OPEN ACCESS INTERNATIONAL JOURNAL OF SCIENCE & ENGINEERING

AN EXPLORATION & ANALYSIS OF COMMON FEATURE EXTRACTION USING THE PERIOCULAR REGION

Nirgish Kumar,[1] Dr. Vivek Srivastava[2], Komal Nirgish [3]

Research Scholar, Faculty of Engineering, Rama University, Kanpur [1,3]

Dean, Faculty of Engineering, Rama University, Kanpur[2]

nirgish.hbti@gmail.com[1],vivek.hbti@hotmail.com[2],k.komal208@gmail.com[3]

Abstract: **The periocular region is collected with the iris and may be used as a substitute once the iris is clearly obscured. The periocular region are often seen as a sub-region of the face. Therefore, one may expect common facial feature extraction algorithms to supply discriminative feature sets from the per ocular region as they are doing from the face. However, the degree of discrimination of per ocular options remains to be seen. They conjointly counsel that the per ocular region may well be nearly as discriminative because the entire face. Sadly, the experiments performed in those works were rudimentary. The common biometric authentication information and customary facial feature extraction algorithms as they're enforced in an exceedingly per ocular-based biometric system. The face and periocular region the foremost discriminative options area unit extracted, and assess the strength of the periocular region with relevance the environment-influenced considerations a periocular-based biometric system can seemingly encounter.**

Keywords: Peirocular, Feature extraction, discrimination, conjointly, authentication, Grand Challenge, victimization

I INTRODUCTION

Though a per ocular primarily based biometric experiment are often shown to possess similar performance to a face-based biometric experiment, there's still reason to explore why this may be the case. An in depth checks out the options themselves and also the patterns they turn out within the face and per ocular region got to be performed. The standard of information plays associate degree potent role within the performance of biometric recognition systems. Early analysis of in style modalities, cherish the face and iris, use top quality information in affected environments .As expected, techniques tested below these constraints yield higher performance than once victimization quality information.

Situations exist wherever top quality information are often no heritable dependably in real-world applications; however, several others exist wherever reliable information assortment isn't potential. Reacquiring biometric information once the primary acquisition yields poor quality information isn't forever potential, thus analysis is required to form non ideal information helpful. Non-ideal information are often characterized by subject-influence or environment-influence. However, subject influenced considerations aren't freelance of environment-influenced considerations; environment-influenced concerns can seemingly seem insure subject-influenced non-ideal information. If a subject matter is actively attempting to avoid biometric recognition by concealing their face or deed from the camera then the environment-influenced considerations of blur and inconsistent image resolution can seemingly be gift.

Figure 1: An example recording session from FRGC [21].

II DATA

Two completely different datasets were elite to be used during this chapter: The biometric authentication Grand Challenge (FRGC) info and also the biometric authentication Technology (FERET) info. The FRGC info [21] consists of high resolution color pictures of an oversized variety of subjects largely between ages eighteen and twenty two, collected over a 2 year amount from multiple recording sessions involving controlled and uncontrolled lighting conditions, associate degree with an expression and while not. A recording session is that the set of all pictures of a subject matter taken every time the subject's biometric information is collected.

A typical FRGC recording session consists of 4 frontal faces, controlled lighting still pictures, 2 frontal faces, uncontrolled lighting still pictures, and one three-dimensional image. Figure 2.1 shows a group of controlled lighting pictures for one recording session. The controlled lighting pictures were taken in an exceedingly studio setting (two or 3 studio lights) and with 2 facial expressions (smiling and neutral). In controlled conditions, the space between the topic and also the camera is around identical. The still pictures were soft on a four Megapixel Canon Power Shot G2 and have a constituent resolution of either 1704×2272 or 1200×1600 pixels.

The pictures area unit holds on in JPEG format with storage sizes starting from one.2 Mbytes to three.1 Mbytes. FRGC Experiment one is associate degree experimental protocol and information set that's wide won't to compare completely different biometric recognition ways. FRGC Experiment one could be a set of sixteen, 029 still, high resolution, and frontal face pictures taken below controlled lighting conditions. It had been chosen for this work as a result of {the massive the massive the big} face pictures can cause comparatively large per ocular region pictures. FRGC Experiment one measures performance on the

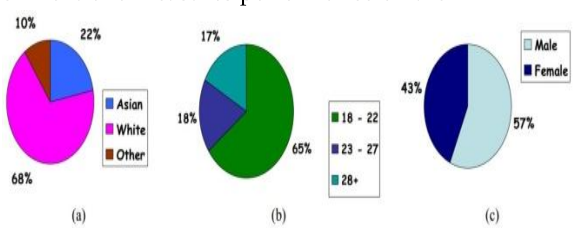

Figure 2: Demographics of FRGC validation partition by (a) race, (b) age, and (c) sex [21].

III METHODOLOGY

The essential biometric experiment temple followed by all experiments during this chapter consists of the subsequent steps: information preprocessing, testing/training partitioning, gallery/probe partitioning, feature extraction, feature comparison, and computation of performance statistics.

Figure 3: Example images from the FERET database [22]

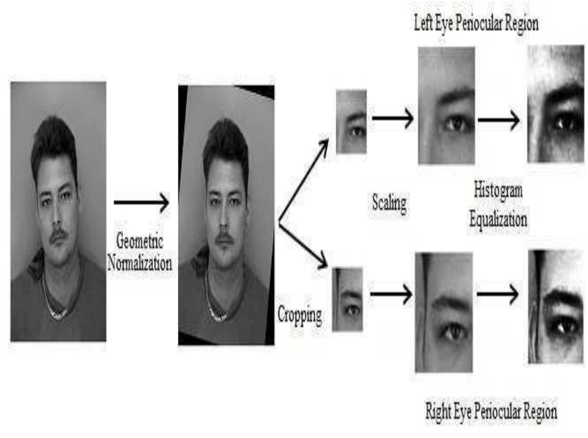

Figure 4: The flow of preprocessing steps applied to a face image to extract its periocular regions

IV DATA PREPROCESSING

- **Geometric Normalization**

The primary step in preprocessing a facial biometric image is geometric standardization that aligns all of the pictures within the dataset to identical special coordinates. A picture of a face are often turned on 3 axes: associate degree axis from the face to the observer (in-plane rotation), a vertical axis dissecting the face rotation and a horizontal axis dissecting the face out-of-plane. The foremost ordinarily used points to correct in-plane rotation in facial pictures area unit the attention centers. Thus the placement of the attention centers should be celebrated to perform correction. Eye center locations for FRGC and FERET were provided by the curators of the databases.

- **Periocular Region Extraction**

The next preprocessing step is to extract per ocular region pictures from normalized and equalized facial pictures. This can be accomplished by putting a sq. Bounding box around every eye, targeted on the post geometric standardization eye center locations. The length of the edges of this sq. Bounding box is adequate to the space between the 2 eye center coordinates, conjointly referred to as the lay to rest ocular distance. In a median face, one bounding box can cowl the region from the middle of the face to the ear and from all-time low of the nose to the center of the forehead. The ensuing per ocular pictures area unit then re-sized to 200×200 pixels to be used within the experiments of this chapter. 200×200 pixels were chosen as a result of it's the dimensions of the littlest per ocular region extracted from the face pictures employed in this chapter.

- **Histogram Equalization**

The last step is bar graph feat, wherever the distinction of the image is increased. This step normalizes the relative illumination levels between pictures by ever-changing constituent intensity values. The bins of a bar graph of a picture that has been equalized can contain around identical variety of pixels. This method ensures that pictures that area unit darker or lighter than a neutral image area unit altered in order that they seem to possess been taken below identical lighting conditions.

The additive distribution perform (CDF) of a bar graph is outlined because the additive add of the values of the bins of a bar graph. A remodel is made which will turn out a replacement image specified the CDF of that new image is around linear. The applying of this remodel to the first image leads to a picture with associate degree equalized bar graph.

V ATTRIBUTE EXTRACTION

The attribute feature extraction step within the basic biometric experiment is that the main purpose of distinction between any 2 completely different experiments during this thesis. Options area unit extracted from every image within the dataset and from every partition within the set. Every feature extraction technique transforms a 2 dimensional image into a 1dimensional feature vector through its own distinctive method. The per ocular region is basically a sub-part of the face; thus, it ought to be expected that common facial feature representations would offer a helpful means that of classifying people victimization the per ocular region. Categories of facial feature representations embrace native look, key point-based, and holistic. The experiments during this chapter can use basic approaches from every category of feature representations in a shot to produce comparisons between the power of the categories of feature representations to supply discriminating options from the per ocular region alone.

Among the native appearance-based feature representations area unit Local Binary Patterns (LBP), Histogram of orientating Gradients (HOG), native part quantization (LPQ), and Weber native Descriptor (WLD). Scale Invariant Feature remodel (SIFT) and accelerated strong options (SURF) were chosen because the key point-based representations.

- **Local Appearance-Based Approaches**

Local Appearance-Based Feature Extraction ways area unit a category of feature extraction techniques that accumulate statistics at intervals native neighborhoods around every constituent of a picture. These statistics embrace the occurrences of sure textures, patterns, and data and area unit usually hold on in an exceedingly one-dimensional feature vector. These experiments create use of 4 native appearance-based feature extraction methods: native Binary Patterns, bar graph of orientating Gradients, native part quantization, and Weber native Descriptors. There is a unit some variations within the manner these forms of options area unit employed in biometric applications, as hostile texture classification.

- **Local Binary Patterns**

Local Binary patterns (LBP) could be a texture classification methodology that was developed by Ojala et al. [16]. LBP accumulates texture data from a picture into a feature vector. This can be accomplished by labeling constituents with a binary variety that's a perform of putting a threshold on the neighborhood around every pixel. A bar graph of those values becomes the output feature vector. Because of the success of lapis a texture classification methodology, it's been used extensively for each biometric authentication [1, 31, 23, 4, and 26] and per ocular recognition [19, 16, 15,3, 29, 28, 18, 10, 8, 9, 11, 12, 14, 13, and 25].

- **Histogram of Oriented Gradients**

Histograph of orientating Gradients (HOG) is a grip and gradient primarily based feature descriptor originally developed by Dalai and Trigs to observe humans in pictures. HOG could be a native appearance-based approach that counts the occurrences of various gradient orientations in localized parts of a picture. Despite the fact that HOG was originally meant for object detection, it's been used for each facial and per ocular recognition [19, 18, 24, 13, 26, and 5]. HOG could be a easy technique that, with the exception of object orientation, is invariant to geometric and photometrical transformation. A changed HOG rule is employed for extracting options from the per ocular region.

- **Local Phase Quantization**

Local Phase Quantization (LPQ) could be a consistency descriptor recently bestowed by Ojansivu et al. [28]. This methodology quantizes the part data of a separate Fourier remodel (DFT) in patch-sized neighborhoods of a picture. The most strength of this native appearance-based feature extraction methodology is that it's projected to be strong to image blurring. Though' originally used for texture classification within the presence of blur, LPQ has conjointly been used for biometric authentication [2]. Like LBP and HOG, the ensuing LPQ codes area unit compiled into a bar graph. The ultimate LPQ code could be a 256 bin bar graph wherever the quintal DFT part coefficients area unit accumulated once binary writing

- **Weber Local Descriptor**

Weber Local Descriptor (WLD) could be a texture descriptor developed by Chen et al.[8]. It had been impressed by Weber’s Law, a psychological law that refers to the perception of amendment in an exceedingly signal. The law states that the amendment in an exceedingly signal which will be simply noticeable is proportional to the magnitude of the first signal.

WLD cares with the magnitude relation between the intensity price of a constituent and also the relative intensity variations of the constituent to its neighbors, conjointly referred to as the differential excitation, and also the gradient direction of a constituent. Chen et al. At first used it for texture classification and face detection.

- **Key point-Based Approaches**

Key point-Based Approaches area unit the category of feature extraction techniques that notice interest points at intervals a picture. These interest points area units usually maxima or minima of filter responses applied to the image. 2 completely different key point-based approaches area unit employed in this thesis. These approaches area unit Scale Invariant Feature remodel (SIFT) and accelerated strong options (SURF).

- **Scale Invariant Feature remodel Lowe**

[19], the developer of Scale Invariant Feature Transform(SIFT),states that SIFT is associate degree approach for police work and extracting native feature descriptors that area unit moderately invariant to changes in illumination, image noise, rotation, scaling and tiny changes in viewpoint. Interest points generated by the SIFT technique correspond to native extreme a of distinction of Gaussians (dog) filters at variable scales. It had been originally developed to be employed in image matching issues and is reportable to be invariant to uniform scaling, orientation, and part invariant to affine distortion and illumination changes. For every key purpose location, the key purpose descriptor is outlined as a bar graph of orientations weighted by the gradient magnitude computed from a neighborhood window of 8×8 pixels round the key purpose location. SIFT has been used varied times for biometric authentication [4, 20, 17] and per ocular recognition [19, 18, 20, 24, 25, 27].

- **Accelerated strong options**

Originally impressed by SIFT, accelerated strong Feature (SURF) descriptors are a well-liked key point-based methodology. It had been developed by Bay et al. And claims to be quicker and a lot of strong to completely different transforms of a picture than SIFT. SURF key points area unit found from maxima within the determinant of the boot matrix of pictures, a matrix created from the convolution of the mathematician second order derivatives with the image.

Alongside the key point’s locations, associate degree orientation is assigned to the purpose and also the descriptor is predicated on the add of Haar moving ridge responses. SURF was originally used for beholding and has conjointly been employed in biometric authentication contexts over the years [6, 7, and 30].

- **Holistic Approaches**

Chemist faces is may be the foremost ordinarily celebrated biometric authentication rule [32]. It uses the mathematical procedure of principle part analysis to supply a low-dimensional illustration of a face from a group of higher-dimensional coaching pictures. In contrast to the opposite algorithms, chemist faces could be a holistic approach to feature illustration as a result of it considers the full face promptly.

VI FEATURE COMPARISON AND COMPUTATION OF PERFORMANCE STATISTICS

The FRGC experimental protocol suggests the utilization of distance measure to work out the similarity between 2 feature vectors. 2 completely different feature vectors with the nearest live of distinction at intervals a group of vectors area unit same to be the nearest match. In associate degree identification experiment the feature vector of a look image is compared to each feature vector within the gallery set and also the Top-N results area unit came back. In an exceedingly verification experiment the feature vector of a look image is compared to each feature vector within the gallery set and people that area unit on top of a threshold area unit declared to be a match. The results reportable for every experiment during this thesis area unit generated victimization town block distance metric

$$d(p,q) = \sum_{i=1}^{n} |p_i - q_i|,$$

wherever p and alphabetic character area unit feature vectors extracted from 2 pictures that have a feature spatiality of n

Focus difference range	True	False matches
0-4.96	592,762	135,590,852
4.97-9.92	156,376	79,650,906
9.93-14.88	36,890	29,765,650
14.89-19.84	9,068	8,333,278
19.85-24.80	2,486	2,087,510
24.81-29.76	734	526,754
29.77-34.72	296	110,328
34.73-39.69	64	15,212
39.70-44.65	0	1,412
44.66-49.61	0	178

Table 1: Focus metric differences between images.

There area unit different ways that of scrutiny options that might seemingly give higher performance, cherish employing a trained classifier sort of a Support Vector Machine (SVM).

VII PERFORMANCE ANALYSIS CONCERNS

A variety of things will cause associate degree unfocused image. The standard of the image can suffer if the camera is unsteady once the image is captured, the topic moves out of the main focus space of the camera, or the topic is moving quicker than the camera’s shutter speed permits.

A very important side in any biometric recognition system is strength to variable focus. The experiments during this chapter value focus within the following manner. The Fourier energy spectrum is often wont to quantify the extent of focus of a picture pictures

Figure 5 : A comparison of unfocused images and their focus metrics.

From left to right: Un-deteriorated Image (171.46), one convolution (167.25), five convolutions (161.36), ten convolutions (156.83).from the FRGC dataset have focus metrics ranging from 182.96 (in focus) to 141.25 (out of focus).

VIII RESULTS AND DISCUSSION

All of the feature illustration techniques performed thus poorly at this task that nothing are often determined supported these results. However, this can be not unexpected; of all the submissions to the meet minimum performing arts rule performed slightly worse than the HOG implementation (5.10% VR at0.1% FAR) bestowed here.

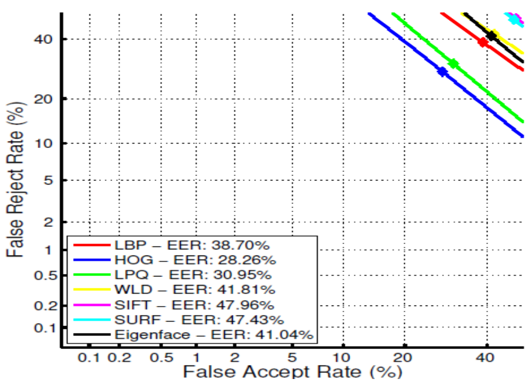

Figure 6 : DET of Experiments testing uncontrolled illumination.

The median performing artist was around half-hour VR at zero.1% FAR. The most effective performing arts rule had a verification rate slightly below eightieth. This rule performed this well on Experiment four solely, that suggests it had been significantly tuned to the current drawback. Sadly, it's a proprietary rule and it's not open for review.

IX CONCLUSION

The work bestowed during this chapter aimed to deal with 3 goals. The primary goal was to look at common biometric authentication information and customary facial feature extraction algorithms as they're enforced in an exceedingly per ocular primarily based biometric system. Experiments were conducted with seven completely different feature representations from 3 different categories of feature extraction ways. Every of the categories of feature extraction ways have a protracted history of use in biometric authentication systems. Victimization these ways, the performance of a biometric authentication system and a per ocular recognition system were compared. Establishing this baseline performance result allowed for addressing the second goal, the more exploration of wherever within the face the foremost discriminative options were found. The experiments bestowed during this chapter supported previous analysis on this question that the per ocular region is that the most discriminative region of the face.

Some samples of discriminative physical options gift within the per ocular region area unit the form of the algebra, the form of the fold on top of the algebra, the presence of wrinkles round the eye, the form of the brow, the thickness of the brow, the feel of the brow, and also the texture of the skin.

ACKNOWLEDGMENT

The authors would like to thanks Dr.Vivek Srivastava, Dean, Faculty of Engineering, Rama University, Kanpur Prof. B.K. Tripathi, HBTU, Kanpur for his guidance in the design of several human vision experiments.

REFERENCES

[1] T. Ahonen, A. Hadid, and M. Pietik¨ainen. Face description with local binary patterns: Application to face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(12):2037–2041, 2006.

[2] T. Ahonen, E. Rahtu, V. Ojansivu, and J. Heikkil¨a. Recognition of blurred faces using local phase quantization. In *Proceedings of the International Conference on Pattern Recognition*, pages 1–4, December 2008.

[3] S. Bharadwaj, H. Bhatt, M. Vatsa, and R. Singh. Periocular biometrics: When iris recognition fails. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, and Systems*,pages 1–6, September 2010.

[4] C. Chan, J. Kittler, and K. Messer. Multi-scale local binary pattern histograms for face recognition. In *Advances in Biometrics*, volume 4642 of *Lecture Notes in Computer Science*, pages 809–818. Springer,2007.

[5] O. D´eniz, G. Bueno, J. Salido, and F. De la Torre. Face recognition using histograms of oriented gradients. *Pattern Recognition Letters*, 32(12):1598–1603, 2011.

[6] P. Dreuw, P. Steingrube, H. Hanselmann, and H. Ney. SURF-face: Face recognition under viewpoint consistency constraints. In *Proceedings of the British Machine Vision Conference*, pages 1–11, September 2009.

[7] G. Du, F. Su, and A. Cai. Face recognition using SURF features. In *Proceedings of the International Symposium on Multispectral Image Processing and Pattern Recognition*, October 2009.128

[8] K. Hollingsworth, S. Darnell, P. Miller, D. Woodard, K. Bowyer, and P. Flynn. Human and machine performance on periocular biometrics under near-infrared light and visible light. *IEEE Transactions on Information Forensics and Security*, 7(2):588–601, April 2012.

[9] A. Joshi, A. Gangwar, R. Sharma, and Z. Saquib. Periocular feature extraction based on LBP andDLDA. In *Advances in Computer Science, Engineering and Applications*, volume 166 of *Advances inIntelligent and Soft Computing*, pages 1023–1033. Springer, 2012.

[10] F. Juefei-Xu, K. Luu, M. Savvides, T. Bui, and C. Suen. Investigating age invariant face recognition based on periocular biometrics. In *Proceedings of the International Joint Conference on Biometrics*, pages 1–7, October 2011.

[11] F. Juefei-Xu and M. Savvides. Unconstrained periocular biometric acquisition and recognition usingCOTS PTZ camera for uncooperative and non-cooperative subjects. In *Proceedings of the IEEE Workshop on Applications of Computer Vision*, pages 201–208, January 2012.

[12] J. Lyle, P. Miller, S. Pundlik, and D. Woodard. Soft biometric classification using periocular regionfeatures. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, and Systems*, pages 1–7, September 2010.

[13] J. Lyle, P. Miller, S. Pundlik, and D. Woodard. Soft biometric classification using local appearance periocular region features. *Pattern Recognition*, 45(11):3877–3885, 2012.

[14] J. Merkow, B. Jou, and M. Savvides. An exploration of gender identification using only the periocular region. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, andSystems*, pages 1–5, September 2010.

[15] P. Miller, J. Lyle, S. Pundlik, and D. Woodard. Performance evaluation of local appearance based periocular recognition. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, and Systems*, pages 1–6, September 2010.

[16] T. Ojala, M. Pietik¨ainen, and T. M¨aenp¨a¨a. Gray scale and rotation invariant texture classification with local binary patterns. In *Proceedings of the European Conference on Computer Vision*, pages 404–420,Dublin, Ireland, June 2000.

[17] V. Ojansivu and J. Heikkil¨a. Blur insensitive texture classification using local phase quantization. In*Proceedings of the International Conference on Image and Signal Processing*, pages 236–243, July2008.

[18] U. Park, R. Jillela, A. Ross, and A. Jain. Periocular biometrics in the visible spectrum. *IEEE Transac- tions on Information Forensics and Security*, 6(1):96–106, March 2011.

[19] U. Park, A. Ross, and A.K. Jain. Periocular biometrics in the visible spectrum: A feasibility study. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, and Systems*, pages 1–6, September 2009

[20] V. Pauca, M. Forkin, X. Xu, R. Plemmons, and A. Ross. Challenging ocular image recognition. *SensingTechnologies for Global Health, Military Medicine, Disaster Response, and Environmental Monitoring;and Biometric Technology for Human Identification VIII*, 8029(1):80291V, 2011.

[21] P. Phillips, P. Flynn, T. Scruggs, K. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek.Overview of the face recognition grand challenge. In *Proceedings of the IEEE Conference on ComputerVision and Pattern Recognition*, pages 947–954, June 2005.

[22] Y. Rodriguez and S. Marcel. Face authentication using adapted local binary pattern histograms. In *Proceedings of the European Conference on Computer Vision*, pages 321–332, May 2006.

[23] Y. Rodriguez and S. Marcel. Face authentication using adapted local binary pattern histograms. In *Proceedings of the European Conference on Computer Vision*, pages 321–332, May 2006.

[24] A. Ross, R. Jillela, J. Smereka, V. Boddeti, B. VijayaKumar, R. Barnard, X. Hu, P. Pauca, and R. Plemmons.Matching highly non-ideal ocular images: An information fusion approach. In *Proceedings of the IAPR International Conference on Biometrics*, pages 446–453, March 2012.

[25] G. Santos and E. Hoyle. A fusion approach to unconstrained iris recognition. *Pattern Recognition Letters*, 33(8):984–990, 2012.

[26] W. Schwartz, H. Guo, and L. Davis. A robust and scalable approach to face identification. In *Proceedings of the European Conference on Computer Vision*, pages 476–489, September 2010.

[27]. Tan, X. Zhang, Z. Sun, and H. Zhang. Noisy iris image matching by using multiple cues. *Pattern Recognition Letters*, 33(8):970–977, June 2012.

[28] D. Woodard, S. Pundlik, P. Miller, and J. Lyle. Appearance-based periocular features in the context of face and non-ideal iris recognition. *Signal, Image and Video Processing*, 5(4):443–455, 2011.

[29] J. Xu, M. Cha, J. Heyman, S. Venugopalan, R. Abiantun, and M. Savvides. Robust local binary pattern feature sets for periocular biometric identification. In *Proceedings of the IEEE International Conference on Biometrics: Theory, Applications, and Systems*, pages 1–8, September 2010.

[30] L. Yunqi, J. Xutuan, S. Zhenxiang, C. Dongjie, and L. Qingmin. Face recognition method based on SURF feature. In *Proceedings of the International Symposium on Computer Network and Multimedia Technology*, pages 1–4, December 2009.

[31] G. Zhang, X. Huang, S. Li, Y.Wang, and X.Wu. Boosting local binary pattern (LBP)-based face recognition.

In *Advances in Biometric Person Authentication*, volume 3338 of *Lecture Notes in Computer Science*, pages 179–186. Springer, 2005.
[32] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of Cognitive Neurosicence*, 3(1):71–86, 1991.

BIOGRAPHY

Nirgish Kumar is pursuing Ph.d Degree, From Faculty of Engineering, Rama University, Kanpur. His research interest fields include Biometric, Machine leaning, computational Intelligence, segmentation techniques, and Data mining. He has published more than 04 papers in various International Journals and Conferences. Presently he is working HBTU Kanpur. He is member of IEEE and paper Reviewers.