ON CROSS SPECTRAL PERIOCULAR RECOGNITION

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ABSTRACT

This paper introduces the challenge of *cross spectral periocular matching*. The proposed algorithm utilizes neural network for learning the variabilities caused by two different spectrums. Two neural networks are first trained on each spectrum individually and then combined such that, by using the cross spectral training data, they jointly learn the cross spectral variability. To evaluate the performance, a cross spectral periocular database is prepared that contains images pertaining to visible night vision and near infrared spectrums. The proposed combined neural network architecture, on the cross spectral database, shows improved performance compared to existing feature descriptors and cross domain algorithms.

***Index Terms*—** Biometrics, Periocular recognition, Cross spectral matching, Neural network

1. INTRODUCTION

Periocular recognition, proposed by Park et al. [1] in 2010, utilizes the periphery of eyes to determine the identity of an individual. Several researchers have proposed algorithms for periocular matching which provide accuracies ranging from 60% to 100%. Researchers have used periocular recognition to improve the performance of both face recognition and iris recognition [1], [2]. It is an invariant region with respect to face recognition and for iris, it acts as an additional information that can be utilized if iris is captured at a distance. Fig. 1 shows sample images of periocular region obtained from both face camera and iris scanner. Face recognition is generally performed with visible spectrum images whereas iris recognition is performed in near infrared (NIR) spectrum. If it is to be used for aiding both face and iris recognition, it is important that periocular matching should yield good performance across different spectrums.

Table 1 summarizes some existing periocular recognition algorithms. Researchers have primarily studied periocular region with respect to either visible spectrum or NIR spectrum or have fused information from two spectrums. However, to the best of our knowledge, cross spectral periocular recognition is not well studied. Therefore, this research focuses on cross spectral periocular recognition and develops a heterogeneous matching algorithm. There are two main contributions of this research: (1) neural network learning-based feature extraction and matching algorithm for cross spectral periocular recognition[1] and (2) IIITD multispectral periocular database that contains 1240 images pertaining to 62 individuals captured using visible spectrum, night vision, and NIR iris cameras.

Fig. 1. Periocular images of two individuals from three different devices.

2. PROPOSED CROSS SPECTRAL PERIOCULAR MATCHING ALGORITHM

Images captured in visible and near infrared spectrums differ significantly and matching cross spectrum images is a challenging research problem. In this section, we propose a neural network learning based algorithm that extracts features from individual spectrum images and combines the information so that it can be used for matching cross spectral images. Fig. 2 illustrates the key concept of the proposed algorithm which includes three learning stages: (1) learning a neural network for spectrum 1 ($Spectrum - 1$ NNet), (2) learning a neural network for spectrum 2 ($Spectrum - 2$ NNet), and (3) jointly updating two neural networks for cross spectral matching. The proposed cross spectral periocular matching algorithm is described next.

1. From the normalized and preprocessed periocular images, PHOG (pyramid of histogram of oriented gradients) [7] descriptors are extracted. PHOG descriptors

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[1]Here, the term recognition is used to represent verification (1:1 matching).

Table 1. Review of some existing periocular recognition algorithms.

Spectrum	Author	Feature	Classifier	Database
Visible - Visible	Park et al. [1]	HOG, LBP, SIFT	Euclidean distance, Distance-Ratio	FRGC version 2.0 and a database collected in lab (30 subjects, 2 sessions)
	Bharadwaj et al. [2]	Circular LBP and GIST	χ^2 distance	UBIRIS V2
	Tan and Kumar [3]	DSIFT + LMF	χ^2 distance	UBIRIS V2, FRGC
	Juefei-Xu et al. [4]	WLBP + UDP	Cosine distance	FG-NET
	Hollingsworth et al. [5]	–	Human Evaluation	ND Collection
NIR-NIR	Tan and Kumar [3]	DSIFT + LMF	χ^2 Distance	CASIA v4
	Woodard et al. [6]	LBP	Manhattan distance	MBGC
	Hollingsworth et al. [5]	–	Human Evaluation	ND Collection

of two periocular images to be matched are concatenated and used as input vector to the neural networks.

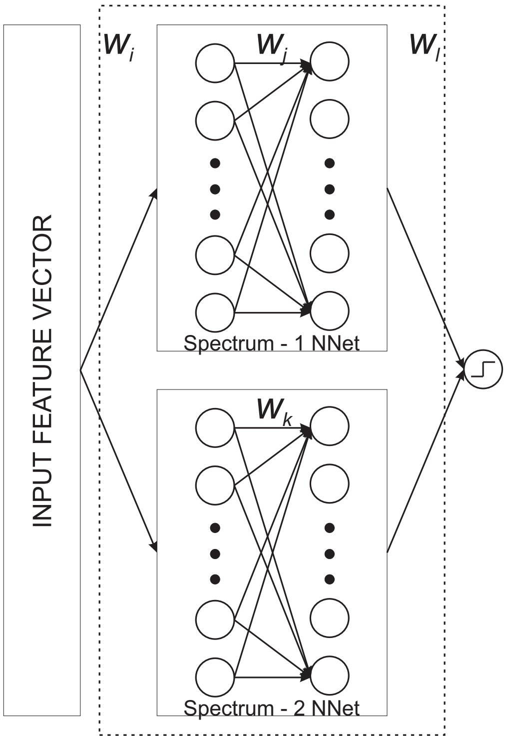

Fig. 2. Illustrating the steps involved in the proposed cross-spectral periocular recognition algorithm.

2. To train the network for the first spectrum, all the genuine (label 0) and impostor (label 1) pairs are given as input to a neural network with 2-hidden layers and radial basis function kernel and sigmoid activation function. Neural network weight (w_j) training is performed using the standard back-propagation with regularization. The fitness function is the verification accuracy at 1% false accept rate (FAR). The trained neural network is represented as $spectrum - 1$ NNet.

3. Same approach is followed for the second spectrum and $spectrum - 2$ NNet is trained with weights w_k.

4. To learn the cross spectral variability, as shown in Fig. 2, $Spectrum - 1$ NNet and $Spectrum - 2$ NNet are combined. Let P_1 be the PHOG feature obtained from spectrum-1 periocular image and P_2 be the PHOG feature of spectrum-2 periocular image. A combined cross-spectral feature vector $P = [P_1, P_2]$ is created and provided as input to the two neural networks, trained on spectrum-1 and spectrum-2 data individually (Steps 1 and 2). The input features are given in a weighted fashion with w_i weights. Undecimated outputs of spectrum-1 and spectrum-2 neural networks are connected to a sigmoid threshold unit in a weighted manner.

5. The combined network is trained on the cross spectral periocular PHOG features. Initially, the weights of the combined network are initialized randomly with w_i and w_l. The weights obtained in Steps 2 and 3 are used as initial weights for respective sub-networks. On the cross-spectral training data, the combined network is trained using regularized backpropagation with verification accuracy at 1% false accept rate as the fitness function. Once trained, the network is used for cross-spectral periocular matching.

The key concept of the proposed algorithm is to first train the classifiers on individual spectrum images and then optimally combine them to mitigate the variations due to difference in spectrums.

3. IIITD MULTISPECTRAL PERIOCULAR DATABASE

Due to lack of an existing cross spectral periocular database, we have created the IIITD Multispectral Periocular (IMP) database. The images are captured in three spectrums: Near-Infrared, Visible, and Night Vision. NIR dataset is created

Table 2. Characteristics of the IIITD multispectral periocular database.

Spectrums	Visible
	Night Vision
	NIR
Number of subjects	62
Number of images per subject	Visible - 5
	Night Vision - 5
	NIR -10
Total number of images	Visible - 310
	Night Vision - 310
	NIR - 620

using Cogent Iris Scanner [8], kept at a distance of 6 inches from the subject. Night Vision dataset is created using Sony HandyCam (in Night Vision mode), and visible images are captured using Nikon SLR camera from a distance of 1.3 meters. The images are captured in a controlled environment. Near-infrared and visible images are captured in proper illumination where as the night vision images are taken in very low illumination conditions. Table 2 summarizes the details of the database and Fig. 3 shows the sample images.

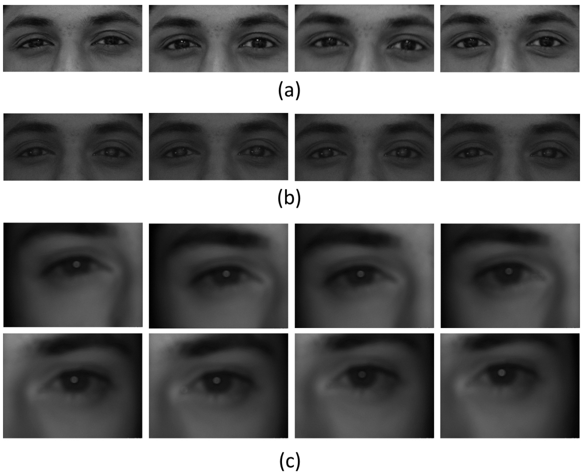

Fig. 3. Sample images from the IIITD multispectral periocular database (a) visible spectrum, (b) night vision, and (c) NIR.

4. EXPERIMENTAL RESULTS

To the best of our knowledge, IMP database is the only database that comprises images pertaining to multiple spectrums. Therefore, the experiments are performed on this database only. The results of the proposed algorithm are compared with Local Binary Patterns (LBP) [9], Histogram of Oriented Gradients (HOG) [10], PHOG [7], and Four Patch LBP (FPLBP) [11] descriptors that are widely used in periocular recognition literature. Periocular region is manually

Fig. 4. Preprocessed images corresponding to all three spectrums.

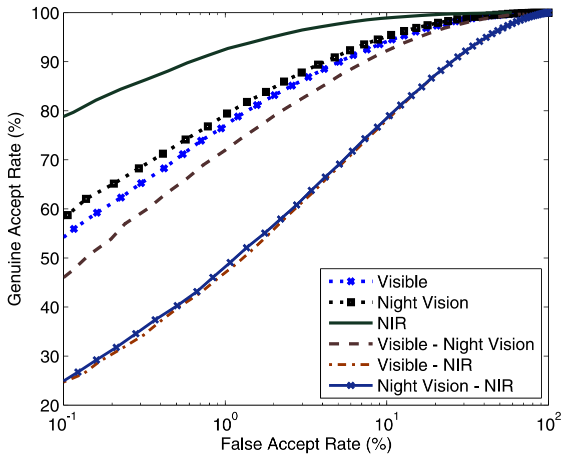

Fig. 5. The ROC curves pertaining to the proposed cross-spectral periocular recognition algorithm.

detected and the images are normalized using the eye coordinates. The images are preprocessed using multi-scale retinex algorithm [12] and resized to 260 $\times$ 270. Fig. 4 shows the preprocessed images that are used for feature extraction and matching. The database is partitioned into non-overlapping training and testing sets comprising all the images of 12 and 50 subjects respectively. The experiments are performed with five times random subsampling. Table 3 shows the results in terms of Genuine Accept Rate (GAR) at 1% False Accept Rate and Receiver Operating Characteristics (ROC) curves are shown in Fig. 5. Key observations of the results are:

- Among the three individual spectrums (visible, night vision, and NIR), existing descriptors yield the best performance in NIR spectrum. The main reason for this performance is the fact that NIR images are resilient to illumination variations. Further, the combination of right and left periocular features generally improves the performance.

- In cross spectral matching, all four descriptors yield very poor performance and the highest verification ac-

Table 3. Verification accuracy of the proposed and existing algorithms.

Spectrum	Verification Accuracy (%) at 1% False Accept Rate						
	Modality/ Algorithm	LBP	HOG	PHOG	FPLBP	Cross-Domain [13]	Proposed
Visible	Left Periocular	19.60	69.48	67.16	60.84	–	71.36
	Right Periocular	20.08	52.12	53.28	45.64	–	60.18
	Combined (R+L)	24.08	66.68	68.24	57.44		76.97
Night Vision	Left Periocular	16.08	78.16	78.60	46.12	–	78.91
	Right Periocular	12.16	71.76	59.75	37.72	–	69.24
	Combined (R+L)	20.20	75.48	71.84	55.04		79.18
NIR	Left Periocular	73.92	86.36	75.4	85.24	–	82.14
	Right Periocular	85.75	87.36	83.24	84.64	–	88.56
	Combined (R+L)	72.56	90.72	85.44	87.68		92.50
Cross Spectral (Visible - Night Vision)	Left Periocular	1.04	12.77	12.98	11.14	35.46	61.87
	Right Periocular	0.51	14.86	13.49	11.12	39.63	63.81
	Combined (R+L)	0.9	14.24	15.26	13.71	43.28	71.93
Cross Spectral (Visible - NIR)	Left Periocular	0.13	0	02.69	1.79	12.75	38.36
	Right Periocular	0.19	0.58	02.05	2.27	12.94	38.02
	Combined (R+L)	0.19	0	01.86	2.10	16.66	47.08
Cross Spectral (Night Vision - NIR)	Left Periocular	0.51	0.96	04.06	1.97	12.82	39.45
	Right Periocular	0.70	0.51	02.24	1.42	13.01	40.36
	Combined (R+L)	0.70	0.13	03.20	1.78	16.93	48.21

curacy achieved is around 15% in the case of PHOG descriptors (score level sum rule fusion of right and left periocular descriptors). This performance reduction substantiates our motivation that cross pectoral periocular matching is a challenging task.

- $Spectrum - 1$ and $Spectrum - 2$ neural networks are also evaluated for matching individual spectrums. In all three spectrums, applying neural network learning improves the accuracy by at least 1.78%. However, a significant reduction of around 50% in accuracy is observed when cross spectral matching is performed using single spectrum trained neural network.
- The proposed algorithm combines two neural networks that are initially trained on individual spectrums and retrained using the cross-spectral training data in a combined fashion. On the test database, the proposed network yields a very large performance improvement. In the three cross spectral experiments (i.e visible to night vision, visible to NIR, and night vision to NIR), the proposed algorithm is 35 - 50% better than existing descriptors.
- The proposed algorithm can be viewed as a cross domain matching algorithm. Therefore, the performance of the proposed algorithm is compared with a recent cross domain matching algorithm [13] (referred as Cross-Domain in Table 3). For the three cross spectral matching experiments, the proposed algorithm outperforms existing algorithm by 20-30%. These experiments show that the proposed algorithm is able to encode the cross spectral information better than the existing cross domain matching algorithm.
- Computationally, the proposed algorithm is fast and on a 2.7 GHz quad core processor with 8GB RAM and MATLAB programming environment, requires less than 2 seconds to perform verification of a gallery probe pair.

5. CONCLUSION

The contribution of this research is two folds: (1) proposed a cross spectral periocular verification algorithm using neural network and (2) prepared a cross spectral periocular database that can motivate other researchers to address this challenging research problem. To the best of our knowledge, both the databases and cross spectral periocular matching algorithms are the first ones in literature. In future, we plan to extend the database size and improve the network learning process for faster training.

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