An Enhanced Approach for Identification of Cosmetic Contact Lenses on Iris Recognition

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Abstract— Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on images of the irises of an individual's eyes, whose complex random patterns are unique and can be seen from some distance. There are several variables that affect the performance of an Iris recognition system. One amongst these covariates are Contact Lenses. There are two types of contact lenses such as the Soft and the Textured lenses which affects the system. It is the contact lenses, especially the cosmetic lenses, which poses a challenge to these recognition systems as it confuses/complicates the natural iris patterns. This paper is trying to analyze in-depth, the effects of contact lenses on iris recognition by making use of the IIIT-D Iris Contact Lens and the ND-Contact Lens Databases, and introduce an improved technique to identify the use of contact lens.

Key words: ND-Contact Lens, IIIT-D

I. INTRODUCTION

Iris is one of the most promising traits of the human biometrics. It is also one of the most used systems especially in large-scale applications such as the one in UAE port of entry and India's UIDAI (Aadhar) projects. In their 1987 patent, Flom and Safir [12] proposed that the texture of iris as a biometric modality. Although, texture analysis of iris was proposed as early as 1987, the first iris recognition algorithm was developed by John Daugman, Ph.D, OBE. [8] in early 1990's. Daugman's algorithm is the basis for essentially all the commercial iris recognition systems and is still the most widelyused approach. It is considered that the features of iris is unique and stable, but recent research has shown that the performance of the iris recognition systems are affected by quite a few variables, such as pupil dilation [20] and sensor interoperability [1], [7]. Another factor that affects the performance of the system, which has received relatively less attention, is the use of contact lenses. Two types of contact lenses are available in the market, transparent (soft) and color cosmetic (textured) contact lenses. With the advancement of technology, the use of contacts has become much more prevalent.

It was thought that the use of soft contact lenses do not affect the performance of the iris recognition system significantly. For example, Negin et al. [29] have stated that "Successful identification can be made through eyeglasses and contact lenses". But, since the purpose of a prescription contact lens is to change the optical properties of the eye, it must, by definition, have some effect on the texture of the iris observed through it [34]. In use, the contact lenses have been shown to reduce the overall accuracy of some iris biometrics systems [3]. A clear, soft, non-textured lens is also able to move relative to the iris, resulting in a marginally different observed effect on the iris texture at each presentation. Some soft lenses also have visible markings on them, which may be observed in different locations from image to image. Sometimes, lenses also have a noticeable boundary between the support region of the lens and the corrective region of the lens, which can also alter the appearance of the iris texture.

Contact lenses are generally used to correct eyesight as an alternative to spectacles/glasses. They are, however, also being used for cosmetic reasons, where the color and texture manufactured into a contact lens is superimposed on the natural texture and color of the iris. It is apparent that the use of a textured lens changes the appearance/texture of an eye in both the visible and the near-infrared spectrum.

The lenses (soft and textured) superimposes its design over the natural design of the iris which makes it difficult for the system to identify the iris correctly. In an ideal environment, the false match performance of the system is around 1 in 1 million. But when a contact lens is used, the performance of the system is affected drastically and accurate match rate drops to around 5-10% in some cases.

II. LITERATURE REVIEW

In his 2003 paper, Daugman [9] mentioned the usage of Fourier transform to detect periodic fake iris patterns that were common in textured lenses manufactured at that time. Although, the newer lenses have multiple layers of printing, making the Fourier response less noticeable and the lens detection by this method less dependable. Also, the dot-matrix style printing method is not used in all the textured lenses.

Lee et al. [26] found out that the Purkinje images would be different between a live iris and a fake iris. They identified a novel iris sensor with structured illumination to detect this difference in Purkinje images. They reported results on a dataset of 300 genuine iris images and 15 counterfeit images. The False Accept Rate (FAR) and False Reject Rate (FRR) was 0.33% on the data, but also suggested that the dataset may be too small to draw generalized conclusions.

X. He et al. [18] proposed training a supportvector machine on texture features in a graylevel co-occurrence matrix (GLCM). They created a dataset of 2000 genuine iris images from the SJTU v3.0 database and 250 textured lens images, among which 1000 genuine lens images and 150 textured lens images were used for training. They reported a correct classification rate (CCR) of 100% on the testing data. Based on a similar approach, Wei et al. [36] analyzed three methods for textured contact lens detection: the measure of iris edge sharpness, characterizing iris texture through Iris-Textons, and co-occurrence matrix. Two class-balanced datasets were made using CASIA and BATH databases for real iris images and a special acquisition for cosmetic contact lenses. Each dataset contained samples of a single manufacturer of textured contact lenses. Correct classification rates for each of the three methods and on the two datasets vary between 76.8% and 100%.

Z. He et al. [19] used multi-scale Local Binary Patterns (LBP) as a feature extraction method and AdaBoost as a learning algorithm to build a colored lens classifier. They obtained a dataset of 600 images with 20 different varieties of fake iris texture, a majority of which were from the textured contact lenses. The training set of 300 false iris images was combined with 6000 images from the CASIA Iris-V3 and ICE v1.0.

Likewise, Zhang et al. [38] probed into the use of Gaussian-smoothed and SIFT-weighted Local Binary Patterns to detect the textured lenses in the images collected with multiple iris cameras. They made use of a dataset of 5000 fake iris images with 70 different textured lens varieties. They recorded a correct classification rate of over 99% when training on assorted data, but this drops to 88% when multiple sensors are used for training and testing purposes.

A. *Effects of Textured Contact Lens:*

The main aim of Yadav et al. [37] was to perform an in-depth analysis on the effects of textured contact lenses on iris recognition and also to propose a novel algorithm which can be used to propose a novel algorithm to detect the usage of contact lenses.

They observed that when no contact lens is being used by the subject, the recognition accuracy is very high, while a soft contact lens is used, the recognition accuracy reduces but still the accuracy is quite high. But when a textured contact lens is used, the accuracy of the iris recognition system plummets drastically.

Their hypothesis was that applying a lens detection algorithm to first reject the cases with obfuscated patterns and allowing only without lens and soft lens iris images can improve the performance of iris recognition algorithms and reduce the false matches at higher verification rates.

They also used a modified LBP classification method to perform their analysis. As per this method, we initially do the feature extraction from the input images and once it is extracted, we perform a model training to classify the acquired images. To perform feature extraction, firstly, each iris image is divided into three regions: (1) pupil, (2) iris, and (3) sclera. The boundaries of the sclera region are determined by two circles with the same center point as the limbic circle but with different radii. The inner radius is 20px smaller than the limbic boundary and the outer radius is 60px larger than the limbic boundary in original image coordinates in an attempt to capture contact lens boundaries that may have shifted into the iris region while also limiting the amount of eyelid and eyelash occlusion.

The Modified Local Binary Pattern analysis is applied to each of the three regions of each image at multiple scales to produce feature values. Unlike traditional LBP, this method does not decompose the image into blocks and independently analyze each block to construct a large feature vector. Instead, the extracted region is treated as one large block. The kernel size for the binary pattern analysis is scaled from 1 to 20 in increments of 1 for a total of 20 different feature sets for each of the three regions and 60 feature sets overall.

17 different classifiers, intentionally sampling a variety of different classifier technologies, were explored as possible approaches to train models on the feature sets. Each of the feature sets described in feature extraction is treated as an independent dataset for the purposes of model training.

For machine learning algorithms that had tunable parameters, a grid search was performed with reasonable values. The predefined folds for each dataset are used to evaluate the performance of each trained model by cross-fold evaluation. If a classifier yielded a correct classification rate (CCR) of 100% on all 10 folds, a model was built using all training data. This process resulted in an ensemble of trained models to be evaluated on the verification set.

Their results showed that if we apply their algorithm on the acquired images before using it for comparisons, we can achieve an improved performance on the iris recognition system.

III. DATABASES

Two databases, namely IIIT-D Contact Lens Iris database and ND Contact Lens database, were used for analysis and algorithm development purposes. Every user in the IIIT-D Contact Lens Iris Database has a non-lens, soft lens and a textured lens image in the database, which helps in providing an in-depth analysis of the effect of contact lenses. This data arrangement makes it ideal for plotting ROC curves for the cases when textured lens detection is not in use and when it is in use to see the performance difference. The ND Contact Lens database gives us a holistic view of the contact lenses because it has varying makes and models of contact lens which makes it ideal for analyzing lens detection algorithms. So, this helps us as classifiers will be trained on the lens features rather than potentially training on subject features. The complete details for both the databases are presented below. These datasets are available to the research community.

A. *IIIT-D Contact Lens Iris Database:*

The IIIT-D Contact Lens Iris (IIIT-D CLI) database is prepared with three objectives: (1) capture images of at least 100 individuals, (2) for each subject, capture images without lens, with prescription lens, and with cosmetic lens, and (3) capture images with changes in iris sensors and lenses. All the lenses in the database are soft lenses manufactured by CIBA Vision and Bausch& Lomb. For textured lenses, only four colors are used. Both left and right iris images of the subjects are captured and therefore, there is a sum total of 202 iris classes. To study the effect of the acquisition device on contact lenses, iris images were captured using two iris sensors: (1) Cogent dual iris sensor (CIS 202) and (2) VistaFA2E single iris sensor. This database contains at least three images for each iris class.

B. *ND Contact Lens Detection 2013 Database:*

The ND Contact Lens Detection 2013 (NDCLD13) database consists of 5100 images and is conceptually divided into three datasets for further evaluation. The first Dataset consists of a training set of 3000 images and a verification set of 1200 images, all acquired with an LG 4000 [4] iris camera. Both the training set and the verification set are divided equally into three classes: (1) images without contact lenses, (2) images with soft, plain contact lenses, and (3) images with textured contact lenses. Dataset II consists of a training set of 600 images and a verification set of 300 images, all images acquired with an IrisGuard AD100 [13] iris camera.

All textured contact lenses in this dataset came from three major suppliers: Johnson& Johnson [6], CIBA Vision [30], and Cooper Vision [2]. Subjects in the database belong to four different ethnic categories (Caucasian, Asian, Black, and Other). Multiple colors of contact lenses were selected for each manufacturer. Some were also toric lenses, meaning that they are designed to correct for astigmatism. Toric lenses are designed to maintain a preferred orientation around the optical axis. As such, they may present different artifacts than non-toric lenses but also may have less variation in the position on the eye.

IV. Problem Statement

A contact lens, or simply contacts, is a thin film worn directly on the surface of the eye. Contact lenses are considered to be medical devices and are worn to correct vision, or for cosmetic reasons. People choose to wear contact lenses for many reasons. Style and cosmetics are often motivating factors for people who would like to avoid wearing glasses or would like to change the appearance of their eyes. And some people wear contacts for functional or optical reasons. A cosmetic contact lens is designed to change the color and appearance of the eye. Cosmetic lenses are also used to drastically modify the appearance of the eye, as depicted in the entertainment industry.

Traditional thought is that clear, soft, non-cosmetic contact lenses do not alter the imaged iris texture enough to be of concern. Because of that reason, we know of no iris biometrics system that attempts to detect or mitigate the effects of clear, soft, non-textured contact lenses.

Textured contact lenses are designed to alter the appearance of the wearer’s eye, providing it with a different color and/or texture. Regrettably, they also greatly reduce the amount of genuine iris texture visible to iris recognition systems. Increasing the chance of a false non-match.

V. Results And Discussions

Textured contact lenses are designed to alter the appearance of the wearer’s eye, giving it a different color and/or texture. Unfortunately, they also greatly reduce the amount of genuine iris texture visible to iris recognition systems. This increases the chance of a false non-match and a false match. Accordingly, these images should be rejected before a template is generated for them. The effect of soft lenses is much less. The genuine iris texture is not concealed to the same extent it is with textured contact lenses. However, the negative impact on verification by soft lens wearers has been documented [24], [3].

It is the hypothesis that applying a good lens detection algorithm to first reject the cases with obfuscated patterns and allowing only images that are without lens can improve the performance of iris recognition algorithms and reduce the false matches at higher verification rates.

The algorithm can be divided into two parts: feature extraction and model training.

A. *Feature Extraction:*

Each iris image is divided into three regions: (1) pupil, (2) iris, and (3) sclera. The boundaries of the sclera region are determined by two circles with the same center point as the limbic circle but with different radii. The inner radius is 20px smaller than the limbic boundary and the outer radius is 60px larger than the limbic boundary in original image coordinates in an attempt to capture contact lens boundaries that may have shifted into the iris region while also limiting the amount of eyelid and eyelash occlusion. Once, the segmentation was completed, Local Binary Pattern analysis [30] is applied to each of the three regions of each image at to produce feature values.

B. *Model Training:*

Each of the feature sets described in feature extraction is treated as an independent dataset for the purposes of model training. These feature sets were fed to the machine learning purposes and the training model was trained using this set. A similar set was prepared for the testing purposes. Using that set, the testing was performed and the results were obtained.

C. *Results:*

The problem of lens detection in an iris image is approached as a three class classification problem: no lens, soft lens, and textured lens. Three types of experiments were performed to evaluate the correct classification rate of the constructed model ensembles on all four datasets: IIIT-D Cogent, IIITD Vista, ND Dataset-I and II. They include the intra-sensor case, inter-sensor cases and multi-sensor cases. The results for the same are mentioned in the below tables and ROC.

VI. Conclusion

Wearing of contact lenses, both soft contacts and textured cosmetic soft contacts, degrades the accuracy of iris recognition. With clear soft contacts, the effect is a relatively small increase in the false non-match rate. With textured contact lenses, the effect is a major increase in the false non-match rate. At a false match rate of 1 in 1 million, which is an often quoted operating point for iris recognition, textured contacts can cause the false-non-match to exceed 90%. Therefore, textured contact lenses could provide an effective way for someone on an iris recognition watch list to evade detection. By performing this project, we try to increase the performance by detecting the iris images consisting of contact lenses at the earliest and hence reducing the false-non-match rate.

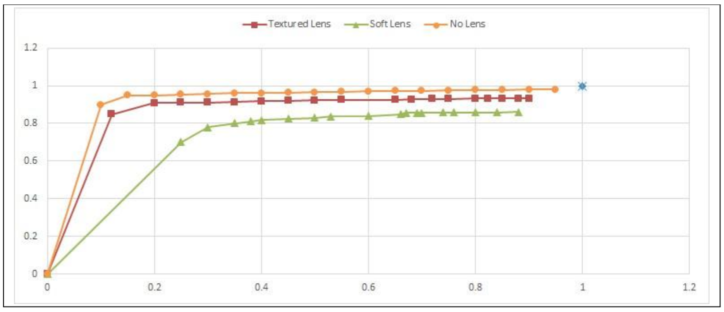

FIGURE I

Fig. 1:

A. ROC

Training Model	**Same Sensor**		**Cross-Sensor**	
	CCR	**Accuracy**	**CCR**	**Accuracy**
AdaBoost	65	72.00	64	81.33
J48	56	60.00	56	66.67
RBF Network	*85*	*97.33*	*82*	*100.00*
JRip	42	36.00	33	37.33
LogitBoost	75	82.67	58	76.00
RandomForest	51	49.33	38	42.67

Table 1: Comparison of the Results Obtained With Rbfnetworks with Other Classifiers

Database	**Classification Type**	**Textural Features**	**GLCM Features**	**Weighted LBP**	**LBP + SVM**	**LBP + PHOG + SVM**	**mLBP**	**Proposed Algorithm**
IIITD Cogent	N-N	33.28	32.76	45.39	65.53	59.73	66.83	72.2
	T-T	77.78	45.44	85.41	89.39	91.87	94.91	97.3
	S-S	42.73	33.34	54.43	42.73	52.84	56.66	62.3
	Total	51.63	37.31	62.06	66.4	68.57	73.01	83
IIITD Vista	N-N	79.75	53.99	43.15	53.37	49.49	76.21	80.1
	T-T	94.36	60.12	90.67	98.64	99.42	91.62	93.1
	S-S	16.43	0	56.11	50.9	59.32	67.52	66.7
	Total	63.73	32.69	63.72	68.04	69.84	80.04	85.5
ND I	N-N	78	73.75	57	70	81.25	85	83.4
	T-T	86	62.25	89.5	97	96.25	96.5	98.2
	S-S	35.84	3.75	51.27	60.15	65.41	45.25	39.3
	Total	66.72	46.62	65.88	75.73	80.98	75.58	73.2
ND II	N-N	47	33	47	42	42	81	89.2
	T-T	86	93	82	100	96	100	97.2
	S-S	0	67	44	54	60	52	65.1
	Total	44.33	64.33	57.67	65.33	66	77.67	85.1

Table 2: Lens Classification Results Of Proposed Algorithm And Comparison With Other Approaches (In %) Where N-N Is None-None, T-T Is Textured-Textured And S-S Is Soft-Soft.

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