# Image Processing Algorithms -A Systematic Study

**Dr. Mahesh Prasanna K, Professor, VCET, Puttur, India, kmpshastry@gmail.com**

**Dr. Shantharama Rai C, Professor, AJIET, Mangalore, csrai@gmail.com**

Abstract: **The paper presents survey towards performance measures, computational cost, pose-invariant face recognition, neural networks, RGB-D (red, green, blue and depth) appearance models, element extraction methods, and various pose and illumination problems. This paper discusses about how the most recent efforts on minimizing drawbacks with respect to changes on illumination on face based images. This paper also considers the above mentioned boundaries; discusses algorithms with high computational cost, despite good performance.**

*Keywords —* ***Active Appearance Models, Binarized neural networks, Computational cost, Convolutional neural networks, Facial recognition, Performance measures, Pose and illumination-invariant face recognition.***

## I. INTRODUCTION

Bio-metric is swotting of behavioural description used to detect a person. Swotting includes facial identity, prints taken from fingers, geometry on hands, tone of voice and other related qualities on biometry. Security systems on computers use such kind of features on biometry. Personal identity becomes mandatory similar to usage of PIN's, Password's, Punching-cards and identity-cards. Biometric rise above the so problems which may be experienced in the identification techniques such as stealing of identity cards, cracking and forgetting of passwords etc. People make utilization of face as an imperative prompt for distinguishing individuals. Making automated way on recognition of face extremely urgent for an extensive variety of business and law requirement applications. Face recognition is a sort of mechanized bio-metric identification technique that perceives an individual in view of their facial highlights as fundamental components of refinement. Hence this research work gives an upcoming method of video-based face acknowledgment.

Despite the fact that face recognition have been a grown-up inquire about territory, nonetheless, there still stay numerous issues that must be overcome to build up a powerful face acknowledgment framework that functions admirably under different conditions, for example, brightening, stance and light posture. Since the review paper on posture brightening invariant face acknowledgment framework are spoken to, so it is exceptionally fundamental to travel toward recognizing what essential methodologies had been received to manage posture enlightenment invariant face acknowledgment framework.

## II. FACE RECOGNITION TECHNIQUES

The objective of developing biometric applications, such as facial recognition, has recently become important in smart cities. Video surveillance, criminal identification, building access control, and unmanned and autonomous vehicles are just a few examples of concrete applications that are gaining attraction among industries. Many scientists and engineers around the world have focused on establishing increasingly robust and accurate algorithms and methods for these types of systems and their application in everyday life. All types of security systems must protect all personal data.

Humans make use of face as an important cue for identifying people [1]. This makes automatic face recognition very crucial from the point of view of a wide range of commercial and law enforcement applications. Although significant work has been done, the current systems are still not close to the human perceptual system. Traditionally, face recognition research has been limited to recognizing faces from still images. Most of these approaches discount the inherent 3-D structure of the face and therefore are very susceptible to pose changes. Face recognition is a kind of automated biometric identification technique that recognizes an individual based on their facial features as essential elements of distinction.

Digital image processing is an ever expanding and dynamic area with applications reaching out into our everyday life such as medicine, space exploration, surveillance, authentication, automated industry inspection and many more areas. These applications involve different processes like image enhancement and object detection [2]. Implementing such applications on a general purpose computer can be easier, but not very time efficient due to additional constraints on memory and other peripheral devices. Application specific hardware implementation offers much greater speed than a software implementation. With advances in the VLSI (Very Large Scale Integrated) technology hardware implementation has become an attractive alternative. Implementing complex computation tasks on hardware and by exploiting parallelism and pipelining in algorithms yield significant reduction in execution times.

 DOI : 10.35291/2454-9150.2021.0198 

Video face recognition is a widely used method in which security is essential that recognizes the human faces from subjected videos [3]. Unlike traditional methods, recent recognition methods consider practical constraints such as pose and illumination variations on the facial images. Our previous work also considers such constraints in which face recognition was performed on videos that were highly subjected pose and illumination variations. The method asserted good performance however; it suffers due to high computational cost. This work overcomes such drawback by proposing a simple face recognition technique in which a cost efficient Active Appearance Model (AAM) and lazy classification are deployed. The deployed AAM avoids nonlinear programming, which is the cornerstone for increased computational cost. Experimental results prove that the proposed method is better than the conventional technique in terms of recognition measures and computational cost.

There are many computer vision approaches proposed to address face detection or recognition tasks with high robustness and discrimination. However, several issues still need to be addressed owing to various challenges; such as head orientation, lighting conditions, and facial expression. The most interesting techniques are developed to face all these challenges, and thus develop reliable face recognition systems. Nevertheless, they require high processing time, high memory consumption, and are relatively complex. A systematic study of all these are presented below.

### A. *Automatic Facial Expression Recognition*

Automatic facial expression recognition has always been a challenging task to understand human behavior from real world images. In recent techniques adopted [4], [5], [6], [7], [8], first, Fast Fourier Transform and Contrast Limited Adaptive Histogram Equalization (FFT + CLAHE) method is applied to compensate the poor illumination. Then merged binary pattern code (MBPC) is generated for every pixel. Two bits per neighborhood are produced to form a 16-bit code per pixel. This code merges local features to improve the effectiveness of facial expression recognition system. MBPC descriptor captures changes along fine edges and prominent pattern around eyes, eye brows, mouth, bulges and wrinkles of the face.

Some review papers emphasizes on color normalization and facial feature extraction which uses LBP (Local Binary Pattern) as an effective feature detection approach.

- *Pros:* MBPC based technique surpasses other techniques with more than 95% and 66% accuracy for holistic and division based approach respectively.
- *Cons:* Noise is not handled in pre-processing stage. Automated systems, not many are currently available. Quite a few options are available to identify a face in an image in an efficient and accurate manner.

### B. *Performance Measures and Computational Cost*

The multi-view subspace learning approaches attempt to narrow the gap between different poses by projecting their features to a common subspace with pose-specific transformations [9]. The nonlinear techniques make up for this imperfection by learning nonlinear projections, but at the cost of lower efficiency in model training or testing. The deep learning-based nonlinear models also require larger training data [10].

- *Pros:* Among the existing techniques, linear models have the advantage in efficiency since the low-dimensional embeddings can be computed directly by matrix multiplication.
- *Cons:* The capacity of the linear models is limited, as the appearance variations resulting from pose changes are intrinsically nonlinear. The common shortcoming of the multi-view subspace learning methods is that they depend on large training data which incorporate all the poses that might appear in the testing phase, but the large amount of multi-pose training data might not be available in real-world applications.

### C. *Pose-invariant Face Recognition*

The capacity to recognize faces under varied poses is a fundamental human ability that presents a unique challenge for computer vision systems. Compared to frontal face recognition, pose-invariant face recognition (PIFR) remains a largely unsolved problem [11], [12], 13], [14], [15]. However, PIFR is crucial to realizing the full [potential of face recognition for real-world applications, since face recognition is intrinsically a passive biometric technology for recognizing uncooperative subjects. Several papers discuss the inherent difficulties in PIFR.

Existing PIFR methods can be grouped into four categories, i.e., pose-robust feature extraction approaches, multi-view subspace learning approaches, face synthesis approaches, and hybrid approaches.

- *Pros:* The engineered features achieve pose robustness by re-establishing the semantic correspondence between two images. The learning-based utilize non-linear machine learning models, e.g., deep neural networks [16]. These machine learning models may produce higher quality pose-robust features.
- *Cons:* The semantic correspondence cannot handle the challenge of self-occlusion or nonlinear facial texture warping caused by pose variation. The learning-based non-linear machine models, usually

 DOI : 10.35291/2454-9150.2021.0198 

suffer due to cost of massive labeled multi-pose training data.

*D. Convolutional Neural networks*

Most of the researchers focused on two scenarios of video-based face recognition: 1) Still-to-Video face recognition, i.e., querying a still face image against a gallery of video sequences; 2) Video-to-Still face recognition, in contrast to the first scenario. First, still and video face images are transferred to an Euclidean space by a carefully designed convolutional neural network; then Euclidean metrics are used to measure the distance between still and video images [17], [18], [19], [20], [21], [22], [23] [24].

- *Pros:* Experimental results show that these methods achieve reliable performance.
- *Cons:* Video-based face recognition still remains a challenging task because of the low quality and large intra-class variation of video captured face images.

*E. Binarized Neural networks*

Binarized Auto-encoders (BAEs) and Stacked Binarized Auto-encoders are proposed to learn a kind of domain knowledge from a large-scale unlabeled facial dataset. By transferring the knowledge to another Binarized Neural Networks (BNNs) based supervised learning task with limited labeled data, the performance of the BNNs can be improved [25], [26], [27].

- *Pros:* A real-world facial expression recognition system can be constructed by combining an unconstrained face normalization method, a variant of LBP descriptor, BAEs and BNNs.
- *Cons:* It was observed that, the training time increases when dropout was added in BNN. Due to noise addition, each training is done in a new random architecture, which increases the training time.

*F. Red Green Blue Depth*

Billy Y. L *et al.* [28, 29, 30] presented novel algorithm which makes use of less worthy Red Green Blue Depth data (R.G.B.D) obtained from sensor on kinect confront acknowledgment beneath testing circumstances. Algorithm removes different characteristics in addition to circuits towards the marked pane. Better quality on Feature Fusion Technique was urbanized which evacuates laid off data also holds just significant descriptions on conceivable greatest class distinguishableness. Likewise bring in a novel three dimensional confront data base attained on sensor on kinect got out towards the examination group. These in formations constitutes of more than five thousand face related pictures (R.G.B.D) on fifty two folks beneath shifting stance, demeanour, brightening and impediments.

*G. Active Appearance Models*

An efficient direct optimization approach that matches shape and texture simultaneously. In this approach, learned correlation between errors in model parameters and the resulting residual texture errors are used. From an initial starting position, the search converges rapidly and reliably. The algorithm can be extended to color images also [31], [32], [33], [34], [35], [36], [37].

- *Pros:* An algorithm that is rapid, accurate, and robust.
- *Cons:* The algorithm is more robust since all image evidence is used; but is slightly slower than Active Shape Model search.

*H. Pose and Illumination Constraints*

Face recognition under pose and illumination variations involves three factors, namely; identity, illumination, and pose. Some approaches derives an identity signature that is illumination- and pose-invariant, where the identity is tackled by means of subspace encoding, the illumination is characterized with a Lambertian reflectance model [38], [39], [40], [41], [42].

Many researchers focused to assess the decreases in performance with respect to two criteria: lighting conditions and subject's poses regarded as covariates of performance; and propose methods to compensate for these, consistently improving the recognition effectiveness. To compensate varying lighting conditions, homomorphic filters and self-quotient images are introduced. To address conditions of pose, projection techniques are derived [43], [44], [45].

- *Pros:* The feasibility of these approaches are demonstrated by using PIE dataset. These techniques consistently improve performance when data is moderately deviated (up to $30^0$).
- *Cons:* Recognition performance depends on the validity of model assumptions, such as the Lambertian reflectance model, the accuracy of normalization, etc.

## III. CONCLUSION

An algorithm is considered efficient if its resource consumption, also known as computational cost, is at low or below some acceptable level. In this view, we find a lagging with regarding the following:

- Quite a few options are available to identify a face in an image in an efficient and accurate manner.
- The capacity of the linear models is limited, as the appearance variations resulting from pose changes are intrinsically nonlinear. Also, deep learning-based nonlinear models also require larger training data.

 DOI : 10.35291/2454-9150.2021.0198 

- The learning-based non-linear machine models, usually suffer due to cost of massive labeled multi-pose training data.
- Video-based face recognition still remains a challenging task because of the low quality and large intra-class variation of video captured face images.

## REFERENCES

[1] K. Mahesh Prasanna, and Nagaratna Hegde, “A Survey on Video based Face Recognition”, International Journal of Computer Engineering, ISSN: 0975-6116, International Science Press, Volume 4, Number 1, January-June 2012, pp 01-07.

[2] K. Mahesh Prasanna, C. Shantharama Rai, “Image Processing Algorithms – A Comprehensive Study”, IJACR (International Journal of Advanced Computer Research), ISSN (print): 2249-7277 ISSN (online): 2277-7970, Volume-4, Number-2, Issue-15, June-2014, pp 532-539.

[3] K. Mahesh Prasanna, and Nagaratna Hegde, “A Fast Recognition Method for Pose and Illumination Variant Faces on Video Sequences”, IOSR (International Organization of Scientific Research) Journal of Computer Engineering, e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 10, Issue 1, Mar-Apr 2013, pp 08-18.

[4] Munir Asim, AyyazHussain, Sajid Ali Khan, Muhammad Nadeem, and SadiaArshid. "Illumination Invariant Facial Expression Recognition Using Selected Merged Binary Patterns for Real World Images." Optik-International Journal for Light and Electron Optics (2018)

[5] Wang, Fasheng, Baowei Lin, Junxing Zhang, and Xucheng Li. "Object tracking using Langevin Monte Carlo particle filter and locality sensitive histogram based likelihood model." Computers & Graphics 70 (2018): 214-223.

[6] Yao, Jing, Xiangyong Cao, Qian Zhao, DeyuMeng, and ZongbenXu. "Robust subspace clustering via penalized mixture of Gaussians." Neurocomputing 278 (2018): 4-11.

[7] Masi, Iacopo, Feng-Ju Chang, Jongmoo Choi, ShaiHarel, Jungyeon Kim, KangGeon Kim, JatupornLeksut et al. "Learning Pose-Aware Models for Pose-Invariant Face Recognition in the Wild." IEEE Transactions on Pattern Analysis and Machine Intelligence (2018).

[8] Xu, Chenfei, Qihe Liu, and Mao Ye. "Age invariant face recognition and retrieval by coupled auto-encoder networks." Neurocomputing 222 (2017): 62-71.

[9] Chu, Wenqing, and Deng Cai. "Deep feature based contextual model for object detection." Neurocomputing 275 (2018): 1035-1042.

[10] Bailly, Kevin, and SeverineDubuisson. "Dynamic pose-robust facial expression recognition by multi-view pairwise conditional random forests." IEEE Transactions on Affective Computing (2017).

[11] Ding, Changxing, and Dacheng Tao. "Pose-invariant face recognition with homography-based normalization." Pattern Recognition 66 (2017): 144-152.

[12] Dou, Pengfei, Shishir K. Shah, and Ioannis A. Kakadiaris. "End-to-end 3D face reconstruction with deep neural networks." In Proc. IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, Hawaii, vol. 5. 2017

[13] Britto, Laurindo, Margareth Lima Maike, Vanessa Regina, Luiz Cesar, CalaniBaranauskas, and Maria Cecilia. "A Kinect-based Wearable Face Recognition System To Aid Visually Impaired Users." IEEE Transactions on Human-Machine Systems (2017).

[14] Boulkenafet, Zinelabinde, JukkaKomulainen, Lei Li, XiaoyiFeng, and AbdenourHadid. "OULU-NPU: A mobile face presentation attack database with real-world variations." In Automatic Face & Gesture Recognition (FG 2017), 2017 12th IEEE International Conference on, pp. 612-618. IEEE, 2017.

[15] Huang, Ke-Kun, Dao-Qing Dai, Chuan-Xian Ren, and Zhao-Rong Lai. "Learning kernel extended dictionary for face recognition." IEEE transactions on neural networks and learning systems 28, no. 5 (2017): 1082-1094.

[16] Liu, Xin, MeinaKan, Wanglong Wu, Shiguang Shan, and Xilin Chen. "VIPLFaceNet: an open source deep face recognition SDK." Frontiers of Computer Science 11, no. 2 (2017): 208-218.

[17] Ding, Changxing, and Dacheng Tao. "Pose-invariant face recognition with homography-based normalization." Pattern Recognition 66 (2017): 144-152.

[18] Ranjan, Rajeev, Vishal M. Patel, and Rama Chellappa. "Hyperface: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition." IEEE Transactions on Pattern Analysis and Machine Intelligence (2017).

[19] Gatto, Bernardo Bentes, Lincon Sales de Souza, and Eulanda M. Dos Santos. "A deep network model based on subspaces: A novel approach for image classification." Machine Vision Applications (MVA), 2017 Fifteenth IAPR International Conference on. IEEE, 2017.

[20] Witham, Claire L. "Automated face recognition of rhesus macaques." Journal of neuroscience methods (2017)-Elsevier.

 DOI : 10.35291/2454-9150.2021.0198 

ISSN : 2454-9150 Vol-07, Issue-02, MAY 2021


[21] Jackson, A. S., Bulat, A., Argyriou, V., &Tzimiropoulos, G. (2017, October). Large pose 3D face reconstruction from a single image via direct volumetric CNN regression. In Computer Vision (ICCV), 2017 IEEE International Conference on (pp. 1031-1039). IEEE.

[22] Zhang, Wei, Xiaodong Yu, and Xuanyu He. "Learning bidirectional temporal cues for video-based person re-identification." IEEE Transactions on Circuits and Systems for Video Technology (2017).

[23] Wang, Haijun, and HongjuanGe. "Object tracking via inverse sparse representation and convolutional networks." Optik-International Journal for Light and Electron Optics 138 (2017): 68-79.

[24] Ning, Guanghan, Zhi Zhang, and Zhiquan He. "Knowledge-Guided Deep Fractal Neural Networks for Human Pose Estimation." IEEE Transactions on Multimedia (2017).

[25] Sun, Wenyun, Haitao Zhao, and Zhong Jin. "An efficient unconstrained facial expression recognition algorithm based on Stack Binarized Auto-encoders and Binarized Neural Networks." Neurocomputing 267 (2017): 385-395.

[26] Zhu, Xiangyu, Zhen Lei, and Stan Z. Li. "Face Alignment In Full Pose Range: A 3D Total Solution." IEEE Transactions on Pattern Analysis and Machine Intelligence (2017).

[27] Wang, Nannan, XinboGao, Leiyu Sun, and Jie Li. "Anchored neighborhood index for face sketch synthesis." IEEE Transactions on Circuits and Systems for Video Technology (2017).

[28] Li, Billy YL, Ajmal S. Mian, Wanquan Liu, and Aneesh Krishna. "Face recognition based on Kinect." Pattern Analysis and Applications 19, no. 4 (2016): 977-987.

[29] Liao, Shengcai, Anil K. Jain, and Stan Z. Li. "A fast and accurate unconstrained face detector." IEEE transactions on pattern analysis and machine intelligence 38, no. 2 (2016): 211-223.

[30] Chen, Jun-Cheng, Vishal M. Patel, and Rama Chellappa. "Unconstrained face verification using deep cnn features." In Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on, pp. 1-9. IEEE, 2016.

[31] Haghighat, Mohammad, Mohamed Abdel-Mottaleb, and WadeeAlhalabi. "Fully automatic face normalization and single sample face recognition in unconstrained environments." Expert Systems with Applications 47 (2016): 23-34.

[32] Huang, Dong, Ricardo Cabral, and Fernando De la Torre. "Robust regression." IEEE transactions on pattern analysis and machine intelligence 38, no. 2 (2016): 363-375.

[33] He, Ran, YinghaoCai, Tieniu Tan, and Larry Davis. "Learning predictable binary codes for face indexing." Pattern Recognition 48, no. 10 (2015): 3160-3168.

[34] Moeini, Ali, HosseinMoeini, and KarimFaez. "Unrestricted pose-invariant face recognition by sparse dictionary matrix." Image and Vision Computing 36 (2015): 9-22.

[35] Rahman, SM Mahbubur, ShahanaParvinLata, and TamannaHowlader. "Bayesian face recognition using 2D Gaussian-Hermite moments." EURASIP Journal on Image and Video Processing 2015, no. 1 (2015): 35.

[36] Timothy F. Cootes, Gareth J. Edwards, and Christopher J. Taylor, “Active Appearance Models”, IEEE Transactions on Pattern Analysis And Machine Intelligence, Vol. 23, No. 6, June 2001.

[37] T. F. Cootes, C. J. Taylor, D. H. Cooper and J. Graham, “Active Shape Models: Their Training and Application” Computer Vision and Image Understanding, Vol. 61, No. 1, p.p. 38-59, 1995.

[38] Sarode, Jagdish P., and Alwin D. Anuse. "Face recognition under pose variations." Int. J. Comput. Sci. Inf. Technol 5.3 (2014): 2689-2693.

[39] Lei, Yinjie, Mohammed Bennamoun, and Amar A. El-Sallam. "An efficient 3D face recognition approach based on the fusion of novel local low-level features." Pattern Recognition 46.1 (2013): 24-37.

[40] Tie, Yun, and Ling Guan. "Automatic landmark point detection and tracking for human facial expressions." EURASIP Journal on Image and Video Processing 2013, no. 1 (2013): 8.

[41] Sharma, Poonam, K. V. Arya, and Ram N. Yadav. "Efficient face recognition using wavelet-based generalized neural network." Signal Processing 93.6 (2013): 1557-1565.

[42] Naseem, Imran, Roberto Togneri, and Mohammed Bennamoun. "Robust regression for face recognition." Pattern Recognition 45.1 (2012): 104-118.

[43] Ekenel, Hazım Kemal, Johannes Stallkamp, and Rainer Stiefelhagen. "A video-based door monitoring system using local appearance-based face models." Computer Vision and Image Understanding 114.5 (2010): 596-608.

[44] Ku, Zhi Kai, CheeFei Ng, and Siak Wang Khor. "Shape-based recognition and classification for common objects-an application in video scene analysis." Computer Engineering and Technology (ICCET), 2010 2nd International Conference on. Vol. 3. IEEE, 2010.

[45] K.C. Lee and J. Ho and M.H. Yang and D. Kriegman", "Video-Based Face Recognition Using Probabilistic Appearance Manifolds", IEEE Conf. On Computer Vision and Pattern Recognition", Vol.1 pp.313-320, 2003.


 DOI : 10.35291/2454-9150.2021.0198 