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Periocular Biometrics using Handcrafted Features for Non-Ideal Images

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Abstract: ***Features from face and iris to authenticate individuals are the most popular biometric traits. Still inclusion of non-ideal images (such as images with variation in pose, tilting head, subjects wearing spectacles and variation in capturing device distance) can degrade the recognition accuracy of any biometric systems. For this scenario, periocular region (nearby region around the eye) based biometric authentication is an emerging method which is used by researchers now a days to improve the recognition accuracy specifically for non-ideal images and when users are non- cooperative. In this context, our key insight is to develop a system considering periocular region as a biometric trait and aim to evaluate its effectiveness for classification of non-ideal images in two different non-ideal scenarios 1) images with different pose variation and 2) images captured from varying camera standoff distance. In this proposed work we have evaluated three different handcrafted feature descriptors 1) Histogram of Oriented Gradients 2) Bag of Feature model and 3)Local Binary Patterns on two different databases 1) ORL face database and 2) UBIPr periocular image database and found that HOG feature descriptor show superior performance as compare to BOF and LBP feature descriptor for periocular region based biometric authentication systems.***

Keywords: Biometrics, Bag of feature model, Histogram of Oriented Gradients, Local Binary Pattern, Non-ideal images, Periocular region.

I. INTRODUCTION

Over the time, as technology is getting enough matured, authentication of an individual identity is a major concern now-a -days. Researchers have already explored several physiological and behavioral biometric traits such as face, gait, hand, palm print, and iris etc. Based on the literature face and ocular are the two most reliable biometric traits [1]. But both have their own limitations and are highly affected by variation in pose, expression, occlusion, aging and user cooperation etc. [2].
Investigators now shifting their focus from face and iris to some new biometric traits such as use of ears, knuckle joints and periocular region etc. Ear biometric generally suffers with the problem of hair occlusion [3] whereas knuckle joint based biometric authentication requires high user cooperation [4] and that is the reason periocular region based biometric. authentication systems are gaining high popularity both as fusion with iris [5] and as a standalone modality [6].

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(a) **(b)**

Fig.1. Example images of periocular region (a) Periocular region which may include both eye (b) Periocular region which may include either left or right eye.

Periocular region as the name suggest is the small area of nearby region around the eyes which may include eyelashes, eyebrow, eye shape, skin texture, eye size and eye corners etc. as shown in Fig.1.

Some advantages of periocular region as a biometric attribute are:

- It is highly suitable for non-ideal images [Fig.2]
- It requires less user cooperation as compare to face or iris based biometric authentication system.
- Iris images comprehensively contained some zone of periocular region in this manner combination of both the modality (iris and periocular) can drastically expand the recognition precision and it doesn't require any additional set up for tests.
- Input images of periocular region requires less storage space as compared to face images because they are only a small segmented region of face images.

Researchers using periocular region as a biometric trait obtained very promising results and reported low error in recognition rate for different scenarios such as in cross spectrum matching [7], hallucination of full face using periocular region [8], image matching after gender transformation [9] and matching of images altered because of medical reason etc. [10]. Presently paraphrase the best challenge in periocular biometric is the matching of non- ideal images [11]. Reason is that non ideal images may suffer with the problem of pose variation, specular reflection, varying camera standoff distance, among others.

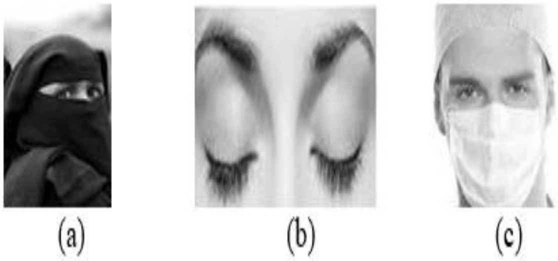

Fig.2. Example of non-ideal images where periocular region-based recognition is useful

In this context, our goal is to evaluate performance of periocular region based biometric authentication system on two different databases UBIPr and ORL face database using three different hand-crafted features descriptors 1) Histogram of Oriented Gradients (HOG) 2) Bag of Feature Model (BOF) and 3) Local Binary Patterns (LBP) for two diverse non perfect situations 1) matching of images with different pose variation 2) matching of images captured in varying camera standoff distance.

Recently researchers implemented various non handcrafted features using deep learning concepts and reported interesting results [12]-[15]. But, the primary concern with deep learning architecture is the requirement of huge size dataset for generalization else model gets overfitted. People solve this problem using transfer learning [16] and with different data augmentation techniques [17]. This can be true that non handcrafted features have their own benefits, but one can never neglect the effectiveness of handcrafted features which resides somewhere in the core of deep learning concepts.

In this work, we have evaluated three different handcrafted features in which HOG and LBP are global feature descriptor where as BOF which consists of SURF (Speeded Up Robust Feature) is a local feature descriptor. The basic difference between local and global feature descriptors is that first one considered image in the form of patches for feature extraction whereas later one considers image as a whole and single entity. Some other handcrafted feature descriptors used in literature which provide promising results are Binary statistical Image features (BSIF) [18], Zernike moments [19] and scale invariant feature transform (SIFT) [20] etc.

To evaluate our proposal, we chose two different databases UBIPr and ORL face database which consists of RGB and grayscale images respectively. UBIPr is currently one of the frequently used benchmarked databases in the community of periocular biometric researchers. One more reason is to use UBIPr and ORL is that both contained images with pose variation up to 30 degree for both left and right side that’s why both are highly suitable for our experiments.

The paper is divided in to 7 sections 1) introduction to periocular region and the proposed work 2) brief study of pre-existing periocular region based biometric authentication systems 3) description of databases 4) description of feature extraction methods used in the proposed work 5) methodology used in the proposed work 6) This section describes how the experiments were performed and the results were obtained while the last section consists of 7) the conclusion , findings and the future work.

II. STUDY OF PREEXISTING PERIOCULAR REGION BASED AUTHENTICATION SYSTEMS (LITERATURE SURVEY)

This section describes the state -of-the-artwork in periocular biometrics, especially those taking LBP, HOG and SURF feature descriptor into consideration.

Park et al. [21] in 2009 were the first who proposed the method to analyze the performance of periocular region as an independent biometric trait. They created their proprietary database of periocular region images and considered two different regions of interest; periocular region with and periocular region without eyebrow. They used LBP with HOG and SIFT as a feature descriptor and with Euclidean distance as a global matcher they obtained nearby 77% recognition accuracy. They also concluded that eyebrow as a feature vectors in periocular region of interest can significantly improve the recognition capability of a system. As an extension of their work in 2011 [22] they use two different dataset one is proprietary and second is Face Recognition Grand Challenge (FRGC) database [23]. This work was mainly concerned to analyze the utility of periocular region in non-ideal scenarios (such as effect of partial face occlusion, pose variation and cosmetic modifications). With the same experimental setup as described above in [21] they found that periocular region based biometric authentication system obtained better recognition accuracy as compared to face recognition systems in non-ideal scenarios.

Later many of the researchers put a lot of efforts to prove the effectiveness of periocular region. The descripted work here in this paper relies heavily on prior work done by many researchers in this area who have used LBP, HOG or BOF as a feature descriptor.

Local Binary Pattern (LBP) It was first released in 1990 and was primarily used for texture matching. One advantage of LBP is that it is invariant to translation and illumination variation. In the literature LBP has many variants proposed such as the use of Circular Local Binary Pattern (CLBP) [24**].** In this method unlike LBP neighbouring pixels were considered in the circle of sweep ‘r’ from the middle pixel this also make the CLBP descriptor rotation and scale invariant. Researchers in [25] used Walsh-Hadamard transform encoded local binary patterns (WLBP/WHTLBP) which was a combination of Walsh Hadamard transform and LBP. Basic concept was to first filter the input image using Walsh Mask then extract local binary patterns from the images. With WHTLBP as a feature descriptor and cosine distance as a matcher they obtained remarkable 100 percent identification rate for age invariant face recognition utilizing periocular area.

Santos et. al. [26] implemented Uniform Local Binary Pattern (ULBP) as a feature descriptor for cross sensor recognition extracted from iris and periocular region. The term uniform is used in ULBP because it can contain at most two bitwise transitions from 1 to 0 or 0 to 1. If the transitions are more than two then pattern is considered as a non-uniform pattern or as a noise.

In ULBP length of feature vector is also less as compare to LBP the reason is assignment of separate label for each uniform pattern.

Mahalingam et al. [27] performed an experiment to analyse the effectiveness of LBP and its two variants 3-Patch Local Binary Pattern (3P-LBP) and Hierarchical 3P-LBP on three different challenging datasets Notre Dame twins, Georgia Tech and Morph in periocular biometrics**.** 3P-LBP was determined by considering and looking at the estimations of three unique patches (local patterns). After examination a solitary value is produced in the code and that would be relegated to the pixel.

Though H-3P-LBP expands the 3P-LBP operator by ascertaining it over various scale of an image. Researchers in [28] used Local Phase Quantization

(LPQ) which primarily quantize the Fourier transform phase in local neighbourhoods of LBP. It is insensitive to image blurring and a very efficient descriptor for blurred and sharp images. Ahmed et. al. [29] used Multi-Block Transitional Local Binary Patterns (MB-TLBP) to implement fusion of iris and periocular region. To create MB-TLBP, rather than utilizing grey level estimation of individual pixel like in LBP and TLBP they consider block of pixels and calculated the average of all grey level values from that block. With this experimental setup they obtained remarkable improvement in recognition accuracy. Whereas authors in [19] used LBP variance. i.e. LBPV which incorporates local contrast information during representation of local texture and achieves rotation invariant feature extraction.

Histogram of Oriented Gradients (HOG) It is a local feature descriptor which first divide the image into small rectangular or circular region known as "cells". For each cell compute a histogram of edge orientations values. Combined all the histogram entries and that can be used as feature vector for describing the objects. In the literature there are some variations of HOG descriptor which researcher use as a descriptor such as Author in [7] implemented Pyramid of Histogram of Oriented Gradients (PHOG) for multispectral periocular matching (near infrared, visible and night vision) using neural network based matching algorithm. unlike HoG, this method does not divide images in to sub images, but features are extracted from the whole image. PHOG obtained best recognition accuracy for the images captured in near infrared spectrum and outperform others from literature in cross spectral matching. Whereas Santana et. al. [30] implemented two different variants of HOG known as HOG concatenated histogram of the facial pattern (FHOG) and HOG concatenated histogram of head and shoulders pattern (HSHOG) and make it multiscale feature descriptor for gender classification on wild dataset (GROUP). With SVM as classifier they obtained more than 90 percent classification accuracy with less than 12 MS execution time.

Speeded Up Robust Features is partially inspired by SIFT descriptor, but it is several times faster than SIFT. It works on the concept of Hessian Matrix and in addition depends on integral images to accelerate the computation. To extract features, it uses Haar wavelet response. Authors in [31] used SURF as a feature descriptor with combination of HOG, LBP, BSIF and local contrast phase descriptor for matching of surgically altered face images and obtained near by 48 percent recognition accuracy which was higher as compared to others in literature till date. Raja et. al. [18] used combination of SIFT, SURF and BSIF to create multi-model authentication system using combination of face, iris and periocular for smartphone authentication and obtained genuine match rate of more than 94 percent.

Some other remarkable findings with handcrafted feature descriptor in the area of periocular biometrics in literature such as Jillela et. al [32] analyzed the utility of periocular region with the fusion of face modality. They utilized images caught from the subjects before and after plastic surgery procedure. For face matching they utilized Pitpatt and Verilook software and for feature extraction they utilized SIFT and LBP feature descriptors. With the fusion of face and periocular modality they acquired 87.4% rank 1 recognition exactness. Smereka et. al [33] implemented two feature extraction methods PDM (Probabilistic Deformation Model) and M-Sift on FOCS and UBIPr dataset. They obtained recognition accuracy of 84.14% and 78.59% for left and right eye respectively for UBIPr dataset. They additional found that shape of the eyebrow for images captured in visible range , and shape of the eye for images captured in NIR range are the most discriminating features in periocular region-based authentication systems. Rattani et al [34] executed a strategy for gender classification utilizing periocular region on VISOB dataset. They used HOG feature descriptor for feature extraction and Multi-Layer Perceptron for classification and obtained a remarkable 90% recognition accuracy.

Unlike these existing methods our method implemented all the three handcrafted feature descriptors LBP, HOG and BOF separately with different variation of support vector machine as classifier for matching of images with pose variation and analyze the effect of standoff camera distance on recognition accuracy of the system.

III. DATABASES USED IN THE PROPOSED WORK

For better comparison and evaluation of three different feature descriptors we have used two different publicly available databases.

A. Orl (Olivetti Research Laboratory (At&T)) [35]

This database contains total 400 gray scale face images of 40 subjects (10 images / subject). All the images are of 112X92 resolutions and. PGM extension are stored in 40 different directories. These images were captured at different occasions with various lighting conditions and delineate diverse facial expressions such as smile and non-smiley face, open and shut eyes and varying facial details such as subject with or without glasses.

B. UBIPr (University of Beira Interior) [36]

This database contains total 10252 Color images with .bmp extension. These images were captured from different camera distance (8m,7m,6m,5m and 4m), different pose variations and with different facial details such as subject with or without glasses etc.

UBIPr database package also contains metadata of images. This metadata contains data about Gender, Camera distance, Pose angle, Gaze angle, Pigmentation, Eye closure, Hair occlusion, Glass, Inner and Outer Eye Corner coordinates, Iris center coordinates, Inner and Outer Eyebrow point coordinates, Eyebrow middle point coordinates and Eye size.

IV. FEATURE EXTRACTION METHODS

A. Local Binary Pattern (LBP)

Primarily concerned with texture-based matching of images and works only on gray scale images. To calculate LBP feature descriptor, consider a pixel and its nXn neighborhood (n must be an integer value). compare the center pixel value with the neighboring pixel values (for selecting neighboring pixel values order can be anticlockwise or clockwise but order must be same for every pixel) now if current pixel value is >=neighboring pixel value then set neighboring pixel value 1 else set it to 0. The neighboring pixels binary values are stored in a 'n' bits binary number (known as LBP MASK), and its decimal equivalent is use to quantize a histogram, which is used to create a feature descriptor and for characterizing the texture.

B. Histogram of Oriented Gradients (HOG)

The best way to extract local information from images is to use the value of intensity gradient of image pixels because magnitude value of gradient of image pixel is always large on corners and edges (because of high intensity change). HOG is a feature descriptor which uses the orientation of gradient values of pixels. For extraction of HOG feature vector, first divide the image in to sub images or cells (small connected regions which can be rectangular or circular). Then consider one cell and for every pixel in this cell calculate a histogram of different gradient directions. Similarly calculate the histogram for all cells and concatenate all the histograms. The concatenated histogram will work as a descriptor. HOG descriptor works on local region or cells that's why they are rotation invariance and least affected by geometric transformation.

C. Bag of visual word model, or bag of features model using SURF as a feature (BOF).

Bag of visual word model use image features as word for image classification. This method creates visual word by first extracting the features which can be detected by any feature detector (Matlab use Speeded Up Robust Feature (SURF) feature detector by default) then based on the similar characteristics of features k mutually exclusive feature clusters are created using K-means clustering algorithm. Center of each feature cluster can be considered as a feature or visual word.

V. PROPOSED METHODOLOGY

For the proposed work the methodology we have followed is appeared in Fig.3.

A. Input Image / Dataset

Detail description of dataset ORL and UBIPr used in the proposed work is already given in section 3.

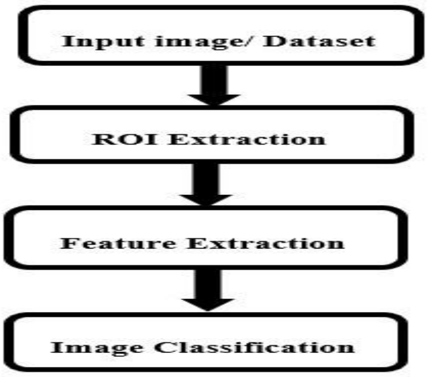

Fig.3. Methodology used for the proposed work

Fig.4.Top Row: Example images from ORL face database

Bottom Row: Example images from UBIPr database some example images from ORL face dataset and UBIPr dataset are shown in top and bottom row of Fig.4 respectively.

B. Region of Interest (ROI) Extraction

Accuracy of periocular region based biometric authentication system is directly depends on size of extracted region of interest from images. Here, for ORL dataset we have implemented an automatic ROI extraction approach using cascade object detector model from computer vision system toolbox (Matlab R 2018a). This model works on the concept of Viola Jones Algorithm [37]. First, we have detected eye region using cascade object detector then we implemented a built in MATLAB function "step" on input images. This step function returns a spatial coordinate of rectangular region of interest which contains the object selected by cascade object detector (eye pairs in our experiment). Based on the spatial coordinate obtained from step function we have extracted the rectangular ROI images of size 16 X 64. Some example images of extracted region of interest from ORL face database is shown in top row of Fig.5.

Since UBIPr dataset consists of periocular region images, still we need to extract the region of interest as per the need of our experiment. Referring the ROI extraction method described in [38], we have followed the steps given below for ROI extraction.

We have considered the inner and outer canthus points as landmark points for ROI extraction. Canthus points are already calculated and provided with metadata in UBIPr database. Say (X_1, Y_1) is the coordinate for inner Canthus points and $(X_2, Y_2)$is the coordinate for outer canthus points.

Step 1: Calculate the Euclidean distance between inner and outer canthus points

$$D\left((X_1,Y_1),(X_2,Y_2)\right) = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \quad (1)$$

Step2: Calculate points $L_p = \left(L_{px}, L_{py}\right)$

$$L_{px} = \frac{(X_1 + X_2)}{2} \quad \text{and} \quad L_{py} = \frac{(Y_1 + Y_2)}{2} \quad (2)$$

Step 3: Calculate top left (X_3, Y_3) and bottom right (X_4, Y_4) coordinate points of rectangular ROI

$$(X_3, Y_3) = \left(L_{px} - 1.2 * D, L_{py} - 0.8 * D\right) \quad (3)$$

$$(X_4, Y_4) = \left(L_{px} + 1.2 * D, L_{py} + 0.8 * D\right) \quad (4)$$

Fig.5.Top Row: ROI extracted from ORL face datasets

Bottom Row: ROI extracted from UBIPr face datasets

Step 4: Extract rectangular ROI with the above calculated points and resize all ROI images to the size of 64 X 128.Some extracted ROI images from UBIPr dataset are shown in bottom row of Fig. 5.

C. Feature Extraction

For this proposed work we have used three feature descriptors Histogram of Oriented Gradients with cell size [2,2], Bag of feature model with Vocabulary size 500 and Local Binary Pattern with 6X6 neighborhood.

D. Image Classification

For the proposed work we have used binary Support Vector Machine (SVM) classifier with HOG features and Local Binary Pattern and multiclass SVM classifier with BOF model for classification. To assess the effectiveness of our classification model on testing data we have calculated confusion matrix and to calculate the recognition accuracy we have use the given formula.

$$Accuracy = \frac{True\ Positive\ Values}{Total\ Number\ of\ images} * 100 \quad (5)$$

VI. EXPERIMENTS AND RESULTS

The proposed work is implemented on MATLAB R2018a. We have performed three different experiments to evaluate the utility of periocular region and for comparative analysis of HOG, LBP and Bag of Feature model as a feature descriptor.

Experiment 1

This experiment evaluated the performance of HOG, LBP and BOF feature descriptor on ORL dataset. Here, we have used HOG feature descriptor and binary SVM classifier with cell size [2 2] and obtained 7812 features per image. Size of cell is very important for HOG feature vector because if we consider large cell size, we can lose small scale information. Next, we have used Bag of Feature model with multiclass SVM classifier and 'Vocabulary Size' 500. Since, Bag of feature model use K-means clustering method, the Value of Vocabulary Size determines the value of K. Last we implemented Local Binary Pattern feature descriptor with 6 X 6 neighborhood pixels and for classification we have used binary SVM classifier. The result we have obtained are shown in Table I.

Experiment 2

In this experiment we have used UBIPr dataset and matching was performed between frontal images and images with pose variation (30 and -30 degree). For this purpose, we have used HOG feature descriptor and binary SVM classifier with cell

Table-I: Classification accuracy on ORL dataset

Training Dataset	Testing Dataset	Classification Accuracy
ORL dataset with HOG and Binary SVM Classifier		
320 images with different pose and facial expression	80 images, with different pose and facial expression	90
ORL dataset with BOF and Multiclass SVM Classifier		
320 images with different pose and facial expression	80 images, with different pose and facial expression	85
ORL dataset with LBP and Binary SVM Classifier		
320 images with different pose and facial expression	80 images, with different pose and facial expression	89

Table-II: Classification accuracy on UBIPr dataset

Training Dataset	Testing Dataset	Classification Accuracy
HOG and Binary SVM Classifier		
4500 images, with 0 degree pose variation	1000 images, with 30 degree pose variation	86
4500 images, with 0 degree pose variation	1000 images, with -30 degree pose variation	88
6000 images, with 0, 30 and -30 degree pose variation	3000 images, with 0, 30 and -30 degree pose variation	93.33
BOF model and Multiclass SVM Classifier		
4500 images, with 0 degree pose variation	1000 images, with 30 degree pose variation	84
4500 images, with 0 degree pose variation	1000 images, with -30 degree pose variation	86
6000 images, with 0, 30 and -30 degree pose variation	3000 images, with 0, 30 and -30 degree pose variation	88.4
LBP and Binary SVM Classifier		
4500 images, with 0 degree pose variation	1000 images, with 30 degree pose variation	85.6
4500 images, with 0 degree pose variation	1000 images, with -30 degree pose variation	87.2
6000 images, with 0, 30 and -30 degree pose variation	3000 images, with 0, 30 and -30 degree pose variation	90.4

size [8 8] and obtained 3780 features per image, BOF model with 'Vocabulary Size',500 and multiclass SVM classifier and LBP with 8 X 8 neighborhood pixels with binary SVM classifier. Results obtained with different feature descriptor are shown in Table II.

Experiment 3

In this experiment we have considered different set of training and testing images which were captured from 8m, 7m ,6m,5m, 4m distance. With HOG, LBP and BOF model as a feature descriptor we have analyze the effect of camera position on classification accuracy of periocular region. From

Table-III: Classification accuracy on UBIPr dataset for the images captured from varying camera distance with HOG and Binary SVM classifier

Training / Testing	8m	7m	6m	5m	4m
8m	96.00	**98.33**	71.66	80	61.66
7m	98.33	94.21	83.33	76.66	78.33
6m	95	95	90.32	85	91.66
5m	90	90	78.33	84.00	93.33
4m	86.66	91.6	90	93.33	84.21

Table-IV: Classification accuracy on UBIPr dataset for the images captured from varying camera distance with BOF model and Multiclass SVM classifier

Training / Testing	8m	7m	6m	5m	4m
8m	72.00	**83.33**	53.33	70	65
7m	70	79.23	55	65	83.33
6m	55	63.33	65.10	66.66	75
5m	78.33	70	56.55	80.00	81.66
4m	65	85	71.66	66.66	65

Table-V: Classification accuracy on UBIPr dataset for the images captured from varying camera distance with LBP and binary SVM classifier

Training / Testing	8m	7m	6m	5m	4m
8m	79	**86**	53	74	75
7m	60	72	73.9	65.22	82.64
6m	67.22	71.24	67.23	67	82
5m	74.56	64.36	67.22	56.86	76.52
4m	65	76.34	74.52	78.58	78.22

Table- VI: Comparison of HOG, BOF model and LBP

Database	HOG	BOF	LBP
ORL	90	85	89
UBIPr (30 degree pose variation)	86	84	85.6
UBIPr (-30 degree pose variation)	88	86	87.2
UBIPr (0,30 and -30 degree pose variation)	93.33	88.4	90.4
UBIPr (max accuracy with 7m camera distance)	98.33	83.33	86

Table-VII: Comparison with existing result

References	Database	Feature descriptor	Result
Raffei et al. [39]	UBIPr	Uniform LBP	85.7
Zahid et al. [40]	UBIPr	M-Sift	85
Santana et al.	UBIPr	M-Sift	84.14
Proposed Approach	UBIPr	HOG	93.33

***LBP*: *Local Binary Pattern, mSIFT: modified Scale Invariant Feature Transform, HoG: Histogram of Oriented Gradients*

Table III, Table IV and Table V we can easily conclude that images captured from 7m camera distance giving better accuracy as compare to other images (captured from varying camera distance). It can also be visualize that feature extracted from HOG provide better result as compare to LBP and BOF model.

VII. CONCLUSION AND FUTURE WORK

The essential target of this work is to assess the utility of periocular region as a biometric trait utilizing three distinctive feature extraction strategies on two unique databases. The proposed strategy got 90% recognition rate for ORL database and ≈ 93 percent recognition rate for UBIPr database both utilizing HOG and Binary SVM classifier which is better than other cutting-edge strategies which have utilized UBIPr database in writing as appeared in Table VII. For images which are captured in non-ideal scenario such as images with 30 or -30 degree pose variation (in UBIPr dataset) our proposed method obtained remarkable recognition accuracy of ≈ 85%. We have also evaluated the recognition accuracy of images which were captured from different camera distance (from UBIPr dataset) and can conclude that images captured from the 7m camera distance (in training dataset) are providing better recognition accuracy as compare to other images captured from varying distance. Based on the comparative analysis of different recognition accuracy obtained using HOG, LBP and BOF model shown in Table VI we can conclude that HOG as a feature descriptor providing better results as compare to LBP and BOF model.
Our future work concerns the analysis of periocular region based biometric systems for subject independent scenario via deep learning approach.

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