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Analysis for Iris and Periocular Recognition in Unconstraint Biometrics

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ABSTRACT

The security and safety concern, being more important worldwide, has been encouraging utilization of biometrics systems. Seeing the numerous advantages over the unconstrained (non-cooperative) biometrics over the traditional way of biometrics, former has attracted the researcher attentions recently. There are various biometrics traits like face, iris and their extended form of unconstrained way of capturing data from subject has put so many challenges in biometrics application. Recently, periocular recognition has been proved to be a useful trait for authentication and verification purpose. In this paper, we have presented parameter analysis of periocular dataset using various pattern recognition techniques to test their effectiveness in unconstrained environment. The main goal of this research work to investigate the techniques of periocular biometrics in unconstrained situation to achieve non-cooperative biometrics.

Keywords—Biometrics, Iris Recognition, Periocular Recognition , HOG, LBP, PCA.

I. INTRODUCTION

Biometrics has been widely studied and applied effectively in several applications like some of them are authentication in highly restricted area, attendance record in office premises, citizenship identification and verification, forensic and security. It exist in several modalities (traits) such as face, iris, fingerprint, gait in order to provide the flexibility to choose one or combine more than one modalities for recognition as per the availability and feasibility associated with objectives of application. Due to easy availability and affordable cost of hardware and devices, biometrics has been a preferred choice even in personal devices like PC, PDA and mobile devices over a password based authentication. Being classified in two broad categories based on the situations to be used in: controlled environment and unconstrained or non-cooperative situations [8], biometrics research has been advancing towards the later category since last few years due to several benefits. The main hurdles in unconstrained biometrics are decline in amount of data and hence information in captured image non-uniformity across the different captures of images in terms of scale, pose and illuminations. Periocular biometrics, where recognition is based on features representing "facial region in the immediate vicinity of the eye [3]" has recently been identified as a extended of iris recognition for biometrics applications and has become a active research area for several research groups across the world. Despite of utilizing iris region as a part, periocular biometrics can be preferred over iris recognition for the reasons reported in [4]. This could be several enough reasoning to exploit periocular biometrics in unconstrained biometrics applications. Park et al has investigated the use of periocular biometrics using the images captured by visible camera. Thus, the

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investigation of efficient methods of periocular biometrics using appropriate dataset has become the objective of researchers. Evaluation of recognition algorithms in unconstrained environment needs wide diversity embedded across the sample images from dataset in terms of pose, scale and illumination. After identifying the need of database which can emulate the unconstrained environment for periocular identification, we have considered set of periocular images captured from various subjects at different scales (captured from different camera distances) with varying pose and illumination. Few of subject face images showing the variation in scale and pose that may occur in unconstrained biometrics are shown in figure 1.

Figure 1: Sample Face Images showing variation in pose and scale from UBIPr Dataset [7]

In this paper, we have presented parameter analysis and optimization of periocular dataset using various pattern recognition techniques to test their effectiveness in unconstrained environment. The main goal of this research work to investigate the use of periocular biometrics in unconstrained situation to achieve non-cooperative biometrics.

The remainder of this paper is organized as follows: Section 2 briefly overviews existing literature for periocular biometrics and discusses the challenges that arise from less constrained environments. Section 3 elaborates pattern recognition methods that can be used for periocular recognition. An experimental results and discussion will appear in section 4. Finally, paper will be concluded with summary of work presented here and future work that can be carried out further

II.RELATED WORK

The first paper in its kind [4] based on periocular biometrics has highlighted the benefits of biometrics recognition using periocular images especially over iris image based recognition. They have presented feasibility study on using periocular information as a biometric. Their study involves mainly investigation with the local descriptors using LBP, HOG and SIFT features. The performance result with these descriptors with and without eye brow has been shown for periocular images. This paper uses two databases and fusion of afore mentioned approaches are applied on them and results in terms of recognition accuracy and CMC curves. In this paper, they used local features as there is possibility of misalignment in corresponding landmarks across the samples used for both gallery and probe images. Another work [3], which is extension of first paper has extensively represented the results with various aspects of periocular recognition which includes role of eyebrows, left or right eye information contribution, manual or automatic segmentations impacts, local and global features effectiveness, performance with fusion of face and periocular biometrics, degradation due to partial occlusion over face images, effect of disguising the eyebrows and masking iris and eye region and analyzing the effect of pose variation and occlusion. The experiments carried in this paper uses FRGC 2.0 database

Another important paper [6] in this area has demonstrated the fusion techniques on periocular and iris images for non-ideal images of the eye characterized by occluded irises, motion and spatial blur, poor contrast and illumination artifacts. The experimental results using MBGC database with score level fusion can improve the recognition performance.

In another paper [5], author compare two GEC-based Type II feature extraction (GEFE) methods for periocular biometric recognition: a steady-state GA and an elitist Estimation of Distribution Algorithm (EDA). These GECs (referred to as GEFEssga and GEFEeda) evolve a population of feature masks (FMs) with the objective of minimizing the number of features needed as well as optimizing the recognition accuracy.

In one of the recent papers [1] , gender and ethnicity were identified using periocular images. Authors use the LBP as feature extractor and SVM classifier. Experiments were performed with FGRC face dataset. A very important conclusion is derived in this paper that classification accuracy obtained by using the periocular images is comparable to that obtained by using entire face images for gender and ethnicity recognition.

III.PATTERN DESCRIPTORS AND PERIOCULAR REGION

Weighted gradient orientation histogram (WGOH) is very popular in both outdoor localization and indoor localization [9]. Several improving and simplifies has carried out on it. Gradient orientation can well deal with illumination changes. Several systems have proved that this method is an efficient approach and can make good recognition results. Unlike color histogram, WGOH first converts an image into gray image. All the processes are based on the gray-image. Then gradient magnitude m(x, y) and gradient orientation angle (x,y) of each pixel are computed to construct the histogram.

The LBP operator was first introduced as a complementary measure for local image contrast [10]. The first incarnation of the operator worked with the eight-neighbors of a pixel, using the value of the center pixel as a threshold. An LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result.

Since the LBP was, by definition, invariant to monotonic changes in gray scale, it was supplemented by an orthogonal measure of local contrast. The average of the gray levels below the center pixel is subtracted from that of the gray levels above (or equal to) the center pixel. Two-dimensional distributions of the LBP and local contrast measures were used as features.

PCA [11] being global descriptor, will be inefficient intuitively as opposed to it's popularity in using face recognition. This fact may be because of the lack of low frequency components present in the eyes in its immediate vicinity.

Dataset Description: To evaluate the algorithms to be used in unconstrained biometrics, dataset with wide diversity should be available. However, MBGC and FRGC dataset, which were used in periocular research work has not provided the necessary variations across the sample images. These datasets has not considered pose variations while generating images of subjects. Though, this dataset has illumination diversity, absence of scale diversity makes it difficult to be used for unconstrained biometrics research. On the other hand, UBIPr [7] dataset has not just captured the variation in pose of the subjects but also subjects were at different distances from the camera leading to variations in scale of face images and hence in periocular samples. Thus, we selected this UBIPr for evaluation of various objectives.

Periocular Region for Feature Extraction: For better performance of recognition, it is necessary to have proper overlapping in periocular images across all periocular images. This fact requires importance in selecting the reference points about which periocular region of interest (ROI) would be cropped. In [1], authors has selected the iris center as a reference point and being this point a center , rectangular region of 3Rx4R pixels was cropped from the face images, R being a radius of iris. In [7], it has been shown that the eye center will give proper overlapping in terms of eye structure across eyes of subjects, even with different gazes. This method is based on two facts, one is iris center changes the position in eye structure without much change in other landmarks position, if gaze changes. Another fact is that iris radius changes or becomes difficult to measure actual radius with different amount of closing always associated with even opened eye. Moreover, closed eye or more than half closed ye leads to impossibility of measuring the iris radius. Though this method can be ideal in obtaining proper overlapping across all the periocular region samples, it's almost rare to directly locate the center of eye due to movement in iris for different gazes. However, the location of eye corners is completely independent of gaze or movement of iris and also of closeness of eyes. Thus column coordinate (y) of eye center can be an average of that of two eye corners (R1y and R2y), while its row coordinate (x) can be same as that of iris center (R0x) as shown in figure 2. The effect of two types of reference points on the grid alignment is shown in figure 3.

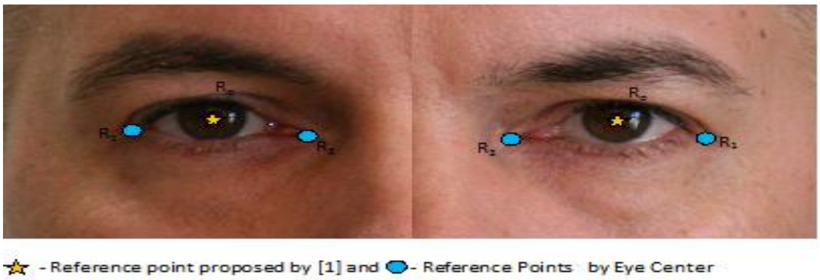

Figure 2. Reference Points selected for cropping Periocular ROI

IV. EXPERMENTAL DISCUSSION AND RESULT

To evaluate the performance of various pattern descriptors for unconstrained periocular recognition, several experiments were performed with dataset. The global descriptor as PCA features and HOG, LGP (Local Gradient Pattern) for local feature extractor were selected in this work. Two sets of experiments were performed here by calculating recognition accuracy for a set of training and testing samples. First, experiment was performed for the various parameters of each descriptor in order to select reasonable values for the set of parameters by observing ROC parameters. However, it was applied on few number of classes than those available in complete dataset (93 out of 500) but executed for left eye, right eye and both eyes independently. The results obtained for HOG and LBP. The one parameter, window grid size (in terms of number of blocks) for both local descriptor was selected as 2(3x4)=6x8. Another parameter, number of bins was determined as 8 for

HOG and 32 for LBP. For PCA features with different number of principle components, ROC parameters values are shown in figure 6. PCA was created using two low resolutions, frontal samples. Number of principle components for PCA descriptor was chosen as 300.

After determining optimized parameters for all descriptors, next goal was to examine the recognition capability of different features such as HOG, LBP and PCA with selected parameters of each feature descriptor. For each experiment, two low resolutions, frontal images of each class were used as gallery images and rest 13 images from each class were used as probe images. These experiments were executed for left eye, right eye and for both eyes separately and with all the classes exist in dataset. The recognition ratios are shown in table 1 with periocular region i.e. horizontal difference in pixels between two eye corners. The performance obtained by HOG and LBP are nearly same but computational complexity of LBP is higher than that of HOG. It can also be seen that recognition with both eyes gives slightly better result as compared to that with individual eyes. As compared to local descriptors, PCA has very poor performance in periocular recognition as opposed to its popular use in face recognition algorithms.

To test the performance using eye corners as reference points over the iris center for selecting periocular region, we repeated above recognition experiment with reference points as iris center proposed in [1] and eye corners proposed in [7]. These experiments were performed with periocular image sample with 0.9EWx1.2EW pixels, EW being as eye width. Recognition accuracy with iris center is shown in table 2. It supports the use of eye corners as reference points to select the periocular region especially in case of unconstrained biometrics, where pose, gaze variations are bound to happen.

Further, we tested the performance with this optimized parameters and techniques and presented the recognition accuracy with different combination of techniques as shown in table 3 and 4 and combining in table 5. This examines the effectiveness of periocular recognition algorithm with different pose of subjects.

Feature Descriptor	Number of Classes	For Left Eye	For Right Eye	For Both Eyes
HOG	93	70.46	74.05	82.15
LBP	93	68.24	67.16	76.12
PCA	93	58.63	59.64	68.75

Table 1: Recognition Accuracy in percentage for LBP, HOG and PCA with periocular region i.e. horizontal difference in pixels between two eye corners

Feature Descriptor	Number of Classes	For Left Eye	For Right Eye	For Both Eyes
HOG	93	66.88	70.60	76.55
LBP	93	62.79	61.57	69.31
PCA	93	46.45	46.45	53.33

Table 2: Recognition Accuracy in percentage for LBP, HOG and PCA with iris center.

V. CONCLUSION AND FUTURE WORK

In this paper, we have presented parameter analysis of periocular dataset using various pattern recognition techniques to test their effectiveness in unconstrained environment. The main goal of this research work to investigate the use of periocular biometrics in unconstrained situation to achieve non-cooperative biometrics. We have optimized the parameters for different feature techniques like HOG, LBP and PCA representations. It has been also observe that new technique of determining the reference point for cropping the periocular sample has given superior performance that that with iris center. Thus this technique can be used to select the periocular region especially in case of unconstrained biometrics, where pose, gaze variations are bound to happen. Further, we examined the performance of periocular recognition for various poses of periocular samples.

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Techniques	Eye	Front Pose	Left Pose @ 30 Degree Aprox.	Right Pose @ 30 Degree Aprox.
HOG	Right	93.1183	64.5161	54.1935
	Left	91.1828	61.5054	47.9570
	Both	94.1935	73.9785	61.5054
LBP	Right	84.7312	53.9785	46.0215
	Left	87.5269	56.1290	44.7312
	Both	89.0323	64.0860	54.8387
PCA	Right	86.4516	32.4731	20.4301
	Left	81.0753	31.8280	26.4516
	Both	91.6129	38.0645	30.3226

Table3: Pose Wise Recognition Accuracy in percentage for Iris Centre using LBP, HOG and PCA Techniques

Techniques	Eye	Front Pose	Left Pose @ 30 Degree Aprox.	Right Pose @ 30 Degree Aprox.
HOG	Right	93.5484	66.6667	61.9355
	Left	91.1828	58.0645	62.1505
	Both	95.0538	73.5484	77.8495
LBP	Right	83.8710	60.8602	56.7742
	Left	87.0968	53.5484	64.0860
	Both	90.1075	68.8172	69.4624
PCA	Right	84.7312	56.5591	37.6344
	Left	83.0108	64.0860	28.8172
	Both	89.0323	69.2473	47.9570

Figure 4: Pose Wise Recognition Accuracy in percentage for Eye Corners using LBP, HOG and PCA Techniques

Techniques	**Eye**	**Front Pose**			**Left Pose @ 30 Degree Aprox.**			**Right Pose @ 30 Degree Aprox.**		
		Iris Center	Eye Corners	Average	Iris Center	Eye Corners	Average	Iris Center	Eye Corners	Average
HOG	Right	93.118	93.548	93.333	64.516	66.666	65.591	54.193	61.935	58.064
	Left	91.182	91.182	91.182	61.505	58.064	59.784	47.957	62.150	55.053
	Both	94.193	95.053	94.623	73.978	73.548	73.763	61.505	77.849	69.677
LBP	Right	84.731	83.871	84.301	53.978	60.860	57.419	46.021	56.774	51.397
	Left	87.526	87.096	87.311	56.129	53.548	54.838	44.731	64.086	54.408
	Both	89.032	90.107	89.569	64.086	68.817	66.451	54.838	69.462	62.150
PCA	Right	86.451	84.731	85.591	32.473	56.559	44.516	20.430	37.634	29.032
	Left	81.075	83.010	82.043	31.828	64.086	47.957	26.451	28.817	27.634
	Both	91.612	89.032	90.322	38.064	69.247	53.655	30.322	47.957	39.139

Table 5: Pose Wise Recognition Accuracy in percentage for Average of Iris Center and Eye Corners using LBP, HOG and PCA Technique