Digital Innovations & Contemporary Research in SCIENCE & ENGINEERING

**Article Citation Format**
A.O. Oloyede, O. Adedara, O.B. Longe, B.M. Adeyemi & D.D. Ogunlana (2016) Statistical Analysis of Age Invariant Feature Extraction Techniques for Face Recognition Systems. Journal of Digital Innovations & Contemp Res. In Sc., & Eng. Vol. 4, No. 4. Pp 59-70

**Article Progress Time Stamps**

**Article Type:** Research Article
**Manuscript Received:** 15th October, 2016
**Review Type:** Blind
**Word Count Post Review:** 3376
**Review/Acceptance Information Sent :** 11th Dec, 2016
**Final Acceptance::** 22nd Dec. 2016
**DOI Prefix:** 10.22624/AIMS/D/V4N4P56

# Statistical Analysis of Age Invariant Feature Extraction Techniques for Face Recognition Systems.

**[1]A.O. Oloyede, O. Adedara, [1]O.B. Longe, [1]B.M. Adeyemi & [3]D.D. Ogunlana**
[1]Department of Computer Science, Caleb University Imota Lagos, Nigeria.
[2]Department of Computer Science, The Federal Polytechnic, Ado-Ekiti, Nigeria
[2]Department of Computer Science, National Open University of Nigeria, Abuja, Nigeria
Email: [1]ayglo55@yahoo.com

## ABSTRACT
Human faces undergo considerable amount of variations in facial texture and shape overtime due to aging. This large variation in facial appearances of the same individual makes most existing Age Invariant Face Recognition Systems (AI-FRS) suffer from high misclassification of faces. Also, the AI-FRS have been proven to be computationally time-inefficient owing to the fact that they are characterized by holistic feature extraction techniques such as Histogram of Gradient (HOG) and insufficient local image information feature extraction techniques such as Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT). In this paper, we discussed various feature extraction techniques such as LBP, GWT, HOG, Principal Component Analysis-Linear Discriminant Analysis (PCA-LDA) and LBP-GWT feature extraction techniques. These techniques were applied on the test images for the purpose of getting the desired results for classification and further evaluation.

**Keywords:** Statistics, Age Invariant, Feature Extraction, Techniques & Face Recognition Systems.

## 1. INTRODUCTION

Human faces undergo considerable amount of variations with aging. Face recognition across ages is an important problem and has many applications, such as passport photo verification, image retrieval, surveillance (Narayanan and Rama, 2006). This is a challenging task because human faces can vary a lot over time in many aspects including facial texture, shape, facial hair and presence of glasses [14] [18]. Moreover, human faces also undergo growth related changes that are manifested in the form of shape and textural variations (Narayanan and Rama, 2006). This aging process also appears in different manifestations in different age groups. Thus, both face detection and recognition across varying ages are still open problems [15].

In addition, the robustness to variations due to factors such as illumination, pose, facial expressions and aging is a significant metric in evaluating face recognition systems [1]. While facial aging is mostly represented by the facial growth in younger age groups, it is also represented by relatively large texture changes and minor shape changes due to the change of weight, presence of wrinkles or stiffness of skin in older age groups above 18 years. Therefore, an age correction scheme needs to be able to compensate for both types of aging processes [16] [17].

## 2. RELATED WORKS

Li *et al.* [11] introduced an advanced algorithm for face recognition against age invariance using multi-feature discriminant analysis (MFDA) which combines scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) to encode the local features. The feature extraction methods considered are local and the resultant system lacks discrimination ability especially when the face of the subject is very small. The system only works accurately for some set of age variant datasets. Combining local extraction methods will produce a more appealing result which is computationally efficient and more accurate and this forms an objective of this research work [17].

Huseyin and Osen [9] used original PCA and subspace LDA methods for feature extraction of the face images. PCA projects images into a subspace such that the first orthogonal dimension of this subspace captures the greatest amount of variance among the images and the last dimension of this subspace captures the least amount of variance among the images. In this respect, the eigenvectors of the covariance matrix are computed which correspond to the directions of the principal components of the original data and their statistical significance is given by their corresponding eigenvalues. PCA was used for the purpose of dimension reduction by generalizing the data while SVM was used for the final classification. Holistic approaches based on PCA and LDA suffer from the curse of dimensionality [20]. That is, the time required for an algorithm grows exponentially with the number of features involved, rendering the algorithm intractable in extremely high-dimensional problems. The result obtained lacks strong discrimination ability and timely inefficient.

Dihong et al [8] developed a new method called Hidden Factor Analysis (HFA). This approach is motivated by the belief that the facial image of a person can be expressed as combination of two components: an identity-specific component that is stable over the aging process, and the other component that reflects the aging effect. In the testing, given a pair of face images with unknown ages, the match score between them were computed by inferring and comparing the posterior mean of their identity factors. This approach is very complex and lacks strong discrimination ability; it also requires a lot of training images and consumes high computational resources [20].

## 3. FEATURE EXTRACTION

The face in machine vision terms is merely an array of pixel values. As a result of feature extraction, an input face will result in feature vector of the subject, which is later used for identification. All faces share the same set of features (eyes, nose and mouth) arranged in the same configuration. The information that makes individual faces unique must be found in subtle variations in the form and configuration of the facial features. Early approaches to identification took a literal approach to feature extraction, which relied on the geometry of fiducial points from the facial features (eyes lids, lips, and nose) and their spatial relationships. The algorithms considered for feature extraction in this work are local binary pattern and Gabor Wavelet Transform.

### 3.1 Local Binary Pattern (LBP)

LBP is advantageous because its local texture character can be described efficiently. The most important property of LBP operator is its tolerance against illumination changes [15]. Also, it is computationally simple to use it in real-time applications. Designers of LBP operators must face three fundamental issues. The first issue is how to describe different local patterns of textures and then how to extract these local patterns. The flowchart of the LBP process for face recognition is presented in Figure 1. Since not all of local patterns are with the same importance to texture analysis, the second issue is how to select the essential subset of these local patterns to represent textures. The third issue is how to use these selected local patterns to form an effective texture descriptor. The original LBP algorithm is a grayscale irrelevant texture analysis algorithm with powerful discrimination [2]. LBP provides a unified description including both statistical and structural characteristics of a texture patch, so that it is more powerful for texture analysis.

LBP is a gray-scale texture operator which characterizes the spatial structure of the local image texture. Given a central pixel in the image, a pattern number is computed by comparing its value with those of its neighborhoods. With the neighborhood set P and a circle of radius R, and the difference between the central pixel "$g_c$" and its neighborhood $\{g_0, g_1, \ldots, g_{p-1}\}$, the value of LBP operator can be obtained as [15]:

$$LBP_{P,R} = \sum_{i=0}^{p-1} s(g_i - g_c) 2^p \quad (1)$$

$$s = \begin{cases} 1 & g_i - g_c > 0 \\ 0 & g_i - g_c \le 0 \end{cases} \quad (2)$$

The original LBP labels the pixels of an image by thresholding the local area, neighborhood of each pixel with the center value and considering the result as a binary number. Equation 1 means pixels greater than the central pixel are mapped to 1, otherwise. Equations 1 and 2 give the computation of $LBP_{P,R}$. After identifying the LBP pattern of each pixel (*i, j*), the whole texture image is represented by building a histogram which is used as a texture descriptor. The LBP histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image, so can be used to statistically describe image characteristics.

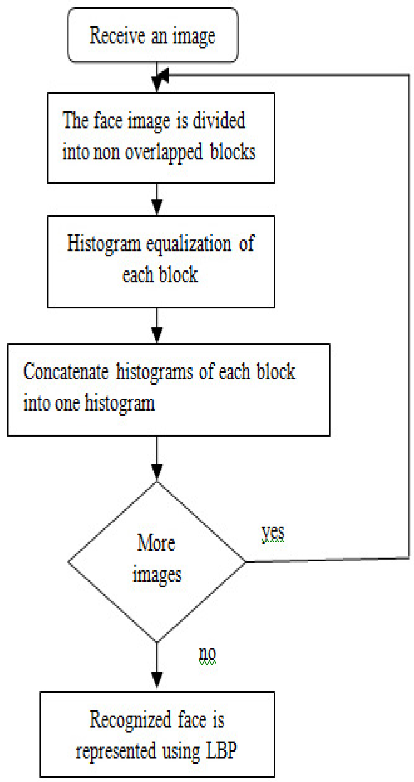



**Figure 1: Flowchart of the LBP Process for face recognition (Ojala *et al.,* 2002)**

The histogram of labeled image $f_i(x,y)$ is defined as (Ahonen and Pietikäinen, 2007):

$$H(i) = \sum_{x,y} I\{f_i(x,y) = i\},\ i = 0, \ldots, n-1 \quad \ldots\ldots\ldots\ldots.(3)$$

where n is the number of different labels produced by LBP operator and

$$I\{x\} = \begin{cases} 1, & x \text{ is true} \\ 0, & x \text{ is false} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots(4)$$

Figure 2a shows the histogram extracted from an image with LBP operator. An LBP histogram in this approach contains information about facial micro-patterns like the distribution of edges, spots and flat areas over the whole image. However, the 68 facial feature points' representation by the LBP operator is presented in Figure 2b. In case of (8, R) neighborhood, there are 256 unique labels, and the dimension of LBP descriptor is 256. The basic LBP histogram is global and represents the facial patterns but their spatial location information is lost [2]. To overcome this issue, spatially-enhanced LBP histogram is calculated. Figure 3. shows the process of computing spatially enhanced LBP histogram. An image is divided into non-overlapping blocks; LBP histogram is calculated from each block and all histograms are concatenated.

Digital Innovations
& Contemporary Research in
SCIENCE & ENGINEERING
Vol. 4 No. 4, Dec. 2016

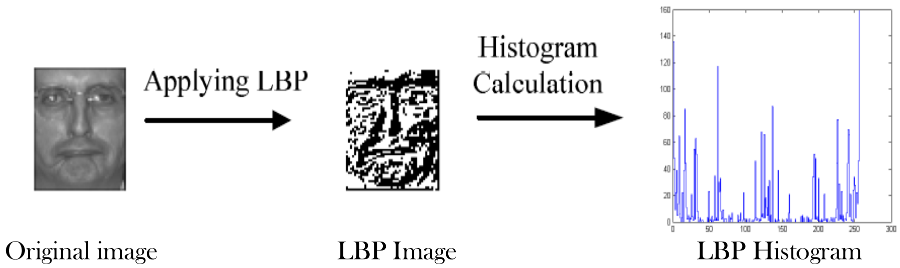



**Figure 2a: LBP histogram for a facial image (Ahonen and Pietikäinen, 2007)**

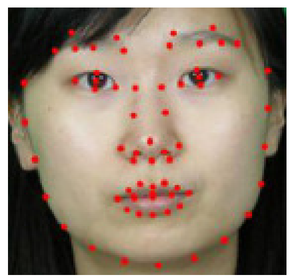


**Figure 2b: The 68 Facial Feature Points (Ahonen and Pietikäinen, 2007)**

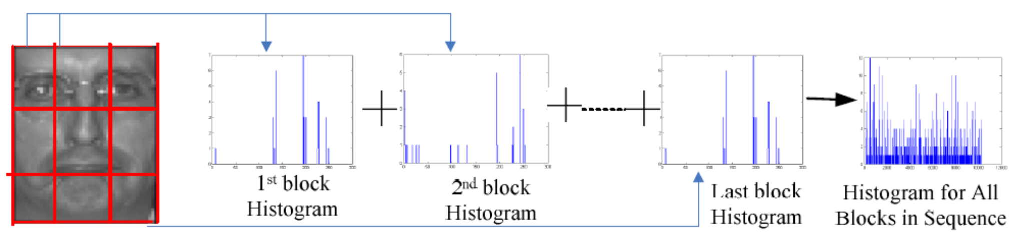



**Figure 3: Spatially-enhanced LBP histogram for a facial image (Ahonen and Pietikäinen, 2007)**

### 3.2 Gabor Wavelet Transform

Wavelet transformation results in strong representations with regard to lighting changes and be capable of capturing substantial facial features. A wavelet transform is created by passing the image through a series of filter bank stages. A Gabor wavelet can be described as a Gaussian kernel function modulated by a sinusoidal plane wave that has an optimal location in both the frequency domain and the space domain [3]. Due to the useful characteristics of Gabor functions, they have been widely and successfully applied for texture segmentation, handwritten numerals recognition, fingerprint recognition and face recognition.

Gabor features are used to represent the features extracted by a set of Gabor wavelets; they are usually called jets when the wavelet family is applied at a certain facial feature point. Gabor wavelets reveal the directional features of an image while providing a fine adjustment for frequency properties [3]. The decomposition of an image $I$ into these states is called the *wavelet* transform of the image. The Gabor wavelet transform uses a set of Gaussian enveloped basis functions that are orthogonal-like basis functions. Gabor wavelets provide analysis and optimized resolution of the input image in both spatial and frequency domains simultaneously. Gabor wavelets are widely used in image analysis and computer vision [6].

Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons [19]. Convolving the image with complex Gabor filters with 5 spatial frequency ($v = 0,\ldots,4$) and 8 orientation ($\mu = 0,\ldots,7$) captures the whole frequency spectrum, both amplitude and phase.

Given an image *I(x,y)*, its Gabor wavelet transform is defined as (Anila *et al.*, 2011):

$$W_{mn}(x, y) = \int I(x_1, y_1) g^*_{mn}(x - x_1,\ y - y_1) d_{x1} d_{y1} \qquad (5)$$

*where*

$^*$indicates the complex conjugate. Since the local texture regions are spatially homogeneous (Anila *et al.*, 2011), the mean $\mu_{mn}$ and standard deviation $\sigma_{mn}$ of the magnitude of transform coefficients will are used to represent the regions for classification such that [4]:

$$\mu_{mn} = \iint W_{mn}(x, y)|\ dxdy \qquad (6)$$

*and*

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(x, y)| - \mu_{mn})^2}\ dxdy \qquad (7)$$

A feature vector can then be constructed using $\mu_{mn}$ and $\sigma_{mn}$ as feature components.

Let $f^i$ and $f^j$ represent the feature vector of test and train image respectively; then, the distance between two images in the feature space can be defined to be (Anila *et al.*, 2011):

$$d(i, j) = \sum_i \sum_j d_{mn}(i, j) \qquad (8)$$

*where*

$$d_{mn}(i, j) = \left| \frac{\mu^{(i)}_{mn} - \mu^{(j)}_{mn}}{\alpha(\mu_{mn})} \right| + \left| \frac{\sigma^{(i)}_{mn} - \sigma^{(j)}_{mn}}{\alpha(\sigma_{mn})} \right| \qquad (9)$$

The test image will then be referred to class $k$ if $d_k$ is the minimum value of $d_i$ for test image.

## 4. MATERIALS AND METHODS

This section presents the statement of the problem, The Developed LBP-GWT feature extraction technique and the performance evaluation metrics.

### 4.1 Statement of the Problem

Most implementations of the currently existing face recognition systems do not cater for age variations in individuals which make them less effective for practical usage. For age-invariant recognition, most existing implementations are based on PCA and LDA which lack strong discrimination ability and timely inefficient for recognition due to large dimensions of the resultant features of such techniques [8]. Dimensionality reduction is important in many domains because it mitigates the curse of dimensionality and other undesired properties of high-dimensional spaces [5].

Holistic approaches based on Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Histogram of Gradients (HOG) suffer from the curse of dimensionality [7] [8]. That is, the time required for an algorithm grows exponentially with the number of features involved, rendering the algorithm intractable in extremely high-dimensional problems. However, Local Binary Pattern (LBP) is a non-parametric operator which describes the local spatial structure of an image [7]. Therefore, a swarm-optimized Local Binary Pattern-Gabor Wavelet Transform (LBP-GWT) age invariant feature extraction technique was developed in this research work [9] [10] [18].

### 4.2 The developed LBP-GWT Feature Extraction Technique algorithms

With the coordinates of the center pixel of an image $I(x,y)$ defined as $(x_c, y_c)$, then the coordinates of his P neighbors $(x_p, y_p)$ on the edge of the circle with radius R can be calculated with the cosine rule:

$$Xp = Xc + R\cos\left(\frac{2\pi p}{P}\right) \qquad (10)$$

The algorithm is as follows:

Input: Training and Test Image set

1. *Initialize temp = 0*
2. *FOR each image I in the training image set*
3. *Initialize the pattern histogram, H = 0*
4. *FOR each center pixel $t_c$ ε I*
5. *Compute the pattern label of $t_c$, LBP using Equation (10)*
6. *Increase the corresponding bin by 1.*
7. *END FOR*
8. *Find the highest LBP feature for each face image*
9. *Apply particle swarm optimization for feature subset selection*

Intermediate Output: Reduced LBP features of face image

In the same vein, the GWT was implemented as a process depicted in the algorithm as follows:

Input: Training and Test Image set

1. *Convolve Image I (x, y) using Gabor wavelets to extract local features at these feature points*
2. *Calculate the mean deviation, $\mu_{mn}$, of the Gabor wavelet coefficients for each point*
3. *Calculate the standard deviation, $\sigma_{mn}$, of the Gabor wavelet coefficients for each point*
4. *Construct Gabor feature vector using $\mu_{mn}$ and $\sigma_{mn}$.*
5. *Apply particle swarm optimization for feature subset selection*

Intermediate Output: Reduced GWT features of face image

*Repeat for all features*

*For each feature in LBP, choose a corresponding feature in GWT*

*Take average of each matching features in LBP and GWT*

*Apply sum rule fusion strategy*

*End Repeat*

## 5. SIMULATION RESULTS

In this research, a swarm-optimized LBP-GWT feature extraction technic was developed and benchmarked with four (4) existing feature extraction techniques which are LBP, GWT, HOG and PCA-LDA. Four face images of varying ages in each of the 82 subjects in FG-NET aging data set were used for test data sets making a total of 328 tested face images. Also, ten face images of varying ages in each of the 82 subjects in FG-NET aging data set were used for train data sets making a total of 820 trained face images.

Digital Innovations
& Contemporary Research in
SCIENCE & ENGINEERING
Vol. 4 No. 4, Dec. 2016

All the algorithms were implemented using MATLAB 7.7.0 (R2008b) on Windows 7 Ultimate 32-bit operating system, AMD Athlon (tm) X2 DualCore QL-66 central processing unit with a speed of 2.2GHZ, 2GB random access memory and 320GB hard disk drive. The performance evaluation metrics that were used to evaluate the developed feature extraction technique are: The False Accept Rate (FAR, The False Reject Rate (FRR), Recognition Accuracy and Recognition Time.

## Oneway

**ANOVA**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| False acceptance | Between Groups | 1339.750 | 4 | 334.938 | 1103.324 | .000 |
| | Within Groups | 10.625 | 35 | .304 | | |
| | Total | 1350.375 | 39 | | | |
| False reflection | Between Groups | 2288.600 | 4 | 572.150 | 2715.288 | .000 |
| | Within Groups | 7.375 | 35 | .211 | | |
| | Total | 2295.975 | 39 | | | |
| Recognition accuracy | Between Groups | 628.565 | 4 | 157.141 | 7E+030 | .000 |
| | Within Groups | .000 | 35 | .000 | | |
| | Total | 628.565 | 39 | | | |
| Recognition time | Between Groups | 21769.930 | 4 | 5442.483 | 1E+032 | .000 |
| | Within Groups | .000 | 35 | .000 | | |
| | Total | 21769.930 | 39 | | | |

## Post Hoc Tests

**False acceptance**

Duncan[a]

| FET LT | N | Subset for alpha = .05 | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| LBP-GWT | 8 | 6.50 | | | | |
| GWT | 8 | | 12.13 | | | |
| LBP | 8 | | | 18.00 | | |
| HOG | 8 | | | | 20.88 | |
| PCA-LDA | 8 | | | | | 21.88 |
| Sig. | | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 8.000.

**False reflection**

Duncan[a]

**False Rejection**

| FET LT | N | Subset for alpha = .05 | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| LBP-GWT | 8 | 15.1 | | | | |
| GWT | 8 | | | | | |
| HOG | 8 | | | 26.88 | | |
| LBP | 8 | | | | 31.63 | |
| PCA-LDA | 8 | | | | | 38.13 |
| Sig. | | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 8.000.

**Recognition accuracy**

Duncan[a]

| FET LT | N | Subset for alpha = .05 | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| PCA-LDA | 8 | 81.7100 | | | | |
| LBP | 8 | | 84.7500 | | | |
| HOG | 8 | | | 86.9200 | | |
| GWT | 8 | | | | 88.4100 | |
| LBP-GWT | 8 | | | | | 93.6000 |
| Sig. | | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 8.000.

**Recognition time**

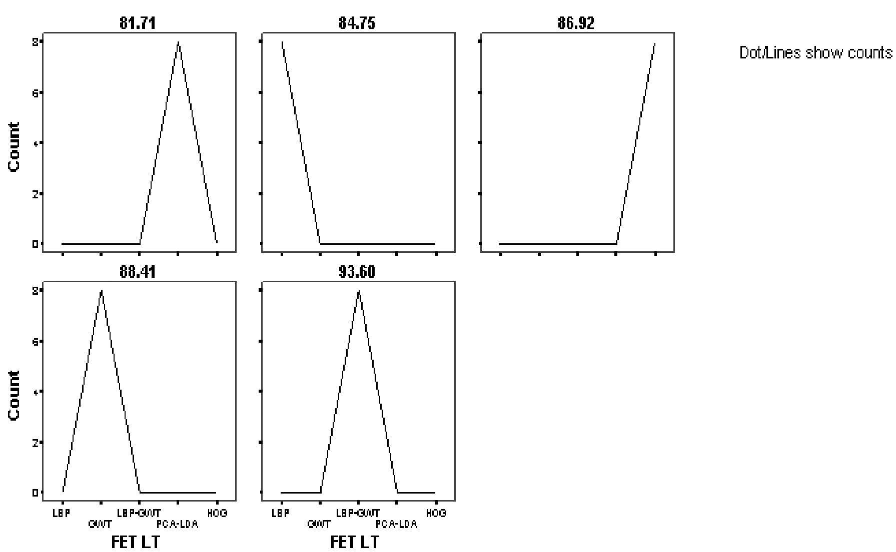
Duncan[a]

| FET LT | N | Subset for alpha = .05 | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| LBP-GWT | 8 | 81.66700 | | | | |
| LBP | 8 | | 101.22100 | | | |
| GWT | 8 | | | 112.69200 | | |
| HOG | 8 | | | | 124.53300 | |
| PCA-LDA | 8 | | | | | 151.42100 |
| Sig. | | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

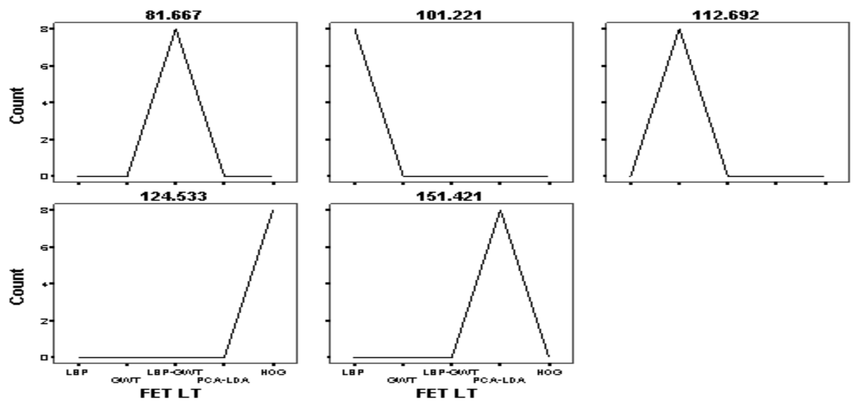
Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 8.000.

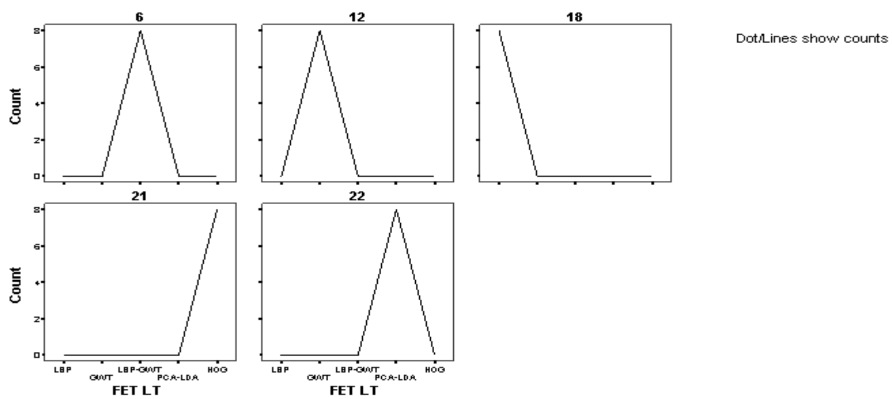
## Interactive Graph of recognition accuracy with FET



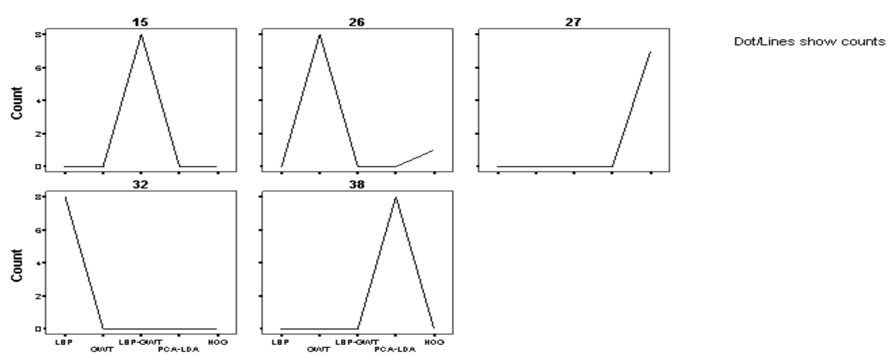
**Interactive Graph of recognition time with FET**




**Interactive Graph of false acceptance with FET**




## Interactive Graph of False Rejection with FET



### 5.1 The results of Analysis of Variance (ANOVA) showing the variance in Feature Extraction Technique (FET) based on False Acceptance

The result indicates that PCA-LDA depicted the highest false acceptance value (21.88 $^{e}$) while LBP-GWT gave the lowest false acceptance value (6.50$^{e}$). The mean value indicated by LBP-GWT is significantly lower ($p \leq 0.05$) compared to those obtained in the remaining FET under consideration. The LBP-GWT is most preferred because it is likely to be more accurate and better in terms of precision of decision making. So, the lower the false acceptance value, the better the level of accuracy in making the right judgment.

### 5.2 The results of Analysis of Variance (ANOVA) showing the variance in Feature Extraction Technique (FET) based on False Rejection

Based on the results of analysis, PCA-LDA indicated the highest false rejection value (38.13 $^{e}$) while LBP-GWT presented the lowest value (15.13$^{e}$). The mean values were found to be significantly different ($p \leq 0.05$) from one another. The result therefore implies that PCA-LDA had the lowest rejection accuracy while LBP-GWT presented the best rejection accuracy.

### 5.3 The results of Analysis of Variance (ANOVA) showing the variance in Feature Extraction Technique (FET) based on Recognition Accuracy

It was observed that LBP-GWT recorded the highest value for recognition accuracy (93.60 $^{e}$) while PCA-LDA indicated lowest value for recognition accuracy (81.71 $^{e}$). The mean values depicted by all the FET considered were significantly different ($p \leq 0.05$) from one another. The result therefore implies that LBP-GWT gave the best recognition accuracy which was followed by GWT, HOG, LBP and PCA-LDA.

### 5.4 The results of Analysis of Variance (ANOVA) showing the variance in Feature Extraction Technique (FET) based on Recognition Time

Based on the result, PCA-LDA indicate the highest value for recognition time (151.421 $^{e}$) while LBP-GWT recorded the least recognition time (81.667 $^{e}$). The mean values of the selected FETs were significantly different ($p \leq 0.05$) from one another. The result therefore implies that LBP-GWT gave the lowest recognition time while PCA-LDA gave the highest recognition time.

## 6. CONCLUSION

This study revealed that the developed swarm-optimized age invariant LBP-GWT feature extraction technique outperforms HOG, PCA-LDA, LBP and GWT feature extraction techniques in terms of FAR, FRR, RA and RT. The developed LBP-GWT feature extraction technique could be integrated into emerging age invariant face recognition systems towards their improved performance

## REFERENCES

[1] Adedeji O. T., Omidiora E. O., Olabiyisi S. O. and Adigun A. A.(2012): *Performance Evaluation of Optimised PCA and Projection Combined PCA methods in Facial Images,* Journal of Computations and Modeling, UK, 2(3): pp. 17-29, ISSN: 1792-8850.

[2] Ahonen T. and Pietikäinen M. (2007): "Soft histograms for local binary patterns", Finnish Signal Processing Symposium, Oulu, Finland. pp. 107-117.

[3] Ali H.A., Hind R.M. and Raghad S.A. (2012): Gabor wavelet Transform in Image Compression, Journal of Kufa for Mathematics and Computer 1(6), pp. 107-113.

[4] Anila S., Bekios C., Buenaposada J. and Baumela L. (2011): "Linear Discriminant Techniques in Gender Recognition", In Proceedings of the IEEE Transactions on Pattern Analysis and Machine Intelligence, 33 (4): pp. 858 – 864.

[5] Babatunde R.S., Olabiyisi S.O., Omidiora E.O. and Ganiyu R.A. (2015): "Local Binary Pattern and Ant Colony Optimization Based Feature Dimensionality Reduction Technique for Face Recognition Systems", British Journal of Mathematics and Computer Science USA, 11(5): pp.1-11.
[6] Bhatt P. N., Jacobs D. W. and Barsi R. (2011): "Comparing images under variable Illumination", In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 610-617.
[7] Biswas S., Aggarwal G. and Chellappa R. (2008): "A Non-Generative Approach for Face Recognition across Aging," in IEEE Second International Conference on Biometrics: Theory, Application and Systems, 2 (1): pp. 132-155.
[8] Dihong G., Zhifeng L., Dahua L., Jianzhuang L. and Xiaoou T. (2013): "Hidden Factor Analysis for Age Invariant Face Recognition", IEEE ICCV Proceedings, pp. 2872-2879.
[9] Hüseyin S. and Önsen T. (2012): "Face Recognition in the Presence of Age Differences using Holistic and Subpattern-based Approaches", Proceedings of the 8th WSEAS International Conference on Signal Processing, pp. 99-98.
[10] Jeremiah R.B., Kevin W.B., Patrick J.F. and Soma B. (2012): "Face Recognition from Video: A Review", International Journal of Pattern Recognition and Artificial Intelligence, World Scientific Publishing Company 16(2): pp. 1-56.
[11] Li X., Hu Y., Gao X., Tao D. and Ning B. (2011): "A Multi-Frame Image Super-Resolution Method", Elsevier, Signal Processing, 90(2): pp. 405–414.
[12] Narayanan R. and Rama C. (2006): "Face Verification across Age Progression", IEEE Transactions on Image Processing, 15 (11), pp. 3349–3361.
[13] Ojala T., Pietikainen M. and Maenpaa T. (2002): "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", IEEE Transaction on Pattern Analysis and Machine Intelligence, 24 (7): pp. 971–987.
[14] Omidiora E.O., Fakolujo O.A., Ayeni R.O., Olabiyisi S.O. and Arulogun O.T. (2008): "Quantitative Evaluation of Principal Component Analysis and Fisher Discriminant Analysis Techniques in Face Images", Journal of Computer Science & Its Application, 15(1): pp. 22-35.
[15] Omidiora, E. O. (2006), A Prototype of Knowledge-Based System for Black Face Recognition Systemusing Principal Component Analysis and Fisher Disriminant Algorithms, Unpublished Ph. D. (Computer Science) Thesis, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[16] Omidiora E. O., Fakolujo O. A., Olabiyisi S. O. & Ayeni R. O.(2007): *A Prototype of a Robust and Secured Access Control System using Principal Component Analysis,* 2nd International Conference on Application of ICT to Teaching, Research, and Administration (AICTTRA 2007), 2: pp. 97-105.
**[17]** Omidiora E. O., Fakolujo O. A. & Olabiyisi S. O. (2008): An Assessment of an Access Control System using Principal Component Analysis and Discrete Cosine Transform, 10th IASTED International Conference on Signal and Image Processing (SIP 2008), 10: **pp.** 262-267.
[18] Raghavender R.J (2008): "Adaptive Frame Selection for Enhanced Face Recognition in Low-Resolution Videos", Thesis Submitted to the College of Engineering and Mineral Resources at West Virginia University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical Engineering.
[19] Shen C. and Bai S. (2006): "Dynamic Facial Expression Recognition Using a Bayesian Temporal Manifold Model", In British Machine Vision Conference (BMVC), Edinburgh, UK, 1: pp. 297–306.
[20] Shinde P.V. and Gunjal B.L. (2012): "Particle Swarm Optimization - Best Feature Selection method for Face Images", International Journal of Scientific & Engineering Research, 3(8): pp. 1-5.