Fast and efficient iris image enhancement using logarithmic image processing

Nadezhda Sazonova[1] , *Stephanie Schuckers*[2]

Department of Electrical and Computer Engineering, Clarkson University
[1] nsazono@clarkson.edu, [2] sschucke@clarkson.edu

Abstract **– Low quality iris images such as blurry, low resolution images with poor illumination create a big challenge for iris recognition systems. We propose a new iris recognition algorithm for enhancement of normalized iris images. Our algorithm is based on the logarithmic image processing (LIP) image enhancement which is used as one of the 3 stages in the enhancement process. Results from processing challenging MBGC iris data show significant improvement in the performance of iris recognition algorithms in terms of equal error rates.**

1. Introduction

Image quality is very important factor in the performance of an iris recognition system. When the higher quality images are not available the iris recognition can be compromised by using the low quality images such as those acquired in a non-invasive, non-cooperative environment, e.g. iris images obtained at a distance and on the move. These images characterized by abundant degrading factors such as low resolution, lighting and contrast, extensive specular reflections, eyelid occlusion, presence of contact lenses and distracting eyeware, etc. Thus, methods for iris image enhancement play an important part in contributing to the accuracy of iris recognition systems. Up until recently, the methods for iris image enhancement were mostly tested on different iris databases that are represented either by very good quality iris images (such as CASIA-IrisV1, IrisBase, Biosecure iris-DS2) or only by images with few deterioration factors (CASIA-IrisV3, UBIRIS v.1, IrisBase non-ideal images). There is a growing demand for iris recognition of images obtained in the non-cooperative environment, such as videos of people passing through airport portals and other on-the-move conditions. New databases are now available with very challenging iris images, characterized by low resolution, poor lighting and contrast, out-of-focus blur, noise due to hair, eyewear, contact lenses, off-angle, etc.: UBIRIS v.2 and MBGC (Multiple Biometric Grand Challenge) iris database for NIR still iris, NIR video iris and NIR face video images.

Various techniques for image enhancement of normalized iris images have been proposed. A group of methods called super-resolution used for reconstruction the blurry or low resolution images was recently developed [1, 2, 3, 4]. Methods showing the best improvement in the verification rates [1, 2] are based on predicting small sub-images (patches) to fill in plausible details in the blurry image from the independent training set of images. Other methods used for enhancing sharpness as well as illumination and noise reduction of normalized iris images include traditional histogram equalization, contrast stretching, unsharp masking, homomorphic filtering [5], deblurring [6], denoising [7], focus correction [8], entropy normalization

[9] and background subtraction [10]. A good review of such methods is given in [11]. A very recently proposed algorithm [11, 12] for local enhancement of biometric images uses SVM training to reduce noise, blur and enhance the illumination. While some of the existing techniques for iris image enhancement are very fast, they concentrate on a single degrading factor (such as noise, blur of illumination), other use multi-factor image enhancement but are relatively slow [11] and/or require substantial training data involved [1, 2]. In this paper we propose a new fast and effective iris image enhancement algorithm based on logarithmic image processing. Our proposed algorithm enhances both sharpness and the illumination (dynamic range) of an image. The proposed LIP-based algorithm showed up to 5% improvement in the verification rates when compared to the other fast methods for image enhancement.

2. Method

We used image enhancement method proposed in [13] based on logarithmic image processing (LIP) [14] applied to the framework of Lee's image enhancement algorithm [15]. This new implementation of Lee's algorithm showed good ability to increase the overall contrast and the sharpness of an image. The LIP image enhancement is described in [13] as follows. First, image intensity function, *F,* is converted to the gray tone function, *f* : *F(i,j) = M - f(i,j)*, where M=256 for an 8-bit image. The gray tone function, in turn, is transformed to the normalized negative gray tone function via:

$$\bar{f} = 1 - \frac{f}{M} \qquad (1)$$

This is called a normalized complement transform. Next, the logarithm of the normalized negative gray tone function is processed by the Lee's original algorithm:

$$\log(\bar{f}'(i,j)) = \alpha \log(\bar{a}(i,j)) + \beta[\log(\bar{f}(i,j)) - \log(\bar{a}(i,j))], \qquad (2)$$

where $\bar{a}(i,j)$ is the mean value of $\bar{f}$ in a *(ηxη)* window centered at *(i,j)*. Enhanced output image F' is obtained by converting $\bar{f}'$ back to the original scale.

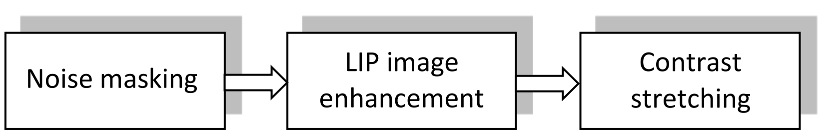


Fig. 1. Outline of the proposed LIP-based iris image enhancement algorithm.

The algorithm is controlled by three parameters: *α, β* and *η*. First parameter, *α*, is used to modify the dynamic range of an image: the dynamic range of the dark (bright) areas of an image is expanded when *α<1* (*α>1*). The smaller the value *α*, the brighter the image will appear. The sharpness of an image is controlled with parameter *β ϵ[0,255]* similar to that of the unsharp masking: greater values lead to the sharper image, although the noise pixels will also be nonlinearly amplified. When $\beta = 1$, the sharpness of the image doesn't change. The proposed iris image enhancement algorithm included LIP image enhancement as one of the steps shown in Fig. 1.

We included noise masking prior to LIP enhancement application and subsequent contrast stretching. The following input parameters were selected to be applied to the normalized iris images: α=0.7, sharpness β =2, η =3. At this point we didn't differentiate between the individual image properties to adjust these parameters. The selection of these parameters was performed using visual preferences of the appearance of the most iris image in the dataset. Contrast stretching (to [0.0 1.0]) was applied to the LIP-processed image in order to increase contrast (see Fig. 2(d)). During this step the noisy parts of the image (specular reflections and the eyelids) tend to take up the highest gray scale values, so that the most important portion of the image still remains in low contrast. To avoid this pitfall, the noisy part of an image were masked with the mean grayscale value of the rest of the image prior to LIP-enhancement and histogram stretching (see Fig. 2(e)). Example of an enhanced image using different version of the LIP enhancement (the original LIP enhancement, LIP enhancement with stretching and the proposed version: masking followed by LIP enhancement and stretching) is shown in Fig. 2. The proposed enhancement algorithm was applied to the normalized iris image of size 128x720. After the enhancement image was downsized to 20x240 before encoding. Downsizing reduced the noise produced by LIP and emphasized the most important details.

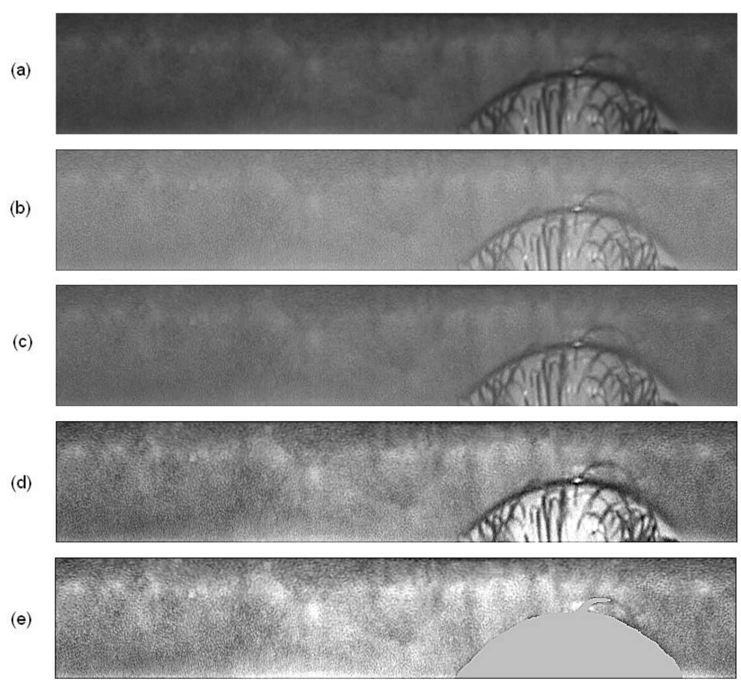
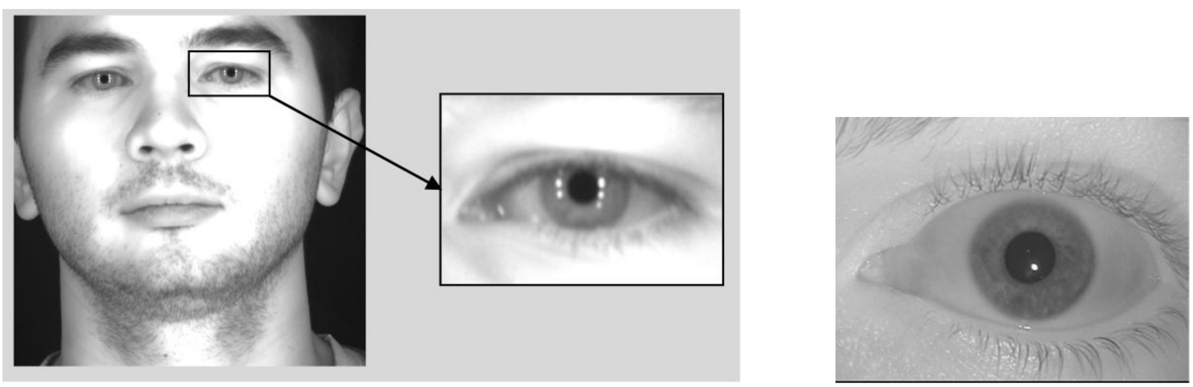


Fig. 2. Iris image enhancement comparison: (a) Original image, (b) LIP-enhanced image with a=0.5, (c) LIP-enhanced image with a=0.7, (d) LIP-enhanced image (a=0.7) with subsequent contrast stretching, (e) proposed

application of the LIP-enhancement: noise is masked with the average gray value, LIP is applied with parameter value a=0.7, finished with contrast stretching stretching [0.0,1.0].

3. Data

We applied our image enhancement algorithm to normalized iris images obtained from the MBGC v.1 data. Gallery images came from NIR iris video, probe images were taken from the NIR face videos. For the recognition process only one image (the sharpest image) was selected from each video sequence. Example images are shown in Fig. 3. The corresponding iris image (left or right) was cropped from the sharpest frame in each NIR face video sequence. NIR iris video and NIR face video images provided on average 220 and 120 pixels across the iris. Video iris images exhibited low contrast but showed reasonable sharpness. The hardest data were represented by the iris images cropped from NIR face videos: they were characterized by low illumination and contrast, low resolution, interfering specular reflections. Data were grouped in four experiments (with possibility of overlapping subjects among gallery and probes): two for left eyes (Left 1 and Left 2) and two for right eyes (Right 1, Right 2). Size of galleries and probes for the experiments ranged 69-72 and 139-140 images respectively.



(a) (b)

Fig. 3. Iris data samples (sharpest frames): (a) MBGC NIR face video (probe), (b) NIR iris video (gallery).

4. Results

We compared the results of iris recognition performance using our iris image enhancement and other popular existing approaches: histogram equalization [5], unsharp masking [5], homomorphic filtering [5] implemented in [16], background subtraction [10]. The selection of the iris image enhancement algorithms for results comparison was based using criterion of the fastest runtime (within 1 sec. using MATLAB 7.3 on 3.06 Ghz processor). Different versions of the application of LIP enhancement: original LIP, LIP with contrast stretching, masking followed by LIP, were also included in the analysis to justify the necessity of three stages in the proposed algorithm. We applied these iris image enhancement algorithms to be used with the same iris segmentation, normalization, noise masking and feature encoding algorithms.

Segmentation was performed based on our own entropy-based approach. Manual detection of segmentation errors based on 216 video iris images and 260 iris images cropped from NIR video face videos resulted in 0.46% of incorrectly segmented from iris videos and 0.77% incorrectly segmented images from NIR face videos. We used Gabor-filters encoding function described in [17] and implemented in [18]. Figures 4 and 5 show the results of different image enhancement methods applied to sample normalized iris images extracted from the MBGC NIR face videos (Fig. 4) and the MBGC iris videos (Fig. 5).

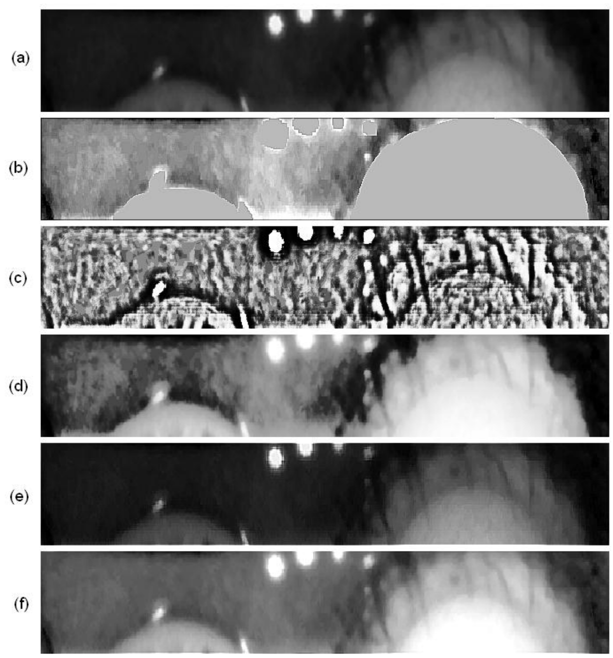


Fig. 4. Image enhancement algorithms applied to a sample normalized iris image extracted from a NIR face video: (a) original image, (b) proposed modified LIP method, (c) background subtraction, (d) histogram equalization, (e) unsharp masking, (f) homomorphic filtering

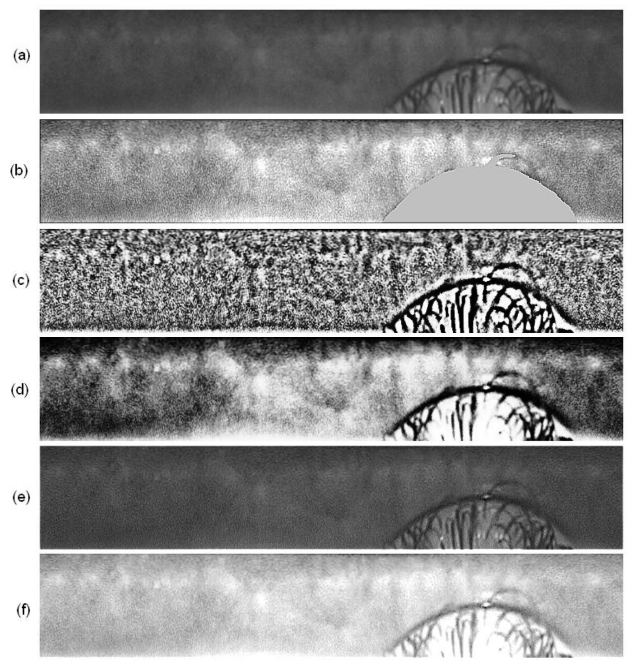


Fig. 5. Image enhancement algorithms applied to a sample normalized iris image extracted from an iris video: (a) original image, (b) proposed modified LIP method, (c) background subtraction, (d) histogram equalization, (e) unsharp masking, (f) homomorphic filtering

Table 1 show the effect of different iris enhancement algorithms on the overall iris recognition performance in terms of the equal error rates (EER). These results indicate that our algorithm provides verification improvement of up to 7.5% in equal error rates over the original (unenhanced) iris image recognition. The proposed algorithm also shows better image enhancement than the other algorithms for up to 5% reduction in equal error rates. In particular, the verification performance of the proposed 3-stage LIP enhancement algorithm exceeds other versions of LIP enhancement application: original LIP, LIP with contrast stretching, masking preceding LIP. The results also exhibit the adverse effect of background subtraction method on the EER due to amplifying the noise in the challenging MBGC images. Figure 6 illustrates typical DET curve (Left 1 experiment) to compare effect of different image enhancement algorithms. Thus, the proposed 3-stage LIP-based iris enhancement algorithm improves the performance of iris verification by up to 5–7.5% in terms of equal error rates.

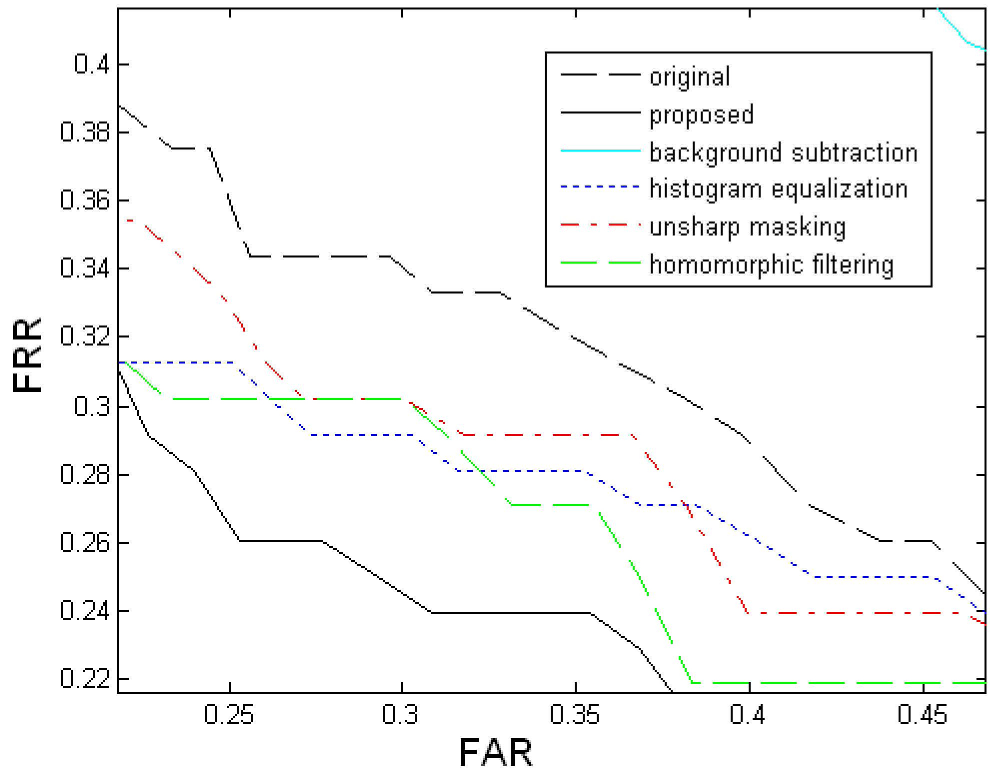


Fig. 6. DET curve for comparing the performance of different algorithms for iris image enhancement versus the original (unenhanced) version and the proposed LIP-based algorithm (Left 1 experiment).

Table 1. EER for iris recognition using different image enhancement algorithms

Method\Experiment	Left1	Left 2	Right 1	Right 2
Original	0.3308	0.2331	0.2433	0.2682
Background subtraction	0.4363	0.3580	0.3958	0.3276
Histogram equalization	0.2892	0.2086	0.2456	0.2291
Unsharp masking	0.3013	0.2084	0.2444	0.2487
Homomorphic filtering	0.3013	0.2281	0.2454	0.2330
Original LIP	0.2977	0.2228	0.2540	0.2266
LIP+contrast stretching	0.2982	0.2212	0.2458	0.2430
Masking+LIP	0.2698	0.2042	0.2393	0.2206
Proposed: Masking+LIP+contrast stretching	**0.2567**	**0.1963**	**0.2437**	**0.1989**

5. Conclusion

We proposed a new fast iris image enhancement algorithm based on the application of the LIP image enhancement algorithm to normalized iris images. It consists of the three stages: masking of noisy regions, application of the original LIP image enhancement algorithm and subsequent contrast stretching. The proposed 3-stage algorithm is suitable for the enhancement of normalized iris images prior to feature extraction. The results show that the proposed enhancement algorithm improves the verification performance of up to 5-7.5% in terms of EER on the four MBGC data sets with challenging iris images (low resolution, poor illumination and noise). To our knowledge, this is the first attempt to publish iris image enhancement results on the MBGC Iris experiments. Thus, the proposed iris image enhancement algorithm has potential applicability in iris recognition especially when speed is an issue.

As mentioned before, we used the same LIP parameters uniformly for all images. Future research will include implementation of the adaptive selection of the LIP parameters. In addition, local adaptive iris image enhancement will be developed to reduce the difference in illumination between various parts of an iris image and testing the enhancement algorithm on more data.

References

[1] J. Huang, L. Ma, T. Tan, Y. Wang, "Learning Based Resolution Enhancement of Iris Images," National Laboratory of Pattern Recognition, Institute of Automation Chinese Academy of Sciences, P.O. Box 2728, Beijing, 100080, P.R. China. 2008.

[2] W.T. Freeman, Thouis R.J., and E.C. Pasztor, "Example based super-resolution," *IEEE Computer Graphics and Application*, 22(2):56–65, March-April 2002.

[3] K. Sauer, J. Allebach, "Iterative reconstruction of band-limited images from nonuniformly spaced samples," *IEEE Trans. Circuits System*, CAS-34:1497–1505, 1987.

[4] M. Irani and S. Peleg, "Improving resolution by image registration," *GMIP*, vol. 53, pp.231–239, 1991.

[5] R.C. Gonzalez, R.E. Woods, "Digital Image Processing," second ed., Prentice-Hall, Englewood Cliffs, NJ, 2002.

[6] S.K. Kang, J.H. Min, J.K. Paik, "Segmentation based spatially adaptive motion blur removal and its application to surveillance systems," *Proc. Int. Conf. Image Process. , vol.* 1, pp. 245–248. 2001.

[7] R. Malladi, J.A. Sethian, "Image processing via level set curvature flow," *Proc. Nat. Acad. Sci.,* vol. 92 (15), pp. 7046–7050, 1995.

[8] D.G. Sheppard, K. Panchapakesan, A. Bilgin, B.R. Hunt, M.W. Marcellin, "Removal of image defocus and motion blur effects with a nonlinear interpolative vector quantizer," *Proc. IEEE Southwest Symposium on Image Analysis and Interpretation,* pp. 1–5. , 1998.

[9] P.J.N. Kapur, A.K.C. Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," *Comput. Vision Graphics Image Process.* Vol. 29, pp. 273–285. 1985.

[10] L. Ma, T. Tan, Y. Wang, D. Zhang, "Efficient iris recognition by characterizing key local variations," *IEEE Trans. Image Process.* Vol. 13 (6), pp. 739–750. 2004.

[11] R. Singh, M. Vatsa, A. Noore, "Improving verification accuracy by synthesis of locally enhanced biometric images and deformable model," *Signal Processing .* Vol 87, pp. 2746–2764. 2007.

[12] M. Vatsa, R. Singh, A. Noore, "SVM Based Adaptive Biometric Image Enhancement Using Quality Assessment Studies in Computational Intelligence,". *Speech, Audio, Image and Biomedical Signal Processing using Neural Networks.* Vol. 83, Springer Berlin / Heidelberg. Pp. 351-371. 2008.

[13] G. Deng, L.W. Cahill, and G.R. Tobin, "A study of the logarithmic image processing model and its application to image enhancement," *IEEE Trans. Image Process*., Vol. IP-4, pp. 506- 512, 1995.

[14] M. Jourlin, J.C. Pinoli, "A model for logarithmic image processing," *J. Microscopy*, vol. 149, pp. 21-35, Jan. 1988.

[15] J.S. Lee, "Digital image enhancement and noise filtering by use of local statistics," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-2, pp.165-168, Mar. 1980.

[16] P. D. Kovesi. MATLAB and Octave Functions for Computer Vision and Image Processing. School of Computer Science & Software Engineering, The University of Western Australia. Available from: http://www.csse.uwa.edu.au/~pk/research/matlabfns/

[17] L. Masek, "Recognition of Human Iris Patterns for Biometric Identification," Thesis, The University of Western Australia, 2003.

[18] L. Masek, P. Kovesi, "MATLAB Source Code for a Biometric Identification System Based on Iris Patterns," The School of Computer Science and Software Engineering, The University of Western Australia. 2003. Available from: http://www.csse.uwa.edu.au/~pk/studentprojects/libor/sourcecode.html