

# A Novel method for Face Recognition

Sonali Priyadarshini



Department of Computer Science and Engineering  
National Institute of Technology Rourkela  
Rourkela, Odisha, 769 008, India

# A Novel Method for Face Recognition

*Thesis submitted in partial fulfilment  
of the requirements for the degree of*

**Bachelor of Technology**

*in*

**Computer Science and Engineering**

*by*

**Sonali Priyadarshini**

(Roll: 111cs0151)

*under the supervision of*

**Prof. Banshidhar Majhi**

**NIT Rourkela**



**Department of Computer Science and Engineering  
National Institute of Technology Rourkela  
Rourkela, Odisha, 769 008, India**



Department of Computer Science and Engineering  
**National Institute of Technology Rourkela**  
Rourkela, Odisha, 769 008, India.

**Dr. Banshidhar Majhi**  
Professor

May, 2015

## Certificate

This is to certify that the work in the thesis entitled ***A Novel Method for Face Recognition*** by ***Sonali Priyadarshini*** bearing roll number 111cs0151, is a record of her work carried out under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering.

**Banshidhar Majhi**

## Acknowledgement

First and foremost, I would like to thank my supervisor Prof. B. Majhi for introducing me to this exciting area of Biometry. I am especially indebted to him for his guidance, support and patience with me throughout the course of my research. He taught me the essence and principles of research and guided me through until the completion of this thesis. It is due to his faith in me that today I am submitting this thesis. It has been my privilege working with him and learning from him.

I would like to thank Prof. Ratnakar Dash for showing me innovative research directions for the entire period of carrying out the research and his faith in me that I can do the work. I would also like to thank Mr. Shradhananda Beura for listening and extending his help. I am obligated to all the professors, batch mates, Phd scholars, and friends at National Institute of Technology Rourkela for their kind cooperation.

I owe my largest debt to my family, and I wish to express my heartfelt gratitude to my father for his encouragement, constant prayers, and continued support. My parents have given me all their love and support over the years; I thank them for their unwavering commitment through good times and hard times.

*Sonali Priyadarshini*

# Abstract

In this thesis, a novel method for face recognition system is proposed. It is a three stage process, first features are extracted, as per requirements features are selected then faces are classified according to their respective classes.

In section I, Principal Component Analysis (PCA), for feature extraction is used and Euclidean distance is used for identification.

In section II, a face recognition system based on enhanced local Gabor binary sequence is used for effective face feature extraction and neural network is being used for classification. As local binary pattern (LBP) is very resistive to illumination changes, it is a good option for coding fine details of facial visual aspect and texture.

In section III, Back-Propagation network (BPN) is being used in various fields. Rule of thumb or "error and trial method" are usually used to determine different parameters like learning rate and number of hidden neurons. Therefore, a simulated-annealing-based approach denoted by SA+ BPN is proposed to get the optimum parameter settings for the network. The proposed method is resistant to slight variation in imaging conditions and poses. The algorithms that have been applied are tested on ORL Face Database and Yale Database.

**Keywords:** Gabor, feature extraction, feature selection, PCA, Euclidean Distance, LBP, BPN, simulated annealing

# Contents

<b>1</b>	<b>Introduction</b>	<b>10</b>
1.1	Face as a biometric . . . . .	11
1.2	Face database . . . . .	12
1.3	Thesis Organisation . . . . .	13
<b>2</b>	<b>Literature Review</b>	<b>14</b>
2.1	Structure and Procedure . . . . .	14
2.1.1	Face Detection: . . . . .	14
2.1.2	Feature Extraction: . . . . .	15
2.1.3	Face Recognition: . . . . .	15
2.2	Fundamental of pattern recognition . . . . .	15
2.2.1	Different kinds of pattern recognition (four categories)	16
2.2.2	Dimension Reduction: Domain-knowledge Approach and Data-driven Approach . . . . .	17
<b>3</b>	<b>PCA based Feature Extraction and Reduction</b>	<b>18</b>
3.1	Principal Component Analysis . . . . .	18
3.2	Alorithm . . . . .	19
3.3	Recognising An Unknown Face . . . . .	21
3.4	Results . . . . .	21
<b>4</b>	<b>Wavelet-based generalised neural network</b>	<b>22</b>
4.1	Introduction . . . . .	22
4.2	The Proposed Approach . . . . .	23
4.3	Results . . . . .	26

<b>5</b>	<b>Simulated-annealing-based approach for parameter optimization of BPN</b>	<b>27</b>
5.1	Literature Review . . . . .	27
5.2	The proposed Approach . . . . .	27
5.3	Results . . . . .	29
<b>6</b>	<b>Conclusion</b>	<b>31</b>

# List of Figures

1.1	Typical examples of sample face images from the Yale face database . . . . .	12
1.2	Typical examples of sample face images from the ORL face database . . . . .	13
2.1	Configuration of a general face recognition structure . . . . .	14
2.2	The general structure of a pattern recognition system . . . . .	16
3.1	The original basis are $x$ and $y$ . $\phi$ is the first principal component	19
4.1	Kernel Images of Gabor Filter . . . . .	24
4.2	Kernel Images of Gabor Filter . . . . .	24
4.3	Example of LBP calculation . . . . .	25



# List of Tables

3.1	Results of PCA . . . . .	21
4.1	Results of ORL Database . . . . .	26
4.2	Results of ORL Database . . . . .	26
4.3	Results of Yale Database . . . . .	26
5.1	10-fold classification result of Yale database . . . . .	29
5.2	10-fold classification result of ORL Database . . . . .	30

# Chapter 1

## Introduction

The face is our essential center of consideration in social life assuming a vital part in passing on personality and feelings. We can perceive various countenances adapted all through our lifespan and distinguish faces initially even following quite a while of division. This expertise is very hearty in spite of vast varieties in visual boost because of evolving condition, maturing and diversions, for example, whiskers, glasses or changes in haircut.

Computational models of face acknowledgment are fascinating in light of the fact that they can contribute to hypothetical learning as well as to handy applications. PCs that perceive countenances could be connected to a wide assortment of assignments including criminal distinguishing proof, security framework, picture and film preparing, personality check, labeling purposes and human-PC cooperation. Shockingly, adding to a computational model of acknowledgment is very troublesome in light of the fact that faces are unpredictable, multidimensional and important visual boosts.

Our point, which we accept we have come to, was to build up a system for face acknowledgment that is quick, vigorous, sensibly straightforward and precise with a generally basic and straightforward calculations and strategies. The cases gave in this theory are ongoing and taken from our own particular surroundings.

We can perceive a well known individual under extremely antagonistic lighting conditions, from fluctuating points or perspectives. Scaling contrasts or distinctive foundations don't change our capacity to perceive appearances and we can even perceive people with simply a small amount of their face obvious or even following quite a while have passed. Besides, we have the capacity to perceive the characteristics of a few thousand people whom we have

met amid our lifetime. In this way, its a true test to construct a mechanized framework which measures up to human capacity to perceive faces.

## 1.1 Face as a biometric

Biometrics are computerized techniques for perceiving an individual in light of a physiological or behavioral feature. The diverse highlights that are measured are face, fingerprints, hand shape, calligraphy, iris, retinal, vein, and voice. Face acknowledgment has various qualities to suggest it over other biometric modalities in specific circumstances. Face recognition as a biometric determines various points of interest from being the essential biometric that people utilization to perceive each other. It is very much acknowledged and effortlessly seen by individuals, and it is simple for a human administrator to mediate machine choices in fact face pictures are frequently utilized as a human-confirmable reinforcement to machine-driven unique finger impression recognition frameworks.

Face recognition has the preference universality and of being general over other real biometrics, in that everybody has a face and everybody promptly shows the face. (Though, for occasion, fingerprints are caught with substantially more trouble and a huge extent of the populace has fingerprints that can't be caught with quality sufficient for recognition.) With some design and co-appointment of one or more cams, it is anything but difficult to procure face pictures without dynamic cooperation of the subject. Such aloof distinguishing proof may be attractive for customization of client administrations and purchaser gadgets, whether that be opening a house entryway as the owner strolls up to it, or altering mirrors and auto seats to the drivers presets when taking a seat in their auto.

## 1.2 Face database

Research community can use a lot of standard datasets available in the internet for the algorithm development and reporting results. Distinctive databases are gathered to address an alternate kind of test or varieties, for example, enlightenment, posture, impediment, and so on. In this undertaking, I have utilized the ORL database which contains 400 dark scale pictures in PGM organization of 40 subjects. The pictures are at determination 92x112 pixels, with 256 dimensions levels every pixel. For a few subjects, the pictures were taken at distinctive times, shifting the lighting, outward appearances (open/ shut eyes, grinning/ not grinning) and facial points of interest (glasses/ no glasses). All the pictures were taken against a dull homogeneous foundation with the subjects in an upright, frontal position (with resilience for some side development). The Yale Face Database contains 165 grayscale pictures in GIF arrangement of 15 people. There are 11 pictures every subject, one every distinctive outward appearance or design: focus light, w/glasses, cheerful, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink. Some example pictures of this



Figure 1.1: Typical examples of sample face images from the Yale face database



Figure 1.2: Typical examples of sample face images from the ORL face database

### 1.3 Thesis Organisation

The rest of the thesis constitutes the following six chapters-

**Chapter 2:** Steps in Face Recognition/Literature Review

This chapter outlines different steps of face recognition in detail.

**Chapter 3:** PCA based feature extraction and Classification for Face Recognition

This chapter outlines the algorithm for PCA and the classification

**Chapter 4:** Wavelet-based feature extraction

This chapter discusses effective face recognition method which used two local based descriptors, Gabor Wavelets and Local Binary Pattern(LBP).

**Chapter 5:** Simulated Annealing-based approach for simultaneous parameter optimization

This approach search for the best parameters for the BPN network architecture using the simulated annealing cooling method. This method prevents from trap into local maxima or minima. .

**Chapter 6:** Conclusion

In this chapter, results of various approaches are compared and best method is proposed.

# Chapter 2

## Literature Review

### 2.1 Structure and Procedure

In this report, image-based face recognition is focused. A picture taken from a digital camera is given, we'd like to locate whether a face exists in that picture or not and who the person is. Towards this goal, the face recognition procedure is separated into three steps: Face Detection, Feature Extraction, and Face Recognition as shown in Fig.



Figure 2.1: Configuration of a general face recognition structure

#### 2.1.1 Face Detection:

The fundamental function of this step is to focus (1) whether human faces are in a given picture, and (2) where these faces are situated at. Patches containing every face in the input image are produced as output. The main goal is to make further face acknowledgment framework more vigorous and simple to outline, so face alignment are done to legitimize the scales and orientations of these patches. Other than serving as the pre-processing for face acknowledgment, face recognition also could be utilized for region of interest detection, video and image classification, etc.

### **2.1.2 Feature Extraction:**

After the face recognition step, human-face patches are separated from pictures. Straightforwardly utilizing these patches for face recognition have a few drawbacks, to begin with, every patch generally contains more than 1000 pixels, which are so vast it would be impossible form a hearty recognition framework. Second, face patches may be taken from distinctive cam arrangements, with diverse face articulations, enlightenments, and may experience the ill effects of impediment and disarray. To defeat these downsides, highlight extractions are performed to do in- arrangement pressing, measurement decrease, remarkable quality extraction, and clamor cleaning. After this step, a face patch is generally changed into a vector with fixed dimensions or an arrangement of fiducial focuses and their comparing areas.

### **2.1.3 Face Recognition:**

After devising a representation of each face,the final step is to recognize the identities of those faces.A face dataset has to be created to achieve the desired goal of a automatic recognition.For every individual, a few pictures are taken and their features are removed and put away in the database. At that point when an information face picture comes in, we perform face detection and feature extraction, and contrast its feature with every face class put away in the database. There have been numerous examines and calculations genius postured to manage this grouping issue, and which will be examined in later segments. The two general uses of face recognition, one is Identification and another is verification. Face identification means a face picture and a stored dataset will be given , we need the system to recognize who he/ she is or the most plausible Identity; while in verification, given a face picture and a supposition for the Identity, we need the system to inform genuineness about the guess.

## **2.2 Fundamental of pattern recognition**

Before going into details of techniques and algorithms of face recognition, I will like to make a throw some light about pattern recognition. The discipline, pattern recognition, includes all cases of recognition tasks such as speech recognition, object recognition, data analysis, and face recognition, etc. In

this section, we won't discuss those specific applications, but introduce the basic structure, general ideas and general concepts behind them.

In order to generate a system for recognition, we always need data sets for building classes and compare similarities between the test data and each class. A test data is usually called a “query” in image retrieval literatures. From fig 2.2, we can easily notice the symmetric structure. Starting from the data sets side, we first perform dimensions reduction on the stored raw dataset. After dimension reduction, each raw data in the data sets is transformed into a set of features, and the classifier is mainly trained on these feature representations. When a query comes in, we perform the same dimension reduction procedure on it and enter its features into the trained classifier. The output of the classifier will be the optimal class (sometimes with the classification accuracy) label or a rejection note (return to manual classification).

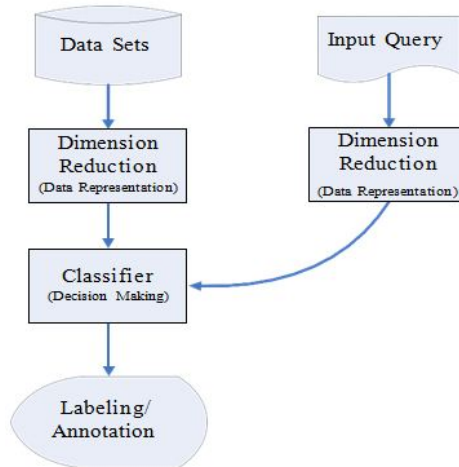


Figure 2.2: The general structure of a pattern recognition system

### 2.2.1 Different kinds of pattern recognition (four categories)

Methods of pattern recognition can be arranged into four classes: Template matching, statistical approaches, syntactic approach, and neural networks. The template matching class manufactures a few layouts for every name class



and contrasts these formats and the test example to accomplish a suitable choice. The statistical approaches, which removes learning from preparing information and uses various types of machine learning instruments for dimension reduction and recognition.

The syntactic approach is regularly called the guideline based pattern recognition which is based on human learning or some physical guidelines, for instance, the word arrangement and word rectification obliges the assistance of linguistic uses. The term, learning, is alluded to the standard that the recognition framework uses to perform certain activities. At last, the no doubt understand neural systems is a structure taking into account the acknowledgment unit called perceptron. With distinctive quantities of perceptrons, layers, and advancement criteria, the neural systems could have a few varieties and be connected to wide recognition cases.

## **2.2.2 Dimension Reduction: Domain-knowledge Approach and Data-driven Approach**

There are two main categories of dimension reduction techniques: domain-knowledge approaches and data-driven approaches. The domain-knowledge approaches perform dimension reduction based on knowledge of the specific pattern recognition case. For example, in image processing and audio signal processing, the discrete Fourier transform (DFT), discrete cosine transform (DCT) and discrete wavelet transform are frequently used because of the nature that human visual and auditory perception have higher response at low frequencies than high frequencies. Another significant example is the use of language model in text retrieval which includes the contextual environment of languages.

In contrast to the domain-knowledge approaches, the data-driven approaches directly extract useful features from the training data by some kinds of machine learning techniques. For example, the eigenface which will be discussed in next chapter determines the most important projection bases based on the principal component analysis which are dependent on the training data set, not the fixed basis like the DFT or DCT.

# Chapter 3

## PCA based Feature Extraction and Reduction

### 3.1 Principal Component Analysis

PCA is a linear transformation which is orthogonal too. It transforms the data to another coordinate system such that most noteworthy difference by any projection of the data lies on the first coordinate, the second most prominent fluctuation comes up in the second coordinate, etc. The idea of PCA is shown in figure 3.1. Eigenfaces also called as Principal Components Analysis (PCA) find the minimum mean squared error linear subspace that represents from the original N dimensional data space into an M-dimensional feature space. By doing this, Eigenfaces (where commonly M is not as much as N) accomplish dimensionality reduction by utilizing the M eigenvectors of the covariance matrix comparing to the largest eigenvalues. The subsequent basis vectors are acquired by finding the ideal basis vectors that maximize the total variance of the projected data (i.e. the set of basis vectors that best describe the data). Generally the mean  $\bar{x}$  is extracted from the information, so that PCA is equal

to Karhunen-Loeve Transform (KLT). So, let  $X_n$  be the the data matrix where  $x_1, \dots, x_m$  are the image vectors (vector columns) and  $n$  is the number of pixels per image. By solving the eigenvalue problem the KLT basis is obtained :

$$C_x = \phi \Lambda \phi^T$$

where  $C_x$  is the covariance matrix of the data:

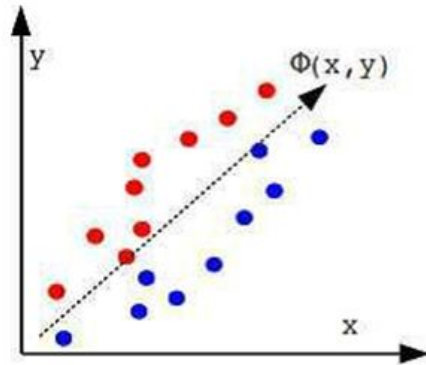
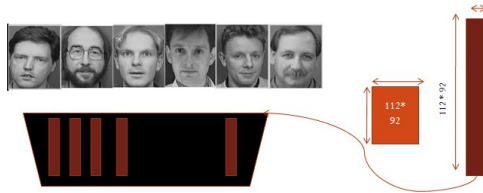


Figure 3.1: The original basis are  $x$  and  $y$ .  $\phi$  is the first principal component

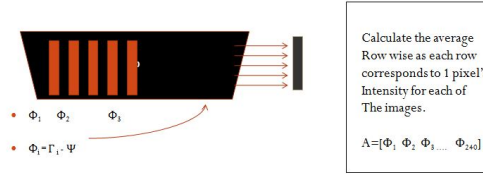
## 3.2 Algorithm

**Step 1:** Create a training set and load the training set. Training set consists of 240 images, per person 6 images.

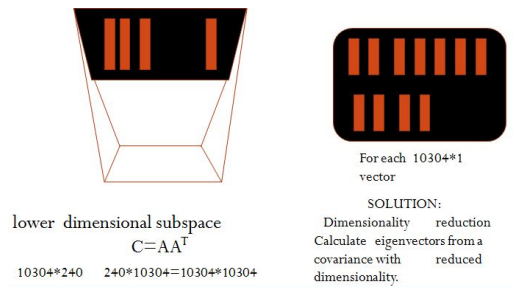
**Step 2:** Training the Recognizer Convert faces images in training set to face vectors



**Step 3:** Training the Recognizer Normalize the face vectors: calculate the average face vectors Subtract average face from each face vector



**Step 4:** Reduce the dimensionality of the training set vector



**Step 5:** Calculate the eigenvectors from the covariance matrix vector

$C = A^T A$

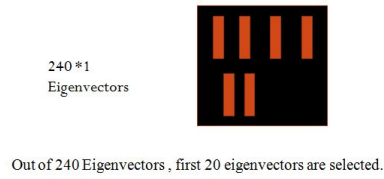
$240 * 10304 \quad 10304 * 240 = 240 * 240$   
 Covariance matrix  $C$ , now is of size  $240 * 240$   
 It will return 240 eigenvectors each of  $240 * 1$  dimensionality!

**Step 6:** Select  $K$  best eigenfaces, such that  $K \leq 240$  and can represent the whole training set vector

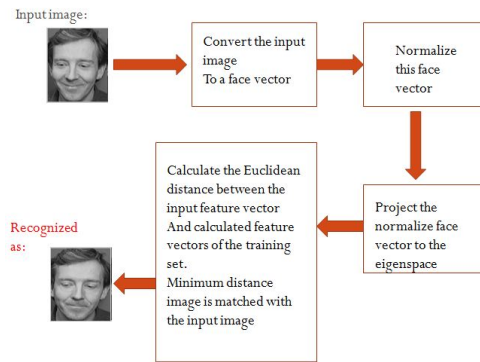


Out of 240 Eigenvectors, first 20 eigenvectors are selected.

**Step 7:** Project the images into the subspaces to generate the feature vector vector



### 3.3 Recognising An Unknown Face



### 3.4 Results

The results are shown in Table no 3.1 as above.

PCA	Training Set	Testing Set	Accuracy
Euclidean Distance	240 Faces	160 faces	95%

Table 3.1: Results of PCA

# Chapter 4

## Wavelet-based generalised neural network

### 4.1 Introduction

In this method , local feature based descriptors is concentrated ,and showed that face recognition accuracy can sunstantially be amended by merging two most flourishing local appearance descriptors,Gabor wavelets and Local Binary patterns(LBP).

- LBP is fundamentally a finely scaled descriptor which captivate small texture details;
- As LBP is resistive to illumination variances,it can code fine details of facial visual aspect and texture,which is very effective for the recognition accuracy;
- Facial contour and visual aspect information over a ambit of coarse scales is encoded by Gabor features;

In this work,I formulated an effective face recognition approach based on local Gabor binary pattern sequence,which is vigorous to the fluctuations in imaging conditions ,and offers higher recognition efficiency as equated to the subsisting state-of-art methods.The feature vectors,which are reduced, are individually normalized and ,then chained into a single combined feature vector and classification is done by neural network.Concatenation of feature is done to scale down the complexness of neural network.

## 4.2 The Proposed Approach

1. Filter bank Design:- The normalized compact closed form of the 2-d Gabor filter function is thus given by:

$$g(x, y) = \frac{f^2}{\pi\gamma\eta} e^{-\alpha^2 x_r^2 + \beta^2 y_r^2} e^{j2\pi f x_r}$$

where  $x_r = x \cos \theta + y \sin \theta$  ,  $y_r = -x \sin \theta + y \cos \theta$  ,

$$\alpha = \frac{|f|}{\gamma}$$

and

$$\beta = \frac{|f|}{\eta}$$

$\theta_k = \frac{k2\pi}{n}$  for  $k = 1, 2 \dots n - 1$  and  $n$  is the number of orientations

$f_k = \frac{f_{max}}{a^{-k}}$  for  $k = 0, 1 \dots m - 1$  and  $m$  is the number of frequency scales

$$f_{max} = .25 , a = \sqrt{(2)}$$

A gabor feature matrix is given by :

$$FeatureMatrix = \begin{pmatrix} r(x, y; f_0, \theta_0) & r(x, y; f_0, \theta_1) & \dots & r(x, y; f_0, \theta_{n-1}) \\ r(x, y; f_1, \theta_0) & r(x, y; f_1, \theta_1) & \dots & r(x, y; f_1, \theta_{n-1}) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ r(x, y; f_{m-1}, \theta_0) & r(x, y; f_{m-1}, \theta_1) & \dots & r(x, y; f_{m-1}, \theta_{n-1}) \end{pmatrix}$$

where  $m=5$  and  $n=8$  So, total number of cells in feature Matrix=40

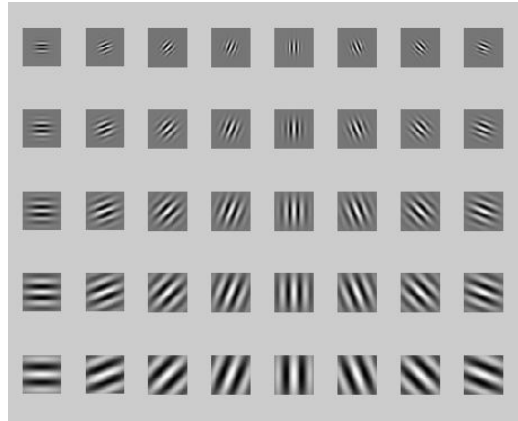


Figure 4.1: Kernel Images of Gabor Filter

**2. Decomposition of Input Image using the Filter Bank :**

Convolute the face image with the 40 gabor kernels to extract features.

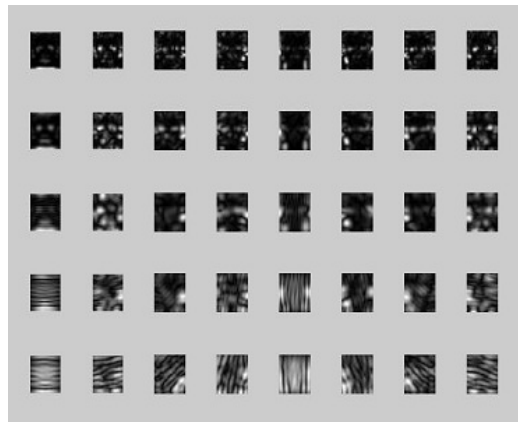


Figure 4.2: Kernel Images of Gabor Filter

And the absolute value of the Covoluted images is taken.



### 3. LBP Operator:

It is used to summarise local gray-level structure. The operator takes a local neighbourhood around each pixel, thresholds the pixels of the neighbourhood at the value of the central pixel, and uses the resulting binary-valued image patch as a local image descriptor.

$$S(f_p - f_c) = \begin{cases} 1, & f_p \geq f_c \\ 0, & f_p < f_c \end{cases}$$

with each pixel  $f_p$  ( $p=0,1,\dots,8$ ) and centre value  $f_c$ .

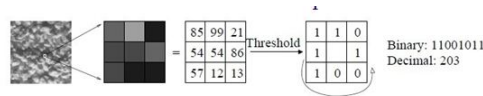


Figure 4.3: Example of LBP calculation

$$LBP = \sum_{p=0}^7 S(f_p - f_c) 2^p$$

4. **Dimension Reduction and feature extraction** The dimension of the feature vector obtained after step 3, is 40 times more than that of the uniform LBP feature.

- (a) Each LGBP image is divided into 9 regions. Mean and variance of each sub-region of the image contributes a row vector of 18 elements. Mean and Variance of 40 LGBP images produce a column vector 720 elements for each image. The Neural network architecture used in this experiment contains of 720 neurons as input, 30 neurons for hidden layer and 40 output neurons for ORL database and 15 output neurons for Yale Database.
- (b) Each LGBP image is divided into 16 regions. Mean and variance of each sub-region of the image gives a row vector of 32 elements. Mean and Variance of 40 LGBP images produce a column vector 1280 elements for each image. The Neural network architecture used in this experiment consists of 1280 neurons as input, 30 neurons for hidden and 40 output neurons for ORL database and 15 output neurons for Yale Database.

### 4.3 Results

The results are tabulated in Table no 4.1 and Table no 4.2 above for ORL database and Table no 4.3 for Yale Database.

Number of Images	number of subregions	Training	validation	Testing	Accuracy
400	9(3*3)	320	40	40	97.5%
400	9(3*3)	300	40	60	98.34%
400	9(3*3)	280	40	80	96.25%
400	9(3*3)	260	40	100	94%
400	9(3*3)	240	40	120	93.33%
400	9(3*3)	220	40	140	88.572%

Table 4.1: Results of ORL Database

Number of Images	number of subregions	Training	validation	Testing	Accuracy
400	16(4*4)	300	60	40	100%
400	16(4*4)	280	60	60	100%
400	16(4*4)	260	60	80	98.75%
400	16(4*4)	240	60	100	97%
400	16(4*4)	220	60	120	95%
400	16(4*4)	220	40	140	92.858%

Table 4.2: Results of ORL Database

Number of Images	Number of subregions	Training	validation	Testing	Accuracy
165	16(4*4)	131	17	17	100%
165	16(4*4)	123	17	25	100%
165	16(4*4)	115	17	33	100%
165	16(4*4)	107	17	41	100%
165	16(4*4)	90	25	50	100%
165	16(4*4)	90	17	58	98.276%

Table 4.3: Results of Yale Database

# Chapter 5

## Simulated-annealing-based approach for parameter optimization of BPN

### 5.1 Literature Review

BPN ,back-propagation is a common neural network model. Its architecture is the multi-layer perceptrons(MLP).The BPN uses "the gradient steepest descent method" to lessen the errors between actual and predictive output functions. The weights in the network are initialized to small arbitrary numbers going from -0.3 to 0.3 . This research proposes how to obtain the optimal parameter settings for network architectures of BPN using simulated annealing approach ,which will give better accuracy.This method saves us from checking arbitrary solutions for parameter setting of BPN using "hit and trial method".

### 5.2 The proposed Approach

**Step 1:** The objective function of SA + BPN is classification accuracy rate of testing data ,that is,number of correctly classified data divided by total number of testing data.As,classification accuracy rate is a maximization function,it is directly proportional to objective function value.Higher classification accuracy rate results in higher objective function value.

**Step 2:** For the instance of maximization,if the objective function value of the next feasible solution is more than that of the current values,it will be accepted as the current solution directly and will keep on searching for next solution.

**Step 3:** According to Metropolis' criteria,the next solution can be accepted even if the objective functional value of the next solution is less than that of the current solution.

**Step 4:** At the beginning,the temperature  $T$  is initialized to be very large value.SA+BPN then,randomly generates a feasible initial solution  $f_x = objFun(x)$  where  $objfun(x)$  is the objective function of calculating the classification accuracy rate of  $x$ .

**Step 5:** Let  $f_{x_1} = f_x$  ( this is the initial solution;therefore the highest objective functional value found so far is  $f_x$  ).

**Step 6:** For each of the iteration,taking  $x$  as the current solution,randomly feasible solution from one random vector is selected which is projected from the current solution  $x$ .

**Step 7:** If the objective function value  $f_y = objFun(y)$  of  $y$ , $f_y$  is greater than  $f_x$ ,then let  $f_x = f_y$  and current solution  $x$  equal to  $y$ .

**Step 8:** If  $f_y$  smaller than  $f_x$  ,then the probability of replacing the current solution  $x$  with  $y$  be expressed as  $(f_y - f_x)/T$ .

**Step 9:** If  $f_y$  is greater than  $f_{x_1}$  ,set  $f_{x_1}$  equal  $f_y$  and the best solution found so far  $x_{opt}$  equal  $y$ ,then temperature is lowered once .

**Step 10:** From  $x_{opt}$  ,the optimal parameter settings for network architecture of BPN can be obtained.

### 5.3 Results

The k-fold approach is utilized to inspect the classification precision rate. This study set k as 10 and the information is partitioned into 10 cuts, then every cut of the information has the same extent of every class of the data. Out of 10 cuts, nine data cuts were used for training, while the remaining one is used as the testing. The system was run for 10 times turn by turn so as to permit every sliced of data to take a turn as the testing data. The rate of exactness in classification of this test was figured by summing the individual exactness rate for every run, the dividing the total by 10.

The outcomes are demonstrated in Table no 5.1 for Yale Database and Table no 5.2 for ORL Database.

	Learning rate	Number of hidden neurons	Accuracy
Slice-1	0.4606	84.9877	80%
Slice-2	0.5794	83.58	80 %
Slice-3	0.7867	89.8974	80%
Slice-4	0.90	73.24	86.67%
Slice-5	0.4382	60	86.67%
Slice-6	0.30	85.70	93.33%
Slice-7	0.30	76.12	73.33%
Slice-8	0.843	78.9406	86.67%
Slice-9	0.3	68.9507	86.67%
Slice-10	0.5536	60.0656	73.33%
Average			81.33 %

Table 5.1: 10-fold classification result of Yale database

	Learning rate	Number of hidden neurons	Accuracy
Slice-1	0.6304	150.0	90%
Slice-2	0.4018	121.596	82.5%
Slice-3	0.6767	112.825	82.5%
Slice-4	0.6917	149.6159	82.5%
Slice-5	0.5488	99.7328	87.5%
Slice-6	0.6562	90.0126	87.5%
Slice-7	0.6482	123.0064	82.5%
Slice-8	.90	145.0796	75%
Slice-9	0.6512	122.897	82.5%
Slice-10	0.5949	90.3282	80%
Average			83.25 %

Table 5.2: 10-fold classification result of ORL Database

# Chapter 6

## Conclusion

As PCA has no effect on expressions and pose it gives good results but illumination variations is a major drawback for PCA algorithm. So, to overcome illumination variations, we have used two local descriptors. A productive face recognition technique is proposed, by utilizing LGBPHS and neural network, which have demonstrated better results notwithstanding for slight appearance varieties because of lighting and expressions. The LGBPHS demonstrated the ability to give the noteworthy highlights of the picture as input to the neural network. The effectiveness is because of the utilization of multi-orientation Gabor decomposition, and the LBP. In the second part, research is connected to the simulated-annealing-based approach for dealing with quest for the best parameter settings for system architectures of BPN. The results are compared for three approaches. The best results are obtained for two local based descriptors, gabor wavelets and local binary pattern (LBP).

# Bibliography

- [1] P. Sharma, K. V. Arya, R. N. Yadav, "Efficient face recognition using wavelet-based generalized neural network", Signal processing, Elsevier, 2012
- [2] W. Zhao, R. Chellappa, P. J. Phillips, "A. Rosenfeld, Face recognition: A literature survey", ACM Computing Surveys (2003) 399–458.
- [3] Dandpat S.K, Meher, S, "Performance improvement for face recognition using PCA and two-dimensional PCA " (ICCCI) 2013
- [4] Shih-Wei Lin, Tsung-Yuan Tseng, Shuo-Yan Chou, Shih-Chieh Chen, "A simulated-annealing-based approach for simultaneous parameter optimization and feature selection of back-propagation networks", Elsevier, 2007