IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727,
PP 17-23
www.iosrjournals.org

Composite Feature Extraction based on Gabor and Zernike Moments for Face Recognition

D. N. Satange[1], Akram Alsubari[2], R. J. Ramteke[2]
[1]*(Department of Computer Science, Arts Commerce and Science College Kirannagar Amravati, India)*
[2]*(School of Computer Sciences / North Maharashtra University, India)*

Abstract: *This paper presents the experimental evaluation of Gabor filter and Zernike moments for extracting the face features. The dimensionality of the input image is reduced for the overloading process of Gabor filters. 40 sub-images were obtained from the original images by using the Gabor filters in 5 scales and 8 orientations. From each sub-image, four Zernike features were extracted. Thus, the total numbers of features are 160. The k-Nearest Neighbor (k-NN) classifier is used for the matching purpose. The experiments were performed in the ORL and NC-Face database of Facial Expressions. The recognition rate in the ORL database is 98.5% and the rate in the NC-Face database of Facial Expression is 89.23%. In the proposed system, the performance was found to be satisfactory as compared to the existing system.*

Keywords: *Facial Expression, Gabor filter, KNN, ORL, Zernike moments*

I. Introduction

Face is what a human being gets right from his birth. The facial features are considered to be the permanent identification marks. A man is known by his identification features such as the scar in the check, the distance between each part of face, texture features, etc., all these are considered as the face features. These characteristic features of the face are used even today in recording the identification features in the database. Therefore, the human face recognition has received substantial attention from researchers in biometrics, pattern recognition, and computer vision communities over the past few decades for solving the outstanding challenges which exist in the uncontrolled environment [1]. For recognizing the face, it does not require the cooperation of individual with the system. Therefore, it is an intuitive and nonintrusive method for recognizing people. The 2D face recognition systems still encounter difficulties in handling facial variations due to head poses, lighting conditions and facial expressions [2], which has introduced a large amount of intra-class variations. Range images are captured by a 3D sensor and it has contained the facial surface shape information. The 3D shape information does not change much, due to pose and lighting variations, which can change the corresponding intensity image significantly. The 3D face recognition has been demonstrated for enhancing the accuracy of recognition [3,4].

P. Yang, et al. [2] have presented the face recognition based on the Gabor features and 100 features were selected as a feature vector for each subject. Also, the researchers have proposed the AdaBoost Gabor feature for reducing the dimensional and the discriminant as well. Bouzalmat et al. [3] have convoluted the Fourier Transform and Gabor filter for generating the feature vectors, 40 Gabor filters were used for their experiment. Linlin [5] have extracted 200 Gabor features by using the boosting algorithm. Then, those features are combined with the Support Vector Machine (SVM) for building a two-class. Chandan Singh et al. [6] have combined the global and local feature of the face. The global features were extracted by using the Zernike moments. The local features are extracted from the histogram-base by using the Weber Law Descriptor (WLD). Karim Faez et al. [7] have presented the performance comparison of three feature extraction techniques: Zernike moment, Pseudo-Zernike moment and Legendre moment. The authors concluded from their comparison, the Legendre moment is obtained a better result as compare with Zernike moment and Pseudo-Zernike moment. Sarode et al [8] have used the Zernike moment for extracting the face features and genetic algorithms for selecting the best feature. H. Ouanan et al. [9] presented a framework to combine Gabor filter, Zernike moment and random projection for dimensionality reduction with SVM classifier. In the previous work, we have implement the Discrete Wavelet Transform and Local Binary Pattern [27] for extracting the face features.

The rest of the paper is organized as follows. The second section introduced the proposed method. Where section three is the databases description. The experiment and result are shown in section four. Finally, the conclusion is presented in section five.

II. Proposed method

The proposed methodology is employed to extract the face features from the Gabor filters and Zernike moments. The length of feature vector is 160 which are sufficient for the face recognition. The proposed system has four stages: preprocessing, Gabor filtered images, applying Zernike moment and classification using KNN. Fig.1 has Shown the proposed methodology and the detail description in the following sections.

1. Preprocessing

In this stage, image is preprocessed before the feature extraction and classification. Here size reduction, Gabor filter setting and to form a Gabor-filtered images for the feature extraction. In this method, the images are sets to equal size of rows and column as 32×32, 64×64, 128×128.

2. Gabor Filter

Gabor filters are generally used in texture analysis, edge detection, feature extraction, etc. Gabor filters are classes of special band pass filters. The equation given below gives Gabor filters.

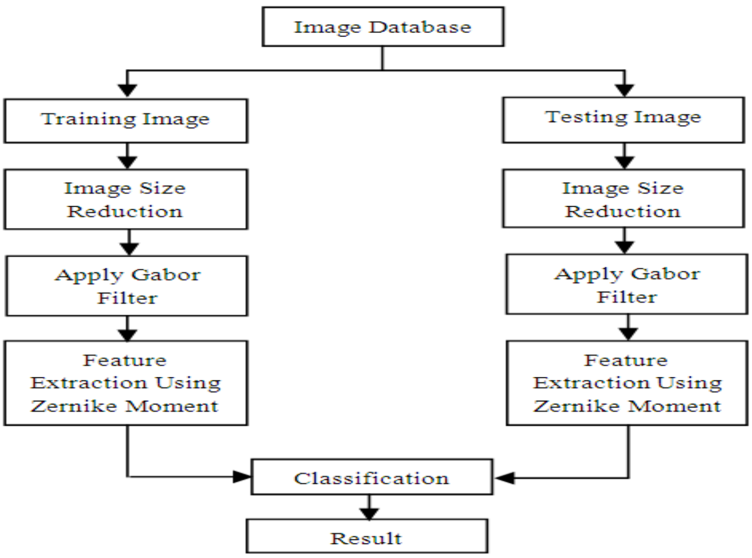


Fig 1. The Proposed Method(Gabor-Zernike)

$$G(x,y,\theta,\lambda,\varphi,\sigma,\gamma) = e^{-\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} e^{i\left(2\pi\frac{x'}{\lambda}+\emptyset\right)} \quad (1)$$

Where $x' = xcos(\theta) + ysin(\theta)$

$y' = -xsin(\theta) + ycos(\theta)$

θ = Orientation of the wavelet.

$\lambda =$ Wavelength or frequency of the wavelet.

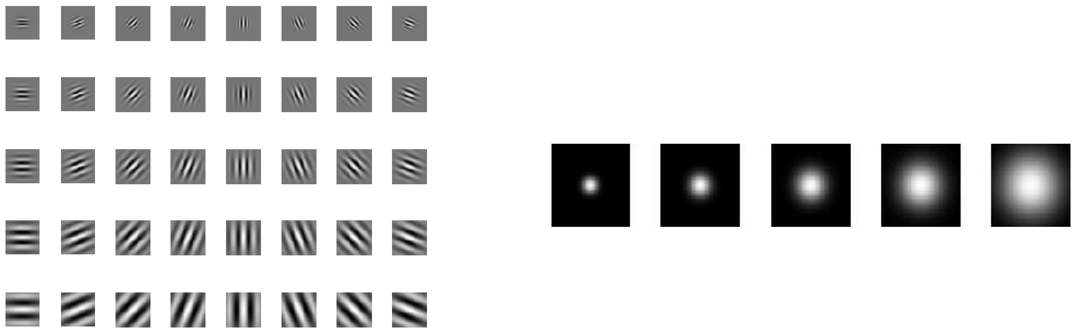
φ = Phase, σ = Radius of the Gaussian (Scale).

γ = Aspect ratio of the Gaussian.

$e^{-\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)}$ is the Gauss function. Where, x and y are the range of values for the length and breadth of the Gabor mask. Gabor filter is then convolving to the image to form the Gabor filtered images as.

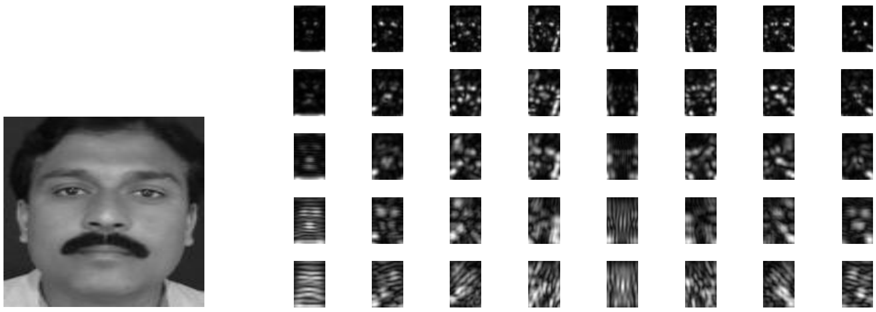
$$f(x,y) = I(x,y) \times G(x,y) \quad (2)$$

i.e., they allow a certain 'band' of frequencies and reject the others. When a Gabor filter is applied to an image, it gives the highest response at edges and at points, where the texture features are changing. A filter responds to a particular feature, means that the filter has a distinguishing value at the spatial location of that feature. When we apply convolution kernels in spatial domain, that is, the same holds for other domains, such as frequency domains. The important advantages of Gabor filter are the invariance to illumination, rotation, translation and scale.



(a) (b)

Fig 2. (a) Real part of the Gabor Filters of the Filter Bank (b) Magnitude part of the Gabor Filters of the Filter Bank



(a) (b)

Fig 3. (a) Sample Face Image [11], (b) Gabor Filter Response (Magnitude) images.

3. Zernike Moments

Zernike moments are mapping of an image on to a complex Zernike polynomial which is orthogonal to each other. Having some desirable properties such as robustness to rotation invariance and noise. The Zernike moments of order n with repetition m is obtained by the following equations:

$$Z_{nm} = \frac{n+1}{\pi}\sum_x \sum_y f(x,y)V_{nm}(x,y),$$
$$x^2 + y^2 \leq 1 \qquad (3)$$

Here is Zernike moment Z_{nm}on rotated image have the same magnitudes. Therefore, $|Z_{nm}|$can be used as the rotation invariance features. $V_{nm}(x,y)$ is a Zernike polynomial on a unit circle $x^2 + y^2 \leq 1$.

$$V_{nm(x,y)} = V_{nm}(\rho,\theta) = R_{nm}(\rho)\exp(jm\theta) \qquad (4)$$

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} (-1)^s \frac{(n-s)!}{s!\left(\frac{n-|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \qquad (5)$$

Where, n is a nonnegative integer which represents the order of Zernike moment and m represents the repetition. Satisfying the condition $n - m$ is Even and $|m| \leq n$. Also $\rho = \sqrt{x^2 + y^2}$ and $\theta = \tan^{-1}\frac{y}{x}$

4. Database

Face databases are categorized in various criteria such as pose, illumination, expression and occlusion as well as captured in different distances. There are many standard databases available online such as ORL, YALE, FERET, etc. But the ORL database was selected for testing the methodology and compare the result with the existing works.

4.1 ORL Database

The AT&T face image database (formerly known as the ORL database) contains a set of face images taken between April 1992 and April 1994 from 40 people [10]. There are 10 different images of each person taken at different times, illuminations, and facial expressions like open or closed eyes, smiling or not smiling and facial details like glasses. All the images have a dark homogeneous background and the subject is in an upright, frontal position. The size of each image is 92×112 pixels, with 256 grey levels per pixel.

4.2 NC-Face Database

The NC-Face (Narasamma College) database contains the static images of human face of Indian domain with number of Subject (Male, Female, Age) with Pose, illumination and different facial expression images such as happiness, sadness, anger, disgust, fear and surprise [11], using the high-resolution Sony camera. The collection is done with indoor (infrared) and outdoor using CCTV camera. The database contains 11040 static images of using digital Camera of 160 subjects. And 7200 images of using CCTV Camera of 144 subjects. Images from different quality cameras should mimic real-world conditions and enable robust face recognition algorithms testing. The facial expression database images collected in controlled condition, subject to giving information for various facial expressions such as neutral happiness, sadness, anger, contempt, fear and surprise. And one neutral expression and two images for each expression. Total 15 face images of the single subject for facial expressions. The total number of images in facial expression database is 2400. Fig.4. shows the images of expressions.

Fig 4. Facial Expression images of single subject of NC-Face

III. experiment and result analysis

The proposed system was tested on the standard database ORL, which is publicly available and mostly researcher prefer to test their methodologies on this database. So, the ORL database is more easy to compare the performance analysis of the proposed system. Then, the same methodology was tested on the local database of Indian domain NC-Face (Facial Expression database).

1. Zernike Moments Experimentation

In this experiment, the ORL Database is divided into 50% as training and 50% as testing. Also, set various orders of Zernike moment from order 1 to order 14 for evaluation with different image size 32X32, 64X64, 128X128. The recognition rate increased from Zernike moment order 1 to 6 and from order 7 to 14 was decreased, so Zernike moments of order 6 is achieved better result than the other orders using only 16 feature of single image for recognition. The recognition rates are 79%, 79%, 78% for image size 32X32, 64X64, 128X128 respectively. From the below Table.1., the input image has various dimensionalities (32×32, 64×64, 128×128) but the recognition rates are similar. When the image size is large, the execution time is increasing. Thus, 32×32 was selected for the further experiments.

Table 1. The Result of Zernike Moments on ORL Database

Zernike Orders	Total Features	Image Size 32×32	Image Size 64×64	Image Size 128×128
1	2	24.5	25.5	27
2	4	56	57.5	59
3	6	66	65.5	66
4	9	72.5	73	72.5
5	12	75	74.5	75.5
6	**16**	**79**	**79**	**78**
7	20	78	78.5	77
8	25	75	74.5	75
9	30	78.5	78.5	75
10	36	76	76	76
11	42	77.5	75.5	76
12	49	72.5	72.5	73
13	56	73	72.5	73.5
14	64	69	69.5	69.5

2. Gabor-Zernike Experimentation

In this experiment, 8 orientation and 5 scale of Gabor filters were used, which achieved the highest recognition rate. If the different combination of orientation and scale is used for evaluation the rate is reduced. Then the face image is divided into 40 sub-image by using the Gabor filter. For selecting different order and repetition of Zernike moments, applied on the 40 Gabor filter images, to form a Gabor Zernike feature. Here, the input image is 32×32 for minimizing the execution burden. The input face image is convolving to the 40 Gabor filters to form 40 Gabor filtered images, then applying the Zernike moment with combined order from 0 to 10 with all orientations, as shown in Table 2. If we combine the Zernike moment of orders from 0 to 4. Zernike moments have 9 features up to the order 4. So, 40 Gabor filtered images produce 360 Gabor-Zernike features, gives 97.5% as recognition rate, with 38.91 second recognition time. If Zernike moment order is increasing total Gabor-Zernike features is rapidly increasing, but recognition rate is still constant and further decreasing again. So, best result obtained using the less order of Zernike moments. In this paper, K-Nearest Neighbor (KNN) Classifier is used for evaluating the proposed Gabor-Zernike features. instead of all orders of Zernike moments, the lower order is concentrated and selecting the various combination of the Zernike moment of order and repetition.

The proper order and repetition of Zernike moments on Gabor filtered images, with combined features and Accuracy as shown in Table 3. Only 3 Zernike features were selected from each sub-image (8 orientation, 5 scale so, total 40 sub-images), the total number of features are 120 with 97% recognition rate. When 4 Zernike features were extracted from each sub-image, the recognition rate will be increasing up to 98.5% and 160 is the length of feature vector. Where, 5 Zernike features are decreased the recognition rate to 97.5%. Thus, the 4 Zernike features from each sub-image are achieved the better result. Also, only 3 images of training are sufficient for higher rate of recognition i.e. 96.7 %. Table 4. Shows as training and testing combination of images for recognition. Here training images 8 or 9 gives 100 % recognition.

Table 2. The Result of Gabor-Zernike Moments (Order and Repetition) on ORL Database

Order	**Zernike Features**	**Total Gabor-Zernike Features**	**Recognition rate**	**Recognition Time**
0	1	40	93	22.03
0-1	2	80	95	14
0-2	4	120	96	17.22
0-3	6	240	96.5	26.21
0-4	**9**	**360**	**97.5**	**38.91**
0-5	12	480	97.5	53.4
0-6	16	640	97.5	75.8
0-7	20	800	97.5	101
0-8	25	1000	97	132.74
0-9	30	1200	97	170
0-10	36	1440	96	211

Table 3. The Result of Gabor Zernike of Selected Zernike Moment (Order, Repetition) On ORL Database

Number of Zernike features	**Zernike Moment (order, repetition)**	**Total Features (Gabor + Zernike)**	**Accuracy (%)**
3	Z 0,0; Z2,0; Z 4,0	120	97%
3	Z 2,0; Z2,2; Z 4,0	120	97%
3	Z 1,1; Z2,2; Z 4,0	120	97%
3	Z 2,0; Z3,1; Z 4,0	120	97%
4	Z 1,1; Z2,0; Z 2,2; Z 3,1	160	97%
4	**Z 2,0; Z2,2; Z 3,1; Z 4,0**	**160**	**98.50%**
5	Z 0,0; Z2,0; Z 2,2; Z 3,1; Z 4,0	200	97.50%
5	Z 1,1; Z2,0; Z 2,2; Z 3,1 ; Z 4,0	200	97.50%

Table 4 The Recognition Rate and Execution Time of Various Training and Testing on the ORL Database

Train / Test images	**Recognition Rate**	**Execution Time In second (Training + Testing)**
1/9	77.44%	43.59
2/8	91.88%	44.35
3/7	**96.70%**	**43.96**
4/6	97.50%	44.44
5/5	**98.50%**	**46.44**
6/4	98.13%	43.83

7/3	97.50%	43.81
8/2	**100%**	**43.93**
9/1	**100%**	**43.65**

The proposed Gabor-Zernike method is applied on NC-Face database of facial expression database. 160 subjects in facial expression database and 15 images are acquired from each subject with a different expression. 6 images were used as training and 9 images as testing. The recognition rate in the facial expression is 89.44%. The result shown in Table 4.

Table 5. The Result of Proposed Method (Gabor-Zernike) on NC-Face Database and ORL Database

Database Portion	Training and Testing	Accuracy (%)
Expression	40% & 60%	**89.44 %**
ORL	50% & 50%	**98.5%**

The Table 6. Shows a comparison of various existing methodologies with recognition rate and used total features or dimensions. Combined features methods have better accuracy than the local and global feature method. Here Proposed combined method Gabor Zernike gives 98.5 % accuracy with minimum features.

Table 6. The Result of Proposed Method and Existing Method on ORL Database

Authors and Year	Feature type	Evaluation technique	Total Features	Recognition Rate
Huang et al. (2014) [12]	Local	LDP	36	91
Yu et al. (2014) [13]	Local	LBP	59	91
Ahonen et al. (2008) [14]	Local	LPQ	256	87.5
Junior et al. (2009) [15]	Local	HOG	81	93.5
Huang et al. (2014) [12]	Global	LPP	52	90.5
Huang (2010) [16]	Global	2D2PCA	702	90.5
		2DPCA	3024	90.5
Lu et al. (2012) [17]	Global	DSNPE	90	96
Singh et al. (2011) [18]	Global	Complex Zernike	124	90.5
		Pseudo Zernike	90	89.5
		Zernike	28	89.5
Yu et al. (2010) [19]	Global	Gabor	39	95.3
en et al. (2012) [20]	Global	PCA	80	93.3
		LDA	39	94.5
Abhishree et al. (2015) [21]	Combined Features	Gabor + AD	348	95.7
Li et al. (2009) [22]	Combined Features	PCA+ LDA	40	93
Huang et al. (2015) [23]	Combined Features	Wavelet + PCA	180	94.2
		Wavelet + LDA	180	97.1
Mandal et al. (2009) [24]	Combined Features	Curvelet + PCA	60	96.6
		Curvelet + LDA		95.6
		Curvelet+ PCA+ LDA		97.7
Peng et al. (2015) [25]	Combined Features	GELM	1024	96.3
Fathi et al. (2016) [26]	Combined Feature	GGZ + HOG	90	98
Proposed Method	**Combined Features**	**Gabor + Zernike**	**160**	**98.5**

IV. Conclusion

This paper has presented the face recognition based on the combination of Gabor filter and Zernike moment. The Gabor filters with 8 orientation and 5 scales were used for enhancing the recognition rate of Zernike moment features. Where, the dimensionality is reduced by 32×32 for decreasing the time of execution and for obtaining a better result as well. From the results, it is concluded that, if the Zernike orders were increasing or decreasing, the recognition was not fixed. In the order of 4 with all repetition, the recognition rate was 97.5% in the ORL database. Thus, only four features were extracted from each sub-image by using the selected Zernike moments of order and repetition. Therefore, the total number of features are 160. The proposed system was tested on the ORL and Facial Expression databases. The recognition rate on ORL is 98.5% which is found to be satisfactory as compared to the existing systems.

Acknowledgements

This work is sponsored by SAP DRS-I (No: F.3-52/2011), UGC New Delhi, India.

References

[1]. Matthew A. Turk and Alex P. Pentland, Face Recognition Using Eigenfaces, *Vision and Modeling Group, The Media Laboratory Massachusetts Institute of Technology* 1991.

[2]. Peng Yang, Shiguang Shan, Face Recognition Using Ada-Boosted Gabor Features, *IEEE International Conference on Automatic Face and Gesture Recognition*, Korea, 356-361, May 2004

[3]. Anissa Bouzalmat and Arsalane Zarghili, Facial Face Recognition Method using Fourier Transform Filters Gabor and R_LDA, *International Conference on Intelligent Systems and Data Processing* (*ICISD*) 2011.

[4]. Chengjun Liu and Harry Wechsler, Independent Component Analysis of Gabor Features for Face Recognition, *IEEE Transactions on Neural Networks, Vol. 14, No. 4*, JULY 2003.

[5]. Linlin SHEN, Gabor Features and Support Vector Machine for Face Identification, *Biomedical Soft Computing and Human Sciences, Vol.14, No.1*, pp.61-66 (2009).

[6]. Chandan Singh, EktaWalia and Neerja Mittal, Robust Two-stage Face Recognition Approach using Global and Local Features, *Springer-Verlag, DOI 10.1007/s00371-011-0659-7*, 2011

[7]. Karim Faez and Nacer Farajzadeh, A Performance Comparison of the ZM, PZM and LM in the Face Recognition System in Presence of Salt and Pepper Noise, *IEEE International Conference on system, man and cybernetics*, Taipei, Taiwan, October 2006.

[8]. Jagdish P. Sarode and Alwin D. Anuse, A Framework for Face Classification under Pose Variations, *3rd International Conference on Advances in Computing, Communications and Informatics(ICACCl)*, Delhi, India. Sep 2014

[9]. H. Ouanan, M. Ouanan and B. Aksasse, Gabor-Zernike Feature Based Face Recognition Scheme, *International Journal of Imaging and Robotics, Vol. 16, issue No.2*, pp. 118-130, 2016

[10]. Olivetti Research Laboratory (ORL) face database. Is available in the following link http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

[11]. Dinesh N. Satange, NC-FACE Database for Face and Facial Expression Recognition, *International Journal of Pure and Applies in Research in Engineering and Technology (IJPRET) Volume 3 (9)* 591-598, 2015

[12]. P. Huang, C. Chen, Z. Tang and Z. Yang, Feature Extraction using Local Structure Preserving Discriminant Analysis, *Elsevier B.V. 0925-2312, Vol. 140, 2014,* pp. 104-113, 2014

[13]. W. Yu, L. Gan, S. Yan g, Y. Ding, P. Jian g, J. Wan g and S. Li, An improved LBP Algorithm for Texture and Face Classification, Springer-Verlag London, *Springer on Signal Image and Video Processing, Vol. 8, Issue 1,* 2014, pp 155-161.

[14]. T. Ahonen, E. Rahtu, V. Ojansivu and J. Heikkil, Recognition of Blurred Faces using Local Phase Quantization, *19th International Conference on Pattern Recognition (ICPR 2008) , IEEE Press*, 2008, pp. 1-4.

[15]. O. L. Junior, D. Delgado, V. Goncalves and U. Nunes, Trainable Classifier-Fusion Schemes: an Application to Pedestrian Detection, *Proceedings of the 12th International IEEE Conference on Intelligent Transportation Systems*, St. Louis, MO, USA, 2009, pp. 432-437.

[16]. G. Huang, Fusion (2D)2PCALDA: A New Method for Face Recognition, *Applied Mathematics and Computation, Vol. 216, Issue.11*, August 2010, pp. 3195-3199.

[17]. J.G Lu, Z. Jin and J. Zou, Face Recognition using Discriminant Sparsity Neighborhood Preserving Embedding, *Knowledge-Based Systems, Vol. 31*, 2012, pp. 119–127.

[18]. C. Singh, N. Mittal and E. Walia, Face Recognition using Zernike and Complex Zernike Moment Features, *Pattern Recognition and Image Analysis, Vol. 21, No. 1,* 2011, pp. 71–81.

[19]. L. Yu, Z. He and Q. Cao, Gabor Texture Representation Method for Face Recognition using the Gamma and Generalized Gaussian Models, *Elsevier on Image and Vision Computing, Vol. 28, Issue. 1*, 2010, pp. 177-187.

[20]. Y. Wen, L. He and P. Shi, Face Recognition using Difference Vector Plus KPCA, *Elsevier on Digital Signal Processing, Vol. 22, Issue.1,* 2012, pp. 140-146.

[21]. T.M. Abhishree, J. Latha, K. M anikantan and S. Ramachandran, Face Recognition using Gabor Filter Based Feature Extraction with Anisotropic Diffusion as a Pre-Processing Technique, *Procedia Computer Science, Vol. 45,* 2015, pp . 312-321.

[22]. J.K. Li, B.J. Zhao, H. Zhang, Face Recognition Based on PCA and LDA Combination Feature Extraction, *First International Conference on Information Science and Engineering*, 2009, pp. 1240-1243.

[23]. Z.H. Huang, W-J. Li, J. Wang and T. Zhang,Face, Recognition Based on Pixel-Level and Feature-Level Fusion of the Top-Level's Wavelet Sub-Bands, *Information Fusion, Vol. 22, 2015*, pp. 95-104.

[24]. T. M andal, Q.M .J. Wu, Y. Yuan, Curvelet Based Face Recognition Via Dimension Reduction, *Elsevier on Signal Processing, Vol. 89, Issue 12*, 2009, pp. 2345-2353.

[25]. Y. Peng, S. Wan g, X. Lon g and B. L. Lu, Discriminative Graph Regularized Extreme Learning Machine and Its Application to Face Recognition, Neurocomputing , Vol. 149, Part A, 2015, pp. 340-353.

[26]. A. Fathi, P. Alirezazadeh and F. Abdali-Mohammadi, A New Global-Gabor-Zernike Feature Descriptor and its Application to Face Recognition, *J. Vis. Commun. Image R.* 2016, doi: http:// dx.doi .org /10.1016/j.jvcir.2016.02.010.

[27]. Akram Alsubari and R. J. Ramteke, Extraction of Palmprint Texture Features using Combined DWT-DCT and Local Binary Pattern, *2nd IEEE International Conference on Next Generation Computing Technologies (NGCT-2016),* Dehradun, Indai, 14-16 October 2016.