Global and Local Quality Measures for NIR Iris Video

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Abstract

In the field of iris-based recognition, evaluation of quality of images has a number of important applications. These include image acquisition, enhancement, and data fusion. Iris image quality metrics designed for these applications are used as figures of merit to quantify degradations or improvements in iris images due to various image processing operations.

This paper elaborates on the factors in [8] and introduces new global and local factors that can be used to evaluate iris video and image quality. The main contributions of the paper are as follows. (1) A fast global quality evaluation procedure for selecting the best frames from a video or an image sequence is introduced. (2) A number of new local quality measures for the iris biometrics are introduced. The performance of the individual quality measures is carefully analyzed. Since performance of iris recognition systems is evaluated in terms of the distributions of matching scores and recognition probability of error, from a good iris image quality metric it is also expected that its performance is linked to the recognition performance of the biometric recognition system.

1. Introduction

Iris image quality assessment is an important research thrust recently identified in the field of iris biometrics [1], [2], [4]. This research is tightly related to the research on nonideal iris. Its major role is to determine, at the stage of data acquisition or at the early stage of processing, what amount of information for the purpose of processing, recognition, and fusion an image contains. Is it useful enough for performing further processing steps or should be discarded? Is it informative enough for being combined with other images and result in improved recognition performance? The quality metrics play an important role in automated biometric systems for three reason: (1) system performance (segmentation and recognition), (2) interoperability, and (3) data enhancement.

Image quality assessment plays an important role in automated biometric systems. Low quality images may have poor lighting, defocus blur, off-angle, and heavy occlusion, which have a negative impact on even the best available segmentation algorithms. Even with perfect segmentation, information losses due to distortions of iris texture or iris image intensity may cause serious problems for encoding and matching algorithms. At the same time, an image of good quality (as it is predicted by an image quality measure or based on visual evaluation) may not be a good iris biometric sample, as it may result in a low matching score when the encoded iris image is compared against an enrolled iris sample from the same iris class. Therefore, iris biometric quality should not be limited to iris image quality.

Previous work on iris image quality can be placed into two categories: local and global analyses. Zhu et al. [17] evaluate quality by analyzing the coefficients of particular areas of iris's texture by employing discrete wavelet decomposition. Chen et al. [5] classify iris quality by measuring the energy of concentric iris bands obtained from 2-D wavelets. Ma et al. [11] analyze the Fourier spectra of local iris regions to characterize out-of-focus and motion blur and occlusions. Zhang and Salganicaff [16] examine the sharpness of the region between the pupil and the iris. Daugman [6] and Kang and Park [9] characterize quality by quantifying the energy of high spatial frequencies over the entire image region. Belcher and Du [3] propose a clarity measure by comparing the sharpness loss within various iris image regions against the blurred version of the same regions. The major feature of these approaches is that the evaluation of iris image quality is reduced to the estimation of a single [6, 16, 5, 9] or a pair of factors [11], such as out-of-focus blur, motion blur, and occlusion.

Iris quality should not be limited to one or two quality factors. All factors that will affect recognition performance should be counted as iris quality factors. A broader range of physical phenomena that can be observed in nonideal iris imagery was characterized by Kalka et al. [7], [8]. The proposed factors include out-of-focus and motion blur, occlusion, specular reflection, illumination, off-angle, and pixel

count. The strength of the phenomena and its influence was evaluated through modified or newly designed iris quality metrics. Based on the extensive analysis carried out by the authors of [7] and [8], these factors affect the segmentation and ultimately recognition performance of iris recognition systems.

This paper elaborates on the factors in [8] and introduces new factors that can be used to evaluate near-infrared (NIR) video and image quality. The main contributions of the paper are as follows. (1) A fast global quality evaluation procedure for selecting the best frames from a video or an image sequence is introduced. (2) A number of new local quality measures for the iris biometrics are introduced. The performance of these quality measures is carefully evaluated.

2. Frame Selection

Modern iris capture devices are often equipped with an algorithm performing selection of high quality frames. Each frame can be further segmented, and the final quality score can be used to select the frame. However, complex segmentation procedure can not follow the frame rate. Then a simple quality factor will be preferred for this purpose. For instance, Daugman suggested using the focus measure to select the best iris frames [6]. For a single value quality score, local maximum on the time axis can be used to select the best quality frames from a NIR iris video.

However, for images captured at a distance, it will not be good to use the whole image to evaluate the quality factor because of the short DOF (Depth of Field). The iris area is just a small part of the frame and there may be two irises exist in a same image. The iris detection and the quality analysis will be done at the same time.

2.1. MBGC Data

Building on the challenge problem and evaluation paradigm of ICE (Iris Challenge Evaluation) 2005 and ICE 2006 [13], the Multiple Biometric Grand Challenge (MBGC) for the first time introduced middle distance near-infrared (NIR) face video (may have one or both irises in each frame) [14]. A system which is similar to the system described in [12] was used for the data collection. On a good quality frame, 8 clear specular reflections can be found close to the center of the pupil. This feature can be used to detect the iris area and measure the level of focus.

For a NIR iris video, first the iris region is detected and cropped. Then the best quality cropped area is selected by using the focus level. To deal with two irises in the same frame, a quality map is used to find local quality maxima which may be attributed to left and right irises or to a falsely detected iris.

2.1.1 Iris Detection

The iris detection is based on the assumption that a strong specular reflection exists inside of the iris area (including pupil). Typically, the intensity value of the specular reflection is very high compared to the intensity value of the iris area. Therefore, the gradient information can be used to locate the eyes within a frame. This is accomplished as follows.

1. Two 2D-order statistic filter, one returning the maximum intensity value and the other returning the minimum intensity value over a neighborhood of size 3×3, are applied locally. The difference of the intensity values within each 3×3 neighborhood are compared to a threshold, denote it as γ_1.

2. A threshold γ_2 corresponding to the value of iris intensity is evaluated based on the histogram of the considered frame.

3. The areas of the frame simultaneously satisfying conditions in (1) and (2) are selected as the potential candidates for being the iris area.

4. Since the previous steps may generate a large number of candidates, an additional geometric information is involved to rule out false iris regions. We use the minimum distance between the eyes as a means to deal with false iris regions.

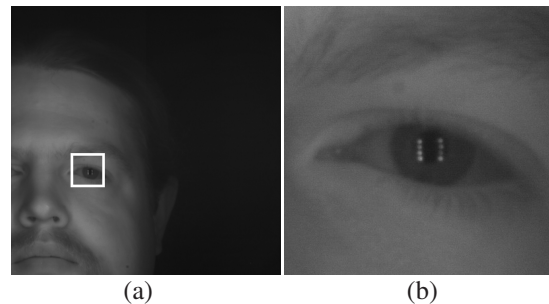An iris detection example is provided in Figure 1.

| (a) | (b) |

Figure 1. Iris detection for a single frame from the NIR face video: (a) the detected iris region, and (b) the cropped iris area.

2.1.2 Quality Map

Once the Iris Detector returns the coordinates of the iris location in a frame, a quick evaluation of iris image quality is performed. Following the Daugman's procedure for selecting the best iris frames [6], we evaluate the level of blur in detected iris region. Processing and encoding every frame in a video is a time-intensive operation. An alternative solution is to select few frames containing high quality iris
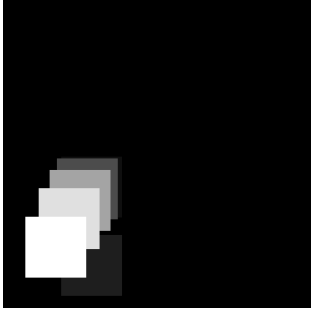
Figure 2. Shown is the quality map for the video sequence displayed in part in Figure 1.

regions and use them for iris recognition. We introduce a global quality map that provides relative information about the quality of the iris regions in different frames.

When each frame is processed, the best quality iris area candidate for each location will be updated. If the current frame have a better candidate than all frames before at that location, then the corresponding quality value and frame number will be updated to the values of the current frame. If the current frame is a worse candidate than the last frame at that location for the first time, then the last frame may be a local maximum in time domain for that location. Corresponding iris area from the last frame will be selected for further examination. After the video is processed, a global quality map with the best quality iris area marked at every location also is finished. At this time, a local maximum of the quality map will be found (these are local maxima in the spatial domain and the global maxima in the time domain), and corresponding iris areas will be selected for further processing.

3. Quality Evaluation

After few video frames are selected based on the video quality map, the detected iris regions are segmented and encoded. Simultaneously, local iris quality factors are evaluated. These quality factors can be later used to enhance performance of an iris recognition system alone or of a multimodal system with iris being one of the modalities. In the following subsection a set of new individual iris biometric quality factors are introduced and procedures to evaluate them are described. The factors are segmentation scores, interlacing, illumination, lighting, occlusion, pixel count, dilation, off-angle, and blur.

3.1. Segmentation Scores

Since the most of local iris quality measures are applied to segmented iris images, the metrics evaluating the precision of the segmentation should be given a higher priority compared to other factors. Two segmentation scores Q_{p_seg}

and Q_{i_seg} introduced in [18] can be used as two distinct quality metrics related to the segmentation itself. These metrics analyze the gradient values along the pupil and limbic boundaries. Larger value of the measures indicate more precise segmentation.

3.2. Interlacing

Poor interlacing is a disturbing artifact. Interestingly, a poorly interlaced image may result in a high focus score in spite of strong defocus of either even or odd lines. These artifacts should be detected. If there is a large difference between odd and even lines then there must be a clear motion related interlacing effect. The image may be either discarded, or divided to two sub-images: odd rows and even rows. The difference between odd rows and even rows $Inter_1$ can be calculated as

$$Inter_1 = \frac{\sum\limits_{i=1:2:m-1} \left(\sum\limits_{j=1:n} \left| I_{(i,j)} - I_{(i+1,j)} \right| \right) * 2}{m * n} \quad (1)$$

for an image I with m rows and n columns. The function must be normalized by subtracting $Inter_2$ calculated using odd or even rows only

$$Inter_2 = \frac{\sum\limits_{i=1:m-2} \left(\sum\limits_{j=1:n} \left| I_{(i,j)} - I_{(i+2,j)} \right| \right)}{(m-2) * n} \quad (2)$$

resulting in

$$Q_{interlacing} = Inter_1 - Inter_2. \quad (3)$$

Note that the high values of $Q_{interlacing}$ indicate poor interlacing.

3.3. Illumination

The contrast of the image is mainly determined by the level and strength of the illumination. The illumination level is the mean intensity value of the iris area:

$$Q_{illumination} = \frac{\sum\limits_{unaffected\ iris\ area} I_{(i,j)}}{\sum\limits_{unaffected\ iris\ area} 1}. \quad (4)$$

To get a more precise estimation of this factor, only unaffected (by occlusion or specular reflections) area is considered. The value that $Q_{illumination}$ can take ranges from 0 to 255. This factor can be affected by the color of the iris. Large values of the measure indicate high illumination value.

3.4. Lighting

Sided or uneven illumination of the iris often results in performance degradation. Illumination pattern can be treated as a low frequency signal that distorts encoded iris images. The variance of the mean intensity evaluated over small blocks is proposed as a measure of the uneven illumination. The calculation of the lighting factor is similar to the procedure described in [8], but without normalization to [0, 1]. Note that bad lighting condition is characterized by a large value of the metric.

3.5. Occlusion

This attribute measure how much of the iris is occluded by other objects such as eyelid, eyelashes and specular reflections. The proposed metric evaluates the percentage of the unoccluded area in the final unwrapped template

$$Q_{ocllusion} = \frac{\sum\limits_{(i,j):\ M_{(i,j)}==0} 1}{\sum\limits_{(i,j):\ M_{(i,j)}>=0} 1} \qquad (5)$$

where M is the binary unwrapped noise mask of the unwrapped iris template where true (1) means information at that location can not be used. The usage of the percentage can reduce the correlation between this quality factor and the resolution factor. This quality factor is similar to the pixel count factor in [8]. Large values of the metric indicate smaller occlusions.

3.6. Pixel count

To distinct it from the occlusion factor, pixel count finds the total iris area even it is affected by occlusions, that is,

$$Q_{pixel\_count} = \sum\limits_{iris\ area} 1. \qquad (6)$$

Large values of the metric correspond to high pixel counts.

3.7. Dilation

The dilation factor measures the degree of the pupil dilation. The high the dilation of the pupil, the high the compression of the iris texture and the less information is available for iris recognition. The value of the dilation factor is calculated by taking the ration of Q_{pixel_count} and the total iris and pupil area

$$Q_{dilation} = \frac{\sum\limits_{iris\ area} 1}{\sum\limits_{iris\ area} 1 + \sum\limits_{pupil\ area} 1}. \qquad (7)$$

The value $Q_{dilation}$ takes is between 0 and 1. This factor also affects pixel count. Note that small pupil dilations are characterized by large values of the metric.

3.8. Off-angle

This factor measures the relative orientation of the iris with respect to the camera. Assuming that the frontal view iris has a circular shape, the off-angle view becomes an ellipse. The off-angle quality factor is a ratio of the two main axes of the ellipse fitted into the iris boundary. These values are obtained after the iris has been segmented.

$$Q_{off-angle} = \frac{b}{a} \qquad (8)$$

where b is the minor axis and a is the major axis of an ellipse. Note that the large values of the metric indicate that that the image is close to frontal view.

3.9. Blur

Both motion and defocus blurs are treated simultaneously. The proposed method uses spectral components of an iris image and involves a number of preprocessing steps.

First, the area of the interest is selected based on the segmentation result. After the parameters of the ellipse such as the ellipse center (x_i, y_i), the major axis a and the minor axis b fitted into the iris region are obtained, we set 250% length of the major axis a as the size of the window and select the iris center (x_i, y_i) as the window center.

Then a small median filter is applied to denoise the image. To compensate the resolution difference, every area of the interest is normalized to 151×151. This size is approximately selected based on the acceptable iris resolution: 120 pixels across the iris. Then a 2D FFT transform is carried to this image in order to extract the frequency information P

$$P = log_{10} |FFT(I_{crop})|, \qquad (9)$$

where I_{crop} is the cropped iris area after the denoising and the normalization.

After the power distribution of P is analyzed, its central area is used to calculate the proper threshold. Currently we select the average power of a centered 13 pixel diamond shaped area (distance to the center of the power spectrum is less than 4) as the threshold γ

$$\gamma = \frac{\sum\limits_{((i-76)^2+(j-76)^2)<16} P_{(i,j)}}{13 * 1.5}. \qquad (10)$$

Then the number of location with a higher power value than the threshold is counted. If the number of locations is large, then the power distribution is flat. As the pupil area usually contributes a large number of low frequency component, an adjustment part involving the dilation information is added. Then the final expression for the Q_{blur} becomes:

$$Q_{blur} = \left(\sum\limits_{P_{(i,j)}>\gamma} 1 \right) * (1 + Q_{dilation}^6). \qquad (11)$$

An example illustrating some steps in evaluation of the blur quality score is provided in Figure 3. This image results in the final blur score 5953.6.

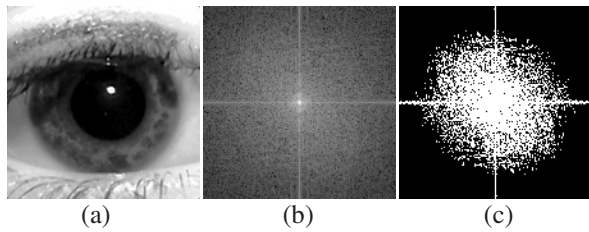(a)   (b)   (c)

Figure 3. Example of blur estimation (a) the cropped area, (b) the power spectrum and (c) the results of thresholding.

Larger values of the metric correspond to a smaller amount of blur.

3.10. Fusion

The quality factors (metrics) can be used individually or combined into a single score through a simple static or an adaptive rule. Among static rules the simple sum rule is a computationally efficient method. More complex (adaptive) rules such as Bayesian, Dempster-Shafer, weighted Sum, or any previously designed fusion strategy to combine classifiers can also be used to combine quality metrics into a single score. These rules are more fundamental and flexible, but require intensive computations.

Our current task is to come up with a super-combination scheme.

4. Results

All experiments were performed using ICE 2005 dataset [10]. The enhancement, encoding and matching procedures followed Daugman's implementation. Since performance of any iris recognition system is evaluated in terms of the distributions of matching scores and recognition probability of error, from a good iris quality measure it is also expected that its performance is linked to the recognition performance of the recognition system.

We perform a number of experiments. For each individual factor, the ICE 2005 dataset was used to form three subsets of images. The first subset was composed of the entire ICE dataset. To form the second and the third subsets, we involved the distribution of values of a selected quality factor. The second set included all images with the value of selected quality factor exceeding 0.75th qauntile. The third set was composed of all images with the value of selected quality factors exceeding 0.9th quantile.

The panes in Figures 4 and 5 each displays three Receiver Operating Characteristic sets obtained using data in subsets 1, 2, and 3. Note that all results can be placed into those based on a relative quality score (in our case, it is the difference of two quality values for two distinct images) and those based on an absolute measure. Examples of relative measures include interlacing, illumination, pixel count and off-angle (Figure 5). The other measures were used as absolute.

From Figures 4 and 5 regardless of the type of the measure, the difference between ROCs formed from the three subsets of ICE 2005 dataset are quite noticeable. This indicates that each individual factor proposed in this work does influence recognition performance of a Gabor filter-based system.
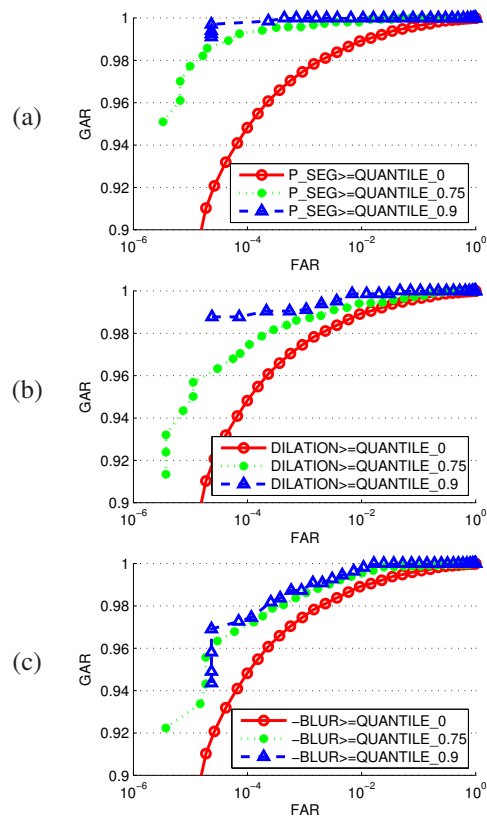

Figure 4. ROC curves for ICE2005 dataset (a) selecting images using pupil segmentation score; (b) selecting images using dilation measure; and (c) selecting images using minus blur measure.

5. Conclusions

This work proposed a number of new absolute and relative (global and local) quality measures for iris video. The performance of the proposed measures was evaluated by analyzing the relationship between the quality of iris images and verification performance of the system (in terms of ROC curves). These relationships indicate that proposed quality measures, when evaluated individually, do substantially influence recognition performance.

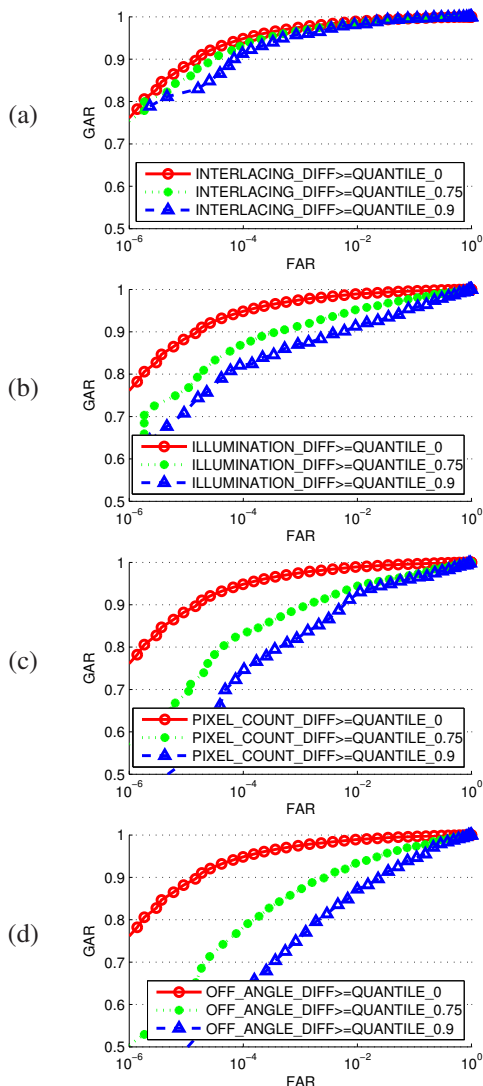The importance of each individual quality factor, eval-

Figure 5. ROC curves for ICE2005 dataset (a) selecting matching scores using interlacing measure; (b) selecting matching scores using illumination measure; (c) selecting matching scores using pixel count measure; and (d) selecting images using off-angle measure.

uation of the degree of their correlation and designing a super-combination rule for the proposed factors is the on-going work in our lab [15].

References

[1] Biometric quality workshop, National Institute of Standards and Technology (NIST), March 8-9 2006.

[2] Biometric quality workshop II, National Institute of Standards and Technology (NIST), November 7-8 2007.

[3] C. Belcher and Y. Du. Information distance based selective feature clarity measure for iris recognition. In *Proc. of the SPIE Symposium on Defense and Security. Conf. on Human Identification Technology IV.*, volume 6494, 2007.

[4] K. W. Bowyer, K. Hollingsworth, and P. J. Flynn. Image understanding for iris biometrics: A survey. *Journal of Computer Vision and Image Understabding*, 110:281–307, 2007.

[5] Y. Chen, S. C. Dass, and A. K. Jain. Localized iris image quality using 2-D wavelets. In *Proceedings of International Conference on Biometrics (ICB'06)*, pages 373–381, January 2006.

[6] J. Daugman. How iris recognition works. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):21–30, January 2004.

[7] N. D. Kalka. Image quality assessment for iris biometric. Master's thesis, West Virginia University, Morgantown, WV, USA, April 2005.

[8] N. D. Kalka, J. Zuo, N. A. Schmid, and B. Cukic. Image quality assessment for iris biometric. In *SPIE 6202: Biometric Technology for Human Identification III*, volume 6202, pages 6202:D1–D11, April 2006.

[9] B. J. Kang and K. R. Park. A study on iris image restoration. In *International Conference on Audio- and Video-Based Biometric Person Authentication*, pages 31–40, 2005.

[10] X. Liu, K. W. Bowyer, and P. J. Flynn. Experiments with an improved iris segmentation algorithm. In *Fourth IEEE Workshop on Automatic Identification Technologies (AutoID)*, pages 118–123, Buffalo, NY, October 2005.

[11] L. Ma, T. Tan, Y. Wang, and D. Zhang. Personal identification based on iris texture analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(12):1519–1533, 2003.

[12] J. R. Matey, O. Naroditsky, K. Hanna, R. Kolczynski, D. LoIacono, S. Mangru, M. Tinker, T. Zappia, and W. Y. Zhao. Iris on the move^{TM}: Acquisition of images for iris recognition in less constrained environments. *Proceedings of the IEEE*, 94(11):1936–1947, November 2006.

[13] National Institute of Standards and Technology (NIST). Iris challenge evaluation (`http://iris.nist.gov/ICE/`).

[14] National Institute of Standards and Technology (NIST). Multiple biometric grand challenge (`http://face.nist.gov/mbgc/`).

[15] N. A. Schmid and F. Nicolo. A method for selecting and ranking quality metrics for optimization of biometric recognition systems. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPR Workshops 2009) Accepted*, pages 1–8, June 2009.

[16] G. Zhang and M. Salganicoff. U.S. patent no. 5,953,440: Method of measuring the focus of close-up images of eyes, September 1999.

[17] X.-D. Zhu, Y.-N. Liu, X. Ming, and Q.-L. Cui. A quality evaluation method of iris images sequence based on wavelet coefficients in "region of interest". In *CIT '04: Proceedings of the The Fourth International Conference on Computer and Information Technology*, pages 24–27, Washington, DC, USA, 2004. IEEE Computer Society.

[18] J. Zuo and N. A. Schmid. An automatic algorithm for evaluating the precision of iris segmentation. In *International Conference on Biometrics: Theory, Applications, and Systems (BTAS'08)*, September 2008.