

Periocular Biometrics: When Iris Recognition Fails

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Abstract—The performance of iris recognition is affected if iris is captured at a distance. Further, images captured in visible spectrum are more susceptible to noise than if captured in near infrared spectrum. This research proposes periotic biometrics as an alternative to iris recognition if the iris images are captured at a distance. We propose a novel algorithm to recognize periotic images in visible spectrum and study the effect of capture distance on the performance of periotic biometrics. The performance of the algorithm is evaluated on more than 11,000 images of the UBIRIS v2 database. The results show promise towards using periotic region for recognition when the information is not sufficient for iris recognition.

I. INTRODUCTION

Advances in biometrics technology has ushered the possibility of large scale biometric recognition systems such as national ID and homeland security projects. Among all the biometric modalities, iris has shown the potential to be discriminating for large number of subjects. There are, however, still many challenges that need to be overcome before iris can become a ubiquitous identification entity in our lives. One major challenge is the invasive and constrained nature of its stop-and-stare capturing mechanism [1]. Since the performance of iris as a biometric is dependent on its capture in a noise free near infrared (NIR) environment, most capture modules are invasive. Also, NIR wavelength prevents suitable capture of iris under outdoor environment. One solution is to capture iris images in the visible spectrum and then perform recognition[1] [2] . This allows for capture at longer distances such as walking through corridors. Over a distance, e.g. 4-8 meters with a reasonably cooperative subject, the eye region can be detected, tracked and captured. However, in such practical environment, there is always a possibility that a sufficiently high quality iris region is not captured. This is due to occlusion (e.g. glasses, blinking, closed eyes etc.) or other noise factors discussed later in detail. In such conditions, we may be able to capture region around the eye, called the *periocular region*. Recent studies have shown that periocular region can be used as a biometric in itself [3]. The authors have found the periocular to be the least invasive among all eye based biometrics. However, existing studies have performed experiments with limited dataset.

This paper focuses on recognizing individuals using periocular region. Specifically, a novel recognition algorithm for periocular biometrics is presented where

- a global descriptor which extracts perceptual properties from the spatial envelope of a given image, known as

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GIST and circular local binary patterns (CLBP) are used for feature extraction.

- UBIRIS v2 [1], an iris database that contains over 11,000 images with varying amount of periocular region is used for performance evaluation. Fig. 1 shows some sample images from the UBIRIS v2 database.
- comprehensive experimental evaluation is performed to assess the effect of capture distance and information content on recognition performance.

Section II describes the challenges of iris recognition on UBIRIS v2 database. Section III presents the proposed algorithm for periocular biometrics. Experimental protocol, results and analysis are discussed in Section IV.

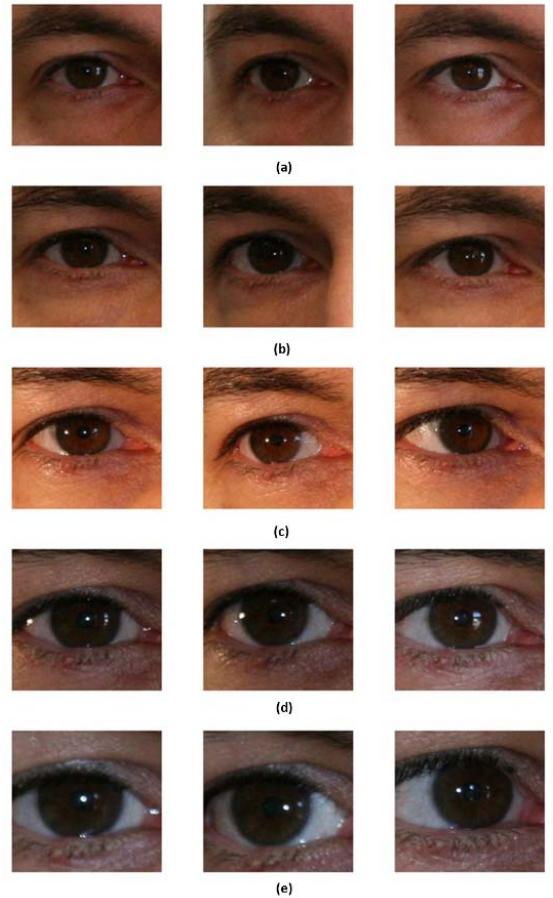


Fig. 1. Sample periocular images from the UBIRIS v2 database at distance (a) 4 meters (b) 5 meters (c) 6 meters (d) 7 meters (e)

II. WHEN IRIS RECOGNITION FAILS

In general, iris recognition is performed under near infrared environment. Researchers are now focusing on recognizing iris at a distance in visible wavelength. However, there are several challenges that still need to be addressed. Recently, an extensive UBIRIS v2 database is released which is meant as a challenging real world database for iris recognition in visible spectrum. This database contains both left and right eye images of different individuals captured over multiple sessions. The purpose of this database is to acquire eye images of moving subjects at varying distances and with sufficient noise factors such as environmental lighting to simulate realistic conditions [1]. The images are captured from 4 to 8 meters. The challenges in the database are scale, occlusion and illumination.

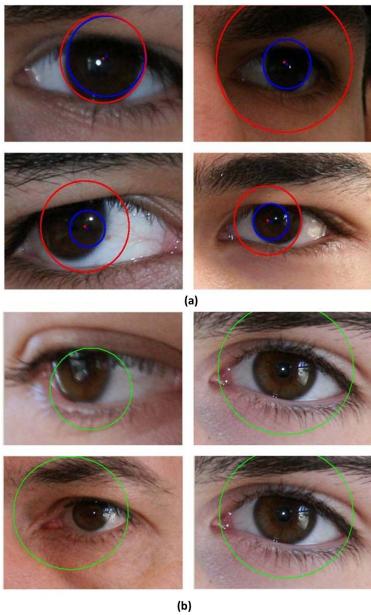


Fig. 2. Examples of poor Segmentation (a) segmentation using [4] (b) segmentation using VeriEye.

- **Scale:** For every subject, 60 images of both eyes (30 images per eye) are captured in two sessions. At different distances the capture devices are not calibrated to account for the change. Therefore, different amount of information is captured at each distance step. As illustrated in Fig. 1(a) at the closest distance sclera and iris regions are more dominating whereas more periocular region is observed in images taken from afar. The unconstrained nature of this database also allows for angular captures, hence it can not be assumed that the images are aligned in any way.
- **Occlusion:** The database is severely ridden with occlusion of eye region due to spectacles, flapped eyelids, eyelashes and hair.
- **Illumination:** To emulate unconstrained environments, images has been captured under variable lighting conditions. This results in eye socket shadow and severe specular reflectance.

The original intent of the database is the development of robust iris recognition algorithms in visible spectrum. At first glance it may seem reasonable to assume that enough iris information can be obtained from the images of the UBIRIS v2 database, especially those that are taken from close distances. However, as shown in Fig. 2, this intuition is incorrect. Both commercial and academic [4] segmentation algorithms perform poorly on this database even after parameter optimization. In the visible wavelength, the intensity difference between pupil and iris is too inconsistent to be used for segmentation. Preprocessing the images to enhance segmentation performance fails as well. Though the aforementioned challenges are equally possible in the NIR domain, visible wavelength accents those challenges. Nevertheless, the extensive nature of this database provides unique insights into the performance of periocular region as a biometrics.

III. PERIOCULAR FEATURE EXTRACTION AND MATCHING

Park *et al* [3] have found that the periocular region is best discriminated through the fusion of global and local descriptors. In this research, we propose a periocular recognition algorithm using perceptual properties of spatial envelope [5] as a global descriptor, that, in a sense, provides the ‘gist’ of an image, and CLBP that encodes local texture features. Further, both the global and local descriptors are fused using weighted sum rule [6]. The match scores of the left and right periocular regions are finally fused using sum rule to improve the recognition performance.

A. Global Matcher - GIST

The objective of using global descriptor for periocular recognition is to obtain a basic and superordinate level description of the perceptual dimensions [5]. While [3] uses the global descriptor for color, shape and texture, a more comprehensive global descriptor is required to describe the information captured in the unconstrained images. GIST descriptor [5] effectively encodes the scene images where the distance between a fixated point and the observer is large (greater than four meters). Here a set of five perceptual dimensions, namely, naturalness, openness, roughness, expansion and ruggedness are used to give a low dimensional, holistic representation of the image. While the nomenclatures of the dimensions come from the original use as scene descriptors, we argue in this work that they can also be good descriptors for periocular region.

- 1) **Degree of Naturalness:** This spatial property describes the distribution of edges in the horizontal and vertical orientations. It describes the presence of artificial elements such as spectacles.
- 2) **Degree of Openness:** The second major attribute describes the presence or lack of points of reference. An image with a higher percentage of periocular regions than sclera and iris region will have less points of reference or be more ‘open’.

- 3) Degree of Roughness: This perceptual attribute refers to the size of the largest prominent object in the image. It evaluates the common global attributes of the image.
- 4) Degree of Expansion: This attribute describes the depth in the gradient of the space within the image.
- 5) Degree of Ruggedness: This attribute gives the deviation from horizontal by assessing the orientation of the contours of the image.

These perceptual properties are correlated with the second-order statistics and spatial arrangement of structured components in the image [5]. They are easy to calculate and can be translated to useful global descriptors of the periocular region. For further details, reader are referred to [5].

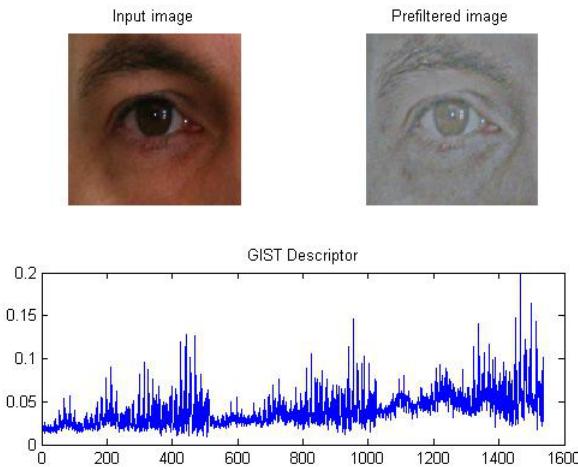


Fig. 3. Illustrates the prefiltered image and its GIST descriptor

B. Local Binary Patterns - CLBP

Local binary patterns [7] originally designed for texture classification however, is widely explored in biometrics, specifically in face recognition. This is due to its computational efficiency and robustness to monotonic changes in gray-level intensities. The local descriptor is calculated by thresholding the neighborhood pixel with the center pixel and encoding the difference in signs as shown in Fig. 4(a). If the gray level intensity of neighboring pixel is higher or equal, the value is set to one otherwise zero. The basic LBP descriptor is calculated using Equation [1]:

$$LBP_{N,R}(p,q) = \sum_{i=0}^{N-1} s(n_i - n_c)2^i \quad (1)$$

$$s(\cdot) = \begin{cases} 1 & \text{if } n_i - n_c \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where n_c corresponds to gray-level intensity of center pixel and n_i corresponds to gray-level intensities of N neighboring pixels.

Ojala *et al* [8] propose scale and rotation invariant local binary patterns where the neighbors are evenly sampled on a circle of radius R from the center pixel. Scale and rotation

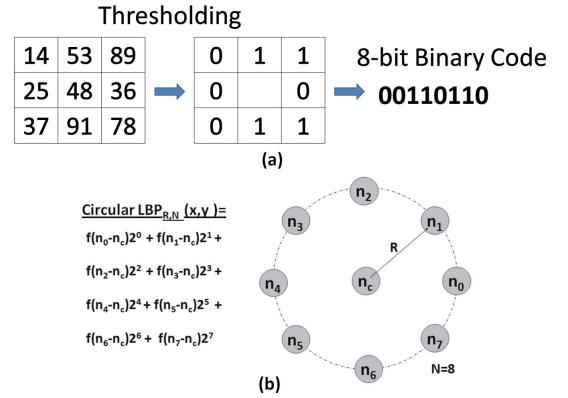


Fig. 4. LBP descriptor (a) Basic LBP and (b) Circular LBP.

invariance property of Circular LBP motivates to capture the discriminating texture features from the periocular region. The periocular region is divided into grids and histogram measuring the frequency of binary patterns is computed for each grid. As shown in Fig. 4(b), the binary patterns are computed by thresholding the gray level intensities of evenly spanned neighbors on the circle with the central pixel of the circle. The final descriptors is computed by concatenating all the local texture histograms.

C. Proposed Algorithm for Periocular Biometrics

Fig. 5 illustrates the steps involved in the proposed recognition algorithm for periocular biometrics. The algorithm starts with feature extraction at global and local level followed by match scores computation and fusion at match score level. The algorithm is described as follows:

- For a given probe image, the local contrast of the periocular image is normalized by applying windowed Fourier transform over a hamming window. The spatial envelope of this normalized image is computed using Gabor filter with four scales and eight orientations. Different sets of orientations and scales provide GIST descriptor of varied lengths. The filter bank provides a descriptor of length 1536, as shown in Fig. 3, that we experimentally observe to be optimal in this context.
- From the original image, circular local binary patterns are extracted. The image is first divided into 64 non-overlapping patches and a descriptor of size 256 is extracted from each patch. This descriptor encodes the local texture features of the periocular image.
- Both the global and local descriptors are extracted for all the gallery images and stored in a template database.
- To match the GIST and CLBP features, χ^2 distance measure is used. Let x and y be the two GIST features to be matched. The χ^2 distance between these two features is computed using Equation [3]

$$\chi_G^2(x,y) = \sum_{i,j} \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}. \quad (3)$$

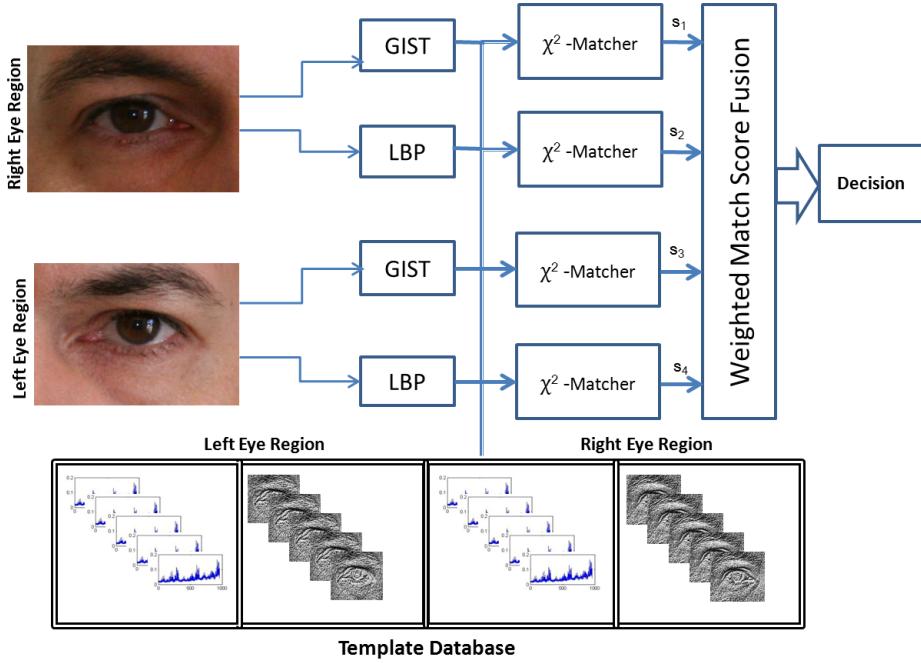


Fig. 5. Illustrates the steps of proposed fusion framework of Local and Global Classifiers

- Similarly, let a and b be the two CLBP features to be matched. The χ^2 distance between these two features is computed using Equation [4]

$$\chi_C^2(a, b) = \sum_{i,j} \frac{(a_{i,j} - b_{i,j})^2}{a_{i,j} + b_{i,j}} \quad (4)$$

where i and j correspond to the i^{th} bin of histogram belonging to j^{th} local region.

- Both the distance scores are normalized using min-max normalization to obtain χ_{Gnorm}^2 and χ_{Cnorm}^2 . To combine the advantages of both the local and global descriptors, both the distance scores are fused using weighted sum rule [6].

$$M_{fused} = w_1 * \chi_{Gnorm}^2 + w_2 * \chi_{Cnorm}^2 \quad (5)$$

where w_1 and w_2 are the weights of GIST and CLBP classifiers respectively.

- Left and right periocular regions are fused at match score levels to further enhance the overall recognition performance as shown in Equation (6).

$$F = M_{fused}^l + M_{fused}^r \quad (6)$$

where M_{fused}^l and M_{fused}^r are fused distance scores for left and right periocular region respectively.

In identification mode, for a given probe periocular region, we repeat this process for all gallery-probe pairs and top matches are obtained using the fused scores F .

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of proposed algorithm is evaluated using the UBIRIS v2 database. The entire database containing over

11,000 images from 261 subjects (captured over quantized distances from 4 to 8 meters) has been divided into gallery and probe partitions as follows:

- There are 60 images per subject, 30 images pertaining to the left periocular region and 30 pertaining to the right periocular region. To make a comprehensive gallery, the first two images per distance unit constitute the gallery datasets. The gallery contains 1844 left and 1845 right periocular images.
- The remaining 3705 left eye (periocular) and 3704 right eye (periocular) images are used as probe.

Experiments are performed in identification mode ($1:N$) and rank-1 identification accuracy is reported along with Cumulative Match Characteristic (CMC) curves, as illustrated in Fig. 6 .

A. Performance Evaluation

The analysis and observations of the experiment are described below.

- GIST descriptors are computed for both left and right periocular images in the database separately. According to the above gallery and probe partitioning, χ_G^2 is computed for both these sets. Rank-1 identification accuracy of 63.34% is obtained for right region and 61.64% is obtained for left region. The fusion algorithm combines match scores of both left and right regions and yields an accuracy of 70.82%. CMC curves for these three experiments are shown in Fig. 6(a).
- Similarly, the CLBP descriptors of left and right periocular images are extracted. χ_C^2 for left and right regions are computed separately. Identification accuracy of the left region is 52.82%, right region is 54.30% and the

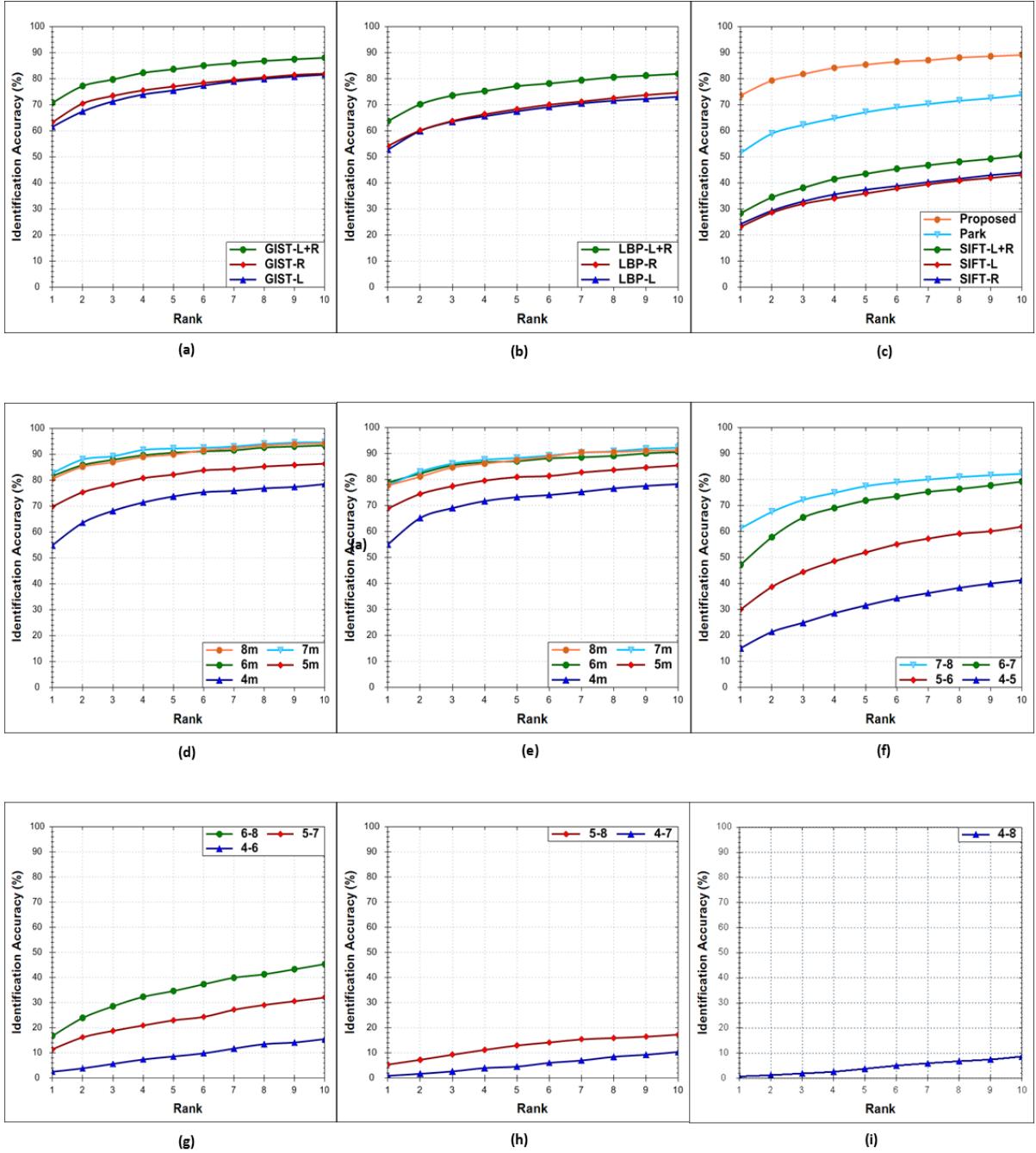


Fig. 6. CMC results of all experiments: (a) Left, Right and Fusion of GIST, (b) Left, Right and Fusion of CLBP, (c) Proposed, SIFT, Park [3], (d) Distance Experiment 1, (e) Distance Experiment 2, (f) Distance Experiment 3 at 1 meter distance difference, (g) Distance Experiment 3 at 2 meter distance difference, (h) Distance Experiment 3 at 3 meter distance difference, and (i) Distance Experiment 3 at 4 meter distance difference.

fusion of left and right regions yields 63.77%. The results of this experiment are shown in Fig. 6(b).

- For a given subject, M_{fused}^l and M_{fused}^r are obtained separately for the left and right periocular region and rank-1 identification accuracy of 73.65% is achieved for fusion of M_{fused}^l and M_{fused}^r . Fig. 6(c) shows the identification performance of the proposed periocular biometrics recognition algorithm. Fig. 6(c) also shows the comparison of the proposed algorithm with the

approach of Park *et al* [3].

- The results show that the recognition rate improves by performing weighted sum rule fusion of the match scores from local and global classifiers as they provide complementary information. This observation is consistent with the observations of Park *et al* [3], however in case of large, real world database, the global classifier outperform the local classifiers.
- It is observed that UBIRIS v2 images taken from 4 and

5 meters do not contain eyebrows whilst the images from afar contain eyebrow regions. Hence, experiments corresponding to CMC curves in Figs. 6(g), (h) and (i) can also be interpreted as experiments of with and without eyebrow region. These experiments clearly show that periocular region provides better identification accuracy with eyebrow region than without eyebrow region.

We also study the effect of distance from capture apparatus on the recognition performance. In the UBIRIS v2 database, each captured image is tagged with distance (between 4 to 8 meters with 1 meter step). Three sets of experiments were performed:

- 1) *Experiment 1:* The gallery consists of two images per distance measure. The recognition accuracy is computed for probe images at each specific distance (from distance 4 to 8 meters). It was observed that identification at distances more than 6 meters is significantly better than identification for less than 5 meters. Hence, for similar setup, images captured between 6 to 7 meters are better for identification purposes.
- 2) *Experiment 2:* In this experiment, both gallery and probe sets comprise images from the same distance. For example, if the gallery contains images captured from 5 meters, the probe set will also have images captured from 5 meters. As shown in Fig. 6(e), the maximum identification accuracy of 78.86% is obtained when gallery and probe are at 6 meters distance. The results suggests that, for a similar capture setup, 6 to 7 meters seem to be the ideal distance of capturing periocular region.
- 3) *Experiment 3:* This experiment is performed to evaluate the performance on all combinations of distance variations i.e. when the distance variation between probe and gallery is 1 meter, 2 meters, 3 meters and 4 meters. This experiment is conducted to analyze the distance tolerance of the proposed algorithm. Here it must be noted that there is profound difference of information in this spatial range. The identification accuracy is presented through CMC curves in Fig. 6(g), (h) and (i), which suggest that the algorithm cannot handle large difference in distance and consequently difference in information content.

These experiments suggest that periocular biometrics can be a good alternative when iris recognition is not feasible, provided it is captured from an optimal distance.

V. CONCLUSION AND FUTURE WORK

This paper presents a novel algorithm for identifying individuals based on their periocular region. The algorithm computes normalized distance scores from (i) GIST, a global descriptor that describes holistic spatial information of an image and (ii) CLBP, a local descriptor that encodes local texture information. These multi-classifier information are fused for both left and right periocular regions for recognition. UBIRIS v2, a challenging iris database which also

contains periocular region was used for performance evaluation. In this research, it was observed that (1) an ensemble of global and local classifiers enhances the identification performance of periocular biometrics, (2) for the UBIRIS v2 database, global features provide better discriminating information than local features, (3) though the proposed algorithm outperforms existing algorithms, it is dependent on the amount of periocular information present in the images, and (4) the presence of eyebrow region enhances the identification accuracy, suggesting that the area consists of important information. In future, we plan to study the effect of expression, wrinkles, makeup and spectacles on periocular biometrics.

VI. ACKNOWLEDGMENTS

This research is partially supported by the Department of Information Technology, Government of India, India.

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