BANSILAL RAMNATH AGARWAL CHARITABLE TRUST'S

VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY

(Department of Electronics & Telecommunication)

A

Project entitled

"Face Recognition By Exploring Information Jointly in Space, Scale and Orientation"

Submitted by

Vedant Bhoj (B80393024)

Prashant Dongarkar (B80393048)

Tejas Chumbalkar (B80393034)

Project & Seminar

B.E. Electronics & Tele-Communication

of

Savitribai Phule Pune University

Under the supervision of

Prof. A. P. Navghane

Year 2014 – 2015

BANSILAL RAMNATH AGARWAL CHARITABLE TRUST'S

VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY

(Department of Electronics & Telecommunication)

CERTIFICATE

This is to certify that the project-

"Face Recognition
By
Exploring Information Jointly in Space, Scale and Orientation"

Has being carried out by

Vedant Rajay Bhoj (B80393024)

Prashant Prakash Dongarkar (B80393048)

Tejas Sharad Chumbalkar (B80393034)

that is allotted to these students based on the their project presentation .

The work is done, on the basis of the work allotted to these students, based on various Project ideas presented by them.

This project report is being submitted as a part of the subject Project (Part 2) at B.E E&TC

Prof. A. P. Navghane	**Prof. (Dr.)P.D.Khandekar**
Guide	H.O.D-E&TC

ACKNOWLEDGEMENT

Gratitude foremost is to Almighty without whose permission, grace, aid and blessings this endeavour would never have begun.

We would like to express our gratitude to **Prof. A.P.Navghane** and **Prof. Y. H. Dandawate** for believing in our abilities and giving us the opportunity to realize them and continuous encouragement and constant availability to solve our problems, this project would never have been possible.

We would like to acknowledge the encouragement rendered by **Prof. (Dr.) P.D.Khandekar,** Head of Department of Electronics and Telecommunications.

We are also thankful to everyone who was involved directly or indirectly in the completion of the project in various aspects, both technical and non-technical. We would like to thank our family, friends and seniors whose patience and support was instrumental in accomplishing this task.

ABSTRACT

Face recognition, as one of the primary biometric technologies, became more and more important owing to rapid advances in technologies such as digital cameras, the Internet and mobile devices, and increased demands on security.

There are various challenges to be faced like different expressions, poses, occlusions and illuminations and time constraint for processing. Recent biological studies indicate that retinal position, spatial frequency and orientation selectivity properties have an important role in visual perception.
The position, spatial frequency and orientation selectivity properties are believed to have an important role in visual perception.

In Crime Investigation it is very important to identify the suspect in a very short time. Local appearance features like Gabor and local binary patterns (LBP's) as opposed to holistic features like PCA and LDA are more stable to local changes such as illumination, expression. To extract discriminant features and enlarge the margin among different persons becomes a critical and difficult problem in face recognition.

The face image is first decomposed into different scale and orientation responses by convolving multi-scale and multi-orientation Gabor filters. Gabor filters exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains. It is invariant to any monotonic grey scale transformation and is, therefore, robust to illumination changes.

Second, local binary pattern analysis issued to describe the neighbouring relationship in image space as well as in different scale and orientation responses.

In this way, information from different domains is explored to give a good face representation for recognition.

LIST OF ABBREVIATIONS

CMI	Conditional Mutual Information
CVC	Computer Vision Centre
DARPA	Defence Advanced Research Project Agency
DCT	Discrete Cosine Transform
EBGM	Elastic Bunch Graph Matching
FERET	Face Recognition Technology
FFT	Fast Fourier Transform
FRGC	Face Recognition Grand Challenge
GPU	Graphics Processing Unit
GTP	Gabor Ternary Pattern
GV-LBP	Gabor Volume Based Local Binary Pattern
GV-LBP-TOP	Gabor Volume –Local Binary Pattern – Three Orthogonal
ICA	Independent Component Analysis
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LGBPHS	Local Gabor Binary Pattern Histogram Sequence
NIST	National Institute Of Standards and Technology
ORL	Otto- Rhino Laryngologie
PCA	Principal Component Analysis

TABLE OF CONTENT

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Humans often use faces to recognize individuals and advancements in computing capability over the past few decades now enable similar recognitions automatically. Early face recognition algorithms used simple geometric models, but the recognition process has now matured into a science of sophisticated mathematical representations and matching processes. Major advancements and initiatives in the past ten to fifteen years have propelled face recognition technology into the spotlight. Face recognition can be used for both verification and identification (open-set and closed-set).

1.1 HISTORY

Automated face recognition is a relatively new concept. Developed in the 1960s, the first semi-automated system for face recognition required the administrator to locate features on the photographs before it calculated distances and ratios to a common reference point, which were then compared to reference data. In the 1970s, Goldstein, Harmon, and Lesk used 21 specific subjective markers such as hair color and lip thickness to automate the recognition. The problem with both of these early solutions was that the measurements and locations were manually computed. In 1988, Kirby and Sirovich applied PCA, a standard linear algebra technique, to the face recognition problem. This was considered somewhat of a milestone as it showed that less than one hundred values were required to accurately code a suitably aligned and normalized face image. In 1991, Turk and Pentland discovered that while using the eigenfaces techniques, the residual error could be used to detect faces in images – a discovery that enabled reliable real-time automated face recognition systems. Although the approach was somewhat constrained by environmental factors, it nonetheless created significant interest in furthering development of automated face recognition technologies. The technology first captured the public's attention from the media reaction to a trial implementation at the January 2001 Super Bowl, which captured surveillance images and compared them to a database of digital mugshots. Today, face recognition technology is being used to combat passport fraud, support law enforcement, identify missing children, and minimize benefit/identity fraud.

1.2 WHY FACE RECOGNITION ?

Given the requirement for determining people's identity, the obvious question is what technology is best suited to supply this information? There are many ways that humans can identify each other, and so is for machines. There are many different identification technologies available, many of which have been in commercial use for years. The most common person verification and identification methods today are Password/PIN known as Personal Identification Number, systems. The problem with that or other similar techniques is that they are not unique, and is possible for somebody to forget loose or even have it stolen for somebody else. In order to overcome these problems there has developed considerable interest in "biometrics" identification systems, which use pattern recognition techniques to identify people using their characteristics. Some of those methods are fingerprints and retina and iris recognition. Though these techniques are not easy to use. For example in bank transactions and entry into secure areas, such technologies have the disadvantage that they are intrusive both physically and socially. The user must position the body relative to the sensor, and then pause for a second to declare himself or herself. That doesn’t mean that face recognition doesn’t need specific positioning. As we are going to analyse later on the poses and the appearance of the image taken is very important.

While the pause and present interaction are useful in high-security, they are exactly the opposite of what is required when building a store that recognise its best customers, or an information kiosk that remembers you, or a house that knows the people who live there. Face recognition from video and voice recognition have a natural place in these next generation smart environments, they are unobtrusive, are usually passive, do not restrict user movement, and are now both low power and inexpensive. Perhaps most important, however, is that humans identify other people by their face and voice, therefore are likely to be comfortable with systems that use face and voice recognition.

1.3 THE PRESENT

With the rapid evolution of the technology and the commercialisation of technological achievements, face recognition became more and more popular, not only for research but also for the use of security systems.

That gave the motive to many researchers, and also companies in order to develop techniques for automatically recognising faces that would find many applications, including security and human-computer interaction. For instance, a face recognising machine could allow automated access control for buildings or enable a computer to recognise the person sitting at the console. Most existing face recognition systems, however, work only for frontal or nearly frontal images of faces. By recognising faces under varying pose, one makes the conditions under which face recognition systems operate less rigid.

1.4 OBJECTIVE:-

To propose a robust face recognition system that is invariant to changes such as illumination ,different expressions, poses, occlusions by exploring features jointly in image space, scale and orientation domain

CHAPTER 2

LITERATURE SURVEY

2. Literature Survey

2.1 HISTORICAL ANALYSIS OF DIFFERENT METHODOLOGIES

These are the different Methodologies used for Face Recognition:-
The performance of face recognition systems has improved significantly since the first automatic face recognition system as follows:-

NAME	TITLE	TOPIC	YEAR
Kanade	JEFFREY F. COHN, ADENA J. ZLOCHOWER, JAMES LIEN and TAKEO KANADE, "Automated face analysis by feature point tracking has high concurrent validity with manual FACS coding"	**First Automated System**	**1973**
Sirvovich & Kirby	M. Kirby and L. Sirovich, "Application of the Karhunen-Loeve Procedure for the Characterization of Human Faces" IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 1, Jan. 1990.	**PCA**	**1987**
Turk & Pentland	M. Turk and A. Pentland, "Face Recognition Using Eigenfaces" Proc. IEEE Conf. on Computer Vision and Pattern Recognition, 1991.	**Eigen faces**	**1991**
Etemad & Chellapa	K. Etemad and R. Chellappa, "Face Recognition Using Discriminant Eigenvectors," *Proc. IEEE Int'l Conf. Acoustics, Speech, and Signal Processing,* Vol. 4, 1996.	**Fisher face**	**1996**
Naruniec & Skarbek	J. Naruniec and W. Skarbek, "Face detection by discrete Gabor jets and reference graph of fiducial points," in Rough Sets and Knowledge Technology. Springer Berlin / Heidelberg, 2007.	**Gabor filter**	**2007**

2.2 Predominant Approaches:

There are two predominant approaches to the face recognition problem: geometric (feature based) and photometric (view based). As researcher interest in face recognition continued, many different algorithms were developed, three of which have been well studied in face recognition literature: Principal Components Analysis (PCA), Linear Discriminant Analysis (LDA), and Elastic Bunch Graph Matching (EBGM).

2.3 Principal Components Analysis (PCA):

Principal Components Analysis (PCA), commonly referred to as the use of eigenfaces, is the technique pioneered by Kirby and Sirivich in 1988. With PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subjects within the images. The PCA approach is then used to reduce the dimension of the data by means of data compression basics and reveals the most effective low dimensional structure of facial patterns. This reduction in dimensions removes information that is not useful and precisely decomposes the face structure into orthogonal (uncorrelated) components known as eigenfaces. Each face image may be represented as a weighted sum (feature vector) of the eigenfaces, which are stored in a 1D array. A probe image is compared against a gallery image by measuring the distance between their respective feature vectors. The PCA approach typically requires the full frontal face to be presented each time; otherwise the image results in poor performance.4 The primary advantage of this technique is that it can reduce the data needed to identify the individual to 1/1000th of the data presented.

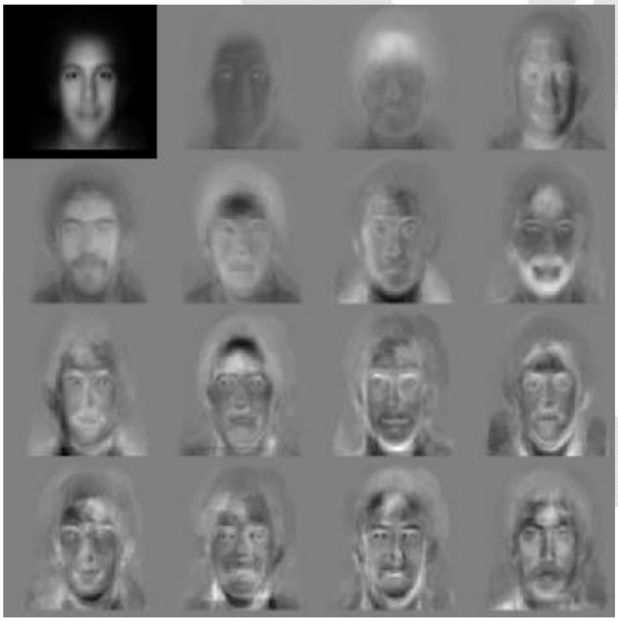


Figure 1: Standard Eigenfaces: Feature vectors are derived using eigenfaces

2.4 Linear Discriminant Analysis (LDA):

LDA is a statistical approach for classifying samples of unknown classes based on training samples with known classes. This technique aims to maximize between-class (i.e., across users) variance and minimize within-class (i.e., within user) variance. In Figure where each block represents a class, there are large variances between classes, but little variance within classes. When dealing with high dimensional face data, this technique faces the small sample size problem that arises where there are a small number of available training samples compared to the dimensionality of the sample space.

Figure 2: Example of Six Classes Using LDA

2.5 Eigen Faces

The Eigenface approach began with a search for a low-dimensional representation of face images. Sirovich and Kirby (1987) showed that Principal Component Analysis could be used on a collection of face images to form a set of basis features. These basis images, known as Eigen pictures, could be linearly combined to reconstruct images in the original training set. In 1991 M. Turk and A. Pentland expanded these results and presented the Eigenface method of face recognition. In addition to designing a system for automated face recognition using eigenfaces, they showed a way of calculating the eigenvectors of a covariance matrix in such a way as to make it possible for computers at that time to perform eigen-decomposition on a large number of face images. Face images usually occupy a high-dimensional space and conventional principal component analysis was intractable on such data sets.

2.6 Elastic Bunch Graph Matching (EBGM):

EBGM relies on the concept that real face images have many nonlinear characteristics that are not addressed by the linear analysis methods discussed earlier, such as variations in illumination (outdoor lighting vs. indoor fluorescents), pose (standing straight vs. leaning over) and expression (smile vs. frown). A Gabor wavelet transform creates a dynamic link architecture that projects the face onto an elastic grid. The Gabor jet is a node on the elastic grid, notated by circles on the image below, which describes the image behaviour around a given pixel. It is the result of a convolution of the image with a Gabor filter, which is used to detect shapes and to extract features using image processing. A convolution expresses the amount of overlap from functions, blending the functions together. Recognition is based on the similarity of the Gabor filter response at each Gabor node. This biologically-based method using Gabor filters is a process executed in the visual cortex of higher mammals. The difficulty with this method is the requirement of accurate landmark localization, which can sometimes be achieved by combining PCA and LDA methods.

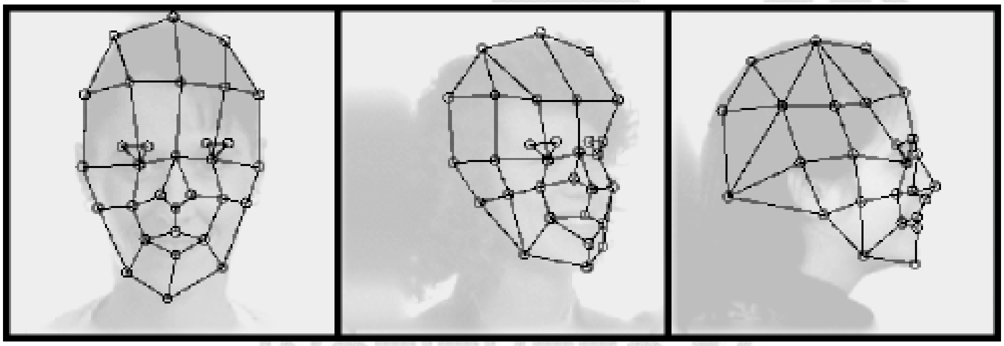


Figure 3: Elastic Bunch Map Graphing.

CHAPTER 3

THEORY

3.1 THEORY:

As rightly pointed by Woody Bledsoe, one of the founders of artificial intelligence, making early contributions in pattern recognition.

This recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, etc. Some other attempts at facial recognition by machine have allowed for little or no variability in these quantities. Yet the method of correlation (or pattern matching) of unprocessed optical data, which is often used by some researchers, is certain to fail in cases where the variability is great. In particular, the correlation is very low between two pictures of the same person with two different head rotations.

In order to face this challenge, it has to know how to differentiate between a basic face and the rest of the background. Facial recognition software is based on the ability to recognize a face and then measure the various features of the face. Every face has numerous, distinguishable landmarks, the different peaks and valleys that make up facial features. It defines these landmarks as nodal points. Each human face has approximately 80 nodal points. Some of these measured by the software are:

- Distance between the eyes
- Width of the nose
- Depth of the eye sockets
- The shape of the cheekbones
- The length of the jaw line

These nodal points are measured creating a numerical code, called a face print, representing the face in the database. In the past, facial recognition software has relied on a 2D image to compare or identify another 2D image from the database. To be effective and accurate, the image captured needed to be of a face that was looking almost directly at the camera, with little variance of light or facial expression from the image in the database.

This created quite a problem. In most instances the images were not taken in a controlled environment. Even the smallest changes in light or orientation could reduce the effectiveness of the system, so they couldn't be matched to any face in the database, leading to a high rate of failure.

Numerous methods have been developed for holistic face recognition with impressive performance. However, few studies have tackled how to recognize an arbitrary patch of a face image. Partial faces frequently appear in unconstrained scenarios, with images captured by surveillance cameras or handheld devices (e.g., mobile phones) in particular.

We develop an alignment-free face representation method based on Multi-Keypoint Descriptors (MKD), where the descriptor size of a face is determined by the actual content of the image. In this way, any probe face image, holistic or partial, can be sparsely represented by a large dictionary of gallery descriptors. A new keypoint descriptor called Gabor Ternary Pattern (GTP) is also developed for robust and discriminative face recognition. Comparisons with two leading commercial face recognition SDKs (PittPatt and FaceVACS) and two baseline algorithms (PCA+LDA and LBP) show that the proposed method, overall, is superior in recognizing both holistic and partial faces without requiring alignment.

Therefore, how to extract robust and discriminant features which make the intra person faces compact and enlarge the margin among different persons becomes a critical and difficult problem in face recognition. Up to now, many face representation approaches have been introduced, including subspace based holistic features and local appearance features.

Typical holistic features include the well-known principal component analysis (PCA), linear dis-criminate analysis (LDA), independent component analysis (ICA), etc. PCA provides an optimal linear transformation from the original image space to an orthogonal eigenspace with reduced dimensionality in sense of the least mean square reconstruction error. LDA seeks a linear transformation by maximizing the ratio of between-class variance and within-class variance.

ICA is a generalization of PCA, which is sensitive to the high-order relationship among the image pixels. Recently, Wang and Tang unify PCA, LDA and Bayesian methods into the same framework and present a method to find the optimal configuration for LDA.

Furthermore, in order to handle the nonlinearity in face feature space, the nonlinear kernel techniques (e.g., kernel PCA, kernel LDA etc.) are also introduced. Local appearance features, as opposed to holistic features like PCA and LDA, have certain advantages. They are more stable to local changes such as illumination, expression and inaccurate alignment. Gabor, and local binary patterns (LBPs) are two representative features. Gabor wavelets capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes. LBP operator which describes the neighboring changes around the central point, is a simple yet effective way to represent faces. It is invariant to any monotonic gray scale transformation and is, therefore robust to illumination changes to some extent.

Recently, some work has been done to apply LBP on the Gabor responses to obtain a more sufficient and stable representation. Zhang *et al* propose LBPs descriptor on Gabor magnitude representation and Zhang *et al.*, perform LBP on Gabor phase information. The global and local descriptors are presented, respectively, and finally fused for face representation. These combinations of LBP and Gabor features have improved the face recognition performance significantly compared to the individual representation. Combining information from different domains is usually beneficial for face recognition. Recent biological studies indicate that retinal position, spatial frequency and orientation selectivity properties have an important role in visual perception.

CHAPTER 4

SELECTION OF ALGORITHM

4.1 SELECTION OF ALGORITHM:

Local appearance features, as opposed to holistic features like PCA and LDA, have certain advantages. They are more stable to local changes such as illumination, expression and inaccurate alignment.

Gabor and local binary patterns (LBPs) are two representative features. Gabor wavelets capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes.

LBP operator which describes the neighbouring changes around the central point, is a simple yet effective way to represent faces. It is invariant to any monotonic grayscale transformation and is, therefore, robust to illumination changes some extend.

These combinations of LBP and Gabor features have improved the face recognition performance significantly compared to the individual representation. Combining information from different domains is usually beneficial for face recognition. Recent biological studies indicate that retinal position, spatial frequency and orientation selectivity properties have an important role in visual perception.

Therefore, we propose to explore information jointly in space, frequency, and orientation domains to enhance the performance of face recognition.

CHAPTER 5

METHODOLOGY

5.1 METHODOLGY

There are mainly three advantages for the proposed method. First, Gabor feature is applied to the face images to alleviate the variations of facial expression and illumination. Second, the LBP is utilized to model the neighbouring relationship jointly in spatial, frequency and orientation domains.

In this way, discriminant and robust information, as much as possible, could be explored. The uniform pattern mechanism is then presented to improve the efficacy of the proposed representation. Third, a feature selection and discriminant analysis method is introduced to make the face representation compact and effective for face recognition. Gabor filters briefly reviews the GV-LBP-TOP and E-GV-LBP representations based upon the Gabor faces. LBP describes the details of weighted histogram distance metric and the process of face recognition.

The main procedure of the proposed joint information extraction is as follows:-

1. First, the multi scale and multi orientation representations are derived by convolving the face image with a Gabor filter bank and formulated as a
   Third order volume.
2. Second, LBP operator is applied on the three orthogonal planes of Gabor volume, respectively, named GV-LBP-TOP in short.

   In this way, we encode the neighbouring information not only in image space but also among different scales and orientations of Gabor faces.

5.2 GABOR FILTER:-

Gabor filters, exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains, have been extensively and successfully used in Face Recognition.

The Gabor kernels used are defined as follows:-

$$\varphi_{u,v} = \frac{k_{u,v}^2}{\sigma^2} \exp\left(-\frac{k_{u,v}^2 z^2}{2\sigma^2}\right) X \left[\exp\left(ik_{u,v}\, z\right) - \exp\left(\frac{-\sigma^2}{2}\right)\right]$$

Where u and v define the orientation and scale of the Gabor kernels, respectively,

z= (x, y), and the wave vector $k_{u,v}$ is defined as:

$$k_{u,v} = k_v e$$

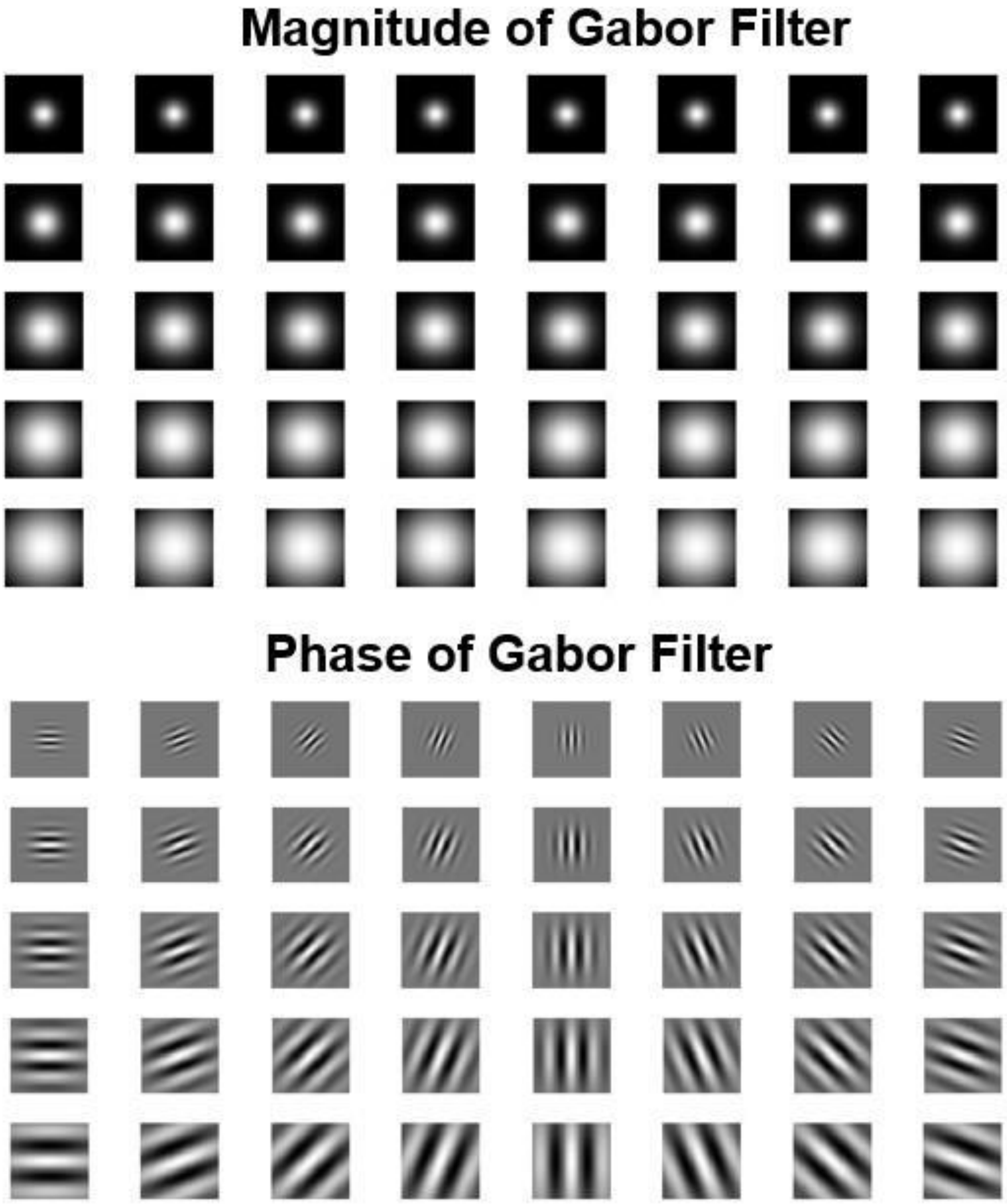
σ is the standard deviation.

where $k_v = k_{max}/f^v$, $k_{max} = \pi/2$, $f = \sqrt{2}$, $\emptyset_u = \pi u/8$.

The Gabor kernels in the above equation are all self-similar since they can be generated from one filter, the mother wavelet, by scaling and rotating via the wave vector. Hence, a band of Gabor filters is generated by a set of various scales and rotations. For every image pixel let's say we have totally 40 Gabor magnitude and phase coefficients, respectively, that is to say, we can obtain 40 Gabor magnitude and 40 Gabor phase faces from a single input face image.

5.3 GABOR FILTER BANK

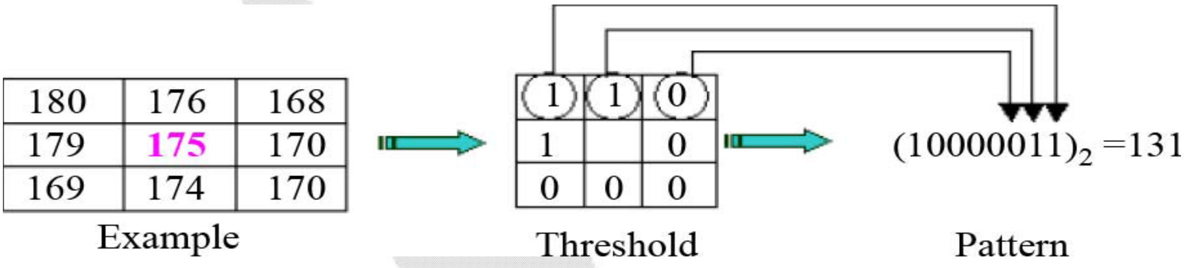
Gabor kernels have five scales **v € {0,1,2,3,4}** and eight orientations **µ €{0,1,2,3,4,5,6,7,9}** to derive the Gabor representation by convolving face images with corresponding Gabor kernels.



For every image pixel we can obtain 40 Gabor magnitude and 40 Gabor phase face from a single input face image.

5.4 Local Binary Pattern (LBP):

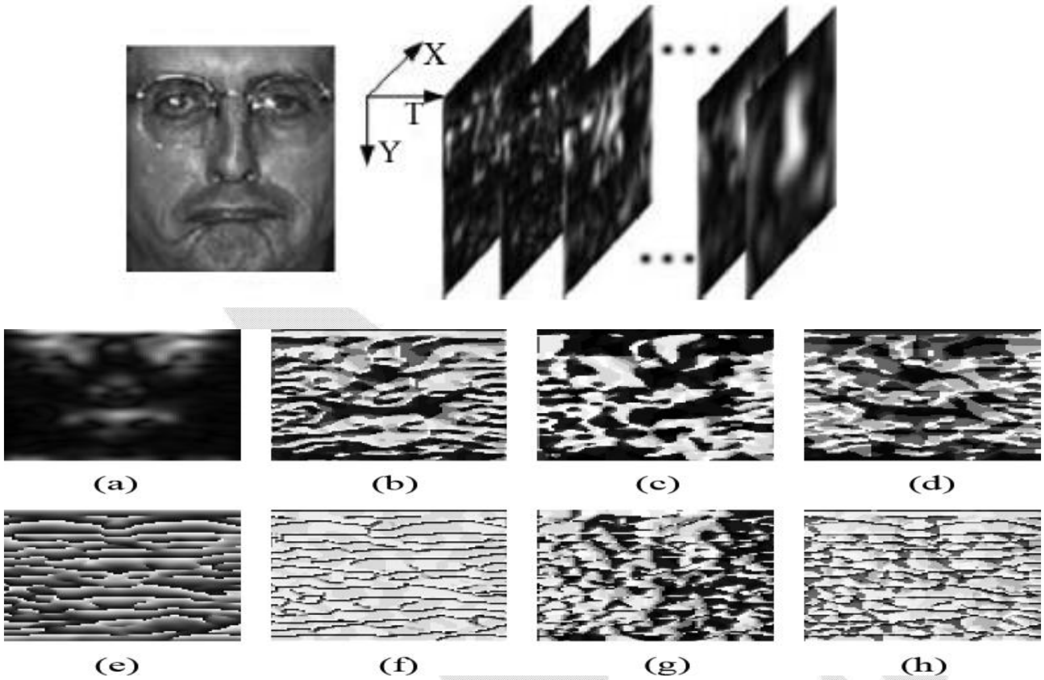
The basic LBP operator labels the pixels of an image by thresholding the 3 X 3 neighbourhood of each pixel with the centre value and considering the result as a binary number (or called LBP codes).



For a face image, the derived Gabor faces are assembled by the order of different scales and orientations to form a third-order volume where the three axes X, Y, T denote the different rows, columns of face image and different types of Gabor filters, respectively.

It can be seen that the existing methods essentially applied LBP or LXP operator on XY plane. It is natural and possible to conduct the similar analysis on XT and YT planes to explore more sufficient and discriminative information for face representation. GV-LBP-TOP is originated from this idea.

It first applies LBP analysis on the three orthogonal planes (XY, XT, and YT) of Gabor face volume and then combines the description codes together to represent faces.



(a) Gabor magnitude and (e) phase faces and (b), (f) their corresponding GV-LBP-XY, (c), (g) GV-LBP-XT, (d), (h) GV-LBP-YT. Fig. Illustrates examples of Gabor magnitude and phase faces and their corresponding GV-LBP codes on XY, XT, and YT planes.

Three histograms corresponding to GV LBP-XY, GV-LBP-XT, and GV-LBP-YT codes are computed as:-

$$H_j(l) = \sum_{x,y} I\big(f_j(\mathrm{x},\mathrm{y}) = l\big), l = 0,1, \dots \dots, L_j - 1$$

The GV-LBP-TOP histogram H is finally derived by concatenating these three histograms H = [H1, H2, H3] to represent the face that incorporates the spatial information and the co-occurrence statistics in Gabor frequency and orientation domains.

5.5 E-GV-LBP

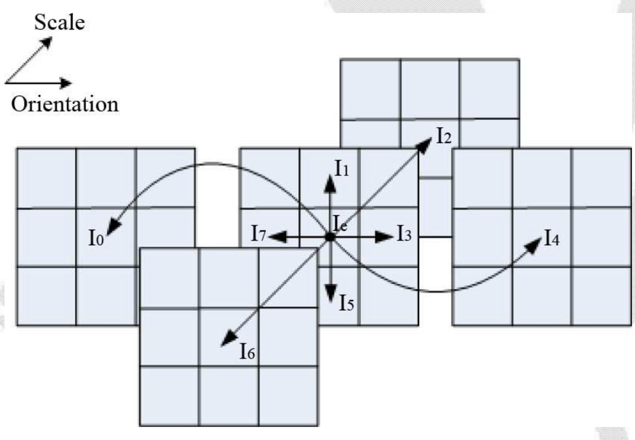
E-GV-LBP models the neighbouring changes around the central point in the joint domains simultaneously for face representation.

After that, a statistical uniform pattern mechanism is adopted and local histogram features based upon the uniform patterns are extracted.

Discriminant classification is finally performed based upon weighted histogram intersection or conditional mutual information (CMI) with linear discriminant analysis (LDA) techniques.

There are mainly three advantages for the proposed method:-

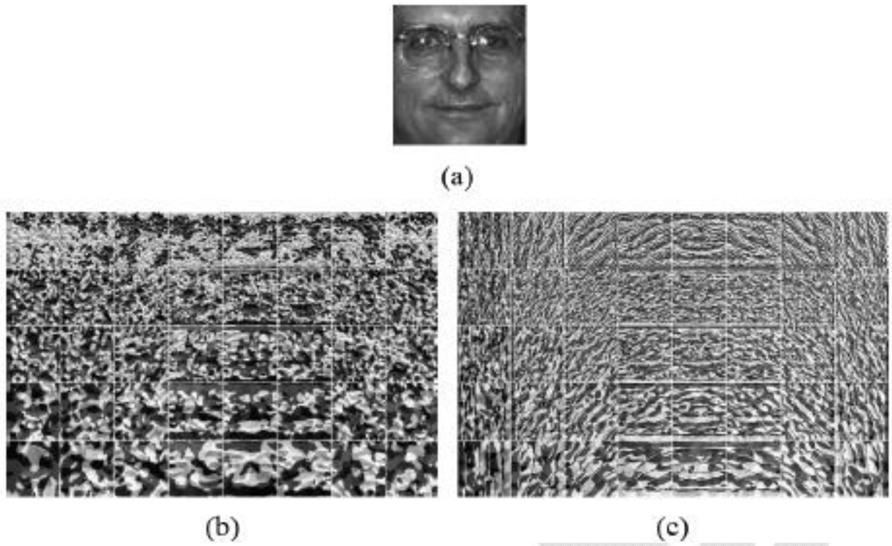
1. Gabor feature is applied to the face images to alleviate the variations of facial expression and illumination.
2. The LBP is utilized to model the neighbouring relationship jointly in spatial, frequency and orientation domains.
3. A feature selection and discriminant analysis method is introduced to make the face representation compact and effective for face recognition.



This is an effective formulation of GV-LBP (E-GV-LBP) which encodes the information in spatial, frequency and orientation domains simultaneously and reduces the computational cost.

For the central point Ic, I0 and I4 are the orientation neighbouring pixels; I2 and I6 are the scale neighbouring ones I1, I3, I5 and I7 are the neighbouring pixels in spatial domains.

Like in LBP, all the values of these pixels surrounded are compared to the value of the central pixel, thresholded into 0 or 1 and transformed into a value between 0 and 255 to form the E-GV-LBP value.



(a) One face image, its E-GV-LBP results on (b) Gabor magnitude faces and (c) Gabor phase faces.

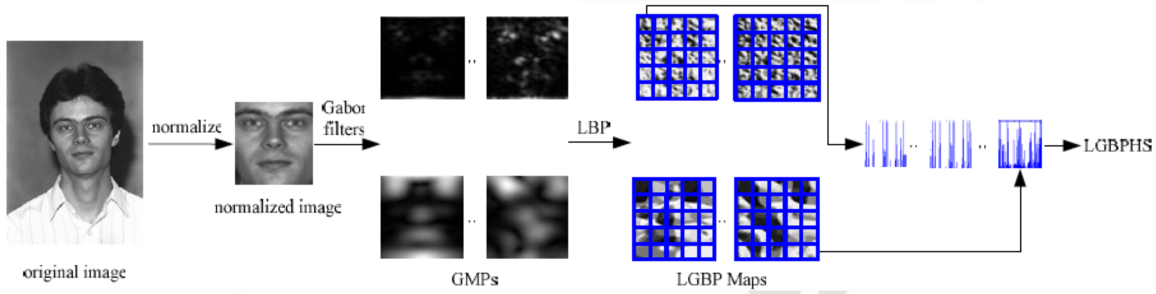
5.6 WEIGHTED HISTOGRAM INTERSECTION (LGBPHS):

The histogram intersection is used as the dissimilarity to measure different Face images.

$$d(H^1, H^2) = \sum_i \min(h_i^1,\, h_i^2)$$

where H1, H2 are two histograms and h_i^1 , h_i^2 denote the bin value.

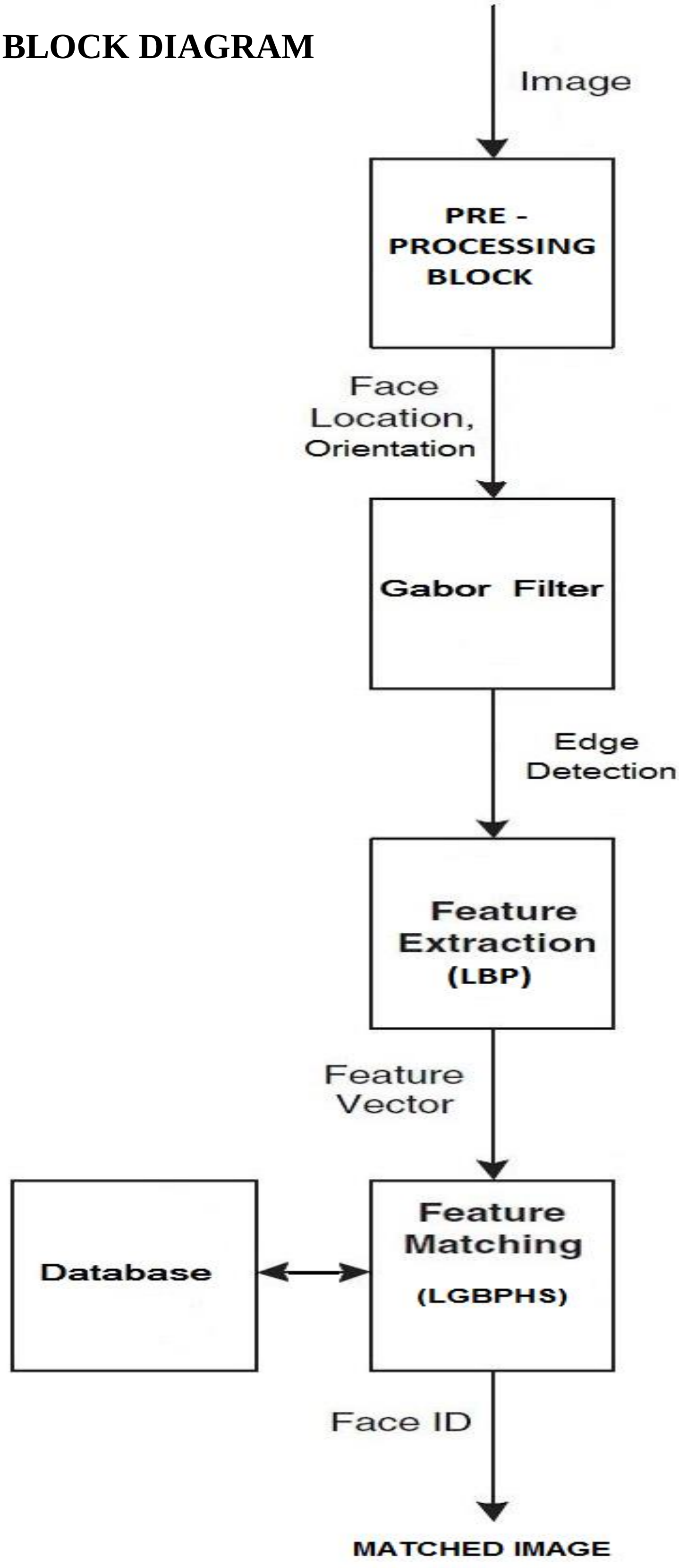
In this method the face image is divided into several blocks. The local histograms are first obtained from different blocks and then concatenated into a histogram sequence to represent the whole face. Thus the face image is depicted successfully at three levels as in local histogram expresses characteristic at regional level which is robust to alignment errors. The areas nearby eyes and nose are more important than others. Therefore, it is sensible to assign different weights onto different blocks when measuring the dissimilarity of two images.



CHAPTER 6

BLOCK DIAGRAM

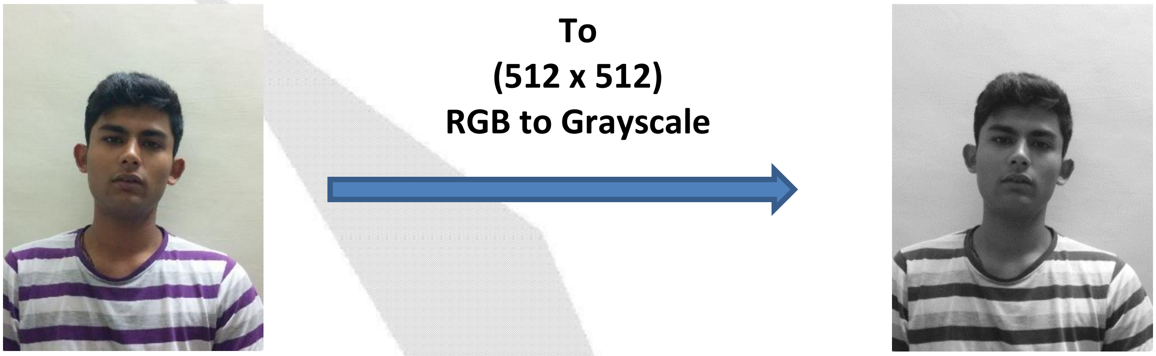
6.1 BLOCK DIAGRAM



6.2 BLOCK DIAGRAM DESCRIPTION

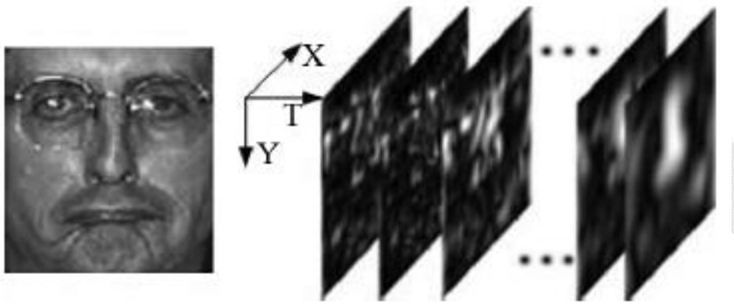
- **PRE-PROCESSING :-**

The raw input image which we are using is not suitable for the processing as per the algorithm. Therefore we have to change the format, the resolution and depth of the image to grey scale.



- **GABOR FILTER :-**

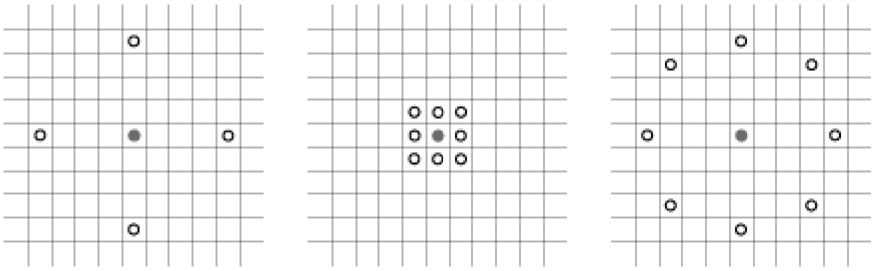
Gabor filters, exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains, have been extensively and successfully used in Face Recognition.



❑ FEATURE EXTRACTION (L.B.P) :-

Local binary pattern (LBP) is a gray-scale invariant texture description operator which labels the pixels of an image by thresholding the neighborhood of each pixel with the center value and considering the result as a binary pattern.

Local binary pattern analysis is used to describe the neighbouring relationship not only in image space, but also in different scale and orientation responses.



(a) $LBP_{(4,4)}$ (b) $LBP_{(8,1)}$ (c) $LBP_{(8,4)}$

Fig. 2: Local Binary Patterns

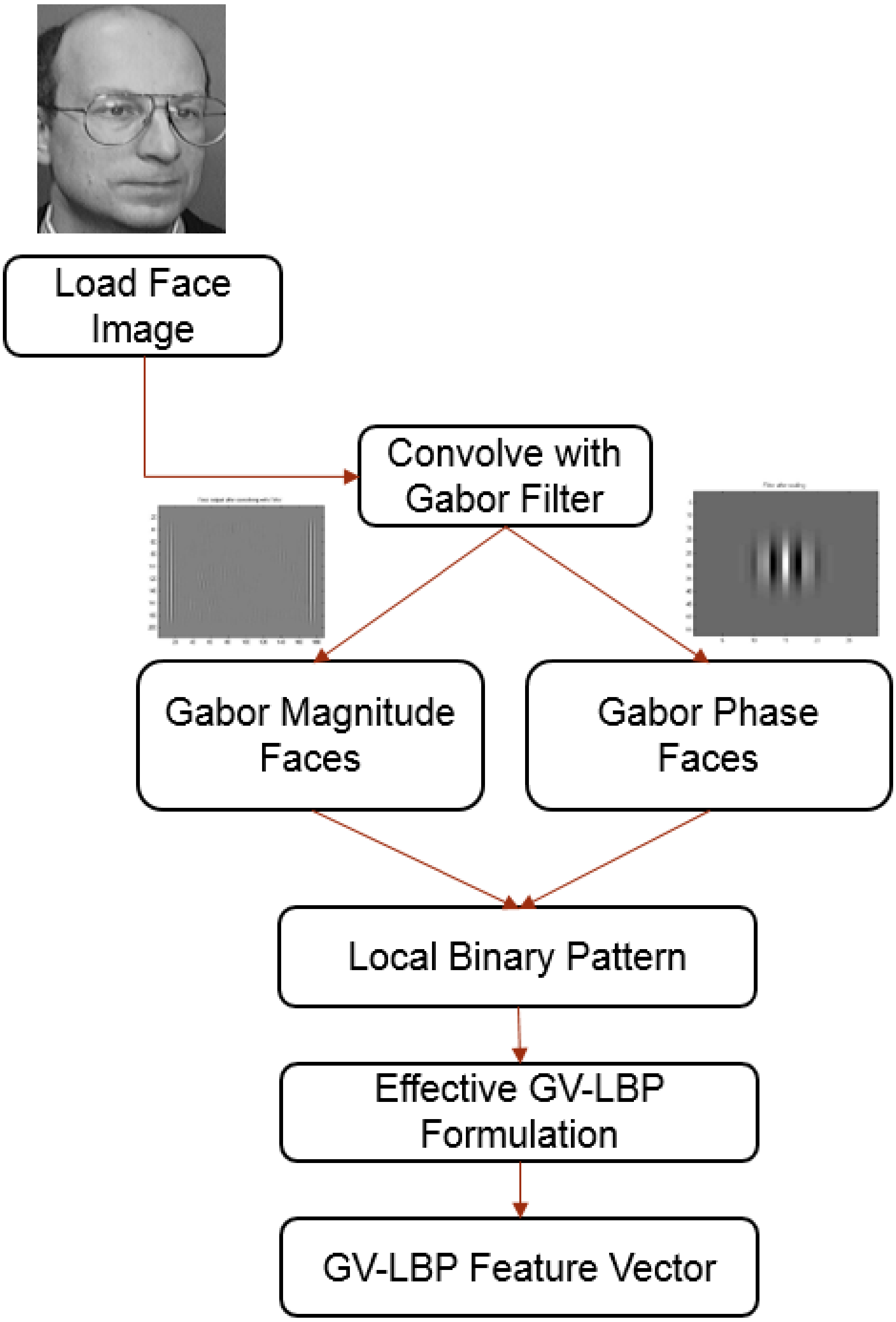
❑ FEATURE MATCHING:-

Discriminant classification is performed based upon weighted histogram intersection or conditional mutual information with linear discriminant analysis techniques.

❑ FACE ID :-

It is the Unique Identity given to each face image stored in the Cloud Database.

6.3 WORKFLOW:


Load Face Image
Convolve with Gabor Filter
Gabor Magnitude Faces
Gabor Phase Faces
Local Binary Pattern
Effective GV-LBP Formulation
GV-LBP Feature Vector

CHAPTER 7

ALGORITHM

7.1 ALGORITHM:-

1) Analysis starts with collection of database. The database consists a total of 200 images of 40 persons (5 of each person) with different poses illumination. This database forms the Training set for our project.

2) An image is taken from the Testing Set as an input image and Gabor filter is applied to it. Gabor filter consist of five scales and eight orientations. Convolving this face image with 8 gabor kernels results in 40 gabor magnitude and 40 gabor phases for a single image.

3) Local Binary Pattern analysis is applied to the gabor images. The pixels of every image is updated by thresholding the 3 X 3 neighbourhood of each pixel with the centre value and considering the result as a binary number (or called LBP codes).

4) The LBP is utilized to model the neighbouring relationship jointly in spatial, frequency and orientation domains.

5) The local histograms are first obtained from different blocks and then concatenated into a histogram sequence to represent the whole face. Thus Histogram analysis is performed to every LBP image.

6) The same process is followed for all the images in the training database and results are stored for comparison.

7) Local histogram obtained from input image is compared with histogram of each image in the database by Histogram Intersection method. Thus 40 such results are obtained. Maximum of them is calculated.

8) The image corresponding to the index of the maximum value is selected from the database.

9) This obtained image is the matched image corresponding to the input image.

CHAPTER 8

SOFTWARE ASPECTS

8.1 MATLAB

MATLAB (**mat**rix **lab**oratory) is a multi-paradigm numerical computing environment and fourth-generation programming language.

Developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, Fortran and Python.

8.2 IMAGE PROCESSING TOOLBOX:-

Image Processing Toolbox™ provides a comprehensive set of reference-standard algorithms, functions, and apps for image processing, analysis, visualization, and algorithm development.

We can perform image analysis, image segmentation, image enhancement, noise reduction, geometric transformations, and image registration.

Many toolbox functions support multicore processors, GPUs, and C-code generation. Image Processing Toolbox supports a diverse set of image types, including high dynamic range, giga-pixel resolution, embedded IC profile.

8.2.1 KEY FEATURES:

- Image analysis, including segmentation, morphology, statistics, and measurement.
- Image enhancement, filtering, and de-blurring.
- Geometric transformations and intensity-based image registration methods.
- Image transforms, including FFT, DCT, Radon, and fan-beam projection.
- Large image workflows, including block processing, tiling, and multi resolution display.
- Visualization apps, including Image Viewer and Video Viewer.
- Multicore- and GPU-enabled functions, and C-code generation support.

8.2.2 Standard and Specialized File Formats:-

MATLAB® supports standard data and image formats including:

AVI	JPEG	JPEG-2000
HDF	HDF-EOS	M4V
MOV	MP4	PNG
TIFF	ASCII	Binary files

It also supports the multiband image formats BIP and BIL, as used by LANDSAT. Low-level I/O and memory mapping functions enable you to develop custom routines for working with any data format.

Using predefined filters and functions we can:

- Filter with morphological operators
- De-blur and sharpen
- Remove noise with linear, median, or adaptive filtering
- Perform histogram equalization
- Remap the dynamic range
- Adjust the gamma value
- Adjust contrast

CHAPTER 9

DATABASE

9.1 FERET Database:

The FERET database is a standard dataset used for facial recognition system evaluation. The Face Recognition Technology (FERET) program is managed by the Defense Advanced Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST). A database of facial imagery was collected between December 1993 and August 1996. In 2003 DARPA released a high-resolution, 24-bit color version of these images. The dataset tested includes 2,413 still facial images, representing 856 individuals.

9.2 AR Database:

This face database was created by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the U.A.B. It contains over 4,000 color images corresponding to 126 people's faces (70 men and 56 women). Images feature frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf). The pictures were taken at the CVC under strictly controlled conditions. No restrictions on wear (clothes, glasses, etc.), make-up, hair style, etc. were imposed to participants. Each person participated in two sessions, separated by two weeks (14 days) time.

9.3 FRGC Database:

The primary goal of the FRGC was to promote and advance face recognition technology designed to support existing face recognition efforts in the U.S. Government.

The FRGC was open to face recognition researchers and developers in companies, academia, and research institutions. FRGC ran from May 2004 to March 2006.

The first aspect is the size of the FRGC in terms of data. The FRGC data set contains 50,000 recordings. The second aspect is the complexity of the FRGC.

The FRGC consist of three modes:

- High resolution still images
- 3D images
- Multi-images of a person.

9.4 ORL Database:

ORL Database of Faces contains a set of face images taken between April 1992 and April 1994 at the lab. The database was used in the context of a face recognition project carried out in collaboration with the Speech, Vision and Robotics Group of the Cambridge University Engineering Department.

There are ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).

The files are in PGM format, and can conveniently be viewed on UNIX (TM) systems using the 'xv' program. The size of each image is 92x112 pixels, with 256 grey levels per pixel. The images are organised in 40 directories (one for each subject), which have names of the form sX, where X indicates the subject number (between 1 and 40). In each of these directories, there are ten different images of that subject, which have names of the form Y.pgm, where Y is the image no. for that subject (between 1 & 10).

Fig. ORL DATABASE

9.5 Self-Created Database:

We implemented our own database which contains face images of the students from our class (B.E. E&TC { A } 2015). There are total 40 images of 13 different students.

The images were taken at different times varying the facial expression and orientation. The files were originally in JPEG format we converted them to TIF format. Initially the resolution of each image was 12 MP. We downscaled each image and finally the size of each image is 512 x 512 pixels.

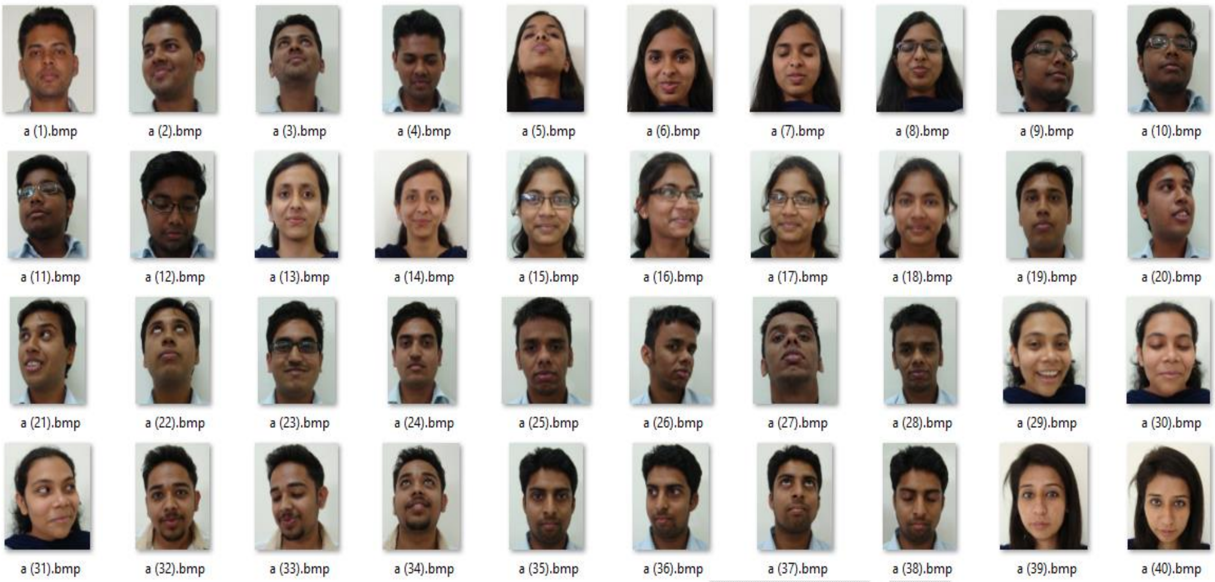


Fig. Self-Created DATABASE

CHAPTER 10

RESULTS

10.1 GABOR FILTER BANK

Bank of Gabor filters can be generated using the kernel by simply scaling and rotating the scaling vector as mentioned previously in the methodologies.

The Gabor filter bank consists of five scales and eight orientations.

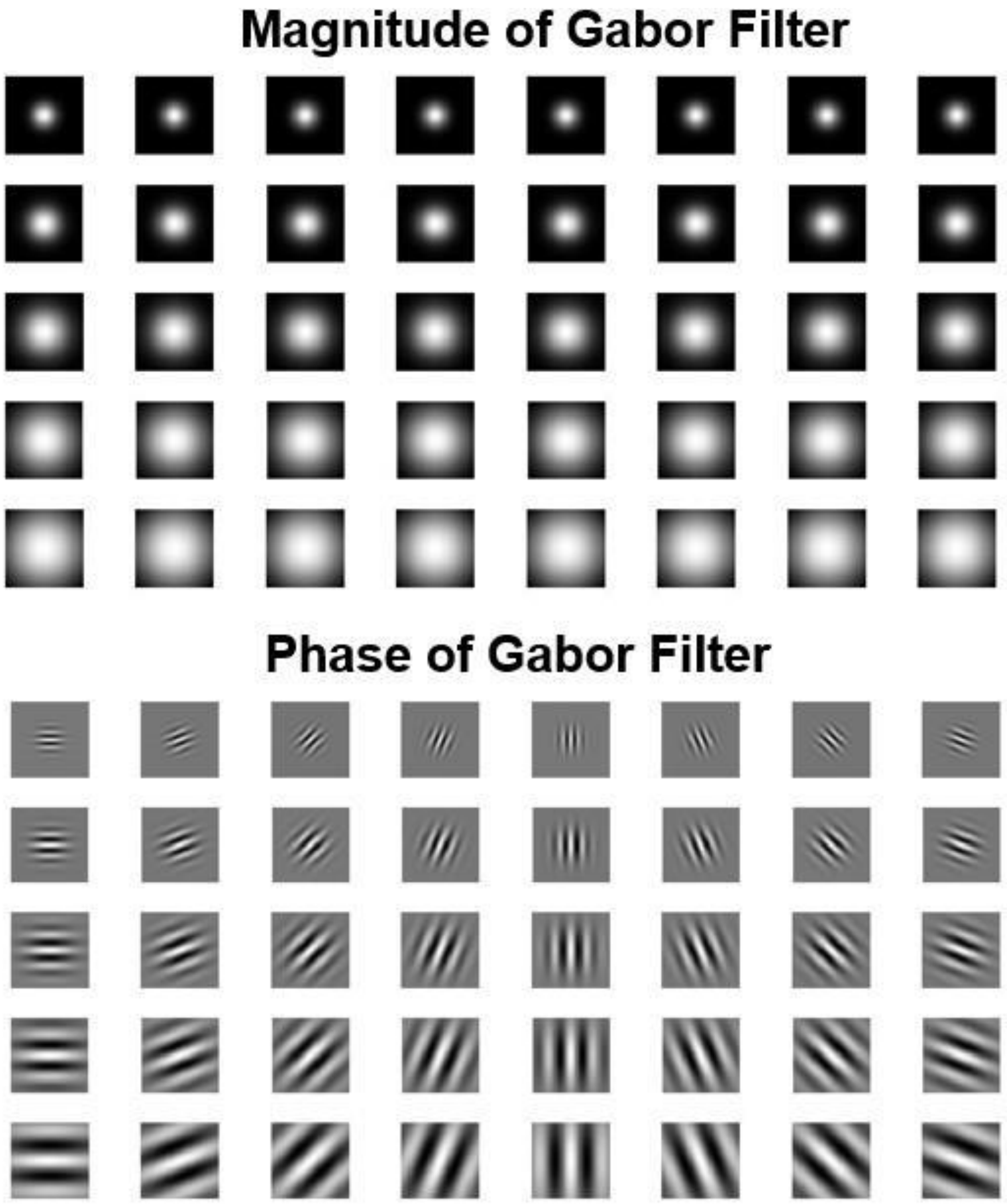
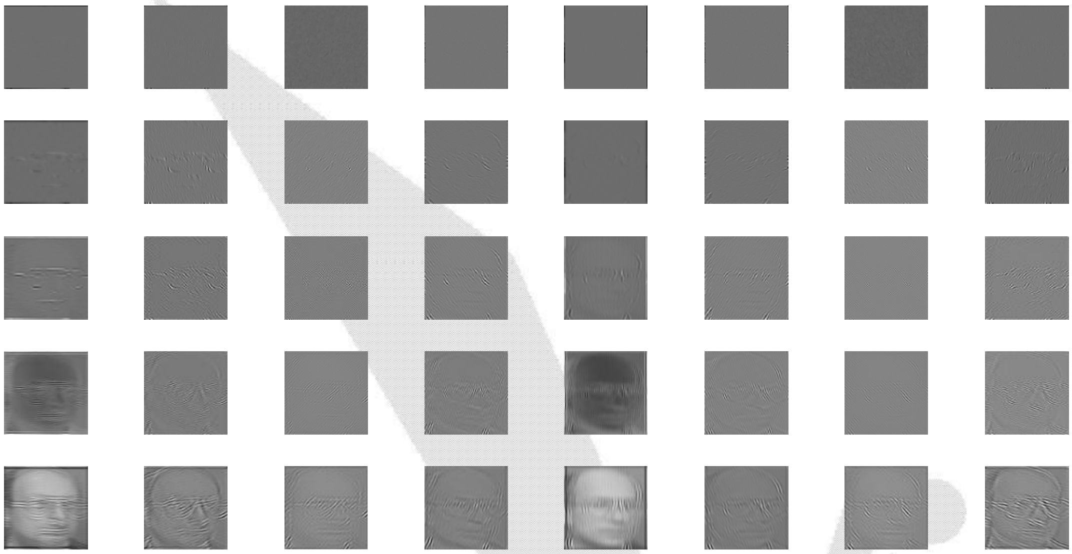


Fig: Gabor Filter Bank

10.2 RESULTS AFTER CONVOLVING WITH GABOR FILTER BANK

For every face image there are total 40 Gabor magnitude and 40 Gabor phase faces after convolving with the Gabor filter bank.

MAGNITUDE OF GABOR FILTER



PHASE OF GABOR FILTER

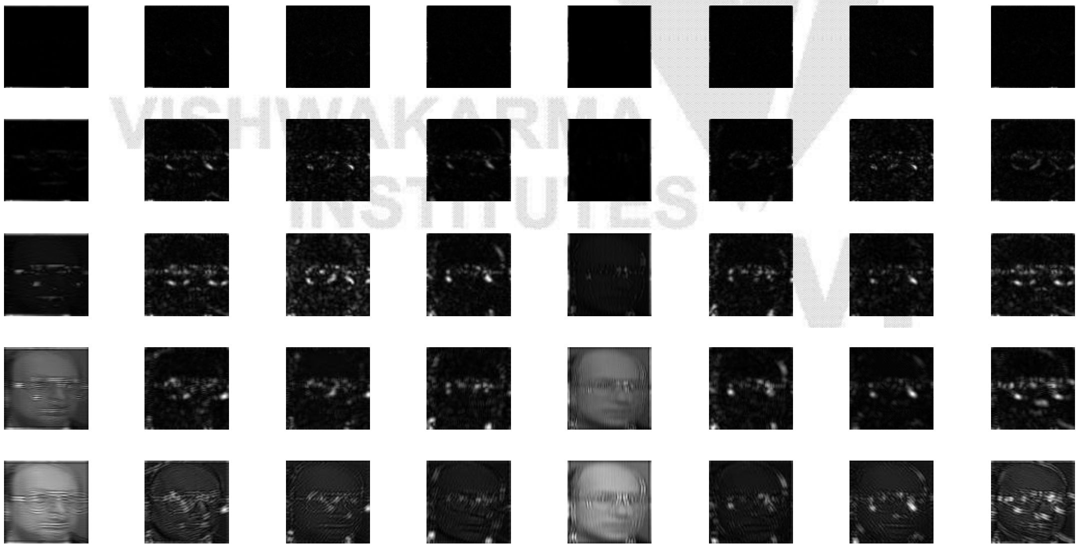


Fig: Gabor Features after image convolved with bank

10.3 RESULT OF LOCAL BINARY PATTERN :

LBP is very strong local descriptor which is useful in describing the micro features of an image. In LBP for every pixel we threshold the 3x3 neighborhood with center value and replace the center value with equivalent binary number. The illustration is shown in the figure below:-

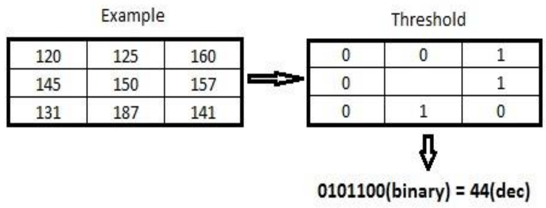


Fig.3: Calculation of LBP code from 3x3 Mask

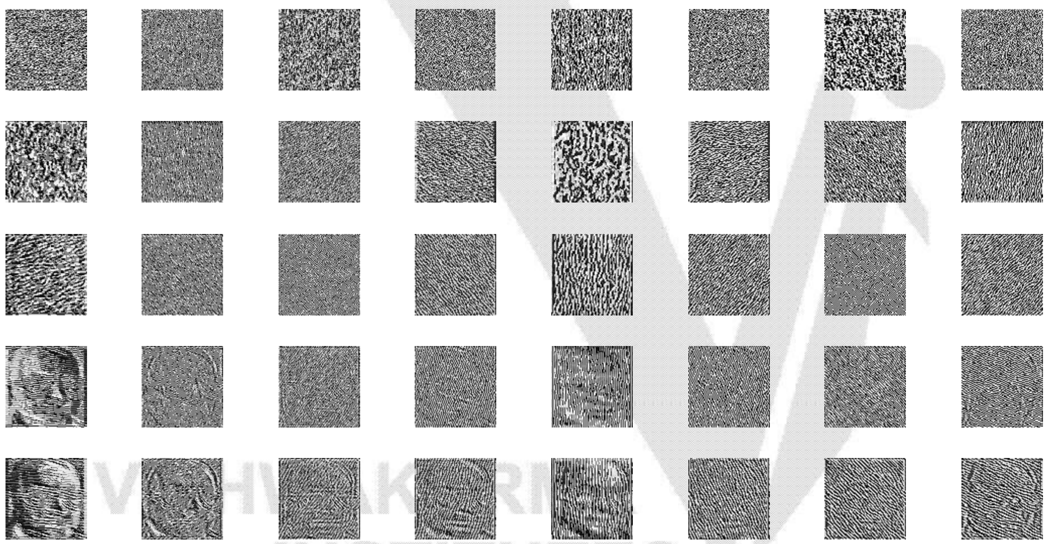


Fig.: Local Binary Pattern of the Input Image

10.4 Local Gabor Binary Pattern Histogram Sequence (LGBPHS)

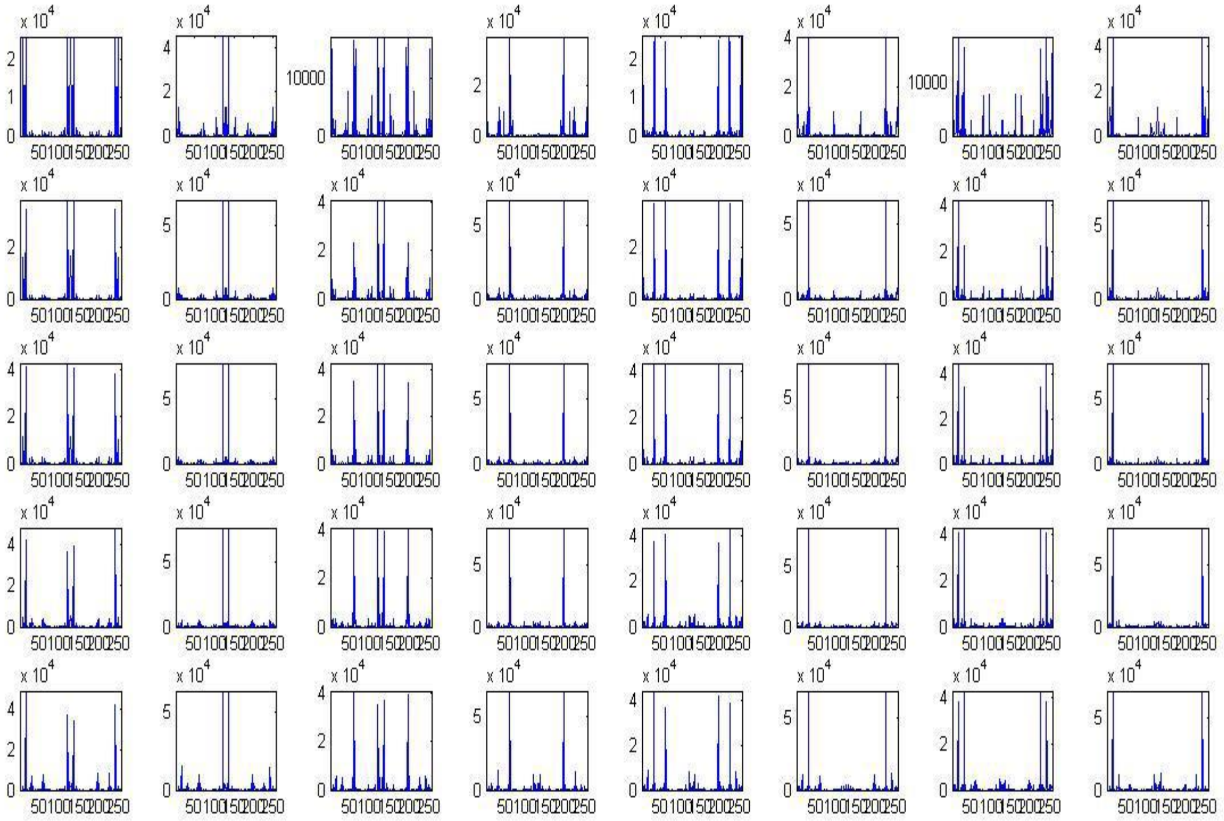


Fig. Local Gabor Binary Pattern Histogram Sequence (LGBPHS):

The difference of face images from same type of person could be greater than those of different ones. Thus to extract discriminant features that makes face recognition robust becomes a challenge. To measure dissimilarity between face image, histogram intersection is used as a novel approach. The histogram based on GV-LBP results is used as measure to recognize face image.

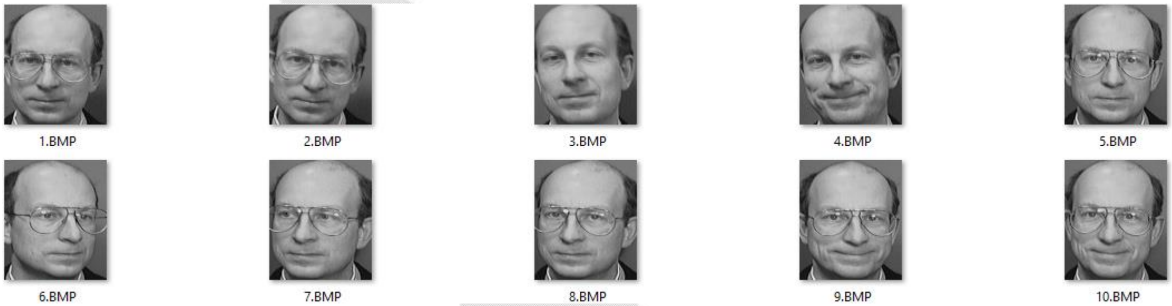
$$d(H^1, H^2) = \sum_i \min(h_i^1,\ h_i^2)$$

Where H^1 and H^2 are two histograms and h_i^1 and h_i^2 denote the bin value corresponding to the histogram. The main intension behind this computation is calculating the common part of the two histograms. The main characteristics of histogram is that they are robust to alignment errors.

10.5 RESULTS BASED ON ORL DATABASE

Input image

TRAINING DATABASE



Matched image

The ORL database consists of 200 images. Resolution of 92 X 112 pixels is used. First image shows the dis-oriented image which is taken as an input image. Result in second image shows that the face is matched properly even if there is an orientation change. Thus results show that the GV-LBP and histogram matching algorithm makes system robust as it is invariant to changes in illumination, orientation and occlusion.

10.6 RESULTS BASED ON SELF-CREATED DATABASE

FOR ORIENTATION

Fig.1: Input Image

Fig.2 Matched Image

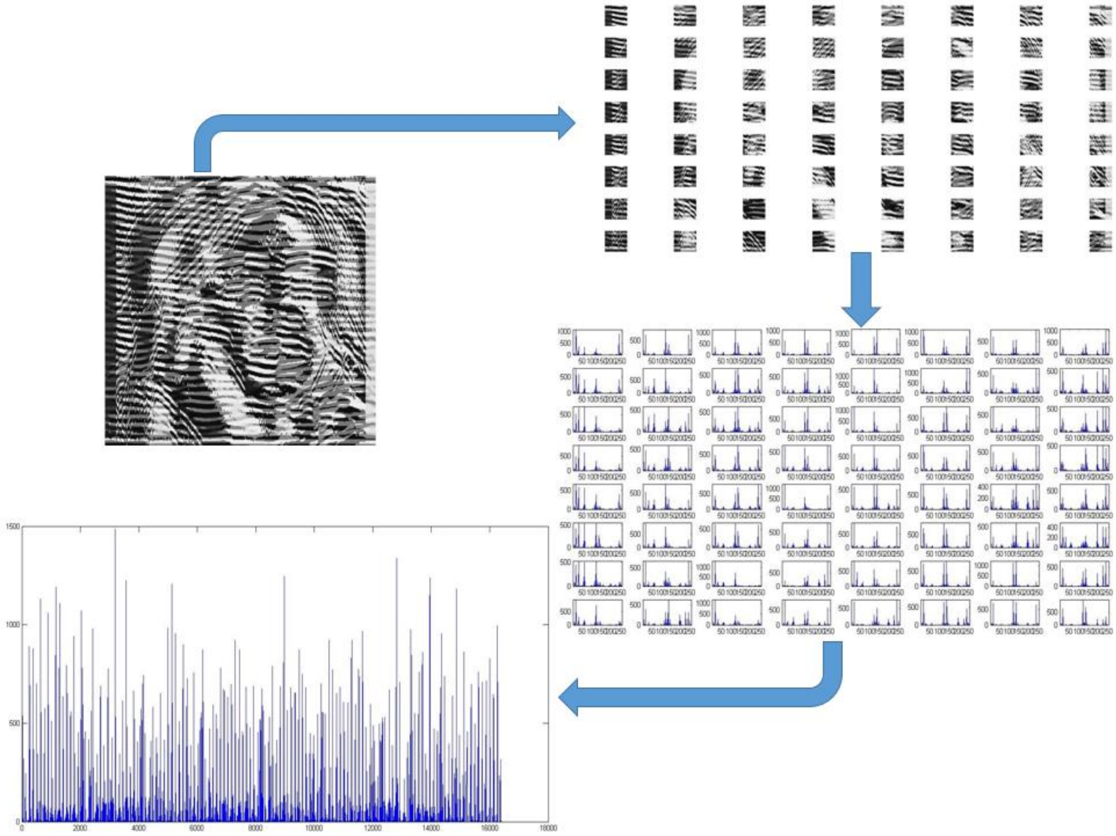
FOR ILLUMINATION

Fig.3: Input Image

Fig.4: Matched Image

For face recognition, database of 50 images is used. Resolution of 512 X 512 pixels is used. Fig (1) and Fig (3) shows oriented and illuminated image respectively which are taken as an input image. Result in Fig (2) and Fig (4) shows that the face is matched properly even if there are orientation and illumination changes. Thus results show that the GV-LBP and histogram matching algorithm makes system robust as it is invariant to changes in illumination, orientation and occlusion.

10.7 LGBPHS – Brief View



Directly comparing the histograms based upon the whole faces may lose the structure information of faces which is important for face recognition. One possible way is to partition the face image into several blocks. The local histograms are first obtained from different blocks and then concatenated into a histogram sequence to represent the whole face. In this way, we succeed to depict the face image at three levels. The GV-LBP-TOP or E-GV-LBP codes contain information in spatial, frequency and orientation domains at pixel level. Local histogram expresses characteristic at regional level which is robust to alignment errors and finally, they are combined together as a global description for a face image to maintain both its accuracy and robustness.

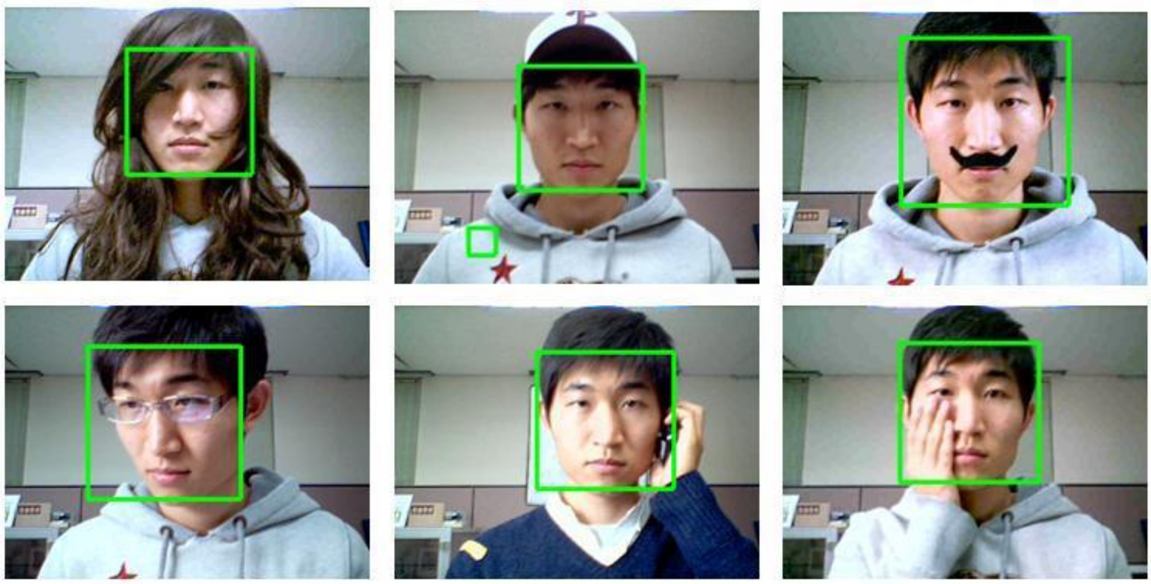
CHAPTER 11

APPLICATIONS

11.1 APPLICATIONS

11.1.1 Face Identification:

Face recognition systems identify people by their face images. Face recognition systems establish the presence of an authorized person rather than just checking whether a valid identification (ID) or key is being used or whether the user knows the secret personal identification numbers (Pins) or passwords. The following are example. To eliminate duplicates in a nationwide voter registration system because there are cases where the same person was assigned more than one identification number. The face recognition system directly compares the face images of the voters and does not use ID numbers to differentiate one from the others. When the top two matched faces are highly similar to the query face image, manual review is required to make sure they are indeed different persons so as to eliminate duplicates.



11.1.2 Access Control:

In many of the access control applications, such as office access or computer logon, the size of the group of people that need to be recognized is relatively small. The face pictures are also caught under natural conditions. The face recognition system of this application can achieve high accuracy without much co-operation from user. Face recognition technology is used to monitor continuously who is in front of a computer terminal. It allows the user to leave the terminal without closing files and logging out. When the user leaves for a predetermined time, a screen saver covers up the work and disables the mouse & keyboard. When the user comes back and is recognized, the screen saver clears and the previous session appears as it was left. Any other user who tries to logon without authorization is denied.

11.1.3 Security:

Today more than ever, security is a primary concern at airports and for airline staff office and passengers. Airport protection systems that use face recognition technology have been implemented at many airports around the world. The following are the two examples. In October, 2001, Fresno Yosemite International (FYI) airport in California deployed Viisage's face recognition technology for airport security purposes. The system is designed to alert FYl's airport public safety officers whenever an individual matching the appearance of a known terrorist suspect enters the airport's security checkpoint. Anyone recognized by the system would have further investigative processes by public safety officers. Computer security has also seen the application of face recognition technology. To prevent someone else from changing files or transacting with others when the authorized individual leaves the computer terminal for a short time, users are continuously authenticated, checking that the individual in front of the computer screen or at a user is the same authorized person who logged in.

11.1.4 Image database investigations:

Searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings. General identity verification: Electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, employee IDs.

11.1.5 Surveillance:

Like security applications in public places, surveillance by face recognition systems has a low user satisfaction level, if not lower. Free lighting conditions, face orientations and other divisors all make the deployment of face recognition systems for large scale surveillance a challenging task. The following are some example of facebased surveillance. To enhance town center surveillance in Newham Borough of London, this has 300 cameras linked to the closed circuit TV (CCTV) controller room. The city council claims that the technology has helped to achieve a 34% drop in crime since its facility. Similar systems are in place in Birmingham, England. In 1999 Visionics was awarded a contract from National Institute of Justice to develop smart CCTV technology.

11.2 FUTURE SCOPE

Face recognition systems used today work very well under constrained conditions, although all systems work much better with frontal mug-shot images and constant lighting. All current face recognition algorithms fail under the vastly varying conditions under which humans need to and are able to identify other people. Next generation person recognition systems will need to recognize people in real-time and in much less constrained situations.

We believe that identification systems that are robust in natural environments, in the presence of noise and illumination changes, cannot rely on a single modality, so that fusion with other modalities is essential .Technology used in smart environments has to be unobtrusive and allow users to act freely. Wearable systems in particular require their sensing technology to be small, low powered and easily integrable with the user's clothing. Considering all the requirements, identification systems that use face recognition and speaker identification seem to us to have the most potential for wide-spread application.

Cameras and microphones today are very small, light-weight and have been successfully integrated with wearable systems. Audio and video based recognition systems have the critical advantage that they use the modalities humans use for recognition. Finally, researchers are beginning to demonstrate that unobtrusive audio-and-video based person identification systems can achieve high recognition rates without requiring the user to be in highly controlled environments.

11.3 CONCLUSION:

This project proposes a novel face representation, which is impressively insensitive to orientation, phase and scale variations. The effectiveness of this approach is due to the robustness of multi resolution and multi orientation Gabor filter, local binary pattern and the histogram intersection algorithm. Experimental evaluations of the proposed approach is done on the ORL and the own database. The results illustrate effectiveness and robustness to the variations of orientation and scaling.

CHAPTER 12

REFRENCES

12.1 REFRENCES :

[1] Zhen Lei, Shengcai Liao, Matti Pietikäinen, **“Face Recognition by Exploring Information Jointly in Space, Scale and Orientation”** IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 20, NO. 1, JANUARY 2011.

[2] Shufu Xie, Shiguang Shan, Xilin Chen, Jie Chen, **“Fusing Local Patterns of Gabor Magnitude and Phase for Face Recognition”** IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 5, MAY 2010.

[3] W. C. Zhang, S. G. Shan, W. Gao, and H. M. Zhang, **“Local gabor binary pattern histogram sequence (lgbphs): A novel non-statistical model for face representation and recognition”** IEEE Transaction 2005.

[4] **“Handbook of face recognition”**, Li S.Z., Jain A. (Springer, 2005).

[5] Xiaoyang Tan and Bill Triggs, **“Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions”** IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 6, JUNE 2010.

[6] B. Zhang, S. Shan, X. Chen, and W. Gao, **“Histogram of gabor phase patterns (hgpp): A novel object representation approach for face recognition”** *IEEE Trans. Image Process.*, vol. 16, no. 1, pp. 57–68, Jan. 2007.