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Finger Vein Image Quality Evaluation based on Support Vector Regression

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Abstract

It has been found that poor quality images decrease the performance of finger vein recognition system, due to missing, vague or spurious features. Therefore, it is important for a finger vein recognition system to evaluate the quality of finger vein images. In this paper, a new method based on Support Vector Regression (SVR) is proposed for finger vein image quality evaluation. In our method, we first manually annotate quality scores for finger vein images in training set and extract five quality features of these images. Then quality scores and quality features are used to build a SVR model, which will be applied to evaluate quality for testing images. In addition, we explore the use of quality score and ascertain that quality score can be used as ancillary information to enhance recognition accuracy for finger vein. Experimental results show that our proposed method is effective for finger vein image quality evaluation.

Keywords: *Finger vein recognition, Image quality evaluation, Support Vector Regression, Soft biometric trait*

1. Introduction

Biometric recognition refers to the use of distinctive physiological characteristics like fingerprints, face, hand geometry, iris or behavioral characteristics such as gait and signature, for automatically recognizing an individual [1]. As one of reliable biometric techniques, finger vein has been well studied recently. Compared with other biometric traits, finger vein patterns have the following advantages [2]: (1) Anti-counterfeiting: it is difficult to forge or steal finger vein, due to the vein is hidden inside the finger (2) User-friendly: finger vein recognition can be easily accepted by people, because non-invasive and non-contact capture ensures convenience and health for the user. (3) Liveness: the finger vein pattern can only be taken from a live body. In addition, the size of image capture device in finger vein recognition is smaller than that in other vein recognitions, such as, dorsal vein recognition [3], palm vein recognition [4].

However, the performance of finger vein recognition relies heavily on the quality of finger vein images. In actual situation, there are always a part of poor quality images, because of constantly changing environment, individual differences, and the various performances of devices [5]. It has been found that poor quality images decrease the performance of the finger vein recognition system, due to missing, vague or spurious features. Therefore, it is vital for finger vein recognition system to evaluation the imaged quality before performing further processing. Figure 1 shows some typical finger vein images with poor quality.

Over the past years, several methods have been proposed for the quality evaluation of finger vein images, which can be placed into two categories: classification based methods and score based methods.

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Classification based methods usually categorize finger vein images into several classes. Yang et al. [5] used Support Vector Machine (SVM) model to classify finger vein images into two types: low quality and high quality. Wang *et al.* [6] extracted five features of each image as the parameters of finger vein image quality evaluation, and mages are classified into three types, *i.e.*, low quality, better quality and high quality. In contrast, score based methods always compute a quality score for every finger vein image. Xie *et al.* [7] presented a quality evaluation method for finger vein images based on hierarchical vein feature, and computed quality scores from the major vein pattern quality and minor vein quality. Ma *et al.* [8] presented a signal to Noise ratio based on human visual system (HSNR) as quality evaluation index, and integrated it with other four quality evaluation indexes to obtain the total image quality score of finger vein image. Qin *et al.* [9] divided a finger vein image into a set of non-overlapping blocks and evaluated a local quality score for each block according to the curvature in the corresponding Radon space, based on which a global quality score of the finger vein image is computed.

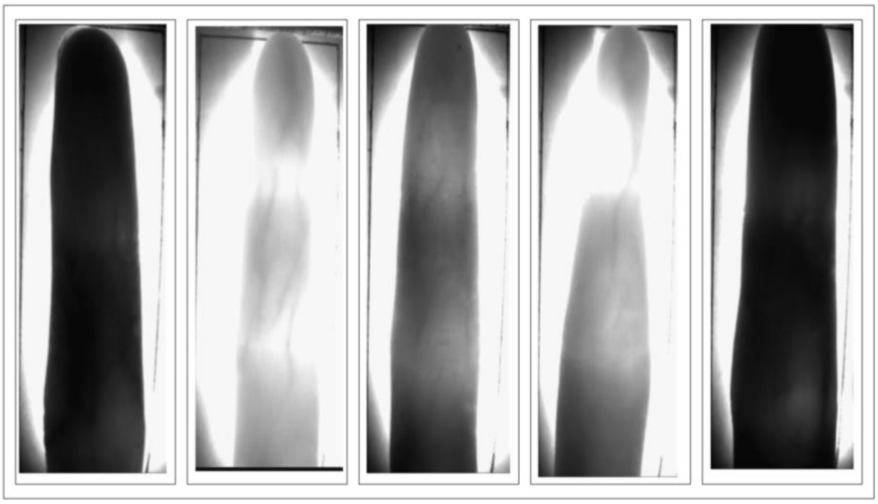

Figure 1. Examples of Finger Vein Images with Poor Quality

In many cases, score based methods are superior to classification based methods since classification based methods are too arbitrary. For example there are two finger vein images, the first image with quality score 59 may be classified into low quality measured by classification method, while the second one with quality score 60 may be divided into high quality. In this case they will face very different processing even their quality difference is very small. However, there are still limitations of the existing score based methods. Some of previous methods linearly weight evaluation features to obtain image quality score, others use single feature to get score. But weighing is linear model which limited to address nonlinear problems and single feature cannot comprehensively evaluate the quality of finger vein images.

In this paper, we propose a new score based method for finger vein image evaluation. Unlike the previous score based methods where linear models are used and weights are determined experimentally, we introduce SVR to establish the relationship between quality score and quality evaluation features. And five evaluation features are used to comprehensively reflect the finger vein quality.

When exploring the use of quality score, we find that the differences of image quality existing between different individuals are very useful but often ignored. Inspired by this, we use the quality score as soft biometric trait to enhance the recognition accuracy for finger vein under three frameworks (i.e., the fusion framework, the filter framework and the hybrid framework) proposed in [10].

The remainder of this paper is organized as follows: Section 2 details our proposed method. Section 3 provides the experimental results. We conclude the paper in Section 4.

2. The Proposed Method

In this section, we describe the proposed method in detail. In training set, we first manually annotate quality scores for finger vein images, and then extract five quality evaluation features of these images. A SVR model is learned based on quality scores and quality evaluation features. In testing set, we use the learned model to evaluate quality for testing images. The framework of the proposed method is illustrated in Figure 2.

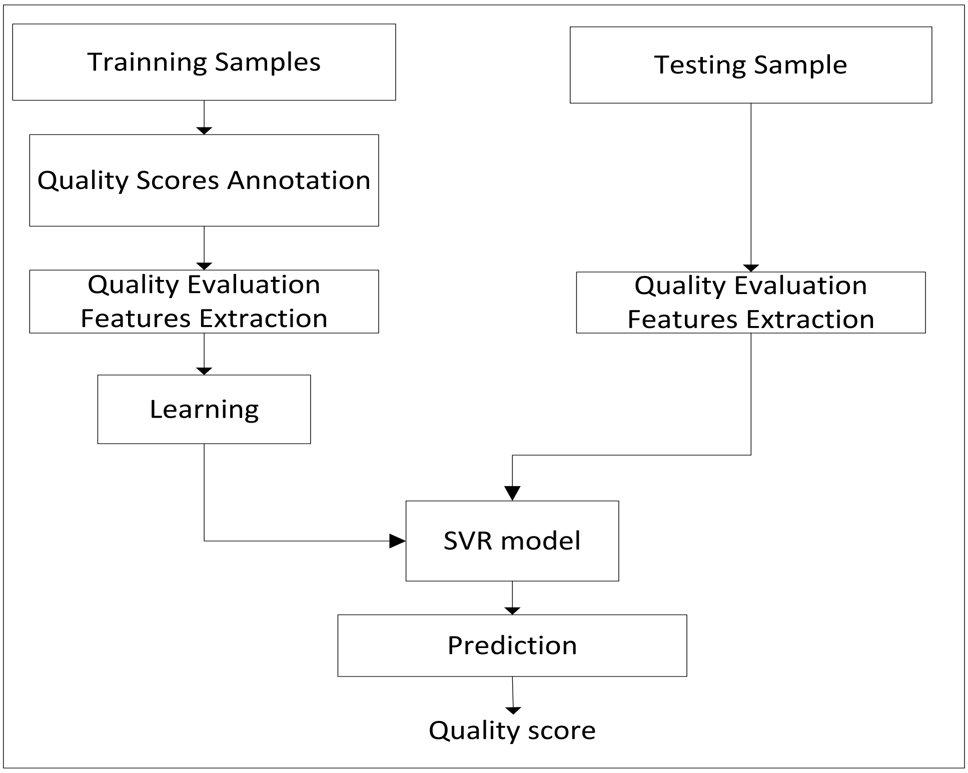

Figure 2. Framework of the Proposed Method

2.1 Quality Scores Annotation

We manually annotate quality scores of finger vein images in training set, and these quality scores are normalized into the interval [0, 1]. In the process of annotation, we follow such a principle: high quality image with clear and comparative abundant vascular pattern will be given a higher score. In contrast, low quality image with a blurred and less vascular pattern or very dark or light will be given a lower score. The typical finger vein images (after ROI extraction) and their quality scores are shown in Figure 3. The distribution of manually annotated quality scores in training set is shown in Figure 4, and the corresponding statistics of the scores are listed in Table 1. From Figure 4 and Table 1, we can see that a few images get low scores while most of the scores are concentrated in the interval [0.6, 0.9], which is consistent with the actual situation.

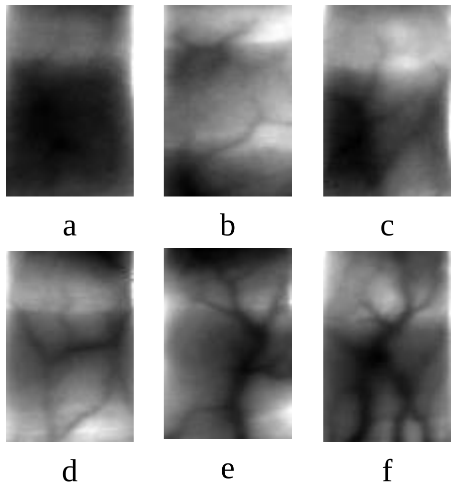

Figure 3. Typical finger vein images (after ROI extraction) and their quality scores. The normalized quality scores of (a) (b) (c) (d) (e) (f) are 0.2931, 0.3943, 0.4031, 0.6933, 0.7388 and 0.8200 respectively.

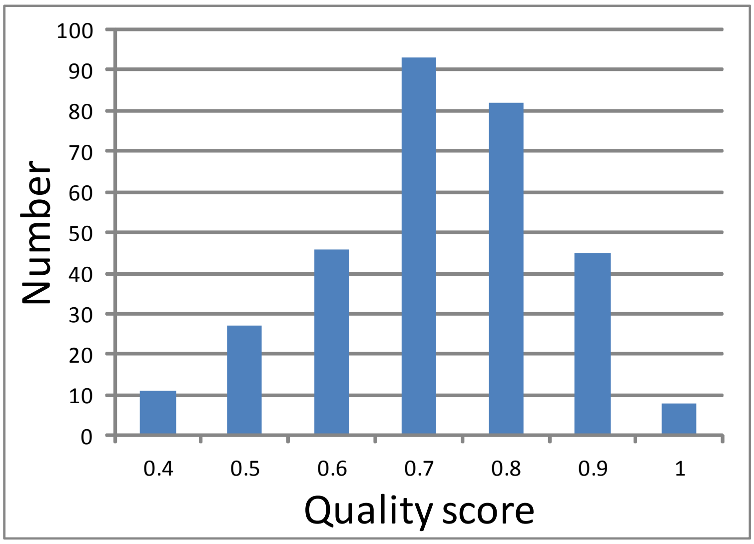

Figure 4. Distribution of Manual Annotated Quality Scores in Training Set

Table 1. Statistics of Manual Annotation Quality Scores in Training Set

Quality Score	<=0.4	(0.4,0.5]	(0.5,0.6]	(0.6,0.7]	(0.7,0.8]	(0.8,0.9]	(0.9,1]	Total
Number	11	27	46	93	82	45	8	312

2.2 Quality Evaluation Features Selection

Feature selection is an important part for quality evaluation. There are two types of features used in finger vein image quality evaluation, which are local level feature and global level feature. Local level feature reflects regional information, while global level feature reflects the overall information. In order to fully reflect the image information, the local level features, *i.e.*, image contrast, gradient and Gabor based feature, and the global level features, i.e., information capacity and information entropy, are used for finger vein image quality evaluation.

To obtain local level feature of finger vein image, we partition a given image into non-overlapping blocks of size $b \times b$ pixels. We respectively use N to represent the total number of blocks in an image, B to represent one block and S to represent the total number of pixels in one block.

Image Contrast: As explained in [5], Image contrast reflects the gray level difference of the finger vein. For each block B average variance is computed as follows:

$$C = \sqrt{\frac{\sum_{i=1}^{S}\left(x_i - x_M\right)^2}{S}} \tag{1}$$

where x_M represents the average of the gray value of block B, and x_i is the gray value of a pixel in block B. Image contrast is given by

$$QF_1 = \frac{1}{N}\sum_{j=1}^{N} C_j \tag{2}$$

Gradient in Spatial Domain: Gradient is revealing the clarity of the ridge–valley orientation in an image [11]. The covariance matrix of the gradient vectors for a block B is given by

$$J = \frac{1}{S}\sum_{p \in B} g_p g_p^T \equiv \begin{bmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{bmatrix} \tag{3}$$

where $g_P = \left(g_p^x, g_p^y\right)$ denote the gradient of point p in block B.

The above symmetric matrix is positive semi-definite with eigenvalues and λ_1, λ_2 and $\lambda_1 \geq \lambda_2$. The normalized coherence measure is defined as

$$k = \frac{\left(\lambda_1 - \lambda_2\right)^2}{\left(\lambda_1 + \lambda_2\right)^2} = \frac{\left(j_{11} - j_{22}\right)^2 + 4j_{12}^2}{\left(j_{11} + j_{22}\right)^2} \quad 0 \leq k \leq 1 \tag{4}$$

If the local region has a distinct ridge-valley orientation, then $\lambda_1 \gg \lambda_2$ results in $k \approx 1$, inversely if the local region is of poor quality, then $\lambda_1 \approx \lambda_2$ results in $k \approx 0$. The feature of gradient in spatial domain is given by

$$QF_2 = \frac{1}{N}\sum_{i=1}^{N} k_i \tag{5}$$

Gabor based Feature: The characteristics of the Gabor filter, especially for frequency and orientation representations, are similar to those of the human visual system [12]. Ref. [12] applied Gabor filter based feature to identify blocks quality of fingerprint images. Refer to finger vein recognition, the Gabor filter has been successfully applied to it [13-14]. Hence we introduce Gabor based feature of finger vein image as a quality evaluation feature. The 2D Gabor filter is defined as follows:

$$h\left(x, y, \sigma_x, \sigma_y\right) = exp\left[-\frac{1}{2}\left(\frac{x_{\Theta_k}^2}{\sigma_x^2} + \frac{y_{\Theta_k}^2}{\sigma_y^2}\right)\right] \times exp\left(i2\pi f x_{\Theta_k}\right) \; k = 1, \ldots, m \tag{6}$$

where $y_{\Theta_k} = -x\sin\Theta_k + y\cos\Theta_k$ and $x_{\Theta_k} = x\cos\Theta_k + y\sin\Theta_k$, f is the frequency of the sinusoidal plane wave.

Once the parameters of the Gabor filter are determined, the Gabor feature at point (X, Y) can be defined as follows:

$$g\left(X,Y,\Theta_k,f,\sigma_x,\sigma_y\right)=\left|\sum_{x=-b/2}^{b/2-1}\sum_{y=-b/2}^{b/2-1} I\left(X+x,Y+y\right)h\left(x,y,\Theta_k,f,\sigma_x,\sigma_y\right)\right| \tag{7}$$

The standard deviation value G of block B is computed as follows:

$$G=\sqrt{\left(\frac{1}{m-1}\sum_{k=1}^{m}\left(g_{\Theta_k}-\overline{g_\Theta}\right)^2\right)} \qquad \overline{g_\Theta}=\frac{1}{m}\sum_{k=1}^{m} g_{\Theta_k} \tag{8}$$

where $\Theta_k=\left(k-1\right)/m, k=1,...,m$.

A block is marked as a good quality block if G is greater than a predefined threshold value, T_q, Gabor based feature is given by

$$QF_3=\frac{N_g}{N} \tag{9}$$

where N_g represent the number of good quality blocks.

Information Capacity: Information capacity [15] is a quality evaluation feature of digital images based on 2-D histograms. The logarithmic transformation of the peak normalized histogram in the information capacity formula reflects the low-pass logarithmic response characteristics of human visual system. For a point $\left(x,y\right)$, its 2-D histogram is defined as follows:

$$Num\left(G_1,G_2\right)=P\left\{\left[f\left(x,y\right)=G_1\right]\cap\left[f\left(x,y+1\right)=G_2\right]\right\} \tag{10}$$

where $f\left(x,y\right)$ is the gray value of the point $\left(x,y\right)$, $P\left\{A\right\}$ denotes the occurrence of the event A and $Num\left(G_1,G_2\right)$ denotes the frequency of the event. The 2-D peak logarithm normalized histogram as follows:

$$Norm_{log}\left(G_1,G_2\right)=\frac{\log\left[Num\left(G_1,G_2\right)\right]}{\log\left\{max\left[Num\left(G_1,G_2\right)\right]\right\}} \tag{11}$$

The feature of information capacity is given by

$$QF_4=lb\left[1+\sum_{\omega}Norm_{log}\left(G_1,G_2\right)\right] \tag{12}$$

where lb is the base-2 logarithm operator, and $\omega=\Omega$ (i.e., $0\le G_1\le 255$, $0\le G_2\le 255$).

Information Entropy: Entropy is a statistical measure that summarizes randomness [16]. The information entropy of finger vein image is described as:

$$QF_5=\sum_{i=0}^{255}p\left(i\right)\log_2 p\left(i\right) \tag{13}$$

where $p\left(i\right)$ represents the probability that pixels in the ith grey-level in an image.

2.3 Learning SVR Model and Prediction

SVR is the most common application form of SVMs [17] which has been applied to many fields. More specifically, SVR has been successfully applied to quality evaluation [18-19] in natural image field. Due to its advantages on solving nonlinear problems, we apply the SVR to the finger vein quality evaluation.

In our method we use $\varepsilon - SVM$ as the regression model [20]. In the training phase, the selected five quality evaluation features $(QF_1, \ldots, QF_5)$ are used to train model and our goal is to solve the following optimization problem:

$$w = \arg\min_{w} \frac{1}{2} w^2 + C\sum_i \xi_i + C\sum_i \xi_i^* \tag{14}$$

s.t.

$$\sum_n w_n k(x_i, x_n) + b - y_i \le \varepsilon + \xi_i, \xi_i \ge 0 \tag{15}$$

$$y_i - \sum_n w_n k(x_i, x_n) - b \le \varepsilon + \xi_i, \xi_i, \xi_i^* \ge 0 \tag{16}$$

where x_i is the feature vector of the ith image, y_i is the manually annotated quality score of ith image and $k(\cdot,\cdot)$ is the kernel function. We use polynomial function as the kernel function:

$$k(x, x_i) = \left(\gamma x^T x_i + r\right)^d, \gamma > 0 \tag{17}$$

After solving the above optimization problem, the image quality score of a testing image can be computed as:

$$f(x) = \sum_i k(x, x_i) w_i + b \tag{18}$$

We use LIBSVM toolbox [21] to train this image quality evaluation model, Mean Squared Error (MSE) is used as evaluation criteria. MSE (lower value is better) represents the error associated with the model which can be computed as:

$$MSE = \frac{1}{l} \sum_{i=1}^{l} \left(f(x_i) - y_i \right)^2 \tag{19}$$

where $f(x_i)$ is the predicted score, y_i is manually annotated quality score, and l is number of images.

3. Experimental Results and Analysis

3.1 The Experimental Database

We use the PolyU finger vein database [14] to evaluate the performance of the proposed method. This database is collected from 156 volunteers in two separate sessions. In each session, each of the subjects provided six finger vein images and six finger texture images from the index finger to middle finger. In our experiment we only use the finger vein images. The number of finger vein images of each volunteer is different due to only 105 subjects turned up for the imaging during the second session. So, we use six finger vein images of each finger from all volunteers, which include a total 1872 images.

We split the dataset into three non-overlap sets: a training set of 312 images (one image per finger), a validation set of 624 images (two images per finger) and a testing set of 936 images (three images per finger). The training set and the validation set both have manually annotated quality scores.

3.2 Experiments Setting

Three experiments are performed to evaluate the effectiveness of the proposed method. Experiment 1 verifies the effectiveness of the learned regression model. Experiment 2 is designed to confirm the advantage of using all features compared with using part of them (i.e., using single feature, using one type of features, using one type and part of another type of features). In experiment 3 the image quality score will be used as soft biometric trait to enhance the performance of finger vein recognition.

3.3 Experiment 1

In this experiment we will demonstrate the effectiveness of the learned regression model. We use training set to train SVR model and validation to test the model. MSE is used to evaluate the regression performance which has been introduced in Section 2.

Experiment result shows that MSE is 0.0031 on validation set, and Figure 5 vividly illustrates the effectiveness of the model. At the same time, Figure 6 and Table 2 show that the distribution of predicted quality scores in validation set by learned model is conformity with the distribution of manually annotated scores in training set. All of these results illustrate that the learned SVR model is reliable.

Table 2. Statistics of Manually Annotated Quality Scores in Training Set and Prediction Quality Scores in Validation Set

Quality score	<=0.4	(0.4,0.5]	(0.5,0.6]	(0.6,0.7]	(0.7,0.8]	(0.8,0.9]	(0.9,1]	Total
Training set	11	27	46	93	82	45	8	312
Validation set	0	36	156	209	163	51	9	624

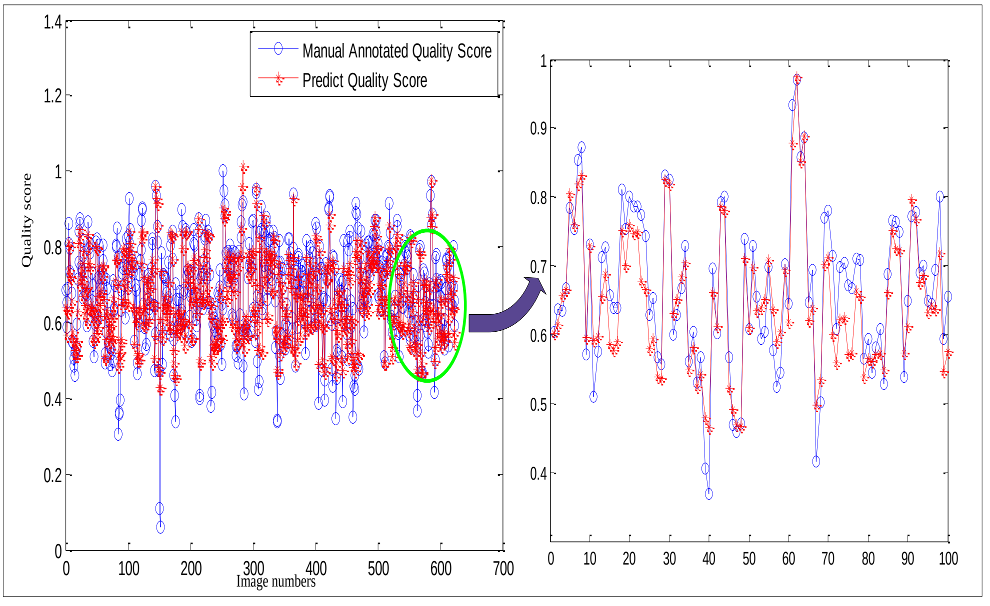

Figure 5. Line Chart of Manually Annotated Quality and Predicted Quality Scores in Validation Set

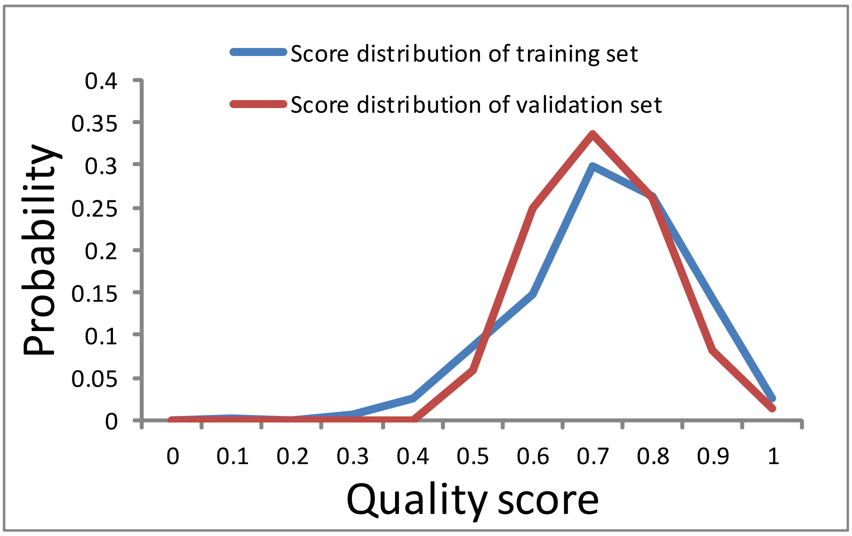

Figure 6. Distribution of Manually Annotated Quality Scores in Training Set and Prediction Quality Scores in Validation Set

3.4 Experiment 2

Experiment 2 is designed to confirm that the combination of five features is the best choice for evaluate the quality of finger vein images compared with using part of them. In Table 3 we list MSEs of single feature and different combination of features on the validation set.

From Table 3, we can see that the combination of the five quality evaluation features achieves the best performance. It also shows that the MSE is less than 0.03 even using one feature only, which indicates that each feature has certain power to predict image quality.

Table 3. MSEs Using Different Quality Evaluation Features in Validation Set

Feature(s)	MSE
Image contrast	0.0163
Gradient	0.0071
Gabor	0.0274
Information capacity	0.0136
Information entropy	0.0115
Image contrast+ Gradient +Gabor	0.0042
Information capacity +Information entropy	0.0111
Image contrast+ Gradient +Gabor+ Information capacity	0.0036
Image contrast+ Gradient +Gabor+ Information entropy	0.0034
Image contrast+ Gradient +Gabor+ Information capacity+ Information entropy	0.0031

3.5 Experiment 3

In this experiment, the quality scores of testing set will be used as soft biometric trait, and we want to verify that the quality scores predicted by the proposed method can enhance the finger vein recognition performance under the three frameworks namely Filter, Fusion and Hybrid proposed in [10].

Quality scores of testing set are predicted using the SVR model built in experiment 1. The performances of finger vein and soft biometric based frameworks (using both finger vein and quality score) are shown Figure 7, and the corresponding EERs are listed in

Table 4. We can see from the experimental results that all three frameworks perform better than finger vein, which illustrate the quality scores can enhance the finger vein recognition performance. The experimental results also confirm that our proposed method is effective for finger vein image quality evaluation.

The EER is 6.54% of finger vein which use LBP operator as finger vein feature. We choose 0.18 as the filter threshold which will be used in filter framework and hybrid framework. In filter framework, user with the quality matching score greater than the threshold will be rejected as imposter user, otherwise, the finger vein pattern will be used to continue identity recognition. By filtering, there are 111621 inter-class matchings to be reduced in finger vein recognition, which holds 25.5634% of all inter-class matchings. In fusion framework, the quality matching score and finger vein matching score are fused using the weighted sum rule, and the EER is down to 4.97%. In hybrid framework, which includes filter and fusion phases, EER is down to 4.88%, and the number of inter-class matchings is also reduced as filter framework.

Table 4. EERs of Finger Vein and Soft Biometric based Frameworks [10] in Testing Set

	Finger vein	Filter	Fusion	Hybrid
EER (%)	6. 54	5.97	4.97	4.88

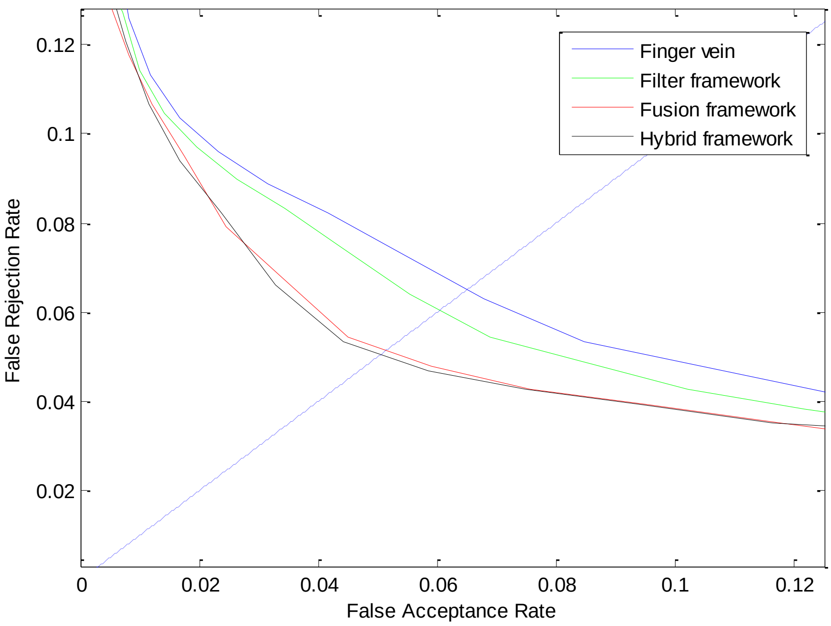

Figure 7. ROC Curves of Finger Vein and Soft Biometric based Frameworks [10] in Testing Set

4. Conclusion

In this paper, we use SVR to find the mapping function between quality score and quality evaluation features of finger vein image, which can overcome the limitation to solving nonlinear problem of previous methods. In order to comprehensively reflect the finger vein image quality, the local level and global level features are combined to train the proposed image quality evaluation model. In addition, we use quality score as a soft biometric trait to enhance the recognition accuracy for finger vein. Experimental results demonstrate that our proposed method is effective for finger vein image quality evaluation.

It should be point out that the proposed method need to manually annotate score for training set, we will explore quality evaluation method of finger vein image with less manually intervention.

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