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A Novel Visible Iris Recognition using Color Monogenic Wavelets

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Abstract

Visible light (VL) iris recognition technology[1] has a growing number of applications in the field of security and citizen identification with the growing number of surveillance cameras and smartphone cameras that acquire iris images in the visible wavelength range. The problem of iris recognition has also led to a growing interest in the development of robust algorithms for visible light iris recognition. Visible light iris recognition is also important for better results on light-colored irises which observe a richer capturing of iris patterns in the visible light range as compared to the Near-Infrared (NIR) range.

VL iris images have been shown to have more noise in the form of shadows and reflections and are not as efficient as NIR iris images in capturing iris patterns for dark-colored irises. In this research work, a novel color monogenic wavelength based VL iris feature extraction is performed on widely used VL databases (PolyU[2] and UTIRIS[3]). The results of the proposed algorithm outperform the commonly used algorithms for NIR iris recognition

Keywords: Biometrics, Visible Iris Recognition, Color Monogenic Wavelets, Riesz Transform.

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Introduction

With the increasing use of iris recognition technology nowadays in various security and citizen identification applications such as the border crossing system and the Aadhaar (UIDAI)[4] project in India, it is becoming increasingly important to have more and more robust image recognition algorithms. Almost all of the iris recognition systems in operation today work in the near-infrared (NIR) spectrum for iris image acquisition. Iris acquisition at the near-infrared wavelength has its advantages as at that wavelength, we observe lesser reflections caused by the flash (which pose a larger occlusion problem in the visible light wavelength) and dark-colored irises are also better captured in the NIR wavelength as shown in Figure 1. Moreover, as Daugman[5] and Hosseini[3] have shown, NIR iris images also have fewer shadows and diffuse reflections as compared to visible light iris images. As has been seen in Hosseini's work,[3] dark-colored irises, with a lower pheomelanin content can't absorb enough visible light and hence the rich distinguishing patterns get hidden on these irises during visible light acquisition. However, NIR acquisition brings these patterns to the fore and is more suited for dark-colored irises. On the flip side, light-colored iris, having a high pheomelanin contect, show their rich stromal patterns during VL acquisition while most of this distinguishing information is lost in

NIR acquisition. Figure 1 shows the above phenomenon. There has been an increasing interest in visible light iris recognition due to the increasing use of close circuit and other surveillance cameras which operate in the visible light wavelength and can capture images at a distance. These surveillance cameras employed at most public places which can capture images of various biometrics, including iris from a distance and the growth of smartphone cameras and higher

cost of NIR cameras are also some of the contributors to this growing interest. A number of works on visible iris recognition have come out in the recent past. With the additional color information in the VL iris images, attempts have been made at effectively using this color information to build a more robust VL iris recognition system. Hosseini *et al.*[3] uses a shape analysis method and then fuses the NIR-extracted features with the VL-extracted melanin patterns to improve the overall iris-matching accuracy on the UTIRIS database, while Radu *et al.*[1] and Zhang *et al.*[6] fuse color information from different color channels to train their

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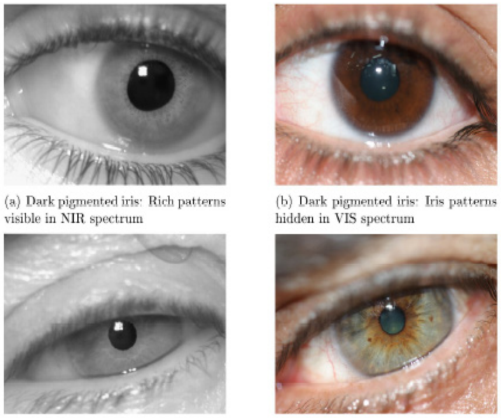

(a) Dark pigmented iris: Rich patterns visible in NIR spectrum
(b) Dark pigmented iris: Iris patterns hidden in VIS spectrum
(c) Light pigmented iris: Iris patterns hidden in NIR spectrum
(d) Light pigmented iris: Rich patterns visible in VIS spectrum

Fig. 1: Iris Patterns captured in different spectrums from the UTIRIS Database

classifiers using learning algorithms. Trokielewicz *et al.*[7] use a smartphone camera to acquire high-quality VL iris images and achieve remarkable results using traditional iris recognition methods. So far, none of the work uses an analytic signal-based approach while using the color information for VL iris recognition. The proposed algorithm, based on monogenic color wavelets, has its roots in Daugman's local phase features based approach and uses the 2D analytic signal for color images, the monogenic color wavelet, for the extraction of local features of color iris images. We compare the performance of color monogenic wavelets against 2D Gabor filter and 1D log Gabor filter in same-spectrum matching. With the rise of VL iris acquisition, interest in matching the classical NIR images against the VL images has also increased. Attempts have been made in the past to build an algorithm for cross-spectral iris recognition, most noticeably by Ramaiah and Kumar,[2] who use 1D log Gabor features on a bi-spectral database with pixel correspondence. Sample images from the database can be seen in Figure 1. While achieving remarkable accuracy in same-spectrum iris recognition in both spectrums (4% EER for NIR and 7% EER for VL), their method falls short in cross-spectral matching and gives relatively poor results (34% EER). The poor performance of 1D log Gabor features in cross-spectral matching, the performance of monogenic wavelets in iris recognition in our previous work[8] and the fact that the VL irises are color images prompted us to employ Color Monogenic Wavelets for the purpose of cross-spectral iris recognition, as we felt by using monogenic color wavelets, we could take advantage of not just the color information in these images which gets lost during the RGB-to-Grayscale conversion, but also the superior local feature extraction ability of monogenic wavelets.

The algorithms that work well for NIR iris images might not work well for VL iris images because of the challenges that come with VL iris images. VL iris images have been shown to have more noise in the form of shadows and reflections proposed algorithm outperform the commonly

Table 1: EERs in % for VL-VL iris matching using the three algorithms on properly segmented images from the PolyU database

Database	*Daugman*	*Masek*	*Proposed*
PolyU - Properly Segmented	5.97	5.09	3.96
PolyU - Large Subset	7.05	5.07	6.91
UTIRIS - Properly Segmented	10.91	8.57	5.19

Table 2: EERs in % for VL-VL iris matching for each color channel using the three algorithms on properly segmented images

Database	*Daugman*	*Red channel Masek*	*Proposed*
Polyu - properly segmented	6.83	5.34	4.47
Utiris - properly segmented	11.43	8.59	5.75
Database	Daugman	Green channel Masek	Proposed
Polyu - properly segmented	6.43	4.86	3.95
Utiris - properly segmented	10.12	9.07	5.23
Database	Daugman	Blue channel Masek	Proposed
Polyu - properly segmented	8.90	7.08	4.90
Utiris - properly segmented	11.42	10.03	8.53

used algorithms for NIR iris recognition and are not as efficient as NIR iris images in capturing iris patterns for dark colored irises. This fact can also be seen in the works of Ramaiah and Kumar in[2] and Abdullah *et al.* in.[9]

The performance of their algorithms is almost invariably better in NIR-NIR matching compared to VL-VL matching. We believe that using the color information present in VL iris images through the use of color monogenic wavelets would give better results than the algorithms which discard the color information present in the iris images. The added benefit of extracting local monogenic features as opposed to local Gabor features also makes our proposed algorithm primed to outperform the other two widely used algorithms, namely Masek [10] and Daugman.[5] To the best of our knowledge, this is the first attempt being made to use local "color monogenic features" to perform iris recognition experiments.

Monogenic Wavelets

The application of wavelets to a three-dimensional function only became possible after the introduction of the monogenic signal,[17] which is an accurate extension of the 1D-analytic signal to higher dimensions. The monogenic color signal and the subsequently introduced color monogenic wavelets, which is being studied extensively by Soulard *et al.*[11,12] are tools that enable a non-marginal (processing all three channels simultaneously) study of a color image.

A 2D color image can be thought of as 3 vector-valued 2D signals given by (1).

$$S_C = [S^R \quad S^G \quad S^B] \qquad (1)$$

A marginal approach would be to apply Riesz transform[13] to each channel separately, as done in the grayscale case. Instead, Demarcq[14] and Soulard[11] propose a color monogenic signal and monogenic wavelet which is given by (2) and (3) respectively.

$$S_M = [S_R \quad S_G \quad S_B \quad S_{r1} \quad S_{r2}] \qquad (2)$$

$$\psi_M = [\psi_R \quad \psi_G \quad \psi_B \quad \psi_{r1} \quad \psi_{r2}] \qquad (3)$$

Where, the individual components of are given by (4)

$$\begin{aligned} \psi_R &= [\psi \ 0 \ 0]^T \\ \psi_G &= [0 \ \psi \ 0]^T \\ \psi_B &= [0 \ 0 \ \psi]^T \end{aligned} \qquad (4)$$

$$\psi_{r1} = \begin{bmatrix} \frac{x}{2\pi\|x\|^3} * \psi_R \\ \frac{x}{2\pi\|x\|^3} * \psi_G \\ \frac{x}{2\pi\|x\|^3} * \psi_B \end{bmatrix} \quad \psi_{r2} = \begin{bmatrix} \frac{y}{2\pi\|x\|^3} * \psi_R \\ \frac{y}{2\pi\|x\|^3} * \psi_G \\ \frac{y}{2\pi\|x\|^3} * \psi_B \end{bmatrix} \qquad (5)$$

Where, s_{r1} and s_{r2} are x and y components of the Reisz Transform applied to the 2D signal given by $s_R+s_G+s_B$.

Feature Extraction

We use the segmentation, normalization and matching steps used by Libor Masek[10] in his algorithm. So, we use the circular Hough transform for segmentation and Daugman's Rubber Sheet model[5] for normalization. However, the proposed algorithm uses monogenic color wavelets for feature encoding of the normalized iris images. The encoded features are then matched between two images by calculating the fractional Hamming Distance between them.

We extract the local features, namely phase, orientation and amplitude of a color image using the directional Riesz transform. First, the orientation is calculated using Di Zenzo's color structure tensor[11,15] at each scale. After careful analysis, we chose scales 3 and 4 as at those scales the phase information extracted was more prominent as can be seen in Figure 2. Furthermore[16] shows us that the local orientation is also a good representation of the local structure of the image. Keeping these two things in mind, we have encoded the local color phase and orientation at each scale in two bits. Keeping in line with Daugman's[5] and Masek's[10] algorithms, we ignore the local amplitude information as it has been shown to not contain much structural information.

On encoding the local orientation and phase at each pixel in two bits, we have a feature vector of size 2*2*(height of rubber sheet)*(width of rubber sheet) at each scale. We use fractional Hamming distance between the feature vectors of the two images under consideration to compare them.

Experimental Results for Vl Rgb Images

The experiments were conducted on the VL images from PolyU and UTIRIS databases. Two subsets of the PolyU database (a smaller one with properly segmented images and a larger one containing

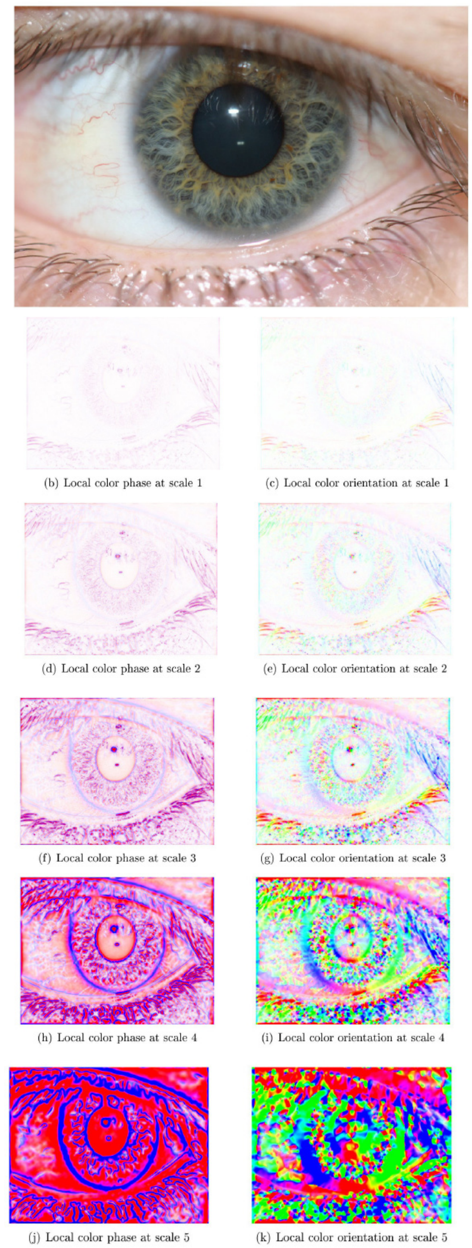

Figure 2: Iris Patterns captured in different spectrums from the UTIRIS database

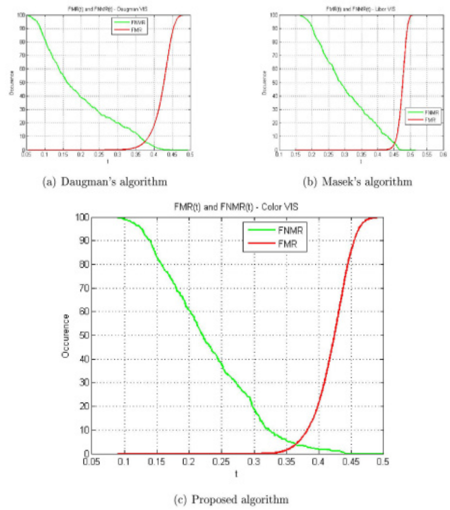

Figure 3: ROCs for VL-VL iris matching using the three algorithms on properly segmented images from the PolyU database

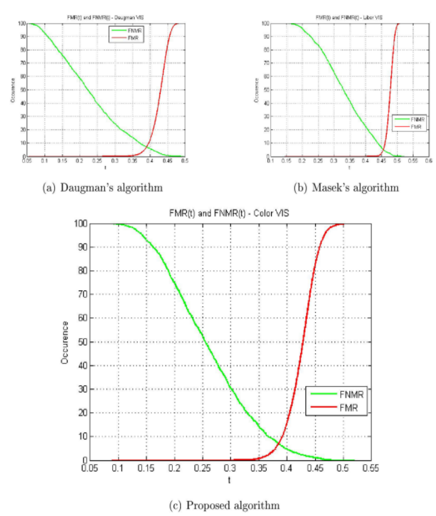

Figure 4: ROCs for VL-VL iris matching using the three algorithms on a larger set of images from the PolyU database

some images with poor segmentation) and one subset of the UTIRIS database with properly segmented iris images were used here. Figure 3, 4 and 5 show the ROCs obtained for each of the methods and Table 1 lists the EERs obtained. Our algorithm outperforms the established algorithms for VL iris matching, as seen in Table 1 for properly segmented iris images. Again, the powerful local feature extraction of color monogenic wavelets leads to the proposed algorithm performing at par if not better than the established algorithms for VL- VL.

Expetimental Results on Each Rgb Channels Vl Rgb Images

We also performed our experiments on each of the three channels of the RGB images by running all three algorithms separately on red, blue and green channels of the normalized

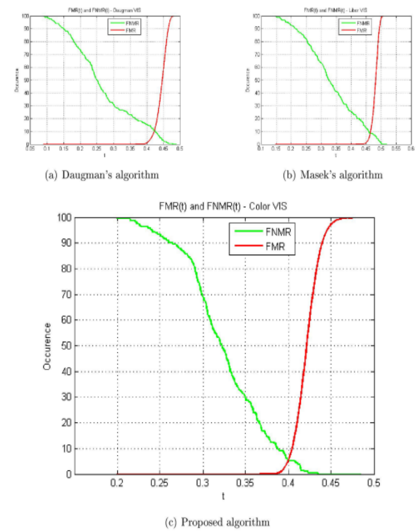

Figure. 5: ROCs for VL-VL iris matching using the three algorithms on properly segmented images from the UTIRIS database

iris images. Our algorithm again outperforms the established algorithms for the case of single channel matching for each of the channels of RGB iris matching, as seen in Table 2 for properly segmented iris images.

But the results we are more interested in are the performance of the proposed approach on the RGB image, its grayscale version and each channel. The EERs of this experiment are listed in Table 1. While the EER values in Table 2 show the superior performance of the proposed algorithm on VL iris images, the EER values in Table 2 show that the proposed algorithm can do well on each color channel of the normalized as well as the grayscale iris image. This shows us the robustness of local color monogenic features for color as well as grayscale or single-color channel images. The right most column in Table 1 shows us the superior performance of our algorithm for RGB images as opposed to single-channel images and reinforces our claim that the monogenic color wavelets effectively utilize the color information present in iris images for accurate results in VL image recognition. It is important here to note that although the green channel seems to be performing well (at par with RGB iris image) here, it might only be a result of the color of irises used in the database or the sensor used for acquiring the images, and we can never rely on one channel to perform better than other channels as can be seen from the results of[9] where their experiment on UTIRIS database shows red channel to be performing better than the green and blue channels. A study performed in[7] shows different color channels performing differently depending on the color if the irises being matched. This is why we promote the use of color monogenic wavelets for visible light iris recognition. We feel that they perform a holistic color analysis and are more robust to the performance being affected by the colors of the irises used in the database.

Conclusion

There is a need for a robust Visible Light Iris Recognition algorithm with the emergence of high-quality smartphone cameras and the increasing number of surveillance cameras that work in the visible light wavelength range. Visible Light Iris recognition is a tougher problem as compared to Near-Infrared Iris recognition because of the noise present in VL iris images in the form of reflections and shadows. The Color Monogenic Wavelets, which combine monogenic wavelets' power in extracting an image's local features with their ability to analyze the color information present in RGB images, produce superior performance in NIR-NIR and VL-VL iris recognition for the PolyU and UTIRIS iris databases. They efficiently analyze the local features of a normalized iris image in terms of shape as well as color to outperform Gabor filter-based iris recognition algorithms and can be useful, especially for visible light iris recognition.

References

[1] P. Radu, K. Sirlantzis, G. Howells, S. Hoque, F. Deravi, A visible light iris recognition system using colour information, 9th IASTED *International Conference on Signal Processing, Pattern Recognition and Applications* (SPPRA2012).

[2] N. Pattabhi Ramaiah and Ajay Kumar, "Towards more accurate iris recognition using bi-spectral imaging and cross-spectral matching capability," *IEEE Transactions on Image Processing*, vol. 26, pp. 208-221, January 2017.

[3] Mahdi S. Hosseini, Babak N. Araabi and H. Soltanian-Zadeh,"Pigment Melanin: Pattern for Iris Recognition," *IEEE Transactions on Instrumentation and Measurement,* vol.59, no.4, pp.792-804, April 2010.

[4] Aadhaar [online] Unique Identification Authority of India. https://uidai.gov.in/

[5] J. Daugman, How iris recognition works, *IEEE transactions on circuits and systems for video technology* 14 (1) (2004) 21-30.

[6] H. Zhang, Z. Sun, T. Tan, J. Wang, Iris image classification based on color information, in: 21st *International Conference on Pattern Recognition* (ICPR 2012), 2012, pp. 3428-2430.

[7] M. Trokielewicz, E. Bartuzi, Cross-spectral iris recognition for mobile applications using high-quality color images, Journal *of Telecommunications and Information Technology* (2016) 91-97.

[8] P. Birajadar *et al*., "A novel iris recognition technique using monogenic wavelet phase encoding," *2016 International Conference on Signal and Information Processing (IConSIP)*, 2016, pp. 1-6.

[9] M. A. M. Abdullah, S. S$. Dlay, W. L. Woo, J. A. Chambers, A novel framework for cross-spectral iris matching, *IPSJ Transactions on Computer Vision and Applications* 8 (2016) 1-11.

[10] L. Masek, Recognition of human iris patterns for biometric identification, Bachelor of Engineering report, School of Computer Science and Software Engineering, the University of Western Australia.

[11] R. Soulard, P. Carre, C. Fernandez-Maloigne, Vector extension of monogenic wavelets for geometric representation of color images, *IEEE transactions on image processing* 22 (3) (2013) 1070-1083.

[12] R. Soulard, P. Carre, Elliptical monogenic wavelets for the analysis and processing of color images, *IEEE transactions on signal processing* 64 (6) (2016) 1535-1549.

[13] E. Stein and G. Weiss, Introduction to Fourier Analysis on Euclidean Spaces, Princeton, NJ: Princeton University Press, 1971.

[14] G. Demarcq, L. Mascarilla, P. Courtellemont, The color monogenic signal: a new framework for color image processing, *IEEE Proceedings of the International Conference on Image Processing* (ICIP).

[15] S. Di Zenzo, "A note on the gradient of a multi-image," Comp. Vision, Graphics, and Image Proc., vol. 33, pp. 116-125, 1986.

[16] D. K. Hammond, Representing and modeling images with multiscale local orientation, Ph.D. thesis, Courant Institute of Mathematical Sciences, New York University

[17] M. Felsberg, The monogenic signal, *IEEE transactions on signal processing* 49 (12) (2001) 3136-3144.