COMPREHENSIVE ASSESSMENT OF IRIS IMAGE QUALITY

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ABSTRACT

Iris image quality critically determines iris recognition performance and the quality metrics of iris images are also useful prior information for adaptive selection of optimal recognition strategy. Iris image quality is jointly determined by multiple factors such as focus, occlusion, off-angle, deformation, etc. So it is a complex problem to assess the overall quality score of an iris image. This paper proposes a novel framework for comprehensive assessment of iris image quality. The contributions of the paper include three aspects: (i) Three novel approaches are proposed to estimate the quality metrics (QM) of defocus, motion blur and off-angle in an iris image respectively; (ii) A fusion method based on likelihood ratio is proposed to combine six quality factors of an iris image into an unified quality score; (iii) A statistical quantization method based on \textit{t}-test is proposed to adaptively classify the iris images in a database into a number of quality levels. Extensive experiments demonstrate the proposed framework can effectively assess the overall quality of iris images. And the relationship between iris recognition results and the quality level of iris images can be explicitly formulated.

Index Terms— Iris recognition, image quality assessment, defocus, motion blur, off-angle

1. INTRODUCTION

Iris recognition as a reliable personal identification method has important applications in our society. However, usability is the largest bottleneck of iris recognition and it is very difficult to capture high-quality iris images due to the limited effective imaging volume of iris sensors. So it is inevitable that the image sequences acquired by iris cameras have wide distribution of quality measures. Iris image quality is closely related to the result of iris recognition so we need to select high-quality iris image samples from the input sequences to improve iris recognition performance. With fast development of iris recognition algorithms, some poor quality iris images can also be processed using adaptive preprocessing and recognition algorithms. For example, if we know the off-angle value of an iris image in advance, we can correct it before recognition. So iris image quality assessment is a critical module in iris recognition systems.

The image quality factors that affect iris recognition performance mainly include defocus, motion blur, off-angle, occlusion, deformation and light variation as depicted in Fig.1. Iris image quality assessment has attracted the attention of researchers and there have been a number of methods [1, 2, 3] proposed to address individual quality metric or quality measure (abbreviated as QM). However, comprehensive assessment of iris image quality is still a complex and challenging problem because the overall iris image quality score is jointly determined by multiple factors and there is not a well-accepted criteria or standard to define the weight of each factor in iris image quality. A straightforward approach is to fuse the QMs into a quality score (QS). There are several methods on QS fusion in literature. Belcher et al. [4] used different normalization functions for each QM and fused them with multiplication. Nathan et al. [3] proposed to use the Dempster-Shafer theory to combine all the QMs into a QS. Zuo et al. [5] adopted a multivariate adaptive mapping using feed forward neural network with two hidden layers for fusion of the QMs.

Since the fused QS is continuous and the adjacent values of QS are not distinct, it is necessary to quantify QS into several quality levels (QL) to improve the statistical significance of iris image quality values. However, how to decide the number of QLs is a frequently encountered problem in quality evaluation. In [6], Grother et al. demonstrated the quantized quality levels (QL) was more appropriate than the continuous QS practically. And they measured the significant difference of genuine distributions between adjacent QLS to determine the number of QLS, but the used Kolmogorov Smirnov (KS) test is too complicated in practice.

In this paper, we propose a comprehensive scheme to assess the quality scores of iris images. Firstly, we present three novel methods to measure defocus, motion blur and off-angle accurately. Then we employ the improved likelihood ratio-based fusion method [7] in the QM fusion stage to get the quality score. Finally, the \textit{t}-test is applied to decide the number of quality levels.

The remainder of this paper is organized as follows. Section 2 describes the details of the proposed method. Section 3 provides the experiments and analysis. Section 4 summarizes the paper.
2. IRIS IMAGE QUALITY

The framework for comprehensive assessment of iris image quality is illustrated in Fig. 2.

![Fig. 2. The flowchart of our proposed method](image)

2.1. Individual quality metric assessment

2.1.1. Defocus

The focus value of an iris image is commonly estimated by the output of high pass filtering result with the entire image [1, 2] or a fixed region of interest (ROI) [3]. However, the high-frequency information on non-iris image regions cannot represent the focus value of iris texture. So the key point is how to select appropriate image regions for focus estimation.

We propose a method for patch selection to attenuate the effect of the eyelid, eyelash and spot light. Firstly, two original patches are chosen (see Fig. 3(a)). Then, we predefine two threshold values, \( \text{thresh}_{\text{high}} \) and \( \text{thresh}_{\text{low}} \). If the gray value of a pixel in two patches is in the range \([0, \text{thresh}_{\text{low}}]\) or \([\text{thresh}_{\text{high}}, 255]\), it is regarded as the defective pixel. The numbers of defective pixels of two patches are denoted by \( DP_i | i = 1, 2 \) (1, 2 stand for the left and right patch, respectively). If both \( DP_i \) is equal to zero, two patches are chosen for defocus assessment as shown in Fig. 3(a), otherwise, the patch with smaller \( DP_i \) is chosen as shown in Fig. 3(b). Our strategy not only reduces the effect of the eyelid, eyelash and spot light but also is robust to the asymmetry of eyelid.

![Fig. 3. ROI selection for defocus assessment. (a) No effect of eyelid, (b) Asymmetry by left tilt of eyelid, (c) The \((5 \times 5)\) convolution kernel](image)

Then, the \((5 \times 5)\) convolution kernel which is proposed by Wei in [2] is adopted to measure the defocus degree in the chosen ROI.

2.1.2. Motion blur

Because motion blur can compress the frequency band of perpendicular orientation of motion, directional filter is applied in the frequency domain to measure the degree of motion blur in [3]. However, the algorithm relies on tuning the parameters of the directional filter group: the scale of directional filter and the angle interval. Thus, we propose an alternative method based on Radon transform to improve the motion blur estimation.

Figure 4 displays the process of motion blur assessment module. The original iris image is converted into the frequency domain by FFT as shown in Fig. 4(b). Then we apply the Radon transform in the overall filtered frequency domain to estimate the motion orientation as follows:

\[
\hat{\Theta} = \arg \max \limits_{\theta \in [0, 180]} \| \text{Radon}(F(I)) \| 
\]  

where \( F(I) \) is the fourier transform of input iris image, \( \hat{\Theta} \) is the motion orientation. Radon stands for the overall image Radon transform (see Fig. 4(c)). We do not need to allocate the scale and angle interval. The obtained orientation of motion is defined as the principal orientation. The response of Radon transform in the principal orientation is denoted by \( RH(y) \) (see Fig. 4(d)), and it is smoothed by a Gaussian filter to remove the outliers. Given the \( RH(y) * G(\sigma) \), the definition "slice" which is defined in [3] is introduced to measure the QM of motion blur.

![Fig. 4. Procedure of motion blur assessment. (a) The motion blurred iris image, (b) FFT of the iris image, (c) Radon transform, (d) The response of Radon transform in principle direction](image)

2.1.3. Off-angle

Usually, the pupil is modeled as an ellipse, and the circularity of the pupil is measured to define the degree of off-angle [3, 8]. However, the pupil of iris images which is on-angle may not be circular. Figure 5 displays the negative examples against [3, 8]. The number below the figure is the ratio between the major axis and the minor axis of an ellipse. The smaller the number is, the higher the degree of off-angle is. Assuming that there are one or more light sources in the imaging acquisition system, the direction of light sources is approximated to the optical axis and we define the reflection from the light source as the main spots. Based on the geometrical relationship between the main spots and iris center, we can discard the extreme off-angle iris images. In the following, we take the iris image with two main spots for example. If there is only one main spot in the imaging system (for example in ICE 1.0), we define the distance between the main spot and the iris center as the QM of off-angle.

The scalable spot operator and the threshold method are associated to detect the main spots. Firstly, an original iris image is transformed into the binary image based on the adaptive threshold method and get the spot candidates, in which oversize light spots are discarded. Secondly, a scalable square template is constructed as a high pass filter. The scale of the scalable square template is twice the size of the corresponding spot. Finally, the responses of all spot candidates filtered by their corresponding square templates are ranked in ascending order, and the top two spots are used as the main spots. The maximum distance between the main spots and the iris center is defined as the QM of off-angle. If the QM is larger than the radius of the pupil, the iris image is regarded as off-angle.
by [6], in terms of the genuine distribution, we use \( t \) adjacent levels have significantly different performance [6]. Inspired alternative is to quantify QS into several levels, among which it is hard to explicitly formulate the relationship of these two. A robust assessment should predict the performance precisely. However, it is difficult to deal with the problems because they would attenuate the effect of partial QMs with small value.

To solve the above problems, we propose a new fusion algorithm based on likelihood ratio fusion algorithm adopted in [7]. In the fusion stage, we substitute the probability density with probability distribution since the probability distribution is monotone along with the quality degree and robust to outliers. The QMs of defocus, motion blur, off-angle, occlusion, dilation and mean value in valid iris region mentioned above are combined together. The fusion QS is defined as follows:

\[
QS(u) = \prod_{i=1}^{n} \frac{F(u_i | H_1)}{F(u_i | H_0)}
\]

where \( F(u_i) \) is the \( i \)-th probability distribution of QMs, and \( n \) is the number of QMs. \( H_1 \) and \( H_0 \) represent the positive and negative samples respectively. There are two advantages of the fusion algorithm. First, we only need to label the iris images into two classes based on each QM respectively, for example, focus versus defocus. Second, the product rule is better than the weighted sum rule because it does not attenuate the effect of QMs.

2.3. Quality levels determination

It is accepted that images with different quality contribute to the performance of the system differently, therefore a good quality assessment should predict the performance precisely. However, it is difficult to explicitly formulate the relationship of these two. A robust alternative is to quantify QS into several levels, among which adjacent levels have significantly different performance [6]. Inspired by [6], in terms of the genuine distribution, we use \( t \)-test [10], one kind of statistical hypothesis test, to automatically divide iris images into distinct groups with significant different performance. \( T \)-test assesses whether the means of two groups are statistically different from each other when the test statistic conforms to a normal distribution. Hence, it is the best choice because the distribution of hamming distance used for iris recognition is a Bernoulli distribution [11] which can be approximated by a normal distribution. In experiments, \( p \)-value is calculated based on the \( t \)-test. If the \( p \)-value between adjacent QLs is larger than the 0.005, it indicates these two QLs are not significantly different and also demonstrates the division of the QLs is too fine.

3. EXPERIMENTAL RESULTS

3.1. Database

For the purpose of validating the effectiveness of the individual QM assessment, the database (abbreviated as DB1) is constructed, which contains 119 clear images, 112 defocused images, 102 motion blurred images and 52 off-angle images.

After that, we constructed a database (abbreviated as DB2) which contains 1000 iris images from 20 subjects, and there are 50 images per subject. DB2 is a subset from original iris images sequences including both good and poor quality iris images, and the quality range in DB2 is larger because there are more poor quality iris images in original image sequences. DB2 and ICE 1.0 are used to testify the robustness of our proposed method in different databases. The images of ICE-Left and 500 iris images of 10 subjects from DB2 are used as the training set respectively. The images of ICE-Right and the reminder of DB2 are used as the testing set severally.

3.2. QMs of defocus, motion blur and off-angle

The proposed individual QMs is tested in DB1. The Off-angle assessment is a coarse classification, it is not necessary to assess the degree of off-angle but only to judge whether the iris image off-angle or not.

3.3. Quality score and Quality levels

QS is the overall indicator as a prediction for the performance of recognition system. The higher the quality level of iris images is, the better the performance they get. As shown in Table 2, \( q_i \) and \( q_{i-1} \) stand for the adjacent QLs, taking the ICE as an example, when the number of quality levels is three, all of the \( p \)-values are zero. However, one more level is added, the \( p \)-value between \( q_1 \) and \( q_2 \) is larger than 0.005, it means that the distributions between \( q_1 \) and \( q_2 \) are not significantly different and these two QLs should be combined.

**Table 1. CCR FOR different QMs**

<table>
<thead>
<tr>
<th>Num.</th>
<th>Clear</th>
<th>Defocus</th>
<th>Motion</th>
<th>Off-angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>119</td>
<td>112</td>
<td>102</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>CCCR(_{thresh=8 \times 10^{-6}})</td>
<td>100%</td>
<td>100%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>MCCR(_{thresh=155})</td>
<td>91.60%</td>
<td>-</td>
<td>89.22%</td>
<td>-</td>
</tr>
<tr>
<td>OCCR</td>
<td>100%</td>
<td>-</td>
<td>-</td>
<td>96.15%</td>
</tr>
</tbody>
</table>

We adopt the Correct Classification Rate (CCR) to evaluate the performance of individual QMs. \( DCCCR_{thresh=8 \times 10^{-6}} \) is defined as the CCR between the clear vs. defocused iris image, and the same as \( MCCR_{thresh=155} \) and \( OCCR \). From Table 1 and Fig. 6, we can see the proposed methods are robust and accurate, especially in defocus assessment.
Fig. 6. Distribution of QM assessment. (a) clear vs. defocused images (b) clear vs. motion blurred images together. Besides, the EERs are not ascending along with the iris image quality when the QLs is four. Three quality levels are suitable to ICE 1.0. Table 2 also illustrates there are more quality levels in DB2, it is a fact that the range of quality in DB2 is larger because it is from the original image sequence.

Fig. 7. The ROC curves of different quality levels. (a) ROC curves on ICE 1.0 test set, (b) ROC curves on DB2 test set

Table 2. $T$-test for deciding the number of quality levels

<table>
<thead>
<tr>
<th>Quality Level</th>
<th>EER</th>
<th>$P_{value}$, $Q_i$, $q_i$-1</th>
<th>Quality Level</th>
<th>EER</th>
<th>$P_{value}$, $Q_i$, $q_i$-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE 1.0</td>
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<td></td>
<td>DB2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.000928</td>
<td></td>
<td>1</td>
<td>0.044489</td>
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<tr>
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<td></td>
<td>0.228350</td>
<td>0</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

In this paper, we have proposed new methods to assess the quality of iris images affected by defocus, motion blur and off-angle. A simple yet effective fusion approach is presented for fusing all the quality measures to a quality score. Extensive experiments demonstrate the quality score is robust to predict the performance of the iris recognition. In future, we can enhance the iris image based on the quality score to improve the performance of the system.

5. ACKNOWLEDGEMENT

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6. REFERENCES


$^1$In matching stage, we adopt the two lobe OM proposed in [12]