Robust Contact Lens Detection using Local Phase Quantization and Binary Gabor Pattern

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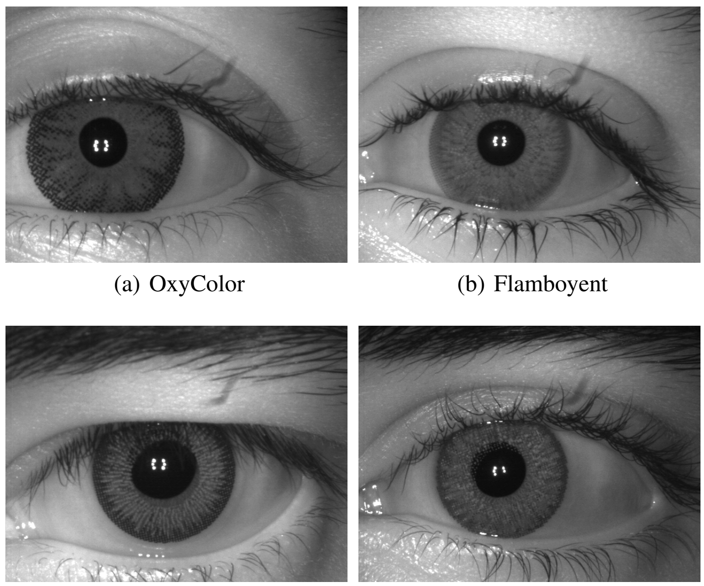
Abstract. Due to its resistance to circumvention, iris has been used as a prime biometric trait in border crossings and identity related civil projects. However, sensor level spoofing attacks such as the use of printed iris, plastic eyeballs and contact lens pose a challenge by helping intruders to sidestep security in iris based biometric systems. Attacks through contact lenses are most challenging to detect as they obfuscate the iris partially and part of original iris remains visible through them. In this paper, we present a contact lens dataset containing 12823 images acquired from 50 subjects. Each subject has images pertaining to no lens, soft lens and cosmetic lens class. Verification results with three different techniques on three datasets suggest an average degradation of 3.10% in EER when subject is wearing soft lens and 17.34% when subject is wearing cosmetic lens. Further we propose a cosmetic lens detection approach based on Local Phase Quantization(LPQ) and Binary Gabor Pattern(BGP). Experiments conducted on publicly available IIITD Vista, IIITD Cogent, ND_2010 and self-collected dataset indicate that our method outperforms previous lens detection techniques in terms of Correct Classification Rate and false Acceptance Rate. The results suggest that a comprehensive texture descriptor having blur tolerance of LPQ and robustness of BGP is suitable for cosmetic lens detection.

1 Introduction

Iris has emerged as a prime biometric trait in the past decade. It has been deployed in large scale biometric identification programs such as UIDAI in India[6], RIC in Brazil[5] and EIDA in UAE [2]. One of the reason behind use of iris is its resistance to circumvention. Unfortunately sensor level spoofing attacks such as use of printed iris, artificial eyeballs and contact lenses have raised the issue of iris liveness detection in the biometric community.

Broadly, contact lenses can be classified into two categories based on their appearance - soft lens and cosmetic lens. Soft lenses are transparent in nature and are used to correct vision problems such as myopia, hypertropia and astigmatism. Cosmetic contact lenses have a pattern printed on them that changes the appearance of human iris apart from correcting vision of the subject. The texture printed on the cosmetic contact lens partially obfuscates the original iris pattern. Although it has been shown experimentally that the use of cosmetic contact lens leads to decrease in both identification and verification accuracy [26,18], a rigorous study using multiple recognition schemes on multiple datasets has not been been carried out yet. This is of utmost importance as an increase in false Rejection Rate can assist a criminal in eluding detection. Moreover, an impostor may also be able to impersonate iris of another subject by wearing a custom made cosmetic contact lens.



(a) OxyColor (b) Flamboyent

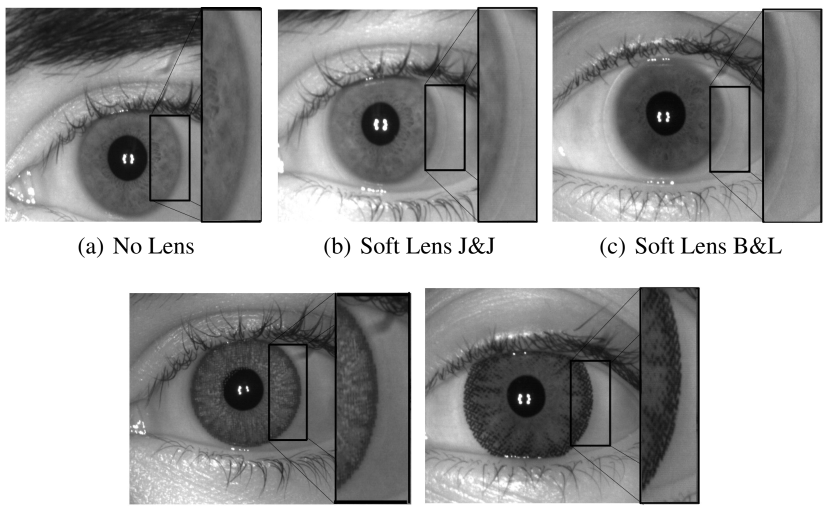
(c) O2Max (d) Freshlook

Fig. 1: Cosmetic Lens from Different manucturers

Among various sensor level attacks on iris biometric systems, detection of cosmetic contact lens is most challenging. As lens covers the iris partially, dilation and constriction of pupil is visible through the lens. Hence pupilary response based on lighting changes cannot be used to determine the presence of the lens accurately. Moreover, printed pattern on cosmetic lens differs depending on the manucturer as shown in Figure 1.

Several hardware and software based cosmetic lens detection schemes have been proposed in past decade. Hardware based schemes are based on purkinje image formation [20] and stereo imaging [15]. Despite being accurate, these schemes require additional equipment to function. Textural feature based methods utilizing Grey Level Co-occurence Matrix (GLCM) [13], Local Binary Patterns (LBP) [23] and Binary Statistical Image Features (BSIF) [17] have also been proposed. GLCM based features have been used in Wei et al [25] with a Correct Classification Rate (CCR) of 94.1% on a 960 image dataset. He et al [14] used multi-resolution LBP for feature extraction step and AdaBoost for learning most discriminative features. They have also employed kernel density estimation to counter class imbalance in the dataset. On a dataset of 600 cosmetic contact lens images they obtain a false accept rate of 0.67%. LBP weighted through SIFT descriptor has been used in [27]. A correct classification accuracy of 99.14% is achieved over an experimental dataset containing images from 72 subjects. In [19] Komulainen et al have suggested the use of BSIF features for generalizing lens detection over unseen cosmetic lens patterns. However, they have conducted experiments only on a single dataset.

In this paper, we show the effect of contact lenses on iris recognition process using three techniques. Finally we propose a robust cosmetic lens detection technique based on the fusion of two texture descriptors. The proposed contact lens detection technique is tested over three publicly available benchmark dataset IIITD Vista, IIITD Cogent [26,18] and ND_2010 [8] along with self-collected dataset.



(a) No Lens (b) Soft Lens J&J (c) Soft Lens B&L

(d) Cosmetic Lens Freshlook (e) Cosmetic Lens OxyColor

Fig. 2: Example Images from the Our Contact Lens dataset. Right side contains a magnified version of part shown in black box.

Rest of paper is organized as follows. Section 2 introduces our dataset and analyzes the effect of cosmetic contact lens on iris recognition. Next section deals with the issue of designing a robust cosmetic lens detection technique. Section 4 describes the experiments performed over three benchmark datasets along with contact lens dataset collected at our lab. Conclusion and future research directions are discussed in Section 5.

2 Adverse Effects of Contact Lenses on Iris Recognition

Contact lenses are available freely and cheaply in the market from past couple of years. Thus, it becomes important to quantify their effect on iris recognition. To evaluate the effect of contact lenses on some existing iris recognition techniques we have constructed a contact lens dataset containing images collected from 50 subjects. Each subject has been enrolled in three classes - No Lens, Soft Lens and Cosmetic Lens. Soft lenses used by the subjects are manuctured by Bausch & Lomb[1] and Johnson & Johnson[4]. Cosmetic contact lenses from four manucturers are used making the dataset generic. All the iris images have been acquired using Vista 2 iris sensor[7]. Sample images from the dataset are shown in Figure 2. Minimum and maximum number of images acquired for each iris class are 20 and 50 respectively. To the best of our knowledge, it is the largest contact lens dataset in terms of number of acquired images. The database has been uploaded and is available for research purposes under mutual agreement. Table 1 summarizes the dataset.

Class of Images	Cosmetic lens, Soft lens, No lens
Cosmetic Lens Manucturers	O2Max, Flaymboyent, Oxycolor, Freshlook[3]
Cosmetic Lens Color	Hazel, Green, Blue, Gray
Soft Lens Manucturers	Bausch & Lomb [1], Johnson & Johnson [4]
Iris Sensor	Vista Imaging 2 [7]
Images per class	Cosmetic Lens:4218 No Lens:4551 Soft Lens:4054
Minimum/Maximum number of images per eye class	20/50
Total Images	12823

Table 1: Summary of Our Contact Lens dataset

Unlike in [18], where matching has been carried out through a commercial matcher we have used three iris recognition techniques to quantify the performance of iris recognition systems. These include techniques proposed by Masek [21], Daugman [12] and Nigam et al [22]. Log-Gabor and Gabor filtering based approach have been used by Masek and Daugman respectively while Nigam et al have used fusion of a block level variant of local binary patterns and relational measures to extract features from a normalized iris template.

The effect of both soft and cosmetic contact lenses is analyzed by varying the probe lens class keeping the gallery lens class fixed. Two experiments are undertaken in this regard :-

– The gallery lens class is fixed as 'No Lens'. Iris recognition techniques mentioned above are compared on the basis of Correct Recognition Rate(CRR)[16] and Equal Error Rate(EER)[16].
– The recognition technique and gallery lens class is kept fixed to BLBP+RMH[22] and 'No Lens' respectively. Finally the effect of subjects wearing soft lens or cosmetic lens is visualized using Receiver Operating Characteristic(ROC)[16].

Our dataset contains a minimum of 20 images per eye class. For template matching experiments 10 images are taken in gallery set and the rest in probe set. Both the IIITD Cogent and IIITD

Dataset	Technique	Masek [21]				Gabor[12]				BLBP+RMH[22]			
	GC-PC	CRR	D_{CRR}	EER	D_{EER}	CRR	D_{CRR}	EER	D_{EER}	CRR	D_{CRR}	EER	D_{EER}
IIITD Cogent [26,18]	No-No	96.76	-	4.56	-	95.27	-	6.51	-	98.75	-	**3.14**	-
	No-Soft	96.25	0.51	5.41	0.85	92.75	2.52	6.49	0.02	97.50	1.25	**4.17**	1.03
	No-Cosmetic	57.03	39.73	**17.16**	12.60	35.92	59.35	23.80	17.29	68.34	30.41	18.43	15.29
IIITD Vista [26,18]	No-No	99.75	-	2.27	-	99.75	-	2.35	-	100	-	**1.16**	-
	No-Soft	91.50	8.25	8.04	5.77	92.75	7.00	6.87	4.52	93.75	7.25	**5.31**	4.15
	No-Cosmetic	58.79	40.96	26.11	23.84	48.74	51.01	21.17	18.82	70.85	29.15	**12.62**	11.46
Our Dataset	No-No	99.79	-	3.34	-	99.69	-	3.81	-	99.89	-	**1.43**	-
	No-Soft	95.00	4.79	7.36	4.02	95.59	4.10	7.99	4.18	96.66	3.23	**4.86**	3.43
	No-Cosmetic	66.81	32.98	21.31	17.97	52.50	47.19	24.54	20.73	67.38	32.51	**19.59**	18.16
Avg Degdn	No-Soft	-	4.51	-	3.54	-	4.54	-	2.90	-	3.91	-	2.87
	No-Cosmetic	-	37.89	-	18.13	-	52.51	-	18.94	-	30.69	-	14.97

Table 2: Performance Degradation due to use of Contact Lens. GC and PC stand for gallery class and probe class respectively. CRR and EER in %. Avg. Degn. stands for D_{CRR} and D_{EER} averaged over the three datasets.

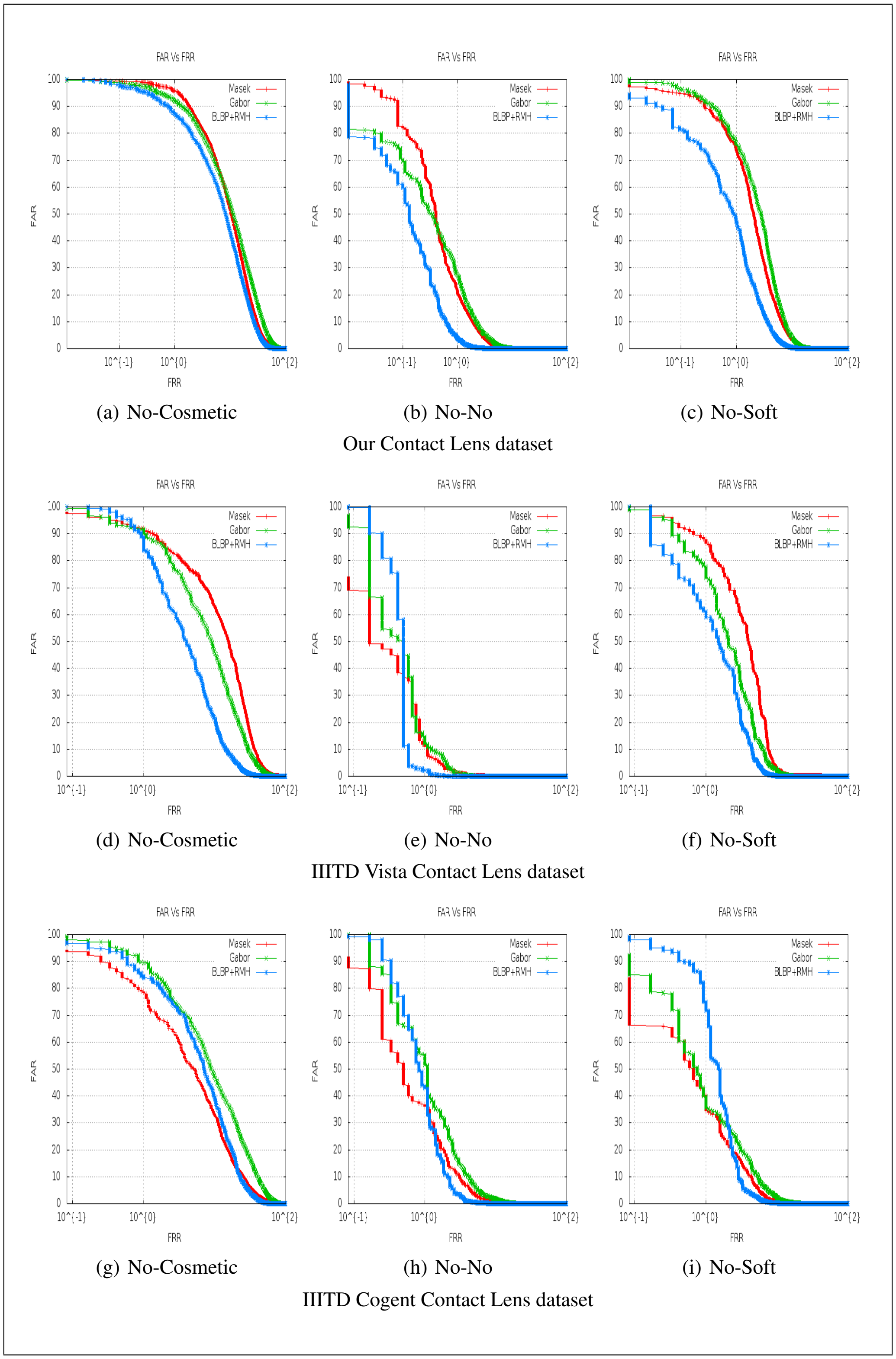
Vista dataset [26,18] have a minimum of 5 images per eye class out of which 3 are taken in gallery set and rest 2 in probe set. Each image is first segmented using technique described in [10] and then normalized according to Daugman's rubber sheet model[12]. Features are extracted from the normalized iris images. The matching results are summarized in Table 2.

ROC curves in Figure 3 illustrates the comparison between iris recognition techniques. For each dataset, EER is minimum when recognition is carried out using BLBP+RMH approach except in the case when cosmetic lens images from IIITD Cogent dataset are matched with no lens images. Although BLBP+RMH performes the best among three techniques, none of these techniques can be said to perform sufficiently well for recognition purpose. Degradation in ERR(D_{EER}) and CRR(D_{CRR}) represent the decrease in EER and CRR relative to the matchings where no lens is present in either gallery or probe images. Average D_{EER} for three recognition techniques over all datasets is 3.10% for soft lens and 17.32% for cosmetic lens while average D_{CRR} is 4.32% for soft lens and 49.7% for cosmetic lens.

ROC curves in Figure 4 supplement the results that cosmetic lens degrade the performance much more than soft lens. This can be attributed to the ct that soft lens is transparent in nature and unlike cosmetic lens, does not have a pattern printed on its surce. However, partial reflection from the surce of soft lens creates artičts in the iris region degrading the performance.

3 Cosmetic Lens Detection

Through the previous section it is evident that cosmetic contact lens degrades the performance of iris recognition irrespective of the technique used to extract features from normalized iris template. One possible solution is to make sure that the subject is not wearing cosmetic lens either in



(a) No-Cosmetic (b) No-No (c) No-Soft

Our Contact Lens dataset

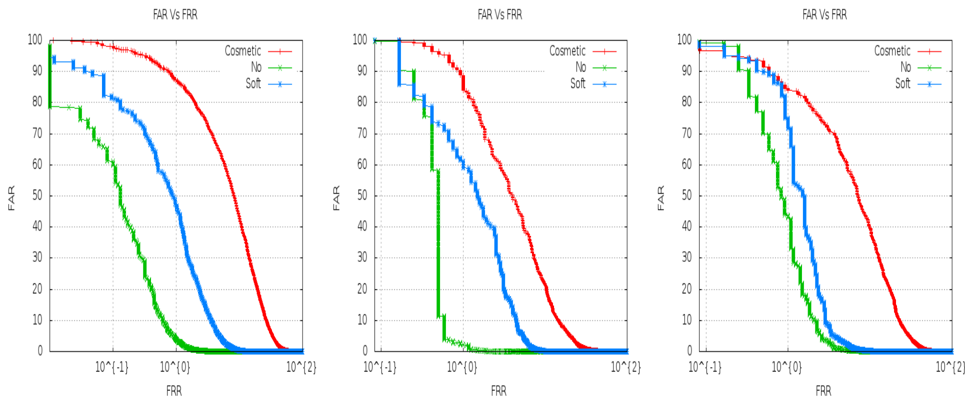
(d) No-Cosmetic (e) No-No (f) No-Soft

IIITD Vista Contact Lens dataset

(g) No-Cosmetic (h) No-No (i) No-Soft

IIITD Cogent Contact Lens dataset

Fig. 3: Receiver Operating Characteristic(ROC) curves comparing performance of different iris recognition techniques. All the graphs use $\log_{10}$ scale for X-axis



(a) Our dataset (b) IIITD Vista (c) IIITD Cogent

Fig. 4: ROC Curve taking "No-Lens" Class as gallery Set and BLBP+RMH[22] as Iris Recognition Technique. All the graphs use $\log_{10}$ scale for X-axis

enrollment or identification phase. This requires the biometric system to detect cosmetic lens in acquired image and force re-acquisition if lens is detected in a image.

Cosmetic lens has a printed pattern which can be distinguished from original iris using texture classification techniques. Previous works addressing cosmetic lens detection have proposed the use of Grey Level Co-occurrence Matrix (GLCM) [25], Local Binary Patterns (LBP) [14,27,26] and Binary Statistical Image Features (BSIF) [19] as texture descriptors for this task. LBP is considered as a reasonable descriptor under illumination variation whereas BSIF uses Independent Component Analysis (ICA) to arrive at a more general texture descriptor. However, none of these descriptors are robust to image blurring, which is frequently encountered during image acquisition.

A possible solution lies in deblurring the image but most of the deblurring techniques introduce new articts making further analysis more cumbersome. Local Phase Quantization [24] based texture descriptor has been proven to be robust to both motion as well as focus blur. Spatial blur is represented as a convolution of original image with a blur function which results in multiplication in the frequency domain. Let I,B and L be the original image, blur function and blurred image in frequency domain. The relation between their phase can be represented as :-

$$\angle L = \angle I + \angle B$$

Assuming that the point spread function(PSF) causing the blur is centrally symmetric, its Fourier transform B possess phase of either 0 or π depending on the sign of B. Thus if $B \geq 0$, $\angle B = 0$ else $\angle B = \pi$. Considering the ct that PSF is rectangular for motion and focus blur and has some positive values of B for small values of frequencies[9], it makes use of Discrete Fourier Transform (DFT) to extract phase information from four low frequency components. The phase information from both real and imaginary part of the components is de-correlated for statistical independence and quantized to values between 0-255 using binary coding. Finally a 256-bin histogram is constructed from the quantized values over all the spatial image positions.

Binary Gabor Pattern [28] uses difference between image regions rather than difference between two pixels as in LBP to make the descriptor more robust to noise. Gabor filters are used to find the difference between regions. The real and complex part of Gabor filter are represented in Equation 1 and Equation 2 respectively. DC component from both real and imaginary parts of Gabor filter is removed before convolving the filters with image to guarantee .

$$g(x, y) = \exp(-\frac{1}{2}(\frac{(x')^2}{\sigma^2} + \frac{(y')^2}{(\gamma\sigma)^2}))\cos(\frac{2\pi}{\lambda}x') \quad (1)$$

$$h(x, y) = \exp(-\frac{1}{2}(\frac{(x')^2}{\sigma^2} + \frac{(y')^2}{(\gamma\sigma)^2}))\sin(\frac{2\pi}{\lambda}x') \quad (2)$$

where $x' = x\cos(\theta)$ + ysin(θ) and $y' = -x\sin(\theta)$ + ycos(θ). θ represents the orientation of the Gabor filter with respect to the normal, γ denotes the spatial aspect ratio, $sigma$ denotes the sigma of Gaussian and λ is the wavelength of the sinusoidal function.

Binary Gabor Pattern combines the benefits of both LBP and Gabor filters. The BGP descriptor for an image is obtained by first convolving the patches in the image by a filter bank containing Gabor filters at 8 different orientations say (G_0 to G_7) as shown in Figure 5. Vector containing the convolved responses R is thresholded on the basis of the sign of response and binarized to obtain vector B . The binarized vector is transformed to a unique number by assigning a binomial ctor 2^i for each value of i in $B = B_i | i = 0..7$ and converting it into its decimal equivalent. Hence the BGP value for a give patch P can be given as :-

$$BGP = \sum_{i=0}^{7} B_i.2^i \quad (3)$$

From the Equation 3 it evident that there are 2^8 unique values possible from 8 bits of B. In order to address rotation invariance, BGP is re-defined as :-

$$BGP_{ri} = MAX(RSFT(BGP, i)|i = 0..7) \quad (4)$$

where RSFT performs a circular bitwise right shift on the 8-bit number 7 times and MAX takes the maximum of these values. For B_{ri}, 36 distinct values are possible. B_{ri} values extracted from both real and complex part of Gabor filter are concatenated to form a 72-bit histogram. Figure 5 shows the complete process of determining BGP descriptor from an image region.

In our contact lens detection scheme, the acquired iris image is segmented and normalized. LPQ histogram is extracted for the normalized iris image. Three Gabor filter banks differing in value of wavelength and scale are initialized. BGP histograms using the filter banks are concatenated to form a 216-bin histogram. Both the LPQ and BGP histograms are concatenated to form a 472 bit feature vector. The feature vector is passed onto a trained SVM classifier which assigns labels for or against the presence of cosmetic lens

4 Experimental Results

Apart from the three datasets mentioned in Section 2 we have also used ND_2010 [8] which contains 1400 images each for no Lens and cosmetic lens class. In all the experiments, 66% of the subjects are used as training set and rest of the subjects as test set.

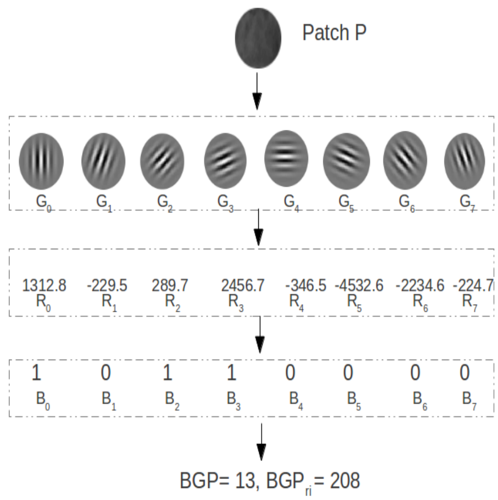


Fig. 5: Calculation of BGP for a particular patch P

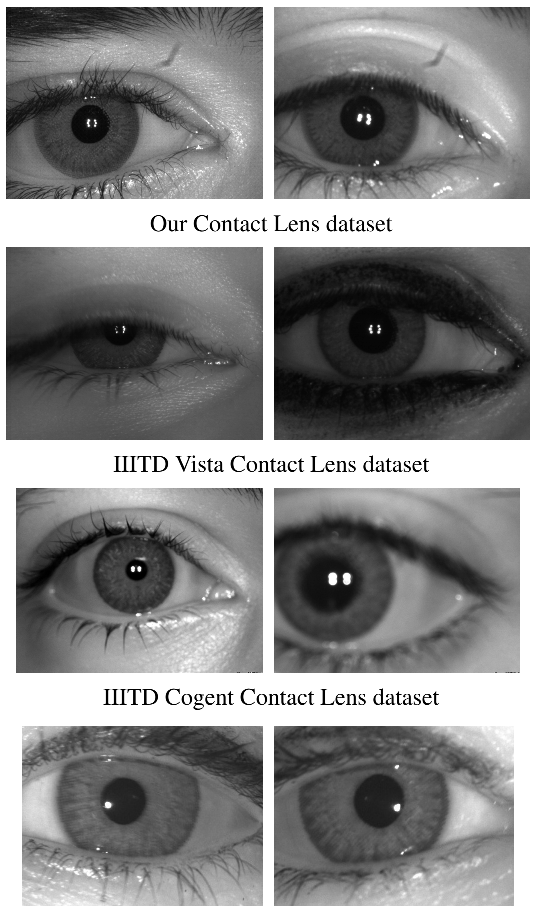
We have compared the result of LPQ+BGP approach with GLCM[25], LBP[14] and BSIF[19] approach. For GLCM, we have used the mean and range of inverse difference moment (f_{idm}), sum average (f_{sa}) and sum entropy (f_{se}) as feature vector mentioned in [25]. For LBP, we concatenated histograms for two LBP operators $LBP^{riu2}_{8,1}$ and $LBP^{riu2}_{16,3}$ together to form the feature vector. The radius and size of features learnt in BSIF are taken to be 3 units and 12 bits respectively because it provided consistent results to the authors in [19]. For BGP, three resolutions $(\lambda_i, \sigma_i)_{i=1..3}$ set as (1.3,0.7),(5.2,2.5) and (22,4.5) are taken to construct three BGP histograms which are concatenated to form a 216 bit feature vector.

We have used Support Vector Machine (SVM) [11] with radial basis kernel for classification purpose. The correct classification rate and false Acceptance Rate for different lens detection techniques is shown in Table 3. Performance of our method is marginally better for IIITD Vista and IIITD Cogent while significantly better for ND_2010 dataset which contains significant number of blurred images. BSIF slightly outperforms our method over our dataset due to its generalizing property as it contains four varieties of cosmetic contact lens.

Figure 6 shows some correctly classified images by the proposed BGP+LPQ approach which were falsely accepted as genuine by other approaches. Note that some adequately blurred images are classified correctly by our approach but not through GLCM,LBP or BSIF features.

5 Conclusion

In this paper, we have evaluated the effect of soft and cosmetic lens on IIITD Vista, IIITD Cogent and cosmetic lens dataset acquired in our lab. Three iris recognition techniques have been used to quantify and firmly establish the degradation of recognition performance both in the case of soft and cosmetic contact lens. Further we compared existing cosmetic lens detection techniques with the proposed technique that uses fusion of LPQ and BGP texture descriptors. Our technique



Our Contact Lens dataset

IIITD Vista Contact Lens dataset

IIITD Cogent Contact Lens dataset

ND_2010 Contact Lens dataset

Fig. 6: Images pertaining to Contact Lens class falsely accepted as No Lens by GLCM,LBP and BSIF but correctly classified by our approach.

Descriptor	GLCM [25]		LBP [14]		BSIF [19]		LPQ+BGP	
Dataset	CCR	FAR	CCR	FAR	CCR	FAR	CCR	FAR
Our dataset	57.05	30.02	97.54	0.55	98.44	**0.55**	**98.91**	0.86
IIITD Vista	50.00	55.88	99.70	0.58	99.70	0.58	**99.85**	**0.29**
IIITD Cogent	36.86	46.07	89.54	12.91	**98.21**	3.29	96.81	**2.82**
ND_2010	56.59	31.11	95.82	6.22	85.93	28.44	**99.12**	**1.55**

Table 3: CCR and R across different Texture Description Techniques. R represents % of cosmetic lens images accepted as genuine.

outperformed LBP, GLCM and BSIF for IIITD Vista, IIITD Cogent and ND_2010 datasets. BSIF performed slightly better than BGP+LPQ over our dataset as there were four different cosmetic lens classes present in the dataset. However, our approach performs significantly better that BSIF for ND_2010 dataset which contain blurred images.

Lot of research has been carried out in countering the sensor level spoofing attacks on iris based recognition systems, most of it is towards exploring new hard-coded texture descriptors. A full proof technique addressing all the challenges like illumination variation, image blurring, sensor interoperability and adaptation to new textures is yet to be discovered.

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