameter to determine the fingerprint enhancement task. Ridge frequency and ridge thickness are used to detect abnormal ridges that are too close or too far whereas ridge thickness and ridge-to-valley thickness ratio are used to detect ridges that are unreasonably thick or thin. Fingerprint ridge distance is defined as the distance form a given ridge to adjacent ridges. It can be measured as the distance from the centre of one ridge to the centre of another. Both the pressure and the humidity of finger will influence the ridge distance. The ridge distance of high pressure and wet finger image is narrower than the low pressure and dry finger. Since the ridge frequency is the reciprocal of ridge distance and indicates the number of ridges within a unit length, the typical spectral analysis method is applied to measure the ridge distance in the frequency field. It transforms the representation of fingerprint images from the spatial field to the frequency field and completes the ridge distance estimation in the frequency field (Yin, et.al. 2004).

3.1.4 Texture feature

Shen, et al. (2001) proposed the Gabor filter to extract the fingerprint texture information to perform the evaluation (Shen, et al. 2001). Each block is filtered using a Gabor filter with different directions. If a block has good quality (i.e., strong ridge direction), one or several filter responses are larger than the others. In bad quality blocks or background blocks, the filter responses are similar. The standard deviation of the filter responses is then used to determine the quality of each block ("good" and "bad"). A quality index of the whole image

is finally computed as the percentage of foreground blocks marked as "good." Bad quality images are additionally categorized as "smudged" or "dry". If the quality is lower than a predefined threshold, the image is rejected.

3.2 Quality estimation measures based on global feature

3.2.1 Consistency Measure (CM)

Abrupt direction changes between blocks are accumulated and mapped into a global direction score. The ridge direction changes smoothly across the whole image in case of high quality. By examining the orientation change along each horizontal row and each vertical column of the image blocks, the amount of orientation changes that disobeys the smooth trend is accumulated. It is mapped into global orientation score, which has the highest quality score of 1 and the lowest quality score of 0. This provides an efficient way to investigate whether the fingerprint image posses a valid global orientation structure or not.
The consistency measure (Lim, et al, 2004) is used to represent the overall consistency of an image as a feature. To measure the consistency, an input image is binarized with optimum threshold values obtained from the Otsu's method (Ostu, N.,1979). The consistency in a pixel position is calculated by scanning the binary image with a 3x3 window as in Eq. 6. It provides a higher value if more neighborhood pixels have the same value as that of the center pixel, representing a higher consistency. The final feature for an input image can be averaged as in Eq. 7.

$$con(i,j)=\begin{cases}0.2\cdot(9-sum(i,j))\cdot(1-c(i,j))+c(i,j) & 4<sum(i,j)\le 9\\ 0.2\cdot sum(i,j)\cdot c(i,j)+(1-c(i,j)) & 0\le sum(i,j)\le 4\end{cases} \tag{6}$$

$$Consistency=\frac{\sum_{i=2}^{255}\sum_{j=2}^{255}con(i,j)}{Num} \tag{7}$$

In these equations, *Num* = *ImageSize/NeighborSize* , *c(i,j)* represents the consistency value of a center pixel and *sum(i,j)* sums the consistency values of the 3x3 window.

3.2.2 Power spectrum

Fingerprint power spectrum is analyzed by using the 2-D Discrete Fourier Transform (DFT) (Chen, et al. 2005). For a fingerprint image, the ridge frequency values lie within a certain range. A region of interest (ROI) of the spectrum is defined as an annular region with a radius ranging between the minimum and maximum typical ridge frequency values. As the fingerprint image quality increases, the energy will be more concentrated within the ROI. The fingerprint image with good quality presents strong ring patterns in the power spectrum, while a poor quality fingerprint performs a more diffused power spectrum. The global quality index will be defined in terms of the energy concentration in this ROI. Given a digital image of size MxN, the 2-D Discrete Fourier Transformation evaluated at the spatial frequency $(\frac{2\pi t}{M},\frac{2\pi s}{N})$ is given by

$$F(t,s)=\frac{1}{NM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}f(i,j)e^{-\iota 2\pi(\frac{ti}{N}+\frac{sj}{M})},\iota=\sqrt{-1} \tag{8}$$

The global quality index defined in (Chen, et al. 2005) is a measure of the energy concentration in ring-shaped regions of the ROI. For this purpose, a set of band-pass filters is employed to extract the energy in each frequency band. High-quality images will have the energy concentrated in few bands while poor ones will have a more diffused distribution. The energy concentration is measured using the entropy.

3.2.3 Uniformity of the frequency field

The uniformity of the frequency field is accomplished by computing the standard deviation of the ridge-to-valley thickness ratio and mapping it into a global score, as large deviation indicates low image quality. The frequency field of the image is estimated at discrete points and arranged to a matrix, and the ridge frequency for each point is the inverse of the number of ridges per unit length along a hypothetical segment centered at the point and orthogonal to the local ridge orientation, which can be counted by the average number of pixels between two consecutive peaks of gray-levels along the direction normal to the local ridge orientation (Maltoni, et al. 2003).

3.3 Quality estimation measures based on classifier

Fingerprint image quality is setting as a predictor of matcher performance before a matcher algorithm is applied, which means presenting the matcher with good quality fingerprint images will result in high matcher performance, and vice versa, the matcher will perform poorly for bad quality fingerprints. Tabassi et al. uses the classifiers defines the quality measure as a degree of separation between the match and non match distributions of a given fingerprint. This can be seen as a prediction of the matcher performance. Tabassi et al. (Tabassi, et al.2004, Tabassi, et al.2005) extract the fingerprint minutiae features and then compute the quality of each extracted feature to estimate the quality of the fingerprint image into one of five levels. The similarity score of a genuine comparison corresponding to the subject, and the similarity score of an impostor comparison between subject and impostor are computed. Quality of a biometric sample is then defined as the prediction of a genuine comparison

3.4 Proposed quality estimation measures based on selected features and a classifier

Some interesting relationships between capture sensors and quality measure have been found in (Fernandez, et al.2007). Orientation Certainly Level (OCL) and Local Orientation Quality (LOQ) measures that rely on ridge strength or ridge continuity perform best in capacitive sensors, while they are the two worst quality measures for optical sensors. The gray value based measures rank first for optical sensors as they are based on light reflection properties that strictly impact the related gray level values repetitive. From the analysis of various quality measures of optical sensors, capacitive sensors and thermal sensors, Orientation Certainty, Local Orientation Quality and Consistency are selected to be participants in generating the features of the proposed system.

Quality assessment measures can be directly used to classify input fingerprints of a quality estimation system. The discrimination performance of quality measures, however, can be significantly different depending on the sensors and noise sources. Our proposed method is not only based on the basic fingerprint properties, but also on the physical properties of the various sensors. To construct a general estimation system that can be adaptable for various input conditions, we generate a set of features based on the analysis of quality measures.

Fig. 6 shows the overall block diagram of the proposed estimation system. The orientation certainty and local orientation quality measures are the two best measures for capacitive sensors; moreover, in this study, we develop highly improved features from these measures, along with the consistency measure, for images obtained from optical sensors and thermal sensors. The extracted features are then used to classify an input image into three classes, good, middle and poor quality, using the well-known support vector machine (SVM) (Suykens, et al. 2001) as the classifier.

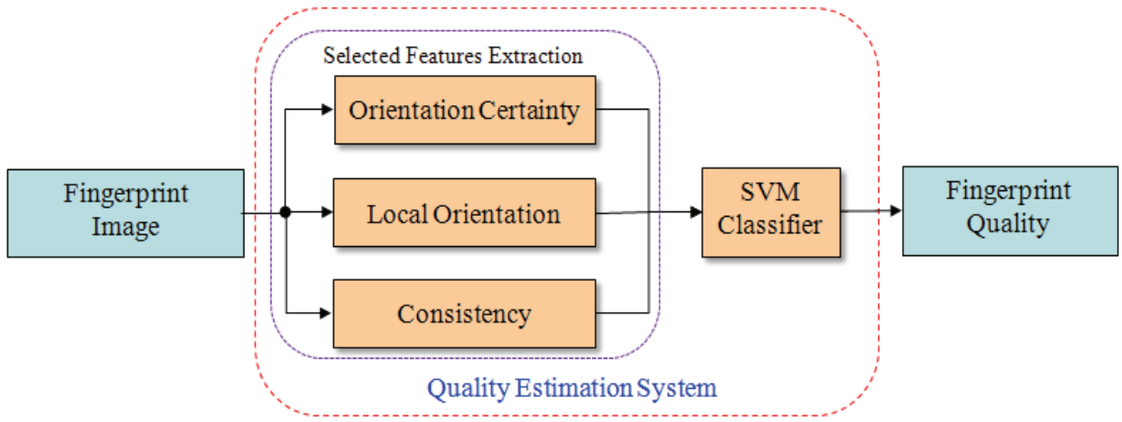


Fig. 6. Selected features and SVM classifier fused fingerprint quality estimation system (Xie et al.2010)

3.4.1 Improved orientation certainty level feature

The average of OCL values are used as features for their estimation system. To make the features more accurate, we introduce an optimization named as "Pareto efficient" or "Pareto optimal" (Xie et al. 2008; Xie et al. 2009, Obayashi et al.,2004) to define four classes of blocks and use the normalized number of blocks as a feature for each class. The Pareto optimality is a concept in economics with applications in engineering and social sciences, which uses the marginal rate of substitution to optimize the multi-objectives. To obtain features from OCL values for the proposed system, we classify blocks into four different classes, from good to very bad, as in Table 3, by selecting three optimal thresholds (x_1, x_2, x_3). Three optimal threshold values are assumed to be located in the ranges shown in Eq. 9 and selected by resolving the multi-object optimization. We define the contrast covered by each class limited by optimal thresholds and find three thresholds that maximize the three areas at the same time.

$$\begin{cases} D_1 = \int_0^{x_1} \left| gOclNum(\mathrm{x}) - bOclNum(\mathrm{x}) \right| \mathrm{dx} & 0 < x \le x_1 \\ D_2 = \int_{x_1}^{x_2} \left| gOclNum(\mathrm{x}) - bOclNum(\mathrm{x}) \right| \mathrm{dx} & x_1 < x \le x_2 \\ D_3 = \int_{x_2}^{x_3} \left| gOclNum(\mathrm{x}) - bOclNum(\mathrm{x}) \right| \mathrm{dx} & x_2 < x \le x_3 \\ D_4 = \int_{x_3}^{1} \left| gOclNum(\mathrm{x}) - bOclNum(\mathrm{x}) \right| \mathrm{dx} & x_3 < x \le 1 \end{cases} \tag{9}$$

In this equation, *gOclNum(x)/bOclNum(x)* represents the number of blocks when the OCL value equals x from the good/bad-quality image. *Di* represents the contrast of a level

between good and bad quality. Obviously, if the contrast becomes larger, then it becomes easier to classify with a higher classification rate. As in Table 2, we define four classes of blocks according to their OCL values. Four OCL features of the estimation system are then defined as the normalized amount of blocks for each class. Fig. 7 shows the distribution of four features for the optical sensor in FVC2004 database. We can infer an obvious tendency that good quality images have larger values of OCL feature 1 and smaller values of OCL feature 4, and bad quality images are on the contrary.

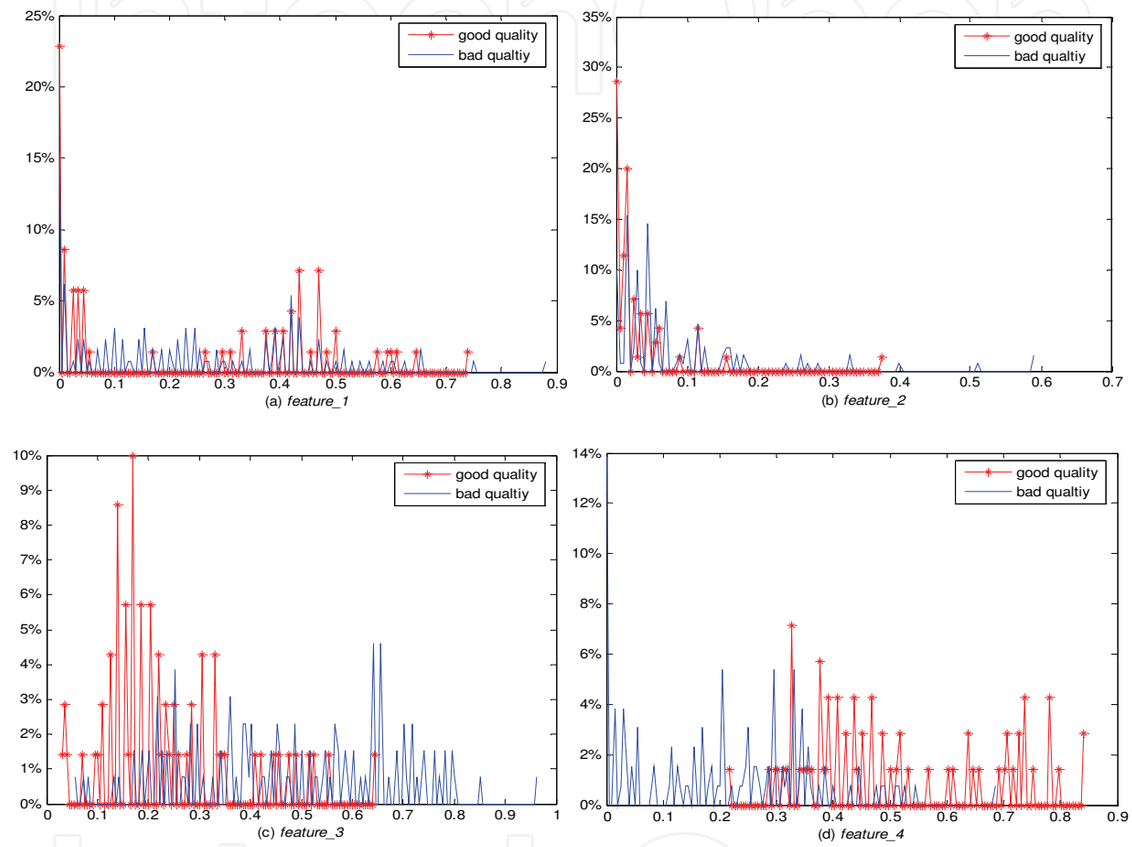


Fig. 7. The distribution of four optical sensor features (Xie,2010)

Classify grade	Grade
0<OCL≤0.2	Good quality block
0.2<OCL≤0.6	Normal quality block
0.6<OCL<1	Poor quality block
OCL=1	Very poor quality block or background

Table 2. Four classes of blocks according to their OCL values

3.4.2 Improved local orientation quality feature

For the thermal sensor, the equilibrium is broken as the ridges and valleys touch the sensor alternately and affected by the environment temperature, sometimes the fingerprint is

coarse. Different from the poor quality image from optical and capacitive sensors, the poor thermal sensor image still has good orientation, and the ridge and valley still separate clearly. However, the consistency of the poor part obviously performs worse than the good quality one. Due to the residue from previous data acquisition or low pressure against the sensor surface, a bad quality image often carries broken ridges or valley regions; however, in a good quality image, ridges or valley regions are fairly consistent. This preliminary local orientation quality of the fingerprint may include some false positives due to the light reflection properties of optical sensors and the orientation calculation based on gray-level values. To compute the new local orientation quality of the quadrants for supplementing the artifact, we design additional steps as below. Based on the previous LOQ method, we label these block quadrants whose orientation change is more than 8 degrees. Fig.8. shows the basic concept of the improved LOQ feature. We can find the block orientation changes only in two directions: horizontal and vertical. A special label is set for each detected quadrant to avoid repeating detection. The amount of new invalid curvature blocks are set as $loq_2(i, j)$. Then, we can get LOQ_2 by the sum of the $loq_2(i, j)$of unrepeated detection quadrants (i, j).

$$loq_2(i,j) = (O_{25} + O_{16}) \cdot Horizontal + (O_{17} + O_{48}) \cdot Vertical \tag{10}$$

$$LOQ_1 = \sum_{i=1}^{M} \sum_{j=1}^{N} loq_2(i,j) \tag{11}$$

If there is orientation change in horizontal, then *Horizontal*=1, otherwise, *Horizontal*=0. *Vertical* is same as *Horizontal*. Therefore, the uniform value of *Improved LOQ* is shown as follows:

$$\text{Im}\,proved \quad LOQ = \frac{LOQ_1 + LOQ_2}{4 \times (BlockNum - Num(OCL = 1))} \tag{12}$$

Where, *BlockNum=Imagesize/Blocksize* and *Num(Ocl=1)* expresses the amount of background blocks among each sub-block partitioned into four quadrants.

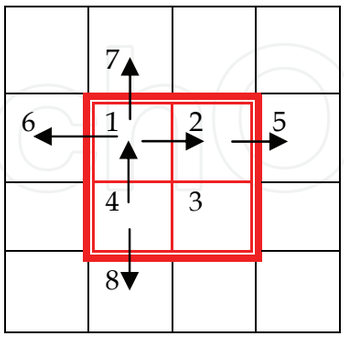


Fig. 8. The basic concept of the improved LOQ feature

3.4.3 SVM (Support Vector Machine) classifier

The SVM is a powerful classifier with an excellent generalization capability that provides a linear separation in an augmented space by means of different kernels (Suykens, et al, 2001). Each instance in the training set contains one target value (fingerprint quality level or score)

and several attributes (extracted features). The four basic kernels are linear, polynomial, radial basis function (RBF) and sigmoid. The kernels map input data vectors onto a high-dimensional space where a linear separation is more likely, and this process amounts to finding a non-linear frontier in the original input space. In the case, the RBF kernel is employed since it nonlinearly maps samples into a higher dimensional space, so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear (Keerthi. and Lin, 2003). For the proposed quality estimation system, each input vector includes five features as in Eq. 12.

$$V = [OCL1, OCL2, OCL3, Consistency, Improved\ LOQ] \quad (13)$$

OCL1, OCL2 and *OCL3* are three independent features chosen from four features related to the OCL measure, representing the normalized amounts of blocks for each grade. *Consistency* stands for the overall consistency, and *Improved LOQ* is the average LOQ computed from the number of blocks with invalid direction changes.

4. Quality estimation performance evaluation

4.1 Datasets

Three public Fingerprint Verification Competition (FVC) databases (FVC2000, FVC2002, FVC2004) are employed to evaluate the performance of the proposed quality estimation system. Several sets of fingerprints from various sensors are included. Table 3 shows the sensor information of fingerprint databases. There are 80 images in each Set_B database and 800 images in Set_A database. Since the proposed quality estimation system is based on the local feature, each image is divided into 64 blocks with the size of 32×32 pixels. Although the types of sensor are adopted in the database, the basis acquisition physical principle is the same for all optical, capacitive and thermal sensors.

	Optical sensor	Capacitive sensor	Thermal sensor
FVC2000	DB1_B, DB3_B	DB2_B	-
FVC2002	DB1_A,DB2_A	DB3_A	-
FVC2004	DB1_A,DB2_A	-	DB3_A

Table 3. Three public databases employed to evaluate the performance.

4.2 Quality benchmark

The NFIS method (Tabassi, E.,2004; Tabassi, E.,2005) is the most widely used method and typical classifier-based methods for fingerprint quality estimation. The method proposed the assumption that fingerprint quality is a predictor of matcher performance. A good quality image will result in a high matcher performance, while a bad quality image will be easily rejected. We relabel the NFIS quality from five levels into three levels, which level 1 is belong to the Good class, level 2-3 is belong to the Medium class and level 4-5 is the Bad class. Fig.9 shows the quality distribution of FVC2002 and FVC2004 by the relabeled NFIS method. As shown in Fig. 9, there are the most Good quality fingerprints in the database FVC2004_DB3 captured by thermal sensors, while the FVC2002_DB3 database captured by the capacitive sensor includes the least Good quality fingerprints. Each fingerprint assigned to a class according to the NFIS quality reclassified to three classes is used to verify the proposed method.

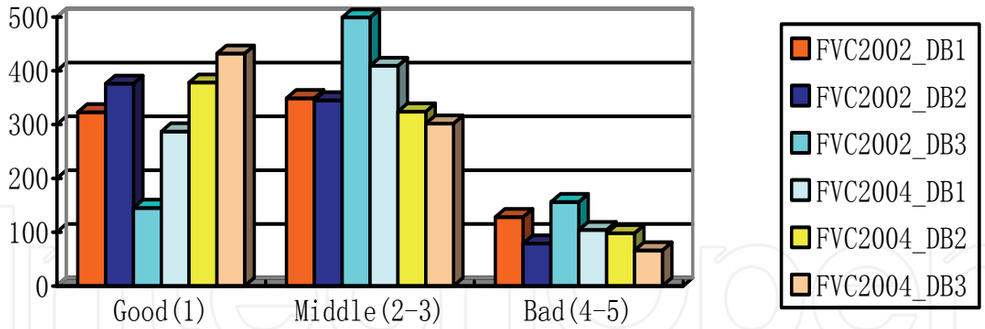


Fig. 9. Quality distribution of the databases regrouped from NFIS with five classes with level1 to level5 into three classes with 'Good', 'Middle', and 'Bad'.

4.3 Quality estimation performance

In the evaluation, the 10% Jackknife procedure is employed by using 90% of the images for training and 10% for testing, respectively. Four different kernels, linear, polynomial, RBF and sigmoid, are implemented for the SVM classifier to investigate the performance with different classifier conditions.

Table 4 shows the classification accuracy rate of the original OCL, CM, LOQ measures and their improved versions when they are used separately as a single quality measure. And they are the result of the simulation where the SVM classifier uses the RBF kernel which shows the better result than other kernels. In comparison with the original average OCL measure, the proposed OCL measure achieves better results for adding the optimal determining system which detects not only the local orientation stabilities but also the global ones. Moreover, for the LOQ measure, accuracy is increased after adding the further orientation step.

	Original Measures			Improved Measures		
	OCL	CM	LOQ	OCL	CM	LOQ
Optical	80.05%	81.68%	77.86%	87.50%	81.99%	81.86%
Capacitive	83.18%	74.62%	87.79%	90.56%	81.61%	89.10%
Thermal	78.84%	77.90%	78.72%	81.96%	89.42%	83.04%

Table 4. Comparison of the accuracy rate of measures when they are used alone for the quality estimation.

OCL, CM and LOQ feature represent different characteristic of the fingerprint. OCL feature measures the orientation stability of the ridge. CM feature implicates the ridge connection and can detect the small noise, while the LOQ feature performs the irregular direction change of ridges. From Table 5, we can find that the classification performance is improved by combining the local measures. These different measures can make up for each other and get better results. The accuracy rate of the proposed combined measure is 95.62%, 95.50%, 96.25% for the optical, capacitive and thermal sensor, respectively. Comparing with the NFIS method, our proposed method reaches the high accuracy with fewer features. In

addition, the local features fused method reduces much computation complexity than the NFIS method, since it needn't to detect fingerprint minutiae before the quality estimation.

	OCL+CM	CM+LOQ	LOQ+OCL	LOQ+OCL+ CM
Optical	92.62%	91.25%	91.00%	95.62%
Capacitive	93.25%	91.88%	92.38%	95.50%
Thermal	94.00%	93.95%	86.14%	96.25%

Table 5. Comparison of the accuracy rate of measures according to their combinations when they are used together for the quality estimation.

As residue fingerprints appear frequently in the database from the optical sensors, the problem that residue images are considered as fingerprints with the best quality cannot be ignored. In the database FVC2004 DB1_A and FVC2004 DB2_A, there are about 82 images of obvious residue. We estimate the image quality both by our proposed method and the Classifier-based method. The comparative results are shown in the Table 6. The error rate of our proposed method is 3.65%, while the error rate of Classifier based method is 12.20%. The Classifier based method mistakes the prior image as the minutiae of the remained fingerprint. The proposed system, however, can avoid this kind of residue mistaken error via the global orientation certainty.

		Fused method			Classifier-based method		
		Good	Medium	Bad	Good (1)	Medium (2-3)	Bad (4-5)
Subjective Quality	Good	44	1	0	43	2	0
	Medium	2	21	0	4	19	0
	Bad	0	0	14	2	2	10

Table 6. Comparison of the proposed fused method to the classifier-based method on the estimation results from residue images

5. Conclusions and further work

In this chapter, we analyzed how the fingerprint acquisition device and individual artifacts can influence the fingerprint quality. The acquisition device developers as well as the users require objective and quantitative knowledge to get a high quality image for the fingerprint authentication. The purpose of the study is to propose the process of the image acquisition device performance evaluation under several kinds of sensors and environments. Since fingerprints have different characteristics according to the sensor technologies, the selection of features for fingerprint quality measurements is closely related to the sensors. The reprehensive quality estimation methods are reviewed including the methods based on local features of the image; methods based on global features of the image and methods based on the classifier. In order to perform well for all kinds of sensors, an effective fingerprint quality estimation method for three kinds of sensors optical, capacitive, and thermal sensors is proposed. Three improved features, OCL, CM and LOQ, are commonly used in the fingerprint estimation. The effective of using these features is verified the improvements through the simulation individually.

To improve matching performance, image processing for enhancement is essential. The quality estimation method can used for evaluate the enchantment performance. Some effective enhancement methods are proposed including a three-step using the locally normalized input images, computes the local ridge orientation and then applies a local ridge compensation filter with a rotated window to enhance the ridges by matching the local ridge orientation (Chikkerur et al. 2007; Fronthaler et al.2008; Hong et al.1998; Yang,et al. 2008c; Yang, 2011a; Yang, 2011b). However, there are five major fingerprint matching techniques: minutiae-based, ridge-based, orientation-based, texture-based and 3rd feature based matching techniques (Liu,et al.,2000; Yang,et al.2008a; Yang,et al. 2008b; Yang, 2011b). The major matching algorithms have their own proclivities of fingerprint images, and use them to verify that the presented fingerprint quality estimation approach is effective to support these matching systems appropriately. Different images are expected for the several of fingerprint matching system. Image quality is used to determine whether the captured image is acceptable for further use within the biometric system. Until now the quality estimation only based on the level 1 and level 2 features, in other words, the present quality estimation method only pay attention to the global ridge pattern and the minutiae. However, human examiners perform not only quantitative (Level 2) but also qualitative (Level 3) examination since Level 3 features are also permanent, immutable and unique (Xie,2010a; Zhao et al. ,2008). New quality estimation for the level 3 feature is expected for adopting the Level 3 based matching system.

Moreover future works include evaluation of anti-spoofing capabilities of the fingerprint readers and comparison of fingerprint image qualities with varies age. Also, skin diseases represent a very important, but often neglected factor of the fingerprint acquirement. Problems with biometrics that still lack understanding include recognition of biometric patterns with high accuracy and efficiency, assurance of infeasibility of fraudulence (Jain et al., 2004) and exploration of new features with existing biometrics and novel types of biometrics. A fingerprint recognition algorithm will be required over the fingerprint images of different levels of the quality to produce the matching score.

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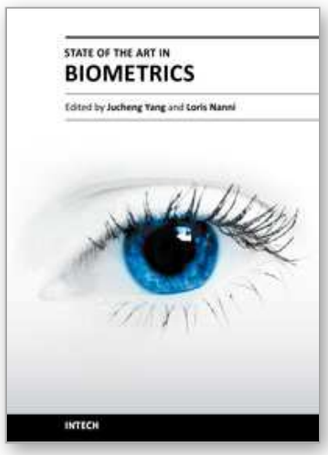
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Biometric recognition is one of the most widely studied problems in computer science. The use of biometrics techniques, such as face, fingerprints, iris and ears is a solution for obtaining a secure personal identification. However, the â€œoldâ€ biometrics identification techniques are out of date. This goal of this book is to provide the reader with the most up to date research performed in biometric recognition and descript some novel methods of biometrics, emphasis on the state of the art skills. The book consists of 15 chapters, each focusing on a most up to date issue. The chapters are divided into five sections- fingerprint recognition, face recognition, iris recognition, other biometrics and biometrics security. The book was reviewed by editors Dr. Jucheng Yang and Dr. Loris Nanni. We deeply appreciate the efforts of our guest editors: Dr. Girija Chetty, Dr. Norman Poh, Dr. Jianjiang Feng, Dr. Dongsun Park and Dr. Sook Yoon, as well as a number of anonymous reviewers

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