American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-7, Issue-10, pp-42-50
www.ajer.org
Research Paper Open Access

Eye-Landmarks Based Face Alignment In Non-Cooperative Face Biometrics

Nilesh Pawar
[1] *Prof. Ram Meghe Institute of Technology & Research, Badnera, Amravati INDIA*
Corresponding Author: D.T.Ingole and M.D.Ingole

ABSTRACT :*Current research in biometrics is being carried out with expectation of making a robust and reliable person identification system to be deployed in unconstrained and non-cooperative environment. However, these kinds of biometric systems predominantly suffer from various covariates (degradation factors). Among several covariates, misalignment is one of the critical issue that brings significant degradation in face recognition system. This is due to improper registration in intra-class samples as well as inter-class samples. In this paper we have proposed and analysed a face normalization technique to overcome the negative impacts of misalignment occurred during face detection. We used the database for experimentation that has a well-structured deviation in pose angles of subjects along with unintentional random non-uniform illuminations which makes the dataset to be more suitable for evaluating algorithms more robustly. The proposed method is based on locating the landmarks of face and then cropping the face region proportional to the parameter obtained from estimated landmarks. This simple way of face normalization has been tested and validated on original face samples used in UBIPosePr dataset. Thus, the objectives of this paper are three-fold. 1) We have proposed the method of normalizing the face overcoming the scale of face that appears in image sample. 2) We experimented with actual face detection algorithms and found our normalization algorithm mitigates the misalignment problem. 3) A very robust and yet well-structured dataset has been used in our experimentation in order to study the behaviours of non-cooperative environment for face recognition system.*

KEYWORDS: *Face recognition, Facial landmarks, Identification system, Misalignment, Non-cooperative, Unconstrained biometrics****.***

Date of Submission:02-10-2018 Date of acceptance: 13-10-2018

I. INTRODUCTION

Biometrics signatures are successfully used in the applications where verification and identification of a person is a major concern. Biometrics has a vital role to play for several of recent applications as mentioned in [1]. As suggested in [2], factors such as scale, usability and accuracy are needed to be considered for any biometrics system. Ideally system should be very precise with high comfort level and with large scale capability. In conventional biometrics systems, the user is made to cooperate with system to submit a biometric signature [1], while in non-cooperative biometrics, a user's biometric signature is captured while he is on move and without any protocol of user-machine interface. This non-cooperative characteristic of identification process is also extended for face biometrics, where face image is captured irrespective of any direction subject is walking by and being captured in the view of camera. This yields the face images with different poses and scales (due to camera-subject distance). Thus, it becomes a non-trivial problem to manage the recognition of a face subject having mostly frontal faces in training or registered database. The face recognition system suffers heavily from the misalignment of face samples across gallery and probe sets. In this paper, we have proposed and analyze a face normalization technique to overcome the negative impacts of misalignment occurred during face detection. The database, we used for experimentation has a well structured deviations in pose angles of subjects along with unintentional random non-uniform illuminations which makes the dataset to be more suitable for experimenting with algorithms designed for non-cooperative environment. This method is based on locating the landmarks of face and then cropping the face region proportional to the parameter obtained from estimated landmarks. This simple way of face normalization has been tested and validated on original face samples used in UBIPosePr dataset. Thus, the objectives of this paper are three-fold. 1) We have proposed the method of normalizing the face overcoming the scale of face that appears in image sample. 2) We experimented with actual face detection algorithms and found our normalization algorithm mitigates the misalignment problem. 3) A very robust and yet well-structured dataset has been used in our experimentation in order to study the behaviours of non-cooperative environment for face recognition system. We observed that proposed method does a good attempt to improve the performance of face recognition in non-cooperative environment, where localizing the face ROI is always a challenging task. The remaining part of the paper is organized as follows.

II. LITERATURE SURVEY

In one of the related papers [3], authors have described new methods to determine the limbic boundary so as to locate and register the eye in non-cooperative environment. Also, some authors have mentioned the problems of non-cooperative biometrics with non-uniform illuminations by employing an intelligent decision combiner [4]. In another research work [5], authors have focussed on the analysis of the ability of segmentation algorithms and process images with heterogeneous characteristics, to simulate the dynamics of a non-cooperative environment. User authentication system was designed to recognize users who are unconscious of a robot or of cameras[6]. In this system, biometrics and semi-biometrics were used to cope with the limited applicability of traditional authentication techniques. Authors also present an approach to identify non-cooperative individuals at a distance from a sequence of images using 3D face models [7, 8]. In one of the papers author [9], focuses on the use of face recognition and gait analysis to achieve the problem of person identification. Another important paper [10], presents three cameras system, to be used in Non-cooperative Long-range Biometric System for Maritime Surveillance. The research work in [11], presents a robust and fast (near real time) iris segmentation approach towards less constrained iris recognition with a accuracy estimated slightly over 98%.The work described in [12] uses soft biometrics description like height, weight, gender, hair, skin and clothing colour. Recent papers [13, 14] have described face recognition at a distance system and to be used in unconstrained environment. Padole et. al. [15] stressed how covariates factors deteriorate periocular recognition, using natural images where factors such as pose variation, distance of the subject, pigmentation and occlusion were included by the acquisition framework instead of simulating them. Inspired by the work of Park et al. [18], they used the same feature extraction techniques, except that ROI centre was computed with relation to eye-corners. This new alignment method led to most significant improvements in detecting the people in unconstraint biometrics. Such type of system is shown in [16]. This work is very much useful to be considered in unconstraint biometrics since the pedestrian samples used in experiments are similar to those will appear in unconstraint biometrics. In another work [16], standard face detector is used, face tracking is achieved by combining a new scale invariant Kalman filter with kernel based tracking algorithm. From each potential face trajectory an angle histogram of neighbouring points is extracted and finally, an Earth Mover's Distance based k-NN classification discriminates true face trajectories from the false ones. Experimented on a video dataset of more than 160 potential people trajectories, this displays an accuracy rate up to 93%. The work presented in [17] detect the face using colour of human skin. Face Recognition is one of the method which is used for identification of person in unconstrained biometrics. Face recognition is the ability to establish a subject's identity based on his facial characteristics. Finally, current limitations and future research directions for face recognition in forensics are suggested [18]. The first fully automatic face identification system was developed by Kanade [19] using a set of facial parameters based on local histograms of gray scale pixel values. The Principal Component Analysis (PCA) method was first applied on face images by Sirovich [20] for image compression, then by Turk and Pentland [21] for identification. The ordered set of eigenvectors corresponds to a set of basis images that characterizes the variation between face images. PCA based approaches reduced the computational burden. Another face recognition method is Linear Discriminant Analysis (LDA) [22], which is based on the Fisher's Liner Discriminant Analysis. The use of separate class labels for each subject in LDA provided better identification accuracy over PCA. The facial appearance changes more drastically at younger ages. In addition to facial aging, there are other factors that influence facial appearance are pose, lighting, expression and occlusion which makes it difficult to study the aging pattern using these two public domain longitudinal face databases [18]. Another method for the person capturing in surveillance video is described in [23] which presents reliable techniques for detecting, tracking, and storing key frames of people in surveillance video. The first component of system is a face detector algorithm, which is based on first learning local adaptive features for each training image, and then using Adaboost learning to select the most general features for detection. In research work [24] multi-pose face detection is demonstrated. Multi-pose face detection plays an important role in unconstraint biometrics because this detected face be further used for the classification of person. A partial face recognition approach without face alignment by eye coordinates or any other fiducial points is proposed in [25]. New methods to improve the modelling of facial images under different types of variations like pose, ambient illumination and facial expression are explained in [26]. It is not always possible to get the images from short distances. An approach to identify non cooperative individuals at a distance from a sequence of images, using 3-D face models is shown in [27]. A face-image, pair-matching approach was developed and tested on the "Labelled Faces in the Wild" (LFW) benchmark that shows the challenges of face recognition from unconstrained images [28]. Eye localization is an important part in face recognition system, because its precision closely affects the performance of face recognition. In [29] a robust eye localization method for low quality face images has shown the improvement in the eye detection rate and localization precision. Understanding the effect of blur is an important problem in unconstrained visual analysis. This problem is addressed in the context of image based recognition by a fusion of image-formation models and differential geometric tools in [30].

III. METHODOLOGY

In face recognition, there is always a misalignment problem. When it comes to automated face detector, it suffers from the misalignment of face across the gallery and probe face samples, leading to a wrong spatial correspondence in feature representation. Fig.1 shows the block diagram to recognize face image. In this method we trained and test face samples to calculate recognition accuracy. From the experimentation we found the best algorithm to detect the face images. Then we apply the face normalization algorithm to determine the face bounding box to reduce the misalignment between the probe and gallery face samples. In our previous work we used eye detector method to normalize face misalignment error [31] After detection we represent the face using HOG algorithm[32]. We used k-NN [33] classifier rank-10 for evaluating the effect of proposed method. We used distinguishable-subject (2nd Order) ranking instead of using conventional score based (1st order). The distinguishable-subject N-ranking is the ranking based on first N different subjects which are close to the test subject. This ranking seems to be reasonable as in typical biometrics where we have 100 subjects to be classified. Ranking based on 5 or 10 subjects reduces the penalty of system drastically.

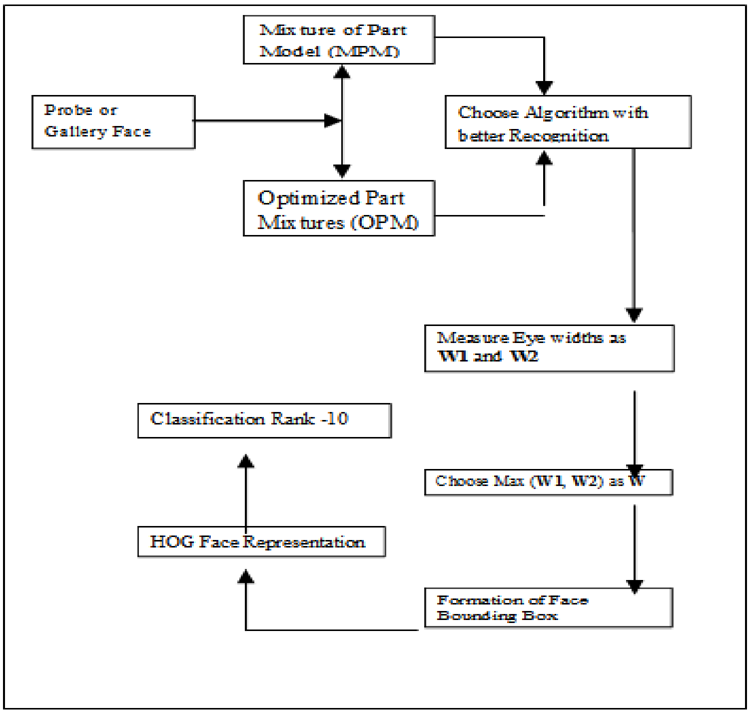
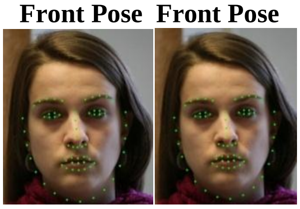


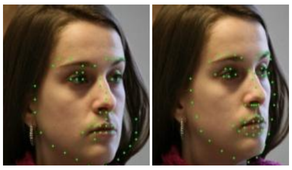
Fig. 1.Block diagram for Face Recognition.

We have used the two methods to detect the landmarks on face samples. Two algorithms are shown in Fig.2

Front Pose Front Pose



Deviated Pose Deviated Pose



A) MPM B) OPM

Fig. 2 Landmark detected for Column-A) Mixture of Part Model (MPM) algorithm. Column-B) Optimized Part Mixtures (OPM) algorithm, Row1- Front Pose; Row2- Deviated pose

IV. ALGORITHM FOR THE FORMATION OF NORMALIZED FACE BOUNDING BOX

1) Step 1: We measured the eye widths of a face detected as shown in Fig.3 as **W1** and **W2**. Eye width of a single eye is the distance between outer landmark eye corner and the inner landmark corner of that eye.
2) Step 2: We select **W** to be maximum width of **W1&W2**. We proposed to use this width **W** as a reference for cropping the detected face sample as shown in Fig.3. The eye width **W** is used to identify the scale of the face. This estimated distance for the face is used to crop the face region in order to align the face sample across gallery and probe samples. Since, eye has a visible and detector friendly pattern, it is a good indicator or reference point for cropping the face. Additionally, it also gives the scale information of face because of which registration of face becomes more accurate as compared to the face samples when cropped using landmark face detector alone.
3) The normalization process of face region is to reduce the negative impacts of misalignment that includes selecting the width and height of the detected face bounding box as shown in Fig.4. The position of the bounding box is determined based on outer eye corners landmark points of both the eyes shown as A and B points in Fig.3.
4) Step 3: The eye width **W** is used to find width and height of normalized detected face bounding box. We have selected outer eye corner landmark point A as first eye corner landmark and point B as second eye corner landmark.
5) Step 4: We choose 0.75**W** left and right from landmark points A and B respectively to select the width of the detected face bounding box.
6) Step 5: Further we choose 1.5**W** to select the upper portion of the face from the eye corner landmarks points A and B.
7) Step 6: Similarly to select the lower portion of the detected face we choose 3.5**W** down from these eye corner landmarks A and B .The selected upper and lower portions of the face determines the height of the detected face bounding box. Further this cropped detected face is used for feature extraction.
8) Step7: In the classification process we used distinguishable-subject (2nd Order) rank -10 to identify the subject.

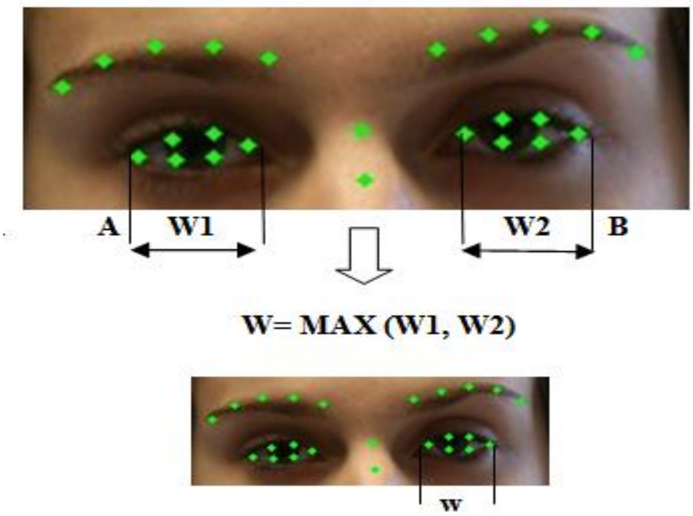


Fig. 3. Selection of Maximum Eye width W

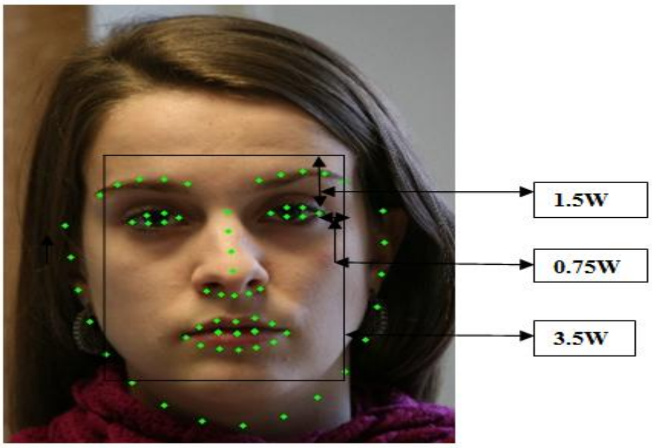


Fig. 4.Formation of face bounding box

V. EXPERIMENTAL RESULTS AND DISCUSSION

We experiment the proposed face detection and alignment techniques and analyze the results. Experiments primarily performed on dataset from [34]. The face images we have used are from the source images used for cropping iris and periocular images [34]. These dataset has very strong structured variations of pose angles and a random unintended variation of illumination across the subject. The intra subject variation of pose angle and illumination are the main reason to use this dataset to test and analyze robustly our proposed face detection and alignment techniques. The UBIPosePr dataset is freely available to the research community. Data was acquired in two sessions at different locations with varying lighting conditions. There are 85 subjects of varying ethnicity. In Session I six samples from each subject with frontal pose were acquired. This was an indoor session with overhead lamps. Subjects were at six meters away from the camera, which resulted in uniform illumination across the samples, with some poorly illuminated data and similarly in session II eighteen samples per subject were acquired. Out of them, six samples are frontal, six samples are left deviated and six have right deviated poses. This was also an indoor session and conducted near open windows, allowing natural light to reflect on subjects with five meters subject-to-camera distance. The left pose set covers angles in negative degrees and right pose comprises positive values.

We have evaluated the proposed face detection and alignment technique robustly on the dataset described above. We used state of art techniques [35 & 36] for landmark detection. These detected landmark positions were used to crop (detection) face images. The proposed technique for cropping the face image was evolved from the objective of aligning the faces in the images within the subjects and among the subjects. Better this alignment, face recognition accuracy will be higher. Face recognition accuracy depends on the factors namely on landmark detection accuracy, position of the face crop and feature representation of the crop face. In our research the feature representation is out of scope and thus we selected only one type of feature representation in terms of Histogram of Oriented Gradient Method (HOG). To recognize persons at different scales, the image is sub-sampled to multiple sizes. Each of these sub-sampled images is searched. In the classification process we used distinguishable-subject (2^{nd} Order) ranking instead of using conventional score based (1^{st} order).database. This reduces the penalty of system drastically and helps to improve performance accuracy. For landmark detection we used two techniques from [35&36]. Based on these methods we crop faces on the basis of landmark positions. We observed that the position of the landmark significantly varies from their actual positions obtained from manual cropping. It is interesting to observe the performance of the landmark detection algorithms and hence face alignment techniques against the face cropped from manual landmark annotations (ground truth).We perform the experiment to calculate the recognition accuracy using three methods of alignments as follows.

1) Face alignment based on manual Landmarks Localization (ground truth) as shown in Table 1.
2) Optimized Part Mixtures (OPM)[35] method of landmark localization as shown in Table 2.
3) Mixture of Part Model (MPM)[36] method of landmark localization as shown in Table 3.

From these tables we observed that recognition accuracy is captured according to angle variations in the database for all the subjects. The numbers of samples in each angle for all the subjects are mentioned in tables. We observed that the recognition accuracy obtained by alignment method based on manual annotation will obviously give higher accuracy as shown in Table 1. This is the baseline expectation for any face alignment techniques. The total recognition accuracy (Rank 10) across all angles is found to be 49.93% for 8X8 HOG, 51.05% for 10X8 HOG and 51.37% for 15X10 HOG. This is shown in Fig.5 10X8and 15X10 Blocks works better for face recognition. After manual annotations base face alignment technique we tested proposed face alignment technique based on two different landmarks detection techniques. Their results are shown in Table 2 and Table 3 .We observed that the overall recognition accuracy (Rank 10) is higher in case of Optimized Part Mixtures (OPM) landmark detection method. This is shown in Fig.6.

We have observed that face alignment method based on Optimized Part Mixtures (OPM)[35] performs better than that of Mixture of Part Model(MPM)[36] landmark detection. Thus we compared now recognition accuracy obtained from Optimized Part Mixtures (OPM) method against that based on manual annotation. This will give us an idea at what extend our proposed method of face alignment approaches toward the face alignment method based on manual annotation. The recognition accuracy (rank-10) for face alignment techniques based on manual landmarks and Optimized Part Mixtures (OPM) are shown in Fig.7.

Significantly we observed that face alignment technique based on Optimized Part Mixtures (OPM) is approaching fairly and significantly to the recognition accuracy of manual landmark. detection. It is worth mentioning the HOG with specification 10X8 block is very close to recognition accuracy obtained by manual annotation as shown in Fig.8. This is valid across all the angles as shown in Fig. 9.

Table 1 . Results with Manual Landmark Localization

Angles →		0	1	2	3	4	5	6	Total	Recognition Accuracy %
No of Test Samples →		510	170	170	170	170	170	170	1530	
HOG 8x8	Rank-1	35.4902	57.0588	37.0588	16.4706	9.4118	4.1176	4.1176	399	26.08
	Rank-5	50.1961	72.9412	57.0588	38.2353	22.9412	17.6471	10.0000	628	41.05
	Rank-10	57.4510	81.7647	66.4706	45.8824	34.1176	27.0588	21.7647	764	49.93
HOG 10x8	Rank-1	37.2549	58.8235	40.5882	20.0000	11.1765	4.1176	4.1176	426	27.84
	Rank-5	51.7647	75.8824	55.8824	38.2353	24.7059	17.0588	10.0000	641	41.90
	Rank-10	61.1765	81.1765	68.2353	46.4706	34.1176	26.4706	19.4118	781	51.05
HOG 15x10	Rank-1	39.0196	60.5882	38.2353	17.6471	8.8235	3.5294	3.5503	424	27.71
	Rank-5	53.7255	75.2941	57.0588	34.7059	22.3529	15.2941	10.0592	639	41.76
	Rank-10	63.7255	82.3529	66.4706	45.2941	32.9412	24.1176	20.1183	786	51.37

Table 2 . Results with OPM Landmark Localization

Angles →		0	1	2	3	4	5	6	Total	Recognition Accuracy %
No of Test Samples →		510	170	170	170	170	170	170	1530	
HOG 8x8	Rank-1	17.4510	42.3529	29.4118	8.8235	6.4706	6.4706	4.2424	255	16.67
	Rank-5	32.3529	62.3529	47.6471	28.2353	18.8235	17.0588	15.1515	486	31.76
	Rank-10	39.0196	68.8235	57.0588	38.2353	29.4118	30.0000	23.6364	618	40.39
HOG 10x8	Rank-1	17.2549	41.1765	30.0000	11.7647	7.0588	5.2941	4.2169	257	16.80
	Rank-5	32.1569	60.0000	47.0588	28.2353	20.0000	18.8235	15.0602	485	31.70
	Rank-10	42.1569	72.9412	58.8235	37.6471	28.2353	29.4118	23.4940	640	41.83
HOG 15x10	Rank-1	17.0588	40.5882	28.2353	7.6471	3.5294	5.2941	3.6585	238	15.56
	Rank-5	29.6078	56.4706	46.4706	26.4706	17.0588	16.4706	12.1951	448	29.28
	Rank-10	38.8235	67.6471	54.1176	35.8824	27.0588	24.1176	21.3415	588	38.43

Table 3 . Results with MPM Landmark Localization

Angles →		0	1	2	3	4	5	6	Total	Recognition Accuracy %
No of Test Samples →		510	170	170	170	170	170	170	1530	
HOG 8x8	Rank-1	8.4314	27.0588	10.0000	5.3571	7.2727	4.1096	6.4516	137	8.95
	Rank-5	16.8627	35.2941	27.6471	20.8333	15.7576	13.0137	12.9032	281	18.37
	Rank-10	21.5686	44.1176	37.6471	27.9762	21.2121	25.3425	20.9677	381	24.90
HOG 10x8	Rank-1	6.8627	24.1176	11.1765	7.7381	9.0909	4.1096	4.8387	132	8.63
	Rank-5	16.6667	36.4706	25.8824	19.0476	13.9394	14.3836	16.1290	277	18.10
	Rank-10	22.3529	44.7059	35.2941	27.3810	21.8182	26.0274	16.1290	380	24.84
HOG 15x10	Rank-1	6.8627	22.3529	14.1176	8.3333	7.9268	4.1958	3.7736	132	8.63
	Rank-5	16.2745	35.8824	24.7059	16.6667	13.4146	11.1888	13.2075	259	16.93
	Rank-10	22.3529	42.3529	33.5294	28.5714	21.9512	21.6783	18.8679	368	24.05

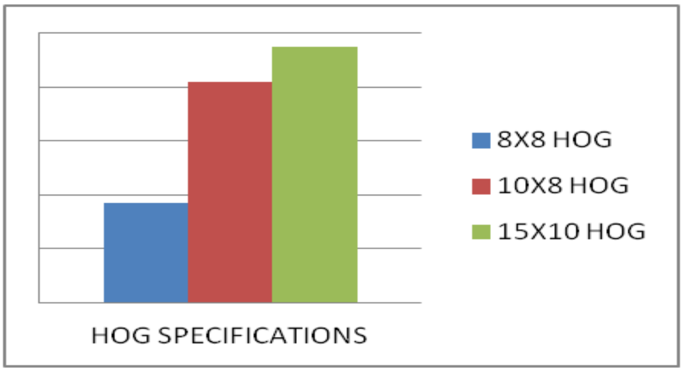


Fig. 5. Recognition accuracy for different HOG specification with Manual (Ideal) Landmarks locations (Rank 10).

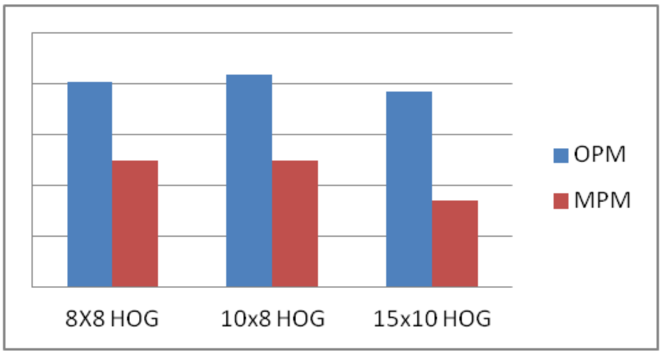


Fig. 6. Recognition accuracy for OPM and MPM (Rank 10).

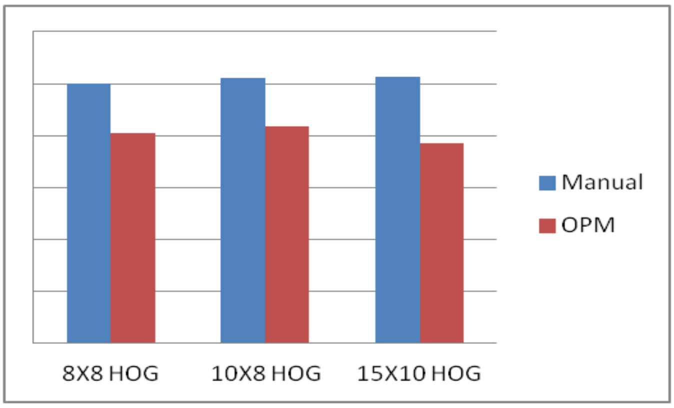


Fig. 7. Recognition accuracy for manual and OPM (Rank 10)

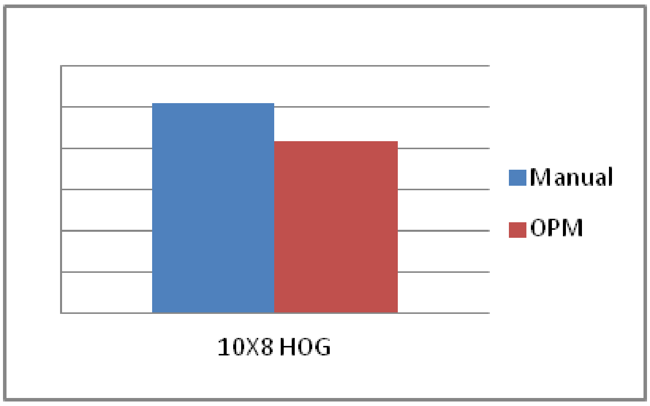


Fig. 8 .Recognition accuracy for 10X8 HOG specification (Manual and OPM Rank 10)

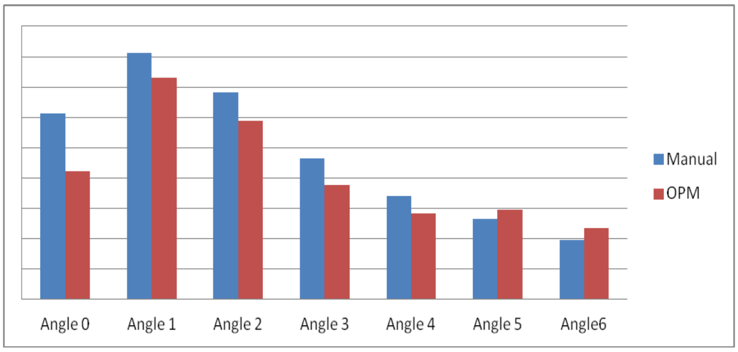


Fig. 9. Recognition accuracy for 10X8 HOG specification at different angles (Manual and OPM Rank 10

VI. CONCLUSION

The face recognition system suffers heavily from the misalignment of the face sample across gallery and probe sets. In this paper we have proposed and analyze a face normalization technique to overcome the negative impacts of misalignment occurred during face detection. The database we used for experimentation has a well structured deviation in pose angles of subjects along with unintentional random non-uniform illuminations which makes the dataset to be more suitable for experimenting with algorithms designed for non-cooperative environment. This method is based on locating the landmarks of face and then cropping the face region proportional to the parameters obtained from estimated landmarks .This simple way of face normalization has been tested and validated on original face samples used in UBIPosePr dataset. We observed that proposed method does a good attempt to improve the performance of face recognition in non-cooperative environment, where localizing the face ROI is always a challenging task.

REFERENCES

[1]. Ricanek, K.; Savvides, M.; Woodard, D.L.; Dozier, G.; ,"Unconstrained Biometric Identification: Emerging Technologies," Computer , vol.43, no.2, pp.56-62, Feb.2010

[2]. Jain, A.K.; Pankanti, S.; Prabhakar, S.; Lin Hong; Ross, A.; "Biometrics: a grand challenge," Proceedings of the 17th International Conference on Pattern Recognition, 2004, ICPR 2004. vol.2, no., pp. 935- 942 Vol.2, 23-26 Aug. 2004.

[3]. [3].Sung, E.; Xilin Chen; Jie Zhu; Jie Yang; , "Towards non-cooperative iris recognition systems," 7th International Conference on Control, Automation, Robotics and Vision, 2002. ICARCV 2002. , vol.2, no., pp. 990- 995 vol.2, 2-5 Dec. 2002.

[4]. Tajbakhsh, N.; Araabi, B.N.; Araabi, B.N.; Soltanianzadeh, H.; Soltanianzadeh, H.; Soltanianzadeh, H.; , "An intelligent decision combiner applied to noncooperative iris recognition," 2008 11th International Conference on Information Fusion,, vol., no., pp.1-6, June 30 2008-July 3 2008.

[5]. Proenca, H.; Alexandre, L.A.; , "Iris segmentation methodology for non-cooperative recognition," IEE Proceedings -Vision, Image and Signal Processing, vol.153, no.2, pp. 199- 205, 6 April 2006.

[6]. DoHyung Kim; Jaeyeon Lee; Ho-Sub Yoon; Eui-Young Cha; , "A Non-Cooperative User Authentication System in Robot Environments," IEEE Transactions on Consumer Electronics, vol.53, no.2, pp.804-811, May 2007.

[7]. Medioni, G.; Jongmoo Choi; Cheng-Hao Kuo; Choudhury, A.; Li Zhang; Fidaleo, D.; , "Non-Cooperative Persons Identification at a Distance with 3D Face Modeling," First IEEE International Conference onBiometrics: Theory, Applications, and Systems, 2007. BTAS 2007., vol., no., pp.1-6, 27-29 Sept. 2007.

[8]. Medioni, G.; Fidaleo, D.; Jongmoo Choi; Li Zhang; Cheng-Hao Kuo; Kwangsu Kim; , "Recognition of Non-Cooperative Individuals at a Distance with 3D Face Modeling," IEEE Workshop onAutomatic Identification Advanced Technologies, 2007, vol., no., pp.112-117, 7-8 June 2007.

[9]. Chellappa, R.; Aggarwal, G.; , "Video Biometrics," 14th International Conference onImage Analysis and Processing, 2007. ICIAP 2007. vol., no., pp.363-370, 10-14 Sept. 2007.

[10]. Xiaokun Li; Genshe Chen; Qiang Ji; Blasch, E.; , "A non-cooperative long-range biometric system for maritime surveillance," 19th International Conference onPattern Recognition, 2008. ICPR 2008., vol., no., pp.1-4, 8-11 Dec. 2008.

[11]. Yu Chen; Adjouadi, M.; Changan Han; Barreto, A.; , "A new unconstrained iris image analysis and segmentation method in biometrics," IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2009. ISBI '09. , vol., no., pp.13-16, June 28 2009-July 1 2009.

[12]. Denman, S.; Fookes, C.; Bialkowski, A.; Sridharan, S.; , "Soft-Biometrics: Unconstrained Authentication in a Surveillance Environment," Digital Image Computing: Techniques and Applications, 2009. DICTA '09. , vol., no., pp.196-203, 1-3 Dec. 2009.

[13]. Wheeler, F.W.; Weiss, R.L.; Tu, P.H.; , "Face recognition at a distance system for surveillance applications," Fourth IEEE International Conference onBiometrics: Theory Applications and Systems (BTAS), 2010 , vol., no., pp.1-8, 27-29 Sept. 2010.

[14]. Podilchuk, C.; Barinov, L.; Hulbert, W.; Jairaj, A.; , "Face recognition in a tactical environment," MILITARY COMMUNICATIONS CONFERENCE, 2010 - MILCOM 2010 , vol., no., pp.900-905, Oct. 31 2010-Nov. 3 2010.

[15]. C. Padole and H. Proenca, "Periocular recognition: Analysis of performance degradation factors in Biometrics," (ICB), 2012 5th IAPR International Conference on, April 2012, pp. 439 –445.

[16]. Xi Zhao; Delleandrea, E.; Liming Chen, "A People Counting System Based on Face Detection and Tracking in a Video," Advanced Video and Signal Based Surveillance, 2009. AVSS '09. Sixth IEEE International Conference on , vol., no., pp.67,72, 2-4 Sept. 2009 doi: 10.1109/AVSS.2009.45.

[17]. Montufar-Chaveznava, Rodrigo. "Face tracking using a Polling Strategy." Int. J. Applied Science, Engineering and Technology 3.3 (2007): 113-117.

[18]. Jain, A.K.; Klare, B.; Unsang Park, "Face recognition: Some challenges in forensics," Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on , vol., no., pp.726,733, 21-25 March 2011 doi: 10.1109/FG.2011.5771338.

[19]. T. Kanade, "Picture Processing System by Computer Complex and Recognition of Human faces," Ph.D. dissertation, Kyoto University, 1973.

[20]. L. Sirovich and M. Kirby, "Low-dimensional Procedure for the Characterization of Human Faces," Journal of Optical Society of America, A, vol. 4, no. 3, pp. 519–524, 1987.

[21]. M. Turk and A. Pentland, "Eigenfaces for Recognition," Cognitive Neuroscience, vol. 3, pp. 72–86, 1991.

[22]. P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," IEEE Trans. on PAMI, vol. 19, no. 7, pp. 711–720, Jul. 1997.

[23]. .Feris, R.; Ying-Li Tian; Hampapur, A., "Capturing People in Surveillance Video," Computer Vision and Pattern Recognition, 2007. CVPR '07. IEEE Conference on , vol., no., pp.1,8, 17-22 June 2007 doi: 10.1109/CVPR.2007.383511.

[24]. .Jie Yan, "Ensemble SVM Regression Based Multi-View Face Detection System," Machine Learning for Signal Processing, 2007 IEEE Workshop on , vol., no., pp.163,169, 27-29 Aug. 2007 doi: 10.1109/MLSP.2007.4414300.

[25]. Shengcai Liao; Jain, A.K., "Partial face recognition: An alignment free approach," Biometrics (IJCB), 2011 International Joint Conference on , vol., no., pp.1,8, 11-13 Oct. 2011 doi: 10.1109/IJCB.2011.6117573.

[26]. Rodrigues, R.N.; Schroeder, G.N.; Corso, J.J.; Govindaraju, V., "Unconstrained face recognition using MRF priors and manifold traversing," Biometrics: Theory, Applications, and Systems, 2009. BTAS '09. IEEE 3rd International Conference on , vol., no., pp.1,6, 28-30 Sept. 2009.

[27]. Medioni, G.; Jongmoo Choi; Cheng-Hao Kuo; Fidaleo, D., "Identifying Noncooperative Subjects at a Distance Using Face Images and Inferred Three-Dimensional Face Models," Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on , vol.39, no.1, pp.12,24, Jan. 2009.

[28]. Wolf, L.; Hassner, T.; Taigman, Y., "Effective Unconstrained Face Recognition by Combining Multiple Descriptors and Learned Background Statistics," Pattern Analysis and Machine Intelligence, IEEE Transactions on , vol.33, no.10, pp.1978,1990, Oct. 2011 doi: 10.1109/TPAMI.2010.230 .

[29]. Dong Yi; Zhen Lei; Li, S.Z., "A robust eye localization method for low quality face images," Biometrics (IJC), 2011 International Joint Conference on , vol., no., pp.1,6, 11-13 Oct. 2011 doi: 10.1109/IJCB.2011.6117499.

[30]. S. Taheri, R. Gopalan, P. Turaga, R. Chellappa, "A Blur-Robust Descriptor with Applications to Face Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 6, pp. 1220-1226, June, 2012.

[31]. Nilesh Pawar and Dr. D.T.Ingole , M.D.Ingole2;" Normalization Method for Misaligned Face Samples in Non-cooperative Biometrics". 2017 International Conference On Smart Technology for Smart Nation, 978-1-5386-0569.

[32]. Sumati Malhotra;Shekhar Singh; S.C.Gupta,," Human Object Detection by HoG, HoB, HoC and BO Features International Journal of Computer Applications (0975 – 8887) Volume 151 – No.8, October 2016.

[33]. SHICHAO ZHANGD;XUELONG LI;MING ZONG, XIAOFENG ZHU, and DEBO CHENG," Learning k for kNN Classification "Article in ACM Transactions on Intelligent Systems and Technology · January 2017 DOI: 10.1145/2990508.

[34]. Chandrashekhar N. Padole; Hugo Proença; "Compensating for pose and illumination in unconstrained periocular biometrics". International Journal of Biometrics (IJBM), Vol. 5, No. 3/4, 2013.

[35]. Xiang Yu_ Junzhou Huang† Shaoting Zhang§ Wang Yan_ Dimitris N. Metaxas," Pose-free Facial Landmark Fitting via Optimized Part Mixtures and Cascaded Deformable Shape Model". IEEE International Conference on Computer Vision, 1550-5499/13 , 2013 IEEE doi :10.1109/ICCV.2013.244.

[36]. X. Zhu and D. Ramanan," Face detection, pose estimation and landmark localization in the wild". In CVPR, 2012. 1, 2, 3, 5, 6.

Nilesh Pawar "Eye-Landmarks Based Face Alignment In Non-Cooperative Face Biometrics "American Journal of Engineering Research (AJER), vol. 7, no. 10, 2018, pp. 42-50