ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Face Recognition Techniques: A Survey

Vishnu Ganesh Phaniharam[1], Bagadi Ravikiran[2], Tusar Kanti Mishra[3]

M. Tech Student, Dept. of C.S.E, ANITS, Visakhapatnam, India[1]

Senior Assistant Professor, Dept. of C.S.E, ANITS, Visakhapatnam, India[2]

Associate Professor, Dept. of C.S.E, ANITS, Visakhapatnam, India[3]

ABSTRACT: This paper presents a review on various facial recognition techniques which exists in today's world and summarizing the differences between them. Searching for robust descriptors has been an important research in computer vision.On a particular database, the accuracy of these facial recognition techniques differs from one algorithm to another. So, the researchers are in a dilemma to use which of these facial descriptors to get the desired results. Hence, I present the list of facial descriptors such as Eigen faces, Fisher faces,Gradient faces, Local Binary Patterns(LBP), Binary Gradient Patterns(BGP) and their corresponding accuracies on different facial databases. These facial descriptors uses different methods to perform facial recognition such as Principal component analysis(PCA), Image gradient orientation, Local binary patterns, Histogram of oriented gradients(HOG). Through this paper, I present a brief explanation of these facial descriptor algorithms and their performances on AT&T database.

KEYWORDS: Local binary patterns(LBP), Principal component analysis(PCA), Histogram of oriented gradients(HOG).

I. INTRODUCTION

Face recognition is a process of identifying a person's face in a digital image or a video. It mainly works on the principle of object recognition, i.e.., where a system can recognize and discriminate between different objects, it has been trained to recognize. It uses computer vision and machine learning to its maximum advantage. It is one of the most active topics in Image processing and Object recognition. Object recognition is a sub discipline of pattern recognition. Face recognition has many applications out of which commonly used are video surveillance, to match the faces in the footage to the existing facial database. It also used as biometric passwords in smart phones as fingerprint passwords used. Recently, it is used in social networking sites to tag the pictures of people automatically. There are a lot of challenges in facial recognition such as illumination, Variations in facial expression, angle between face and camera, wearing glasses, changing facial hair and hairstyles, Noise and Occlusion.

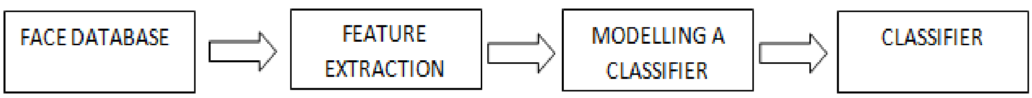

Figure1. Training a face recognition classifier.

To recognize a face, we need to train a system to extract feature of human faces from a facial database and draw conclusions from that database. From theseconclusions, one need to model the classifier which discriminate the facial features to other features.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Figure2. A typical face recognition system.

After training the model, if we pass an input frame then the face is detected by cropping the other portion of photo than that of the face. Then the face is registered and the features of the particular face are extracted and it is matched against the faces in the face database. If the features of the registered face are matched with any of the faces in the database, then we can assure that both faces be owned by the same person. This is how facial recognition process works.

II. LITERATURE SURVEY

Face recognition has lot of applications in various disciplines such as Law enforcement, Entertainment, Smart cards, Information security etc. In law enforcement, it used to track suspects using CCTV control. In Entertainment, it is used for human-robot interaction. In Smart cards, it is used in the process voter registration and driving license. So, a key solution lies in facial representation but a great deal of effort is needed. Deep learning mechanisms helps in building well defined, discriminative facial descriptors, which still plays a dominant role in face recognition applications. Searching for robust descriptors has been an important research in computer vision. A list of past adopted approaches is being discussed here. Eigen faces and Fisher faces are facial descriptors where faces are represented by pixel intensities. They are proposed using linear PCA and have been enhanced by nonlinear PCA. But they are sensitive to Illumination, Variation, Noise and occlusion. Gradient face is a novel descriptor which uses IGO [image gradient orientation] instead of pixel intensities to achieve strong invariance to illumination. But they are sensitive to Local deformation, Rotation, Spatial scale, thus prone to facial expression and poses. Gabor wavelets descriptor extracts micro textual details, fusing these local features can provide global shape information, making it robust to local distortions. It is inefficient to real time applications. Local Binary Patterns (LBP) features are simple and efficient and provide good invariance to illumination. It is limited by extreme lighting. BGP uses features of both IGO domain and LBP, presents a new local facial descriptor. It measures relationships between local pixels in the image gradient domain and encodes the local structures into set of binary strings. Local features extracted by BGP shows stronger orientational power than LBP and Gabor descriptors. It increases discriminative power, simplifies Computational capacity and Scale selectivity.

Table1. Applications of Face Recognition.

Area	Application
Law enforcement	CCTV control, suspect tracking
Entertainment	Human-robot interaction
Smart cards	Voter registration, driver license
Information security	Smart phone login, Secure trading terminals

III. FACE RECOGNITION TECHNIQUES

A. Eigenfaces and Fisherfaces: The aim is to represent a face image as a linear combination of a set of eigenvectors, given training set of ‘M’ images and an unknown face, all of same size. These Eigen faces (eigenvectors) are in fact the principal components of the training set of face images generated after reducing the dimensionality of the training set. To reduce the dimensionality of the training dataset, it uses a method called PCA. PCA is proposed by KarlPearson in 1901. It is mostly used tool in exploratory data analysis and for making predictive models(example: face recognition). PCA is used to reveal internal structure of data by explaining the variance in data. In Eigen faces, the principal component is referred to Eigen face, data point or variable is referred to image and dataset is referred to training set of

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

images. PCA is mathematical procedure that uses orthogonal transformation to convert a set of M face images into a set of K uncorrelated variables called Eigen faces. PCA does not work directly on images; it first converts them to matrix(vector) form. The number of Eigen faces is always less than or equal to the number of original images, i.e.., K<M[8,9, 10].

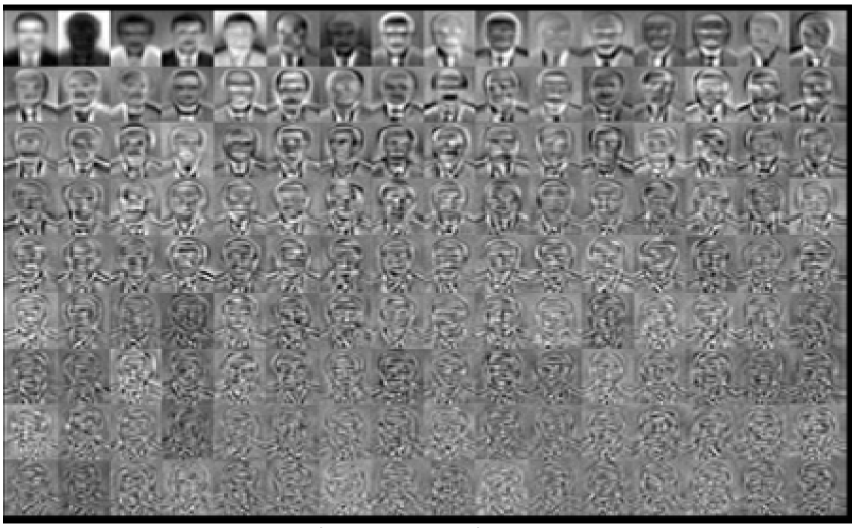

Figure3. Selection of eigenvectors from a training dataset [4].

This transformation is defined in such a way that the first Eigen face shows the most dominant "feature" of the training set of images. And each succeeding Eigen face in turn shows the next most possible dominant "feature", under the condition that the faces are uncorrelated. To reduce the calculations needed for finding these Eigen faces, the dimensionality of the original training set is reduced before they are calculated. Since Eigen faces show the features in the training dataset and each proceeding Eigen face shows less features and more noise. Only few first Eigen faces (K) are selected whereas the rest of the last Eigen faces are discarded. These K Eigen faces can safely represent the whole training dataset because they depict the major features that make up the entire dataset. Therefore, each image in the original training set can be represented in terms of these K Eigen faces. Representing an image this way reduces the number of values needed to recognize it from M to K. This makes the face recognition process faster and free of 'error caused by noise'. PCA can be done by eigenvalue decomposition of a data covariance matrix. The results of a PCA are usually discussed in terms of Eigen face weights(Eigen face proportions) and weight vectors(the weight by which each image in K should be multiplied to get Eigen face proportions)[10,11].When an unknown face comes for recognition, it is also represented in terms of the selected Eigen faces. The Eigen faces representation of unknown face is compared with that of each training set face image. The distance between them is calculated. If the distance is above a specific threshold, then recognize the unknown face of that person otherwise the face of recognized person is displayed[11,12].The only difference between Eigen faces and fisher faces is the process of reducing the dimensionality of training dataset. Eigen faces uses PCA, where fisher faces uses linear discriminant analysis. The linear discriminants obtained on a training datasetare called fisher faces. LDA is used to reduce a dimensionality of dataset with good class separability. Although these two algorithms used for facial recognition, they have their own limitations in illumination, variation, noise and occlusion.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Table2. Comparison of previous works on Eigen faces and Fisher faces.

S.no.	Author	Title	Advantages	Limitations
1.	Rajib saha et al.	Face Recognition using Eigen faces	Extracts useful features by reducing the dimensionality [8].	Prone to other facial poses[8].
2.	Magali segal et al.	Recognition using class specific linear projection	Best in handling variation in lighting and expressions [9].	Prone to variation in facial expression [9].
3.	M. Turk et al.	Eigen faces for Face Recognition	Gives good results in orientation variation [10].	Prone to variation in sizes[10].
4.	Marijea Slavkvic et al.	Face Recognition Using Eigen face Approach	Provides better dimensionality reduction [11].	Prone to variation in illumination [11].
5.	Pentland et al.	Eigen faces and Eigen modules	Gives modular Eigen faces [12].	Prone to variation in orientation [12].
6.	Peter N. Belhumeur et al.	Eigen faces vs. Fisher faces: Recognition Using Class Specific Linear Projection	Insensitive to large variation in lighting direction and facial expression [22].	Prone to cluttered backgrounds [22].
7.	Xiaofei He et al.	Face Recognition Using Laplacianfaces	Preserves the local structure of the image space [23].	It does not deal with biometric characteristics [23].
8.	Alex Pentland et al.	View-Based and Modular Eigen spaces for Face Recognition	Use in face recognition under variable pose [24].	Insensitive to substantial variations in light direction[24].
9.	Ming – hsuan yung et al.	Kernel fisher faces vs Eigen faces: face recognition using kernel methods	Use higher order statistical relationships among the pixels for facial recognition [25].	Insensitive to substantial variations in face pose [25].
10.	Keun-ChangKwak et al.	Face recognition using a fuzzy fisher face classifier	Reduced sensitivity to variations in illumination and viewing directions [26].	Prone to cluttered backgrounds [26].

B. Gradient faces and Histogram of gradient faces: To reduce the illumination problem in facial recognition systems, a new facial descriptor called gradient face is proposed. It uses image gradient orientation (IGO) instead of pixel intensities to achieve strong invariance to illumination. The directional change in the intensity or color of an image is called as image gradient, which is used to extract information from the image. This IGO used to detect edges of a particular image.This HOG descriptor is used to obtain facial features by the distribution of image gradients on the image. Here the image is divided into small connected regions called cells and a histogram of image gradients for pixels within the cell is calculated. Combining these cells of the particular image together forms a facial descriptor. To improve the accuracy, we can divide the larger portion of the image into blocks, in which in turn we can divide them into cells. This process is called 'Normalization', which results in better invariance in illumination and shadowing. These algorithms are sensitive to Local deformation, Rotation, Spatial scale, thus prone to facial expression and poses.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Table3. Comparison of previous works on Gradient faces and Histogram of gradient faces.

S.no.	Author	Title	Advantages	Limitations
1.	M. Ishiwaka et al.	Selection of Histograms of Oriented Gradients Features for Pedestrian Detection	Classifies the given input into pedestrian/ Non -pedestrian [4].	Fails to differ between human like animals such as bear etc.., [4].
2.	N. Dalal et al.	Histograms of Oriented Gradients for Human Detection	Provides better invariance to illumination and Shadowing [13].	Prone to cluttered backgrounds [13].
3.	Chandrasekhar et al.	CHoG: Compressed Histogram of Gradients - A low bit rate feature descriptor	Provides robust object discrimination [14].	Prone to wide range of poses[14].
4.	Stanley Bileschi et al.	Image representations beyond histograms of gradients: The role of Gestalt descriptors	Improves accuracy of object detection by using Gestalt descriptors [15].	Prone to noisy databases[15].
5.	O. Deniz et al.	Face recognition using Histograms of Oriented Gradients	Provides invariance to occlusions, pose and illumination changes [27].	Prone to variation in discrimination [27].
6.	Qiang Zhu et al.	Fast Human Detection Using a Cascade of Histograms of Oriented Gradients	Provides features to achieve fast and accurate human detection system [28].	Sensitive to local deformation [28].
7.	Tomoki Watanabe et al.	Co-occurrence Histograms of Oriented Gradients for Pedestrian Detection	Used to detect pedestrians from images [29].	Prone to differentiation between humans and animals [29].
8.	F. Suard et al.	Pedestrian Detection using Infrared images and Histograms of Oriented Gradients	Used for pedestrian detection applied to infrared images [30].	Prone to spatial scale [30].
9.	Xiaodong Yang et al.	Recognizing actions using depth motion maps-based histograms of oriented gradients	Used to recognize human actions from sequences of depth maps [31].	Prone to variations in facial occlusion [31].
10.	Alexander Klaser et al.	A Spatio-Temporal Descriptor Based on 3D-Gradients	Presents a novel local descriptor for video sequences [32].	Prone to cluttered backgrounds [32].

C. Local binary patterns:LBP is a visual descriptor which is described in 1994. It classifies the image or pixels of the images using the texture classification. It is proved that when we combine Local binary patterns with HOG, we can assure high accuracy in face recognition. In LBP, an image is divided into cells. For each pixel in a cell, compare the pixel value to its 8 neighboring pixels in clockwise or anti-clockwise. When the center pixel value is greater than the neighboring pixel, write the value as"0", otherwise write the value as"1". This pattern gives us a 8-digit binary number. Now, compute the histogram of these values and normalize it. Combining the all normalized values of all cells gives us the facial features of the image [7].

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Table4. Comparison of previous works on Local Binary Patterns and Binary Gradient Patterns.

S.no.	Author	Title	Advantages	Limitations
1.	Md. Abdur Rahim et al.	Face Recognition using Local Binary Patterns (LBP)	Provides similarity measure between images [16].	Prone to facial occlusions [16].
2.	Timo Ahonen et al.	Face Description with Local Binary Patterns: Application to Face Recognition	Provides robustness against face localization error [17].	Prone to pose and lighting variations [17].
3.	Timo Ojala et al.	Multiresolution Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns	Provides very powerful tool for rotation invariant texture analysis [18].	Prone to expression and age variations [18].
4.	Marko Heikkila et al.	Description of Interest Regions with Local Binary Patterns	Very robust to occlusion and illumination changes [19].	Prone to extreme lighting [19].
5.	Weilin Huang et al.	Robust face recognition with structural binary gradient patterns.	Provides invariance against both illumination and local distortions. [1].	Yet to use in real-time applications [1].
6.	Semin kim et al.	Image based coin recognition using rotation invariant region binary patterns based on gradient magnitudes	Provides robustness against rotation and has high accuracies for image based coin recognition [20].	Prone to variation in size of the objects [20].
7.	Ning jiang et al.	Gradient local binary patterns for human detection	Provides feature possible for human detection [21].	Window size used here is fixed [21].
8.	Guoying zhao et al.	Dynamic Texture Recognition Using Local Binary Patterns with an Application to Facial Expressions	It provides local processing, robustness to monotonic gray-scale changes [33].	Limited by extra lighting [33].
9.	Shengcai Liao et al.	Learning Multi-scale Block Local Binary Patterns for Face Recognition	Provides Multi-scale Block Local Binary Pattern [34].	Prone to lighting variations [34].
10.	Caifeng shan et al.	Robust facial expression recognition using local binary patterns	Used in real-world applications where only low-resolution video input is available [35].	Prone to local deformation [35].

D. Binary gradient patterns:BGP uses features of both IGO domain and LBP [1], presents a new local facial descriptor**.**It measures relationships between local pixels in the image gradient domain and encodes the local structures into set of binary strings. Local features extracted by BGP shows stronger orientation power than LBP and Gabor descriptors. It increases discriminative powerby simplifying computational capacity [1].BGP is implemented in 3 steps. Computing image gradient from multiple directions is the first step. Encoding them into binary strings is the second step. Division of structural and non-structural patterns is the final step [1].

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

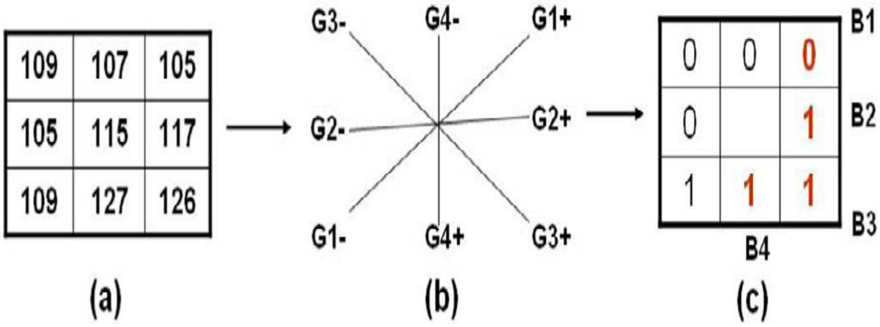

Figure4. Steps of BGP [1].

The basic BGP descriptor is computed from four directions in a square neighbourhood of side length of two units.Similar to LBP-based descriptors, the capability of BGP can be further improved by increasing the number of gradient directions and by enlarging the neighbourhood.It can be seen that certain labels have meaningful structures where four bits of "1"are located consecutively .These are called "structural BGPs".

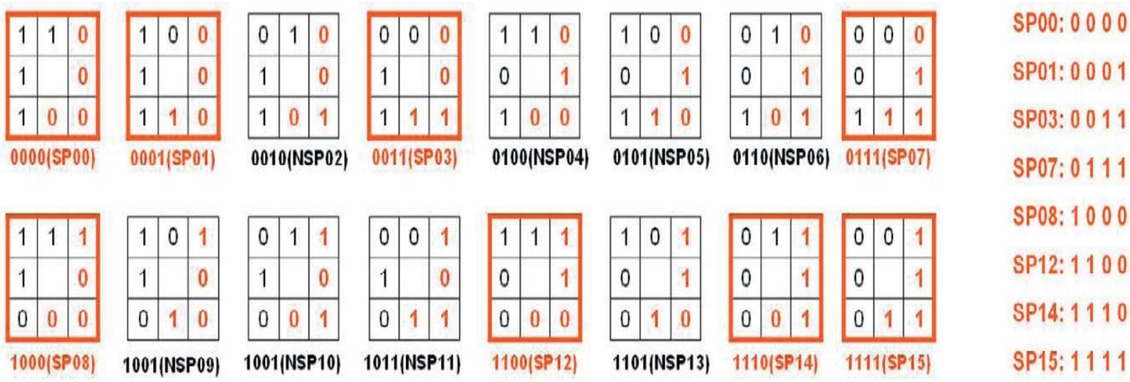

Figure5. Division of structural and non-structural patterns[1].

Table5. Corresponding accuracies of above algorithms on different facial databases.

S.no	ALGORITHM	DATABASE	No. of training samples	ACCURACY
1.	Eigen faces [2]	AT&T	225	88%
2.	Fisher faces [2]	AT&T	210	85%
3.	Gradient faces [3]	AT&T	150	86%
4.	Local binary patterns [1]	AR	100	89%
5.	Binary Gradient patterns [1]	AR	100	93%

IV. CONCLUSION

Through this paper, we have made an attempt to present the review of several papers on facial recognition. Present study reveals that the facial recognition algorithms such as Eigen faces, fisher faces are sensitive to variation, illumination, noise and occlusion. The binary gradient faces facial descriptor has significantly improvements over other algorithms such as discrimination, robustness and complexity. So, it has higher accuracy over other algorithms. We regret to other research analysts whose vital benefactions may have been overlooked.

REFERENCES

1.W. Huang, H.Yin, Robust facial recognition with structural binary pattern, ELSEVIER, Pattern Recognition 68 (2017) 126–140.
2. P. N. Belhumeur, J. P. Hespanha, D. J. Kriegman, Eigen faces vs. fisher faces: Recognition using class specific Linear projection, IEEE Trans. Pattern Anal. Mach. Intel. 19 (1997).
3. T. Zhang, Y. Y. Tang, B. Fang, Z. Shang, X. Liu, Face recognition under varying illumination using gradient faces,IEEETrans. On Image Processing 18 (2009).
4.M. Ishikawa et al. (Eds.): ICONIP 2007, Part II, LNCS 4985, pp. 598–607, 2008.
5. Mathew Turk And Alex Pentland, "Eigen Faces For Recognition"; Journal Of Cognitive Neuroscience Vol.3, No.1,pp.71-86, 1991.
6. B. Zhang, Y. Gao, S. Zhao, J. Liu, Local derivative patternversus local binary pattern: Face recognition withhigh-Orderlocal pattern descriptor, IEEE Trans. on Image Processing 19(2010) 533.
7. H. V. Nguyen, L. Bai, L. Shen, Local Gabor binary pattern whitened pca: A novel approach for facerecognition from singleimage per person, in: Advances in Biometrics, 2009, pp. 269.
8. Rajibsaha et al. face recognition using Eigen faces, www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 5, May 2013).
9.MagaliSegal et al. Recognition Using Class Specific Linear Projection, April 2015.
10. M.Turk and A. Pentland, "Eigen faces for Recognition", Journal of Cognitive Neuroscience, vol.3, no. 1, pp. 71- 86, 1991.
11.MarijetaSlavković, Face Recognition Using Eigen face Approach, SERBIAN JOURNAL OF ELECTRICAL ENGINEERING Vol. 9, No. 1, February 2012, 121-130.
12. Pentland et al. Eigen faces and Eigen modules, 1994.
13.NavneetDalal, Bill Triggs. Histograms of Oriented Gradients for Human Detection. Cordelia Schmid and Stefano Soatto and Carlo Tomasi. International Conference on Computer Vision & Pattern Recognition(CVPR '05), Jun 2005, San Diego, United States. IEEE Computer Society, 1, pp.886.
14. Chandrasekhar et al. CHoG: Compressed Histogram of Gradients - A low bit rate feature descriptor,CVPR 2009.
15. Stanley Bileschi, Lior Wolf Image representations beyond histograms of gradients: The role of Gestalt descriptors.
16. Md. Abdur Rahim, Md. Najmul Hossain, Tanzilla Wahid & Md. ShafiulAzam,Face Recognition using Local Binary Patterns (LBP), By Global Journal of Computer Science and Technology Graphics &Vision Volume 13 Issue 4 Version 1.0 Year 2013 Type: Double Blind Peer Reviewed International Research Journal Publisher: Global Journals Inc. (USA) Online ISSN: 0975-4172 & Print ISSN: 0975-4350.
17. T. Ahonen, A. Hadid, and M. Pietikainen are with the Machine Vision Group, Infotech Oulu, Department of Electrical and Information Engineering, University of Oulu, PO Box 4500, FIN-90014, Finland.
18. TimoOjala, MattiPietikäinen and TopiMäenpää Multiresolution Gray Scale and Rotation InvariantTexture Classification with Local Binary Patterns, Ref: TPAMI.
19. Marko Heikkila, MattiPietikainen , Cordelia Schmid, Description of Interest Regions with LocalBinary Patterns, ELSEVIER, 30 June 2008.
20. Seminkim et al. Image based coin recognition using rotation invariant region binary patterns based ongradient magnitudes, journal of visual communication and image representation, volume 32, oct 2015,pages 217-223.
21. Ning jiang, jiuxu, wenxinyu, satoshigoto, gradient local binary patterns for human detection, IEEE ISCAS 2013, Pages 978 – 981.
22. Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 19, NO. 7, JULY 1997.
23. Xiaofei He, Shuicheng Yan, Yuxiaou,ParthaNiyogi, Hong-Jiang Zhang Face Recognition Using Laplacianfaces, IEEE Trans. on PATTERN ANALYSIS AND MACHINE INTELLIGENCE, MARCH 2005.
24. Alex Pentland, BabackMoghaddam, Thad Starner, View-Based and Modular Eigenspaces for Face RecognitionIEEEConference on Computer Vision & Pattern Recognition, 1994.
25. Ming – hsuanyung ,Kernel fisher faces vs Eigen faces: face recognition using kernel methods, , fifth IEEE conference on automatic face and gesture recognition.
26. Keun-ChangKwak , Face recognition using a fuzzy fisherface classifier, Pattern Recognition Volume 38,Issue 10, October 2005, Pages 1717-1732.
27. O. Déniz , G. Bueno , J. Salido, F. De la Torre ,Face recognition using Histograms of Oriented Gradients, ,Pattern Recognition Letters 32 (2011) 1598–1603.
28. Qiang Zhu, Shai Avidan, Mei-Chen Yeh, Kwang-Ting Cheng Fast Human Detection Using a Cascade of Histograms of Oriented Gradients IEEE Computer Society Conference on Computer Vision andPattern Recognition,TR2006-068 June 2006.
29. Tomoki Watanabe, Satoshi Ito, Kentaro Yokoi,Co-occurrence Histograms of Oriented Gradients for Pedestrian Detection, PSIVT 2009: Advances in Image and Video Technology pp 37-47.
30. F. Suard, A. Rakotomamonjy , A. Bensrhair, A. Broggi, Pedestrian Detection using Infrared images and Histogramsof Oriented Gradients, Intelligent Vehicles Symposium, 2006 IEEE, Print ISSN: 1931-0587.
31. Xiaodong Yang et al. Recognizing actions using depth motion maps-based histograms of oriented gradients, Proceedings of the 20th ACM international conference on Multimedia, Pages 1057-1060.
32. Alexander Klaser et al. A Spatio-Temporal Descriptor Based on 3D-Gradients, BMVC 2008 - 19th British MachineVision Conference, Sep 2008, Leeds, United Kingdom. British Machine Vision Association, pp.275:1- 10, 2008.
33.Guoyingzhao, Dynamic Texture Recognition Using Local Binary Patterns with an Application to Facial

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 7, July 2017

Expressions, IEEE Transactions on Pattern Analysis and Machine Intelligence (Volume: 29, Issue: 6,June 2007), Page(s): 915 – 928.
34. Shengcai Liao, Xiangxin Zhu, Zhen LeiL, unZhangStan Z. Li, Learning Multi-scale Block Local Binary Patterns for Face Recognition, S.-W. Lee and S.Z. Li (Eds.): ICB 2007, LNCS 4642, pp. 828–837, 2007, Springer-Verlag Berlin Heidelberg 2007.
35. Caifengshan et al. Robust facial expression recognition using local binary patterns,.ICIP , IEEE International Conference on Image Processing, 2005.

BIOGRAPHY

Vishnu Ganesh Phaniharam is a M. Tech student in the department of computer science and engineering, ANITS, Visakhapatnam. His research interests are data mining, image processing, IOT etc.

Bagadi Ravikiranis a senior assistant professor in the department of computer science and engineering, ANITS, Visakhapatnam. He is life member of CSI and a member of IEEE. He published several papers in international journals. He has 12 years of experience in teaching and research. His research interest is image processing.

Dr. Tusar Kanti Mishra is an associate professor in the department of computer science and engineering, ANITS, Visakhapatnam. He has 13 years of experience in teaching and research. He published several papers in international journals.Hisresearch interests are pattern Recognition, Image processing, Computational intelligence, Machine learning, Optical character recognition etc.