ISSN No:-2456-2165

Real Time Face Parcing Using Enhanced KNN and DLIB

[1] Nikhil Chug [2] Samarth Mehrotra [3] Sameya Alam [4] Anand Gaurav [5] Girish.N.
[1][2][3][4] BE Students, Department of Information Science and Engineering
[5] Asst. Professor, Department of Information Science and Engineering
[1][2][3][4][5] Dayananda Sagar Academy of Technology and Management, Bangalore, Karnataka, India
[1][2][3][4] Email Addresses

Abstract:- The conventional method of finding a missing person involves lodging an FIR in nearby police station and police will then circulate the person's photo to all the nearby police stations. This process is very time consuming. The idea is to automate this process by using Facial Recognition. The purposed algorithm is implemented using enhanced KNN, dlib and OpenCV. The presented approach uses dlib to generate a total of 68 exclusive facial key features. 136 points are generated in total which are floating point numbers(point 10 precision). Thus, we have decided to use Enhanced KNN algorithm. We use this algorithm for matching faces. This form k groups using the cases that have been registered. The traditional KNN strategy has different deficiencies we propose to upgrade its precision utilizing these techniques. Need of qualities and best neighborhood size are considered to ascertain increasingly exact separation capacities and to get precise outcomes. Rather than basic democratic strategy we propose to utilize likelihood class estimation technique.

Keywords:- *Facial Recognition, Machine Learning, Enhanced KNN, DLIB, PyQt5, DCR, OpenCV.*

I. INTRODUCTION

In India, one of the major issue is the increasing rate of missing children which has crossed almost 170 per day amongst which half of them remain untraced. Not only children but also old person who are suffering from Alzheimer disease go missing. According to a survey The Hindu, amongst the missing, less than 50% are traced.

Facical Recognition(FR) has been a difficult field. It is hard to distinguish a face picture which comprises of changing enlightenments. Neto. J. G. D. S. et.all [3].

The conventional approach to recognize faces involves training the model on large data sets. But in real life scenarios more often than not, limited or even a single sample data is available. Similarly, as we can see in our problem statement ample data is hard to find. We try to train our model using single sample per person (SSPP) Jianquan Gu et.all [1].

Facial features such as eyes, nose, lips and face contour are considered as the action units of face and are extracted using open source software called dlib K. Bharat S Reddy et.all [18]. Dlib is used to generate a total of 68 exclusive facial key features. 136 points are generated in total which are floating point numbers (point 10 precision). Then these generated points are converted to strings with the help of simple encoding.

Sometimes the test image might be of low resolution and image present in our data set is of high resolution. So comparing a low resolution test image to a high resolution image affects the performance of their matching Deep Coupled ResNet (DCR) model is used Lu et.all [2] that consists of two branch and one trunk network. Discriminative features are extracted using this model. Two branch networks which are trained using HR images and targeted LR image are considered working as resolution-specific coupled mappings which also transforms LR and HR features to a space where their difference is minimized. Optimization of model parameters is performed using proposed Coupled-Mapping loss function. The proposed model considers the discriminability and similarities of HR and LR features. Different pairs of tiny branch networks are trained to cope with the different image resolutions Lu et.all [2].

II. METHODOLOGY

- *Face Recognition*

Face acknowledgment is a procedure of distinguishing proof of an individual's face in a picture or video. This incorporates different advances that should be pursued. Figure.1 shows the square chart of the framework, which incorporates face recognition and highlight extraction.

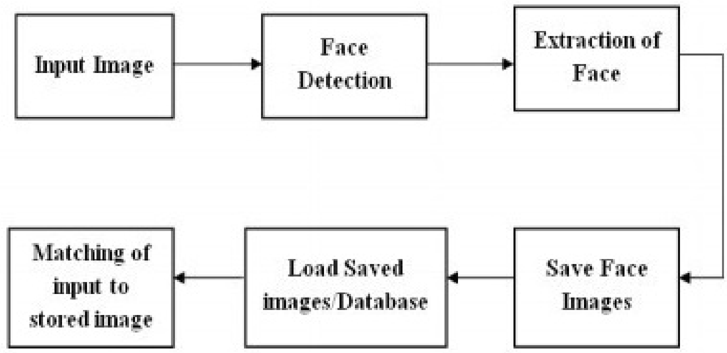

Fig 1:- Face Recognition block diagram

The algorithm is planned in a manner that it extracts 68 unique key facial features. 136 floating key points are generated with a precision of about 10.

These facial key focuses are utilized to particularly recognize facial highlights, for example, nose, eyes, nose, lips which are considered as the activity units of the face.

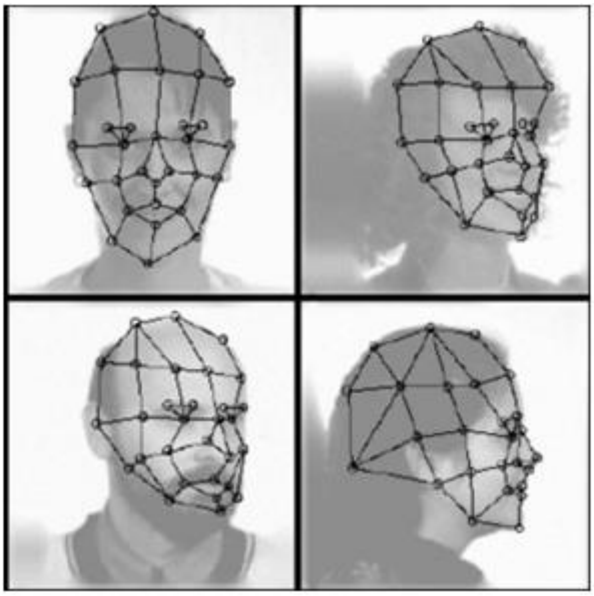

Fig 2:- Feature Extraction

➢ *OpenCV*

Open Source Computer Vision abbreviated as OpenCV is a programming function library and a cross platform providing a common infrastructure. This library mainly aims at real-time computer vision and to speed up the use of machines used in various industries. It also includes efficient algorithms which is more than 2500 in number. This library includes an immense set of state of the art computer vision. This library helps to recognise objects, track camera gestures follow eye movements, extract 3D models of objects, perceive and identify faces, remove red eyes from images, tracking of the moving objects and detect indistinguishable images from an image database setc. these algorithms can be used efficiently in these scenarios. OpenCV has a user community consisting of about 50 thousand people with an estimated number of downloads that exceeds 14 million.

We are using OpenCV to detect the faces and recognize them and to also find any similar images to the test image present in our database.

➢ *Enhanced KNN*

KNN algorithm is mainly used for classification problems but it also includes regression predictive problems.

For measuring the similarity or differences between test instance and training instance, KNN uses standard Euclidean distance. This standard Euclidean distance $d(x_i,x_j)$ is defined in the following equation 1.1:

$$d(xi,xj) = \sqrt{\Sigma}(ar(xi) - ar(xj))^2$$

ISSN No:-2456-2165

KNN considers the most widely recognized closest neighbors to appraise test information. It is characterized in the accompanying condition 1.2:

$$c(x) = \arg\max_c \sum_{i=0}^{k} \delta(c, c(yi))$$

Here $y1, y2, \ldots, yk$ are the k nearest neighbors of test instance, k is the number of neighbors, C represent the finite set of class labels and $\delta(c,c(yi)\text{-} = 1)$ $if\ c = c(yi)$ $and\ \delta(c, c(yi)\text{-} = 0$ $otherwise$ Shweta Taneja et.all [10].

The upgraded KNN calculation incorporates the accompanying advances:

Step 1: Entropy of each credit is determined to get data addition of properties. Needs are alloted to each weight quality dependent on the above estimation.

Step 2: The following stage is to discover the estimation of k for the preparation set.

Step 3: We isolate the preparation set into various clusters.

Step 4: To obtain the center of each cluster, we find mean of every cluster.

Step 5: Using Euclidean Distance formula, we try to determine the cluster which is closest to the test sample to find the K nearest neighbors.

Step 6: The distance between each sample in the cluster and the test sample is calculated using Weighted Euclidean Distance formula and K nearest neighbors are found.

Step 7: The classmark with the most extreme likelihood of chosen k neighbors is picked as the class name of the test. The proposed calculation incredibly lessens the execution time and improves the exactness as it is a blend of grouping and bunching strategies and diminishes the time intricacy.

Classification: The real order of test information is done in this part. This part runs each time when it does characterization.

The calculation is required to decrease the wastefulness of traditional K closest neighbor calculation. The proposed calculation is separated into two significant parts:

- Information pre-handling: In the information pre-preparing part K esteems for the test tests are resolved, the preparation informational index is partitioned into various bunches and weight is given to various groups. Future information is arranged dependent on the aftereffects of the model. This part doesn't influence the proficiency of the calculation as it just runs once in the framework.
- Arrangement: The grouping of the real information is done in this part. This part runs over and over at whatever point the order occurs. X. Xiao et.all [25].

We structured a stream graph so as to clarify the two pieces of our calculation and it is appeared in Figure1 and 2 individually.

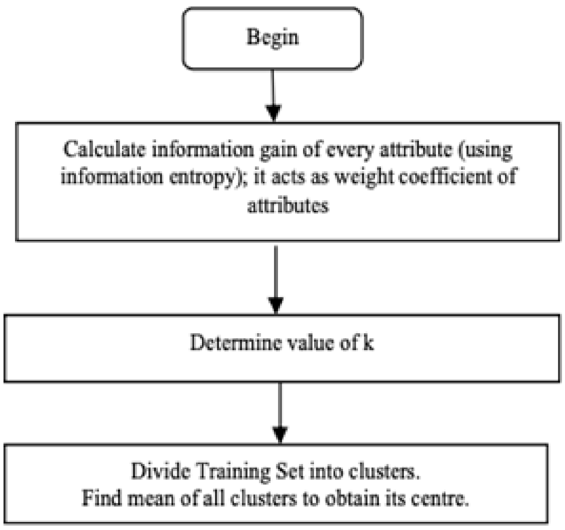

Fig 3:- Data Pre-Processing

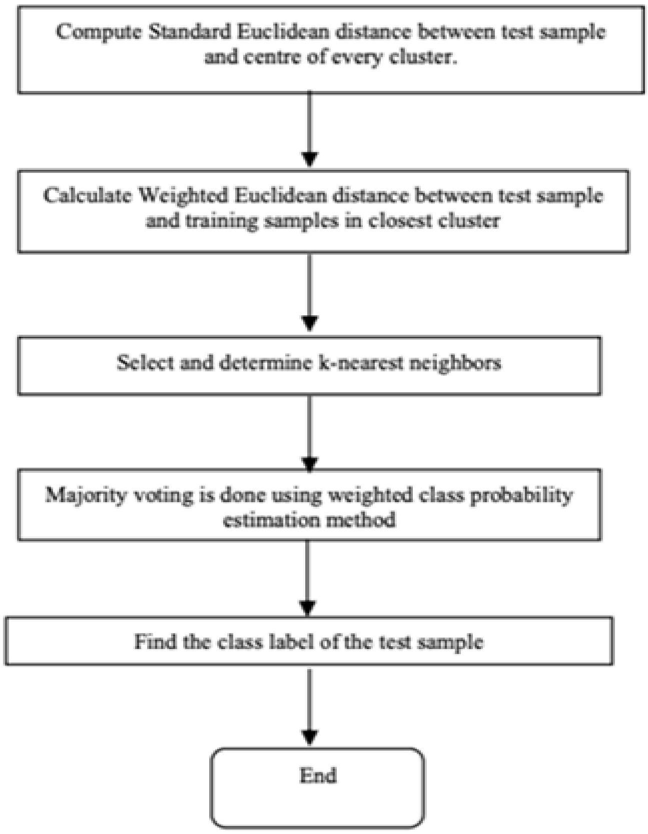

Fig 4:- Classification Process

S.NO	TECHNIQUES	RESULT	ISSUES
1.	Patch based methods and generic learning methods	LRSR achieves higher recognition performance compared to state- of-the-art SSPP	For few datasets, it cannot achieve a promising performance
2.	Deep Coupled ResNet model	Accomplishes better performance than the existing models.	Requires 3 different resolution images for training the model.
3.	Multi Scale & Multi Channel shallow convolution network	The proposed face recognition method outperforms the existing methods in terms of effectiveness and efficiency.	Depth of MMSCM could be increased.
4.	Transfer learning and sample expansion	Achieved 93.17% accuracy.	Model needs pre training
5.	Convolutional Neural Network, Heterogenous Joint Bayesian	Results on SCface dataset shows increase in match rate of 10% by 11%, COX dataset shows match rate of 1% by 12%.	Accuracy of matching could be improved.
6.	KNN Method	The feasibility of the proposed LLK method is successfully evaluated for several visual recognition tasks.	Computational cost is high due to the size of the dictionary.
7.	CNN-RNN	Achieved satisfactory result of about 53%.	Does not focus on certain models.
8.	Discriminative Multi-Dimensional Scaling, MTCNN	Achieved an accuracy of 93.55%	In order to preserve local consistency both HR-HR and LR-LR images needs to be in objective function
9.	R-CNN, CNN	50% Accuracy was achieved.	Low running speed.
10.	HOG	Results on FERET, MobBIO, O2FN, FaceSampler datasets showed an accuracy of 80%.	High Cost and less privacy.

Table 1:- Table on Literature Survey

III. CONCLUSION

In this paper, we present an overview on facial location approach dependent on improved KNN and DLIB. The exploratory outcomes have demonstrated that the proposed technique accomplishes preferable presentation over the regular KNN strategies. Later on, we will concentrate on coordinating the proposed strategy to the current reconnaissance framework without acquiring any additional expenses. Additionally, how to apply the prepared KNN-based model in different fields, for example, ongoing wrongdoing checking, ramble reconnaissance frameworks. This paper gives a general thought regarding the propelled AI calculations and methods used to give answers for the facial acknowledgment and location.

REFERENCES

[1]. Gu, J., Hu, H., & Li, H. (2018). **Local robust sparse representation for face recognition with single sample per person**. *IEEE/CAA Journal of Automatica Sinica, 5(2), 547–554.*

[2]. Lu, Z., Jiang, X., & Kot, A. (2018). **Deep Coupled ResNet for Low-Resolution Face Recognition**. *IEEE Signal Processing Letters, 25(4), 526–530.*

[3]. Neto, J. G. D. S., Caldeira, J. L. M., & Ferreira, D. D. (2018). **Face Recognition based on Higher-Order Statistics**. *IEEE Latin America Transactions, 16(5), 1508–1515.*

[4]. Min, W., Fan, M., Li, J., & Han, Q. (2019). **Real-time face recognition based on pre-identification and multi-scale classification**. *IET Computer Vision, 13(2), 165–171*

[5]. Liu, Q., & Liu, C. (2015). **A Novel locally linear KNN model for visual recognition**. *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[6]. Wei, Z., Liu, S., Sun, Y., & Ling, H. (2019). **Accurate Facial Image Parsing at Real-Time Speed**. *IEEE Transactions on Image Processing, 28(9), 4659–4670.*

[7]. Wu, W., Yin, Y., Wang, X., & Xu, D. (2019). **Face Detection With Different Scales Based on Faster R-CNN**. *IEEE Transactions on Cybernetics*, *49*(11), 4017–4028.

[8]. Yang, S., Zhang, L., He, L., & Wen, Y. (2019). **Sparse Low-Rank Component-Based Representation for Face Recognition With Low-Quality Images**. *IEEE Transactions on Information Forensics and Security*, *14*(1), 251–261.

[9]. C. Ding and D. Tao, "**Robust face recognition via multimodal deep face representation**," IEEE Trans. Multimedia, vol. 17, no. 11, pp. 2049–2058, 2015

[10]. Taneja, S., Gupta, C., Goyal, K., & Gureja, D. (2014). **An Enhanced K-Nearest Neighbor Algorithm Using Information Gain and Clustering**. *2014 Fourth International Conference on Advanced Computing & Communication Technologies*.

[11]. M. Yang, L. Van Gool, and L. Zhang, "**Sparse variation dictionary learning for face recognition with a single training sample per person,**" in Proc. 2013 IEEE Int. Conf. Computer Vision, Sydney, Australia, pp. 689−696, 2013. [10] Gu, J., Hu, H., & Li, H. (2018).

[12]. J. W. Lu, Y. P. Tan, and G. Wang, "**Discriminative multimanifold analysis for face recognition from a single training sample per person,**" IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 1, pp. 39−51, Jan. 2013.

[13]. M. Yang, L. Zhang, J. Yang, and D. Zhang, "**Regularized robust coding for face recognition**," IEEE Transactions on Image Processing, vol. 22, no. 5, pp. 1753–1766, 2013

[14]. Q. Liu and C. Liu, "**A new locally linear KNN method with an improved marginal Fisher analysis for image classification**," in Proc. IEEE IJCB, Sep./Oct. 2014, pp. 1–6.

[15]. M. N. Kan, S. G. Shan, Y. Su, D. Xu, and X. L. Chen, "**Adaptive discriminant learning for face recognition,**" Pattern Recognit., vol. 46, no. 9, pp. 2497−2509, Sep. 2013.

[16]. W. W. Zou and P. C. Yuen, "**Very low resolution face recognition problem**," IEEE Trans. Image Processing, vol. 21, no. 1, pp. 327–340, 2012.

[17]. B. Li, H. Chang, S. Shan, and X. Chen, "**Low-resolution face recognition via coupled locality preserving mappings**," IEEE Signal processing letters, vol. 17, no. 1, pp. 20–23, 2010.

[18]. Reddy, K. B. S., Loke, O., Jani, S., & Dabre, K. (2018). **Tracking People In Real Time Video Footage Using Facial Recognition**. *2018 International Conference on Smart City and Emerging Technology (ICSCET).*

[19]. Min, R., Xu, S., & Cui, Z. (2019). **Single-Sample Face Recognition Based on Feature Expansion.** *IEEE Access*, *7*, 45219–45229.

[20]. Yang, F., Yang, W., Gao, R., & Liao, Q. (2018). **Discriminative Multidimensional Scaling for Low-Resolution Face Recognition**. *IEEE Signal Processing Letters*, *25*(3), 388–392

[21]. Zeng, D., Spreeuwers, L., Veldhuis, R., & Zhao, Q. (2019**). Combined training strategy for low-resolution face recognition with limited application-specific data**. *IET Image Processing*, *13*(10), 1790–1796

[22]. P. F. Zhu, M. Yang, L. Zhang, and I. Y. Lee, "**Local generic representation for face recognition with single sample per person**," in Proc. Asian Conf. Computer Vision Computer on Vision-ACCV 2014, Switzerland, pp. 34−50, 2014.

[23]. M. N. Kan, S. G. Shan, Y. Su, D. Xu, and X. L. Chen, “**Adaptive discriminant learning for face recognition,**” Pattern Recognit., vol. 46, no. 9, pp. 2497−2509, Sep. 2013..

[24]. X. Jiang and J. Lai, “**Sparse and dense hybrid representation via dictionary decomposition for face recognition**,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 5, pp. 1067– 1079, 2015

[25]. X. Xiao, and H. Ding, "**Enhancement of K-nearest Neighbor Algorithm Based on Weighted Entropy of Attribute Value**," Proc. 5th International Conference on BioMedical Engineering and Informatics (BMEI 2012), IEEE Press, Oct. 2012, pp. 1261-1264,

[26]. López-López, E., Pardo, X. M., Regueiro, C. V., Iglesias, R., & Casado, F. E. (2019). **Dataset bias exposed in face verification**. *IET Biometrics*, *8*(4), 249–258

[27]. J. Zou, Q. Ji, and G. Nagy, “**A comparative study of local matching approach for face recognition**,” *IEEE Trans. Image Process., vol. 16, no. 10, pp. 2617−2628, Oct. 2007*.

[28]. T. Ahonen, A. Hadid, M. Pietikainen, "**Face recognition with local binary patterns**", *ECCV*, pp. 469-481, 2004.

[29]. A. M. Martinez, "**Recognizing imprecisely localized partially occluded and expression variant faces from a single sample per class**", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 6, pp. 748-763, Jun. 2002.

[30]. M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, “**Face recognition by independent component analysis**,” *IEEE Trans. Neural Netw., vol. 13, no. 6, pp. 1450–1464, Jun. 2002.*

[31]. B. Boom, G. Beumer, L. J. Spreeuwers, R. N. Veldhuis, "**The effect of image resolution on the performance of a face recognition system**", *Proc. Int. Conf. Control Autom. Robot. Vis., pp. 1-6, 2006.*

[32]. Z. Wang , Z. Miao, Q. Wu, Y. Wan, and Z. Tang , “**Low-resolution face recognition: A review**,” *Vis. Comput., vol. 30, pp. 359–386, Aug. 2013.*

[33]. S. P. Mudunuri and S. Biswas, “**Low resolution face recognition across variations in pose and illumination ,**” *IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 5, pp. 1034–1040, May 2016*

[34]. C. Zhang and Z. Zhang, “**Improving multiview face detection with multi-task deep convolutional neural networks ,**” *in Proc. IEEE Winter Conf. Appl. Comput. Vis., 2014 , pp. 1036–1041.*

[35]. L. Jiang, Z. Cai, D. Wang, and S. Jiang, "**Survey of Improving K-Nearest-Neighbor for Classification,**" Proc. 4rth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007), vol. 1, Aug. 2007, pp. 679-683

[36]. L. Wolf, T. Hassner, Y. Taigman, "**Effective unconstrained face recognition by combining multiple descriptors and learned background statistics**", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 10, pp. 1978-1990, Oct. 2011.

[37]. J. Wu, Z.-H. Zhou, "**Face recognition with one training image per person**", *Pattern Recognit. Lett.*, vol. 23, no. 14, pp. 1711-1719, Dec. 2002.

[38]. F. Schroff, D. Kalenichenko, J. Philbin, "**FaceNet: A unified embedding for face recognition and clustering**", *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 815-823, Jun. 2015.

[39]. A. M. Martinez, "**Recognizing imprecisely localized partially occluded and expression variant faces from a single sample per class**", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 6, pp. 748-763, Jun. 2002.

[40]. J. Pan, X.-S. Wang, Y.-H. Cheng, "**Single-sample face recognition based on LPP feature transfer**", *IEEE Access*, vol. 4, pp. 2873-2884, 2016.

[41]. Liu, J., Jing, X., Lian, Z., & Sun, S. (2015). **Local Gabor Dominant Direction Pattern for Face Recognition**. *Chinese Journal of Electronics*, *24*(2), 245–250.

[42]. Chang, K.-Y., & Chen, C.-S. (2014). **Facial Expression Recognition via Discriminative Dictionary Learning.** *2014 IEEE International Conference on Internet of Things(IThings), and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom)*.

[43]. X. Jiang and J. Lai, “**Sparse and dense hybrid representation via dictionary decomposition for face recognition**,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 5, pp. 1067– 1079, 2015

[44]. Ding, C., & Tao, D. (2015). **Robust Face Recognition via Multimodal Deep Face Representation.** *IEEE Transactions on Multimedia*, *17*(11), 2049–2058.

[45]. S. Baker and T. Kanade, "**Limits on super-resolution and how to break them**," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 9, pp. 1167 - 1183, September 2002.

[46]. H. X. Li, Z. Lin, X. H. Shen, J. Brandt, G. Hua, "**A convolutional neural network cascade for face detection**", *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 5325-5334, Jun. 2015.

[47]. S. Hayashi, O. Hasegawa, "**Robust face detection for low-resolution images**", *J. Adv. Comput. Intell. Intell. Inf.*, vol. 10, no. 1, pp. 93-101, 2016.

[48]. K. Zhang, Z. Zhang, Z. Li, Y. Qiao, "**Joint face detection and alignment using multitask cascaded convolutional networks**", *IEEE Signal Process. Lett.*, vol. 23, no. 10, pp. 1499-1503, Apr. 2016.

[49]. X. He, S. Yan, Y. Hu, P. Niyogi, and H.-J. Zhang. **Face recognition using laplacianfaces**. IEEE Trans. Pattern Anal. Mach. Intell., 27(3):328-340, 2005

[50]. L. Wolf, T. Hassner, Y. Taigman, "**Effective unconstrained face recognition by combining multiple descriptors and learned background statistics**", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 10, pp. 1978-1990, Oct. 2011.