# Fingerprint Image Quality Classification Based on Feature Extraction

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***Abstract*— Fingerprint recognition technology has been widely used in criminal investigation, attendance system, security testing and other fields and has become one of the most mature biometric technologies. Since fingerprint image quality affects heavily the performance of fingerprint recognition system, accurate evaluation of fingerprint image quality has great value in improving the performance of automatic fingerprint identification system and applicability of fingerprint recognition algorithms. In this paper, we mainly investigate fingerprint image quality classification approaches based on feature extraction. We extract six groups of quality features including frequency domain features and spatial domain features, and respectively use methods such as individual quality feature parameter, linear weighted sum, wavelet domain energy, K-means clustering, Support Vector Machine and BP neural network to classify fingerprint images into three types of high quality, medium quality and low quality images. Experimental results indicate that classification accuracy of the method combining six groups of quality feature vector with BP neural network is higher than other methods.**

## I. INTRODUCTION

Fingerprint recognition technology which is widely used in criminal investigation, attendance system, security testing and other fields is one of the most mature biometric technologies[1]. Fingerprint image quality directly affects the performance of automatic fingerprint identification system, and there are many factors which cause decline in fingerprint image quality, such as stains, fingerprints damage, degrees of dryness or wetness. Some of these factors are irresistible, so it is important to evaluate the captured fingerprints quality for improving the performance of automatic fingerprint identification system.

At present, researches on fingerprint image quality are progressing very quickly, and existing approaches for fingerprint image quality estimation can be summarized into the following three categories.

1. Methods based on frequency domain features usually depend on frequency domain features extracted to analyze image quality. Zia[2] evaluated the overall quality of fingerprint image by computing and analyzing Fourier spectrum; Hong[3] and Shen[4] used Gabor filter to obtain the clarity of ridges which is defined as quality block mark;

2. Methods based on spatial domain features compute a measure of image quality based on the features extracted on the spatial domain. Xie[5] extracted the local features from fingerprint images based on Optimized Orientation Certainty Level as quality measurements;

3. Classifier method considers fingerprint image quality as a classification problem to deal with. Tabassi[6] evaluated fingerprint image quality based on classifier by computing the quality and separating degree of each minutiae point extracted from fingerprint images, and used neural network for learning and classification.

In this paper, we extracted six groups of features including frequency domain features and spatial domain features, and respectively used methods such as individual quality feature, linear weighted sum, wavelet domain energy, K-means clustering, Support Vector Machine and BP neural network to classify fingerprint images into three types of high quality, medium quality and low quality.

## II. QUALITY FEATURES EXTRACTION

In this research, a variety of quality features are extracted to evaluate fingerprint image quality. Since different feature parameters can reflect fingerprint image quality in various aspects, we respectively extract two frequency domain features including energy concentration and Gabor feature, as well as four spatial domain features including global orientation change, effective area, spatial coherence and directional contrast to evaluate fingerprint image quality in this paper.

### A. *Energy Concentration*

The two-dimensional Discrete Fourier Transformation ($DFT$) of a fingerprint image $I(i,j)$ of size $M \times N$ is given by

$$F(k,l) = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} I(i,j) e^{-\iota 2\pi (\frac{ki}{N} + \frac{lj}{M})} \quad (1)$$

Although $DFT$ produces a complex-valued output, only the power spectrum $P(k,l) = |F(k,l)|^2$ is often used as it contains most of the geometric structure of an image[7]. The power spectrum is defined as an annular band with radius from ridges minimum frequency to ridges maximum frequency. The better fingerprint image quality is, the more concentrated its energy distribution is.

We use a set of Butterworth low-pass filters to extract the energy from power spectrum of fingerprint images. The Butterworth filter function is defined as follow

$$m_t = 0.06 + t\frac{0.5-0.06}{T}, \quad t = 0,1,2\ldots T-1 \tag{2}$$

$$H(k,l \mid m,n) = \frac{1}{1+\frac{1}{m^{2n}}((\frac{k-a}{M})^2+(\frac{l-b}{N})^2)^n} \tag{3}$$

$(k,l)$ is the pixel index in the power spectrum and $(a,b)$ is the location of the center of the power spectrum. The Butterworth function generates a set of low-pass filters with the cutoff frequency given by $m$ and the filter order given by $n$.

We can get a total of $T$ equally spaced band pass filters $R_t$ by taking two consecutive Butterworth functions, and energy concentration in the $t-th$ band is computed by

$$E_t = \sum_{k=0}^{N-1}\sum_{l=0}^{M-1} R_t(k,l)P(k,l) \tag{4}$$

Energy concentration in the $t-th$ band is normalized as follows

$$P_t = \frac{E_t}{\sum_0^{T-1} E_t} \tag{5}$$

The entropy of energy concentration is defined as

$$E = -\sum_{t=0}^{T-1} P_t \log P_t \tag{6}$$

Finally, energy concentration score is computed by

$$Q_1 = \log T - E \tag{7}$$

## B. Gabor Feature

A fingerprint image $I(i,j)$ is divided into a set of non-overlapping blocks of size $16\times 16$ and we construct $m$ Gabor filters which is described as follows

$$x_{\theta_k} = x\cos\theta_k + y\sin\theta_k \tag{8}$$

$$y_{\theta_k} = -x\sin\theta_k + y\cos\theta_k \tag{9}$$

$$h(x,y,\theta_k,\sigma_x,\sigma_y) = \exp[-\frac{1}{2}(\frac{x_{\theta_k}^2}{\sigma_x^2}+\frac{y_{\theta_k}^2}{\sigma_y^2})]\times\exp(i2\pi f\theta_k) \tag{10}$$

$$k=1,\ldots m$$

where $f$ is sine wave frequency, $\theta_k$ is the direction of the $k-th$ Gabor filter , $\sigma_x$ and $\sigma_y$ are standard deviation of Gaussian envelope along x-axis and y-axis.

We use these $m$ Gabor filters to filter each sub-block, and the Gabor feature of sampling point $(X,Y)$ is given by

$$\theta_k = \frac{\pi(k-1)}{m} \tag{11}$$

$$g(X,Y,\theta_k,f,\sigma_x,\sigma_y) = \left|\sum_{x=-\frac{w}{2}}^{\frac{w}{2}-1}\sum_{y=-\frac{w}{2}}^{\frac{w}{2}-1} I(X+x,Y+y)h(X,Y,\theta_k,f,\sigma_x,\sigma_y)\right| \tag{12}$$

$$k=1,\ldots m$$

So the standard deviation of each sub-block Gabor feature is defined as follows

$$G = \left(\frac{1}{m}\sum_{k=1}^{m}(g_{\theta_k}-\overline{g_{\theta_k}})^2\right)^{\frac{1}{2}}, \quad \overline{g_{\theta_k}} = \frac{1}{m}\sum_{k=1}^{m} g_{\theta_k} \tag{13}$$

If the standard deviation of one sub-block Gabor feature is lower than the threshold $T_q$ which is obtained from the experiments, this sub-block is marked as low quality block, otherwise it is marked as high quality block. So we can get the number of high quality blocks $N_{good}$ and the number of low quality blocks $N_{poor}$, and the score of a fingerprint image based on Gabor feature is given by

$$Q_2 = \frac{N_{good}}{N_{good}+N_{poor}} \tag{14}$$

## C. Global Orientation Change

It is obvious that there are smooth changes in the orientation of high quality fingerprint image and abrupt changes in the orientation of low quality fingerprint image[8]. According to this characteristic, we use global orientation change to evaluate fingerprint image quality. Firstly, a fingerprint image $I$ is divided into a total of $N$ non-overlapping blocks of size $16\times 16$, and then we calcuate the direction of each sub-block as follows

$$V_x(i.j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2\partial_x(u,v)\partial_y(u,v) \tag{15}$$

$$V_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} (\partial_x^2(u,v)-\partial_y^2(u,v)) \tag{16}$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{V_y(i,j)}{V_x(i,j)}\right) \tag{17}$$

$\partial_x(u,v)$ and $\partial_y(u,v)$ are gradient of pixel within sub-block $(i,j)$ along the horizontal and vertical direction respectively and $\theta(i,j)$ is the direction of sub-block $(i,j)$. Using this method, we can obtain the direction of each sub-block. We can compute orientation change of neighborhood of size $3\times 3$ centered at sub-block $(i,j)$ as follows

$$\Delta\theta(i,j) = \sum_{m=-1}^{1}\sum_{n=-1}^{1}\left|\theta(i,j)-\theta(i+m,j+n)\right| \tag{18}$$

So orientation change of the whole fingerprint image is defined by

$$Q_3 = \sum_{k=1}^{N} \Delta\theta_k \tag{19}$$

### D. Effective Area

A fingerprint image $I(i,j)$ is divided into non-overlapping blocks of size $9\times 9$, and then we can calculate average gray value $Mean$ of the whole image and average gray value $Mean(u,v)$ of sub-block $(u,v)$ as follows

$$Mean = \frac{1}{M*N} \sum_{i=1}^{M} \sum_{j=1}^{N} I(i,j) \tag{20}$$

$$Mean(u,v) = \frac{1}{w\times w} \sum_{i=(u-1)\times w-\frac{w}{2}}^{(u-1)\times w+\frac{w}{2}} \sum_{j=(v-1)\times w-\frac{w}{2}}^{(v-1)\times w+\frac{w}{2}} I(i,j) \tag{21}$$

We can determine whether one sub-block is foreground block or not according to the following rules

$$\begin{cases} B(u,v)=0, & if \quad Mean(u,v)\ge Mean \\ B(u,v)=1, & if \quad Mean(u,v)<Mean \end{cases} \tag{22}$$

$B(u,v)=1$ suggests sub-block $(u,v)$ is a foreground block, otherwise it suggests sub-block $(u,v)$ is a background block. In order to reduce the probability of misclassification, we use the following corrective method[9].

$$\begin{cases} B(u,v)=1 & if \quad \sum_{m=u-1}^{u+1} \sum_{n=v-1}^{v+1} B(m,n)\ge 6 \\ B(u,v)=0 & if \quad \sum_{m=u-1}^{u+1} \sum_{n=v-1}^{v+1} B(m,n)< 6 \end{cases} \tag{23}$$

By above method, we could determine accurately whether one sub-block is foreground or not, and compute the number of foreground blocks $N_{foreground}$ and the number of background blocks $N_{background}$. Finally, effective area is defined by

$$Q_4 = \frac{N_{foreground}}{N_{foreground}+N_{background}} \tag{24}$$

### E. Spatial Coherence

A fingerprint image $I(i,j)$ is divided into a set of non-overlapping blocks of size $9\times 9$. The gradient of the gray level intensity at the pixel in block $B$ is defined as $g_s = (g_s^x, g_s^y)^T$. The covariance matrix of the gradient vectors for all pixels in this block is given by

$$J = \frac{1}{w^2} \sum_{s\in B} g_s g_s^T = \begin{bmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{bmatrix} \tag{25}$$

The eigenvalues of the above matrix are given by

$$\lambda_1 = \frac{1}{2}(trace(J) + \sqrt{trace^2(J) - 4\det(J)}) \tag{26}$$

$$\lambda_2 = \frac{1}{2}(trace(J) - \sqrt{trace^2(J) - 4\det(J)}) \tag{27}$$

$trace(J) = j_{11} + j_{22}$, $\det(J) = j_{11}j_{22} - j_{12}^2$. The normalized coherence measure is given by

$$\tilde{k} = \frac{(\lambda_1-\lambda_2)^2}{(\lambda_1+\lambda_2)^2} = \frac{(j_{11}-j_{22})^2+4j_{12}^2}{(j_{11}+j_{22})^2} \tag{28}$$

Once we obtain the spatial coherence of each block in this way, the spatial coherence score can be defined as follows

$$Q_5 = \frac{1}{r}\sum_{i=1}^{r} w_i \tilde{k}_i \ , \quad \omega_i = \exp\left\{ -\frac{\|l_i - l_c\|^2}{2q} \right\} \tag{29}$$

$r$ is the number of foreground blocks, and $w_i$ is the relative weight for the $i\text{–}th$ block.

### F. Directional Contrast

The ridges of high quality fingerprint image are clear and have higher contrast. Whereas, the ridges of low quality fingerprint image are indistinct and have lower contrast[10]. Based on this characteristic, directional contrast is applied to evaluate fingerprint image quality.

A fingerprint image $I(i,j)$ is divided into a total of $N$ non-overlapping blocks of size $8\times 8$. We process all pixels in each block with eight directions filter.Using eight directions filter, we can compute the gray-scale sum value in each direction of the $5\times 5$ neighborhood centered at each pixel in block $B$ which is described as follows

$$S_i(x,y) = \sum_{j=1}^{2} I(P_{ij}), \quad i=1,2,\cdots 8 \tag{30}$$

after sliding the filter over block $B$, the eight directions gray-scale value sum of block $B$ can be obtained by

$$\theta_i = \sum_{x=1}^{8} \sum_{y=1}^{8} S_i(x,y), \quad i=1,2,\cdots 8 \tag{31}$$

and the directional contrast of block $B$ is computed by

$$D_k = \left|\theta_{\max} - \theta'\right|_k, \quad k=1,2\cdots N \tag{32}$$

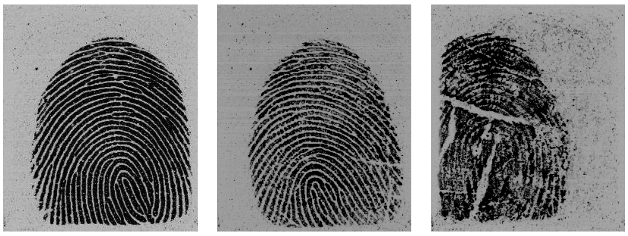
where $\theta_{\max}$ is the maximum gray-scale value sum in eight directions of block $B$ and the direction of $\theta'$ is in a direction perpendicular to the direction of $\theta_{\max}$. So we can compute the direction contrast of each block in this way and the direction contrast score is defined as

$$Q_6 = \frac{1}{C}\sum_{k=1}^{N} D_k \tag{33}$$

These six extracted quality feature parameters are then normalized to values between zero and one so that it is easier to deal with in subsequent procedures.

## III. THE SIMULATION RESULTS AND ANALYSIS

We chose three hundred and five captured fingerprint images to set up fingerprint database, which consists of one hundred high quality images, one hundred and fifteen medium quality images and ninety low quality images. The quality category of these fingerprint images are mainly depended on the human's subjective judgment. Different quality fingerprint images are shown in Fig. 1.



(a) high quality image (b) medium quality image (c) low quality image

Fig. 1 Different quality fingerprint images.

The experimental steps are introduced as follows

1. We extracted six groups of quality features including energy concentration, Gabor feature, global orientation change, effective area, spatial coherence and directional contrast from three hundred and five fingerprint images, from which we could obtain feature matrix consisting of these six groups of quality features;

2. For each group of quality features, we calculated classification accuracy on fingerprint images of different quality categories and total classification accuracy based on minimum error criterion;

3. A set of linear weighted sum from these six groups of quality features can be described as follows

$$Q_{sum} = \sum_{i=1}^{6} Q_i \tag{34}$$

and then calculate classification accuracy of different quality fingerprint images and total classification accuracy based on minimum error criterion;

4. We set up gathering center of six quality features and used the feature matrix as input of K-means clustering method. Then we could obtain classification accuracy of different quality fingerprint images and total classification accuracy;

5. We selected fifty high quality fingerprint images, sixty medium quality fingerprint images and forty and five low quality fingerprint images as svm training set, and remaining images were used as svm testing set. Besides, we used six groups of features extracted from these images as svm input and used quality categories of these images as sample labels, and then trained svm classifier with the training set. Finally, testing set was used on the trained svm in order to obtain classification accuracy of different quality fingerprint images and total classification accuracy;

6. We selected fifty high quality fingerprint images, sixty medium quality fingerprint images and forty and five low quality fingerprint images as BP neural network training set, and remaining images were used as BP neural network testing set. Besides, we used six groups of features extracted from these images and quality category as BP neural network input, and then trained BP neural network with the training set. Finally, testing set was used on the trained BP neural network in order to obtain classification accuracy of different quality fingerprint images and total classification accuracy.

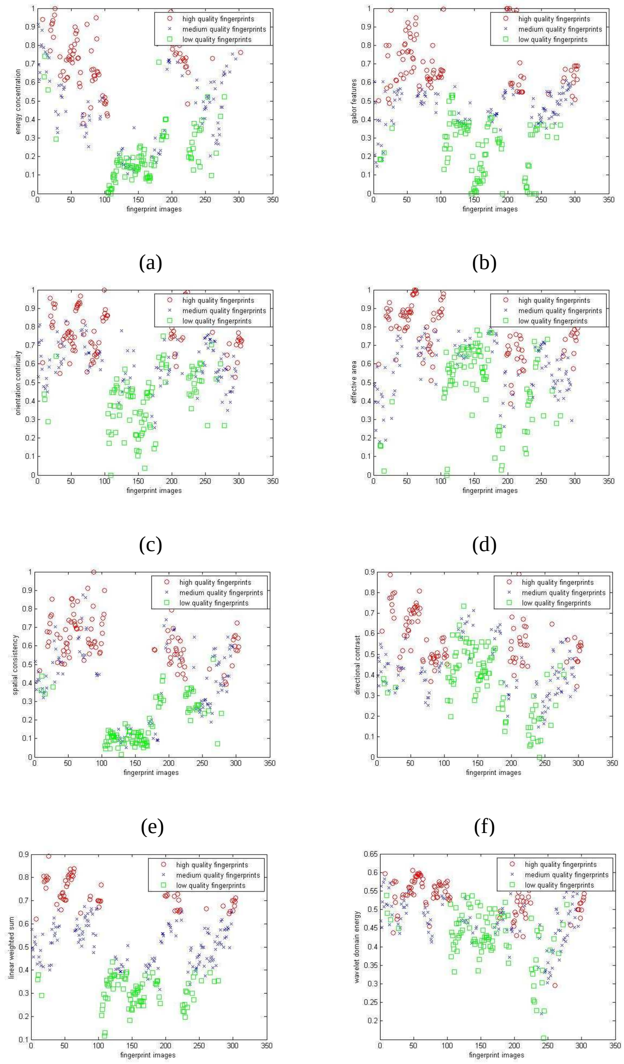
7. Each fingerprint image was decomposed into one low frequency subband and eighteen high frequency subbands using wavelet transform. We compute the cumulative total energy in the subbands 1-18 as follows

$$CTE_k = \sum_{i=1}^{k} energy_i \tag{35}$$

And we could get the overall quality of the image as follows

$$Quality = \frac{CTE_{18} - CTE_4}{CTE_{18}} \tag{36}$$

We could respectively get the quality distribution maps of energy concentration, Gabor feature, global orientation change, effective area, spatial coherence, directional contrast, linear weighted sum and wavelet domain energy as shown in Fig. 2.




(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 2 The quality distribution maps of six individual quality features, linear weighted sum and wavelet domain energy: (a) the quality distribution map of energy concentration; (b) the quality distribution map of Gabor feature; (c) the quality distribution map of global orientation change; (d) the quality distribution map of effective area; (e) the quality distribution map of spatial coherence; (e) the quality distribution map of directional contrast; (g) the quality distribution map of linear weighted sum; (h) the quality distribution map of wavelet domain energy.

The results in table I are classification accuracy on fingerprint images of different quality categories and total classification accuracy with different methods, such as individual quality feature parameter, linear weighted sum, wavelet domain energy(WDG), K-means clustering, Support Vector Machine and BP neural network.

TABLE I
CLASSIFICATION ACCURACY ON FINGERPRINT IMAGES OF DIFFERENT QUALITY CATEGORIES AND TOTAL CLASSIFICATION ACCURACY WITH DIFFERENT METHODS

| Method | High | Medium | Low | Total |
|---|---|---|---|---|
| Q1 | 85.86% | 59.65% | 41.11% | 62.71% |
| Q2 | 86.87% | 82.46% | 80.00% | 83.17% |
| Q3 | 78.79 | 62.28% | 61.11% | 67.33% |
| Q4 | 54.55% | 87.72% | 18.89% | 56.44% |
| Q5 | 77.53% | 61.40% | 56.67% | 65.68% |
| Q6 | 91.92% | 57.02% | 26.67% | 59.41% |
| Qsum | 92.93% | 86.84% | 85.56% | 88.45% |
| WDG | 76.77% | 55.26% | 41.11% | 58.22% |
| K-means | 91.11% | 85.22% | 97.96% | 91.09% |
| SVM | 94.72% | 72.18% | 95.36% | 90.06% |
| BP | 93.88% | 96.49% | 97.78% | 96.03% |

Comparing with individual quality feature classification method, quality classification accuracy of methods based on multi-features is higher. This is because the factors causing differences of fingerprint image quality are so many, yet individual quality feature could only reflect fingerprint quality in one way and multi-features could reflcet quality in a wide range. Wavelet domain energy is rough for assessing the quality of fingerprint image, and the method makes some misclassifications on fingerprint quality categories comparing with classification threshold which is determined based on minimum error decision rule. Comparing with linear weighted sum method, quality classification accuracy of K-means clustering, Support Vector Machine and BP neural network method is higher. It is because the inherent relationship between multi-features and fingerprint image quality is not a linear correlation, and these three methods could build a better nonlinear relationship with fingerprint quality. Quality classification accuracy of the method combining multi-features and BP neural network reaches 96.03%, which is the highest among these three methods

## IV. CONCLUSIONS

In this paper, we mainly investigate fingerprint image quality classification methods based on feature extraction algorithms. We extract six groups of quality features including a variety of frequency domain features and spatial domain features, and respectively use methods such as individual quality feature, linear weighted sum, wavelet domain energy, K-means clustering, Support Vector Machine and BP neural network to classify fingerprint images into three types of high quality, medium quality and low quality. Experimental results demonstrate that quality classification accuracy of the approaches based on multi-features is higher than individual quality feature and wavelet domain energy classification method, and the quality classification accuracy of K-means clustering, Support Vector Machine and BP neural network is higher in comparison with linear weighted sum method. Further experimental investigations are needed to establish direct correlations between the effectiveness of fingerprint image quality estimation algorithm and the performance of fingerprint identification system.

## ACKNOWLEDGMENT

This paper is funded by the National Science Foundation of Heilongjiang Province under Grant 42400621-1-09130.

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