# A 2-DIMENSIONAL GABOR-FILTERS FOR FACE RECOGNITION SYSTEM: A SURVEY

**Taye Oladele Aro, Bamidele Oluwade, Oluwakemi Abikoye, Amos Bajeh**

**Department of Computer Science, University of Ilorin, Ilorin, Nigeria**

Corresponding author: Taye Oladele Aro, taiwo_aro@yahoo.com

***ABSTRACT:*** *An efficient recognition algorithm for human face is a technique discovered to be based on good facial feature representation. A two-dimensional Gabor represents a group of wavelets which capture optimally frequency information and local orientation from a digital image. Gabor filters have been employed greatly and highly considered to be one of the best performing techniques for feature extraction in face recognition owing to its invariant against local distortion initiated by changes in expression, lighting and pose. This paper discusses some reviews on 2-Dimensional Gabor-based facial recognition techniques. The huge feature dimensionality problem associated with Gabor feature is stated and several techniques to reduce this problem are suggested.*

***KEYWORDS:*** *Gabor-filters, face recognition, feature extraction, wavelets, Gabor feature, dimensionality.*

## 1. INTRODUCTION

Face recognition is a biometrical method for verifying and identifying a person's identity by matching input face against known faces in a database ([JD15, Z+14]). The recognition of face is achieved by comparing selected facial features from stored face image datasets in order to identify a query face image ([Bar10]). This biometric technology has been used successfully in applications like surveillance, human-computer intelligent interaction, security systems, access control, digital libraries and telecommunication ([H+14, JR09]). In facial recognition system, one of the major problems is how to describe and extract accurately the features for face image representation ([TT07]). An effective face recognition system is determined by a quality of feature representation method, which also involves the extraction of discriminant information from a face image ([SGP09]). The most essential and unique features are extracted from localized image during feature extraction phase ([KR13]). The feature extraction represents the most important phase of face recognition due to the dependency of face recognition accuracy on the level of features extracted from face image region ([She15]).

Although several algorithms like principal component analysis (PCA), independent component analysis (ICA) and Fisher's linear discriminant analysis (LDA) have been extensively identified to be successful and commonly used techniques for feature extraction in face recognition ([JR09, TBJ12]). Among the face representation techniques, Gabor-filter has been identified to be a robust technique at local and discriminate feature extraction of maximum information from image regions due to their level of similarity in characteristics to those of visual system of a human ([SB06, B+11]). Gabor-filter has gained significant attention in areaSs such as computer vision, object recognition, image processing and pattern recognition ([BL07]). These filters show better spatial locality characteristics, spatial frequency and orientation selectivity which make this extraction method invariant to changes in rotations, translations, scales and illuminations ([DQ04]).

Gabor-filters optimal functionality in face recognition model is traceable to its biological importance (comparable to the receptive fields of simple cells in primary visual cortex) and computational properties (optimal for calculating local spatial frequencies) ([SB06, SJ09]). These filters possess the ability of obtaining many orientation features from an image of face at several scales, with the derived information being of local nature. Gabor-filter has achieved great success and considered as one of the best technique for face representation ([BM12]). Gabor technique ranks high and performs optimally in removing useless and redundant feature in pattern recognition ([IAF12]). In feature extraction method, the Gabor-filter has been proved to be efficient approach for texture segmentation and discrimination in image processing ([GPK02, BLA13]).

This paper focuses only on the review on the past studies on face recognition system using 2-dimensional Gabor-filters for facial features extraction. The curse of dimensionality and various approaches to minimizing the huge Gabor features are discussed. Suggestion on future study is given which will involve the embedded hybridization of two or more dimensionality techniques to be performed on Gabor feature dimensions in order to adequately compress Gabor features and also obtain optimal feature subsets without losing much information in a reasonable time. This in future work will result to development of an improved Gabor-face recognition model.

## 2. BI-DIMENSIONAL GABOR-FILTERS (2-D GABOR FILTERS)

A Gabor filter is a band-pass linear filter used for edge detection in image processing and computer vision ([Bar10, A+15]). The Gabor filters are directly similar to Gabor wavelets since each component may be produced for a number of dilations and rotations ([Dao09]). Gabor filter captures salient visual properties such as orientation selectivity, spatial localization and spatial frequency ([JR09]). These filters have been applied successfully and broadly in several domains such as face detection, handwritten numeral recognition, texture segmentation, edge and fingerprint recognition ([Dao09, TJ12]). The Gabor wavelets generally used in Facial recognition can be defined as follows ([BLA13, LW02]).

$$Gabor(x, y, \mu, v) = \theta(x, y, \mu, v)(\alpha - \beta) \quad (1)$$

Where

$$\theta(x, y, \mu, v) = \frac{\|k_{\mu,v}\|^2}{\sigma^2} e^{-\frac{\|k_{\mu,v}\|^2 (x^2+y^2)}{2\sigma^2}} \quad (2)$$

$$\alpha = e^{ik_{\mu,v} z} \quad (3)$$

$$\beta = e^{-\frac{\sigma^2}{2}} \quad (4)$$

$$\varphi_{\mu,v}(z) = \frac{\|k_{\mu,v}\|^2}{\sigma^2} e^{-\frac{\|k_{\mu,v}\|^2 \|z\|^2}{2\sigma^2}} \left[e^{ik_{\mu,v} z} - e^{-\frac{\sigma^2}{2}}\right] \quad (5)$$

From equation (5) z = (x, y) is the point with the horizontal coordinate x and the vertical coordinate y in the image plane. The parameters $\mu$ and v define the orientation and scale of the Gabor kernel. $\|.\|$ represents the norm operator, and $\sigma$ denotes the standard deviations of Gaussian window in the kernel. The wave vector $K_{\mu v}$ is defined as:

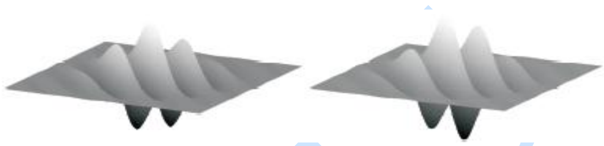
$$k_{\mu v} = k_v \, e^{i\varphi\mu} \quad (6A)$$

where $k_v = \frac{k_{max}}{f^v}$, $\varphi_\mu = \frac{\pi\mu}{8}$ (6B)

$K_{max}$ is the maximum frequency and $f_v$ is the spatial frequency between kernels in the frequency domain. Gabor filters are selected relative to subsequent parameters:

$K_{max} = \frac{\pi}{2}$, $f = \sqrt{2}$, $\sigma = \pi$

The parameters ensure that frequencies are spaced in octave steps from 0 to $\pi$, typically each Gabor wavelet possess a frequency bandwidth of an octave that is sufficient to have less overlap and cover the entire spectrum. Two-dimensional Gabor-filters correspond to a family of bi-dimensional Gaussian functions modulated by cosine function (real part) and sine function (imaginary part) representing orthogonal directions as shown in figure 1.



(a) Real part (b) Imaginary part
**Figure 1. Gabor filter with real and imaginary part ([SGP09])**

### 2.1 Two-Dimensional Gabor Filter for Facial Representation

The common technique for face recognition using Gabor-filters is achieved by a filter bank construction with filters of different scales and orientations to filter a given face image with all the filters from bank as shown in figure 2. The bi-dimensional Gabor wavelet representation of a facial image is derived by the convolution of face with Gabor filters ([BLA13]). The image $I$ convolution with Gabor kernel $\varphi_{\mu v}(z)$ is defined as follows:

$$G_{\mu,v}(z) = I(z) * \varphi_{\mu,v}(z) \quad (7)$$

Where z = (x, y) denotes the image position on coordinate x and y, the symbol * represents the convolution operator, $G_{\mu,v}(z)$ is the convolution result corresponding to the Gabor kernel at orientation $\mu$ and scale v. The filtering process with Gabor filter with a face image is rewritten as follows ([SB06]).

$$G_{\mu,v}(x, y) = I(x, y) * \varphi_{\mu,v}(x, y) \quad (8)$$

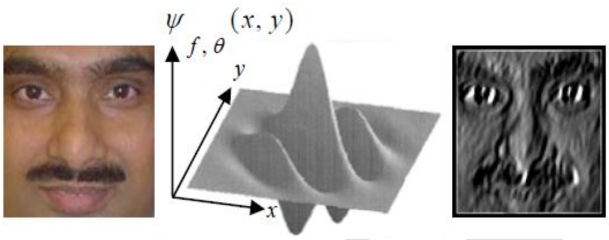
The Gabor wavelet coefficient is a complex function with a real and imaginary part, which can be rewritten as: A face image convolution with Gabor wavelet which can also be illustrated using the following mathematical procedures;
If f (x, y) represents the intensity at the coordinate (x, y) in grey scale face image, its convolution with Gabor filter $\varphi_{f,\theta}$(x, y) is defined as:

$$g_{f,\theta}(x, y) = f(x, y) * \varphi_{f,\theta}(x, y) \quad (9)$$

Where * is the convolution operator and $g_{f,\theta}(x, y)$ denotes the convolution complex result of a face image with a Gabor filter that can be further decomposed into a real and an imaginary part; $\mathcal{R}\{g_{f,\theta}(x, y)\}$ and $\Im\{g_{f,\theta}(x, y)\}$.The magnitude response $\|g_{f,\theta}(x, y)\|$ is stated as:

$$\|g_{f,\theta}(x, y)\| = \sqrt{\mathcal{R}^2\{g_{f,\theta}(x, y)\} + \Im^2\{g_{f,\theta}(x, y)\}} \qquad (10)$$

This magnitude response $\|g_{f,\theta}(x, y)\|$ produces Gabor face features. A feature j of a Gabor wavelet is described by three key parameters. J (z, μ, v) $=\|g_{f,\theta}(x, y)\|$, where z represents position, μ denotes orientation and v represents scale. Hence for a given image I(z) with N × M pixels, the number of Gabor wavelet feature representation is N × M × 40. The convolution of an input image with 40 Gabor filters with 5 different scales (v = 0, 1…, 4) and 8 orientation (μ = 0, 1…., 7) produces the Gabor feature as shown in figure 3.




(a) (b) (c)

**Figure 2. A face image convolution with a Gabor filter, (a) Face image, (b) Gabor filter ( f, $\theta$, $\delta$ ), (c) Gabor filter output ([BL07]).**

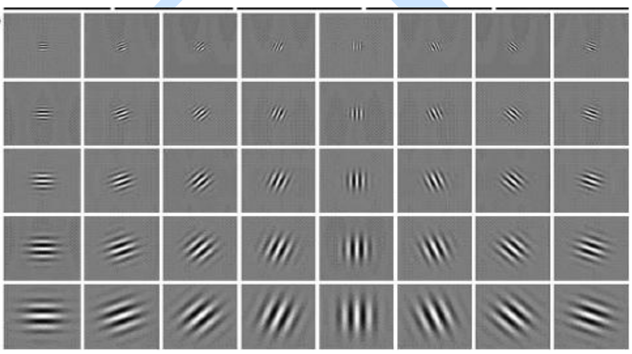


**Figure 3. The 5 scales and 8 orientations for 40 Gabor filters ([TJ12])**

## 2.2 Dimensionality of Gabor Facial Features

A face image is usually denoted by huge dimensional feature vector comprising image pixel values that recapitulates the basic content of a local region using local representation ([ZHE13]). The high dimension of feature problems include consumption of large memory space, prolong computational time and misclassification. The extracted feature dimensions of Gabor-based method is usually so high that when performing classification on the original features of face images, it becomes a more difficult task to achieve. Also, the general method when applying this feature extraction technique involves the creation of filter bank with filters of different scales and orientations to filter a face image with all filters from the bank. Thus, this approach makes the dimensionality of Gabor features very large and resulting to computational complexity of Gabor features ([V+15]). Orthogonality remains the most important component in pattern recognition applications; however the different filters of Gabor filters from the filter bank are not orthogonal in nature ([SGP09]). Hence, this makes any Gabor-based face recognition algorithm final information to be redundant and this might further affect the classification accuracy of any classifier depending majorly on this technique for recognition. In facial recognition, it is generally not certain to distinguish in advance which features will give the best discrimination between feature classes and also not feasible to represent all possible features of the images to be classified. It is therefore necessary to project face image from high feature dimension into feature subspace without losing computational speed and classification accuracy.

## 2.3 Dimensionality Reduction Techniques

A face representation usually begins with a feature reduction process since the huge space of visual information makes the statistical estimation very difficult and time consuming ([GTK 07]). It is not ideal in facial recognition model to directly employ raw original facial features for recognition. Selection of features and feature reduction are significant steps in pattern recognition system ([KFT07]). In facial recognition, each image to be classified consists of thousands of pixels where each pixel is represented by multi-byte value. Classifying this type of image data will be a time consuming and computationally expensive task. The objective of dimension reduction is to extract useful information and reduce the dimensionality of input data into classifiers in order to decrease the computational cost and resolve the problem of curse dimensionality ([Fod02]). Reduction technique is applied to reduce the curse of dimensionality effect, which can be categorised into feature extraction and feature selection ([CB12]). Several dimensionality reduction algorithms exist in recognition of face image such as linear methods

(Principal Component Analysis & Linear Discriminant Analysis) and non-linear methods` (Locally Linear Embedded (LLE) & ISOMAP) ([SBN11]).

### 2.3.1 Principal Component Analysis (PCA)

This method is also referred to as Karhunen-loeve transform (KLT) or Hotelling transform (HT) ([GP93, Fod02]). It is a feature reduction technique which performs a linear mapping of feature of an image into a lower-dimensional subspace (compressed image) in which principal components are not correlated ([KSD15,S+13]). In PCA, huge number of minor features are discarded while the small number of principal components are retained in linear, low-dimensional feature subspace which is known as eigenfaces in face recognition ([HY09]). The face principal components are obtained by projecting two dimensional face images into a one dimensional subspace, then select the principal components which capture the highest variance among individual face images ([S+13]).

### 2.3.2 Linear Discriminant Analysis (LDA)

LDA is another powerful traditional supervised dimensionality reduction method also called Fisher's Linear Discriminant Analysis. It is employed to find intriguing and efficient representation of face vector space ([S+12, Riy15]). This technique reduces the trace ratio between the within class scatter and the between class scatter so that the Gaussian distributed samples as well as separated subspace ([STC10]). The most important function of LDA is to carry out reduction of dimensions while preserving as much of the class discriminatory information as possible. This dimensionality technique searches for feature vectors in the original space that are best discriminant among classes ([KSD15]). LDA combine the independent feature which results into large mean differences between the wanted classes.

### 2.3.3 Isometric Mapping Technique (ISOMAP)

It belongs to the set of commonly used non-linear low-dimensional embedding methods ([TSL00]). Isomap is used for computing a quasi-isometric, low-dimensional embedding of a set of high-dimensional data The algorithm offers a simple method for estimating the intrinsic geometry of a data manifold based on a rough estimate of each data point's neighbors on the manifold. This technique apart from dimensionality reduction task has been applied to wide areas such as head pose estimation, inspection of wood and biomedical data visualization (Tsa10]). Isomap is highly efficient and generally applicable to a broad range of data sources and dimensionalities.

### 2.3.4 Locally Linear Embedding (LLE)

LLE is an unsupervised learning algorithm which belongs to the class of non-linear dimensionality method which is used for computation of low-dimensional neighborhood that preserves embedding of high-dimensional inputs ([RS00]). This method is not like clustering method for local dimensionality reduction, it maps its inputs into a single global coordinate system of lower dimensionality in which its optimizations do not involve local minima ([CB12]). LLE is similar to ISOMAP technique in that it constructs a graph representation of datapoints. The data manifold local properties of LLE are constructed by writing the high-dimensional datapoints as a linear combination of their nearest neighbors ([PP09]). In the low-dimensional representation of data, it retains reconstruction weights in good linear combination.

## 3. RELATED WORK

The application of Gabor wavelets originally applied to recognition of face using Dynamic Link Architecture (DLA) framework ([L+93]). The DLA creates a flexible template comparison between Gabor wavelet representations of different face images. Wiskott et al.([W+97]) employed expansion of DLA using a Gabor wavelet-based elastic bunch graph matching (EBGM) algorithm to label and recognize human faces. The experimental test conducted on the FERET database revealed better recognition rate for frontal face images. The following are different studies conducted by several researchers using Gabor filters as feature extraction technique:-

([LW02]) proposed a novel Gabor-fisher classifier (GFC) for face recognition. The study applied enhanced fisher linear discriminant model (EFM) to an augmented Gabor feature vector obtained from the Gabor wavelet representation of face images. The huge Gabor feature vector was reduced using EFM. The model was tested using six hundred FERET frontal face images corresponding to two hundred subjects, which acquired under different illumination conditions and expressions. The novel GFC achieved 100% accuracy on face recognition using only sixty-two features.

Byuiyan ([BL07]) presented a facial recognition system based on Gabor filter for feature extraction. The study convolved a face image with a series of Gabor filter coefficients at different scales and orientations. Contrast equalization and fuzzily skewed filter technique were introduced at image pre-processing phase for better performance of the recognition model. Fifteen Gabor filters (three for scaling and five for orientations) were used in order to reduce the effect of huge dimension of Gabor features. A neural network based on multi-layer perceptron (MLP) architecture with back propagation algorithm was applied for classification. A principal Gabor filters for face recognition ([SGP09]), a new orthogonal Gabor filters constructed from the linear combination of the original Gabor filters to minimize the large Gabor features. The newly designed filters were derived from correlation matrices of the original filters by means of principal component analysis. XM2VTS and YaleB datasets used to evaluate the model. Results obtained in a series of verification and identification analyses reviewed that the new filters result perform better with low computational complexity.

Improvement of face recognition using modified Fourier Gabor filter proposed by ([Dao09]). The study used four popularly techniques in face recognition datasets (AT&T, IFD, Faces 95 and Yale datasets); the methods are implemented without and with suggested filters. The results showed that the direct application of suggested Fourier-Gabor filter enhances the classification rates for all methods, datasets, training and testing percentage. The highest classification rates obtained when Fourier Gabor filter with batch linear discriminant analysis (FG-Batch-ILDA) used. A 2-dimensional Gabor-filters for facial recognition for feature extraction to produce robust 3-dimensional face feature vector ([Bar10]). A supervised classifier was applied using minimum average distances for feature vectors. The results obtained show the effectiveness of the face recognition system.

Bouzalmat et al. ([B+11]) extracted features of face image based on Gabor-filters as these filters present desirable characteristics of spatial locality and orientation selectivity. The reduction of large feature dimensions into feature subspace achieved by Sparse Random projection (RP) technique. Back Propagation Neural Network (BPNN) was applied on the feature vectors for classification. The model was evaluated using AR database with a collection of twenty people from database. Each person represented by twenty samples, ten used for training and ten for testing. The recognition rate of the model was high with better classification when feature vectors have low dimensions.

Bellakhdhar et al.([BLA13]) presented with a face recognition system using Gabor wavelets, Principal Component Analysis (PCA) and Support Vector Machine (SVM). The model combined magnitude and phase of Gabor filter. The eigenvectors of the face images was extracted using Principal Component Analysis. The classification of face images was achieved using SVM. The performance of the face recognition system was validated applying public and largely used datasets of FRGCV2 and ORL. Results showed that the combination of the magnitude with the phase of Gabor features can achieve better results.

A comparative study on Gabor wavelet features for face recognition with PCA and KPCA ([Zhe13]). Principal Component Analysis (PCA) and Kernel Principal Component Analysis (KPCA) were applied after the feature extraction phase to decrease dimensionality of filtered face images and comparison between the two methods showed the performance of the recognition models. The model was evaluated using the publicly available ORL database. Experimental result reviewed that GABOR-PCA outperformed the GABOR-KPCA method for facial recognition.

Abhishree et al.([A+15]) came up with a face recognition by applying Gabor-filter for feature extraction with Anisotropic Diffusion as a pre-processing technique to enhance the face recognition performance. Gabor filter employed to obtain the features of face image aligned at specific angles. A binary particle swarm optimization based feature selection algorithm was used to find the feature space for optimal feature subset. The model was evaluated on four benchmark facial image datasets; ORL, Color FERET, Cropped Yale B and FEI datasets. The result showed outstanding performance compared with existing methods in the presence of pose, illumination and expression variation.

An efficient face recognition using Gabor filters to extract facial features presented ([TBJ12]). The large dimensional Gabor features were reduced by wavelet transformation. Discriminative common vectors obtained by within-class matrix method to get a feature representation of face images. Radial basis function network was applied for classification. The model was validated with three face datasets: ORL, JAFFE and Essex face database. Experimental results showed that the recognition model reduces the number of features, minimizes the computational complexity and also yielded better recognition accuracy.

A new approach to improve 3D face recognition system performance was developed ([H+15]). The model pre-processed and normalized all images in the database using 2D normalized cross correlation 2DNCC. The 3D face features were extracted by applying a set of selected orthogonal Gabor filters, which minimized the feature vectors extracted when compared to those ones that use complete Gabor filters bank. The study further employed linear discriminant analysis to compress dimensionality of the extracted features before classification. Experimental results showed the effectiveness of the system in term of dimensionality and recognition accuracy when compared with existing systems. The model tested on CASIA and Gavab 3D face image database achieved 98.35% and 85% respectively.

## 4. SUMMARY AND DISCUSSION

Despite the outstanding achievements of Gabor-filters in facial recognition system, this technique suffers high feature dimension ([P+04]). The dimensionality of the input face images from the Gabor filter is usually so high that performing classification on the original images become a more challenging task due to large memory consumption and computational complexity ([Z+05]). Thus, it is necessary for any face recognition algorithm using Gabor filters to project Gabor features from high feature dimension into lower relevant feature subspace without losing computational speed and classification accuracy. Several feature dimensionality reduction methods have been proposed to reduce curse of dimensionality of Gabor features these include; down sampling, feature selection techniques, reduction of filter bank parameters and subspace projection methods before being passed into a classifier ([SGP09]).

The down sampling technique involves the use of only selected feature points, but the final output results to large number of image feature matrix which could cause the loss of feature distinct information and may eventually affect face recognition accuracy ([V+15]). Subspace projection technique involves the mapping of high dimensional features into lower dimensions: - Principal Component Analysis (PCA) applied by many researchers to construct subspace for representing feature class but the principal component which are the largest eigen vector of the co-variance matrix generated are not often the optimal features in lower dimension ([HK05], [B+15]). Independent Component Analysis (ICA) which is a generalization of PCA needs very high computational time for training phase ([M+07]). The Linear Discriminant Analysis (LDA) for feature selection demands much computation time and its performance may be degraded when feature size is large ([BL07]). It is therefore very important to present a new effective dimensionality techniques to select relevant features in Gabor features in order to have better accuracy in classification phase ([AGB09]).

With the feature selection, the complexity and computational cost of classifier can be reduced by minimizing the number of features to be used into measurable forms while still maintaining acceptable recognition accuracy ([M+07]). The selection of optimal feature subset has been identified to be non-deterministic polynomial complete problem ([DCH03, I+12]). There is a need to introduce a robust technique apart from existing algorithms such as population-based meta-heuristic optimization methods in order to avoid prohibitive complexity of optimal Gabor feature subsets selection. Among feature selection methods, meta-heuristic optimization approaches such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO), Particle Swarm Optimization produce effective solution by using knowledge from previous iteration ([KFT07]). Therefore in future work, there may be need to employ a hybridize method for dimensionality reduction techniques.

The combination of convectional linear dimensionality reduction techniques together with meta-heuristic optimization approaches will contribute to the improvement of Gabor-based facial recognition computational model. Since some of the linear feature reduction techniques only perform linear combination of the original features not considering the relevancy of these features. The introduction of meta-heuristic optimization as second level optimization method will help to obtain optimal features or relevant features subsets from the Gabor features, this will allow recognition to be achieved in a reasonable computation time with also an improved recognition accuracy.

## 5. CONCLUSION

This paper reviews several studies conducted in the past using Gabor filters for extraction of features. Gabor-filter method proves to be effective technique for facial recognition system, but the high dimensionality of features results into large computational complexity of this technique. An efficient dimensionality reduction method which involves the application of embedded hybridization of linear dimensionality techniques (Principal Component Analysis, Linear Discriminant Analysis and Independent Component Analysis) that linearly reduce original features of face image and meta-heuristic optimization algorithms (Particle Swarm Optimization, Bat Algorithm, Ant Colony Optimization and Genetic Algorithm) for optimal feature subset selection has been discussed as further study in order to develop effective Gabor-facial recognition technique which will be applicable in reasonable time with improved accuracy.

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