FPGA IMPLEMENTATION OF A NOVEL ROBUST FACIAL EXPRESSION RECOGNITION ALGORITHM

A THESIS SUBMITTED IN PARTIAL FULFILMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF TECHNOLOGY

IN

VLSI DESIGN AND EMBEDDED SYSTEM

BY

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NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

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2012-2014

To my grandfather and parents

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CERTIFICATE

This is to certify that the thesis report entitled **"FPGA Implementation Of A Novel Robust Facial Expression Recognition Algorithm"**, is submitted by **Ms. Yamini Piparsaniyan** bearing Roll No. **212EC2211**, in partial fulfilment of the requirements for the award of **Master of Technology in Electronics and Communication Engineering** with specialization in **"VLSI Design and Embedded Systems"** during session 2012-14 at National Institute of Technology, Rourkela.

This thesis is an authentic work carried out by her under my supervision and guidance. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any Degree or Diploma.

Place: Rourkela
Date: 22nd May, 2014

Prof. Kamala Kanta Mahapatra
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ABSTRACT

A facial expression recognition system depicts about state of mind of a particular by showing their emotions, thus has potential application in various field of human computer interaction (HCI) such as to aid autistic children, robot control and many more. This work presents a robust and hardware efficient algorithm for facial expression recognition which gives very high rate of accuracy. Broadly, human facial expression has been categorized in seven categories, named as anger, disgust, fear, happy, sad, surprise with basic neutral emotion. The process of emotion recognition starts with the image capturing, detecting the face in the image of which emotion has to recognize, extracting robust and unique features of image which makes categorization efficient and classification of features for one of the above mentioned emotion categories. Face detection out of an image is done using existing Bayesian discriminating feature method. An algorithm is proposed for facial expression recognition, integrating Gabor filter bank and its features for feature extraction, statistical modelling which uses principal component analysis PCA and conditional density function for modelling of features and extended Bayes classifier for multi-class classification of emotion in a detected face. The multi class classification strategic has been applied based on highest value of log likelihood after training different emotions class. Robust features are extracted using Gabor filter with 8 frequency and 8 orientations. FPGA implementation of the extended Bayesian classifier is done on Xilinx10.1, Virtex II Pro FPGA using CORDIC unit for trigonometric functions. Facial expression images from JAFFE database have been used for training as well as testing. Very high accuracy (96.73 %) of emotion recognition has been obtained with proposed method.

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Chapter 1
Introduction

Today, in a world of automation, human-computer interaction (HCI) is a wide area of research and applications. As, human to human interpersonal communication can be categorized in two types, verbal communication and non-verbal communication (facial expressions, hand gestures and tone of the voice), where verbal communication is essential yet non-verbal communication plays an important role where expression says a lot more than words, similarly HCI can also be of above two types. Non-verbal communication is backbone of HCI. For HCI, there are two major constraints, first understanding Facial expression and second understanding Hand/arm movement (gesture) [17]. Tactlessly, presently available human–computer interfaces systems are not providing full benefit of these valuable communicative media, thus unable to deliver the advantages of natural interaction to the users. HCI can be more useful if computers can understand facial expression of the user and then act according to the recognized emotion of the user.

The first constraint of HCI is facial expression recognition as emotions are unavoidable part of communication even if we talk of verbal communication. In day to day life, human show many expressions which are outcome of ones' internal state or psychological state, which is response to the events occurring in the surroundings and these expressions form emotions. The movement of main organs of the face such as opening of mouth, widening of eyes, narrowing or frowning of eyebrows and cheek movements play main role in forming and expressing emotions. On the basis of appearance and movements of face organ only human do recognise others' emotions, so the HCI system has to develop which sense the changes and movements in face organs while communication and result in recognised emotions. To make a facial expression recognition system fruitful, fast and accurate response of system are key parameters, failing which results produced may not be useful or turn to be confusing at times, depending on the application of system [1−4].

1.1 Types of Emotion

There are a number of micro facial expression which human expresses such as affection, anger, angst, annoyance, anguish, anxiety, apathy, awe, arousal, boldness, boredom, contentment, curiosity, contempt, depression, desire, disappointment, despair, disgust, dread, embarrassment, envy, ecstasy, euphoria, excitement, fearlessness, fear, frustration, gratitude, guilt, grief, happiness, hatred, horror, hope, hostility, hysteria, hurt, indifference, interest, joy, jealousy, loathing, loneliness, lust, love, misery, nervousness, passion, panic, pity, pride, pleasure, rage, regret, sadness, remorse, satisfaction, shame, shyness, shock, sorrow, suffering, terror, uneasiness, worry, wonder, zeal, zest [13].

For HCI, it is not possible to detect each and every micro facial expression so widely facial expression can be categories in basic seven categories namely **anger, disgust, fear, happy, sad, surprise** and **neutral** [1].

1.2 Applications of Facial Emotion Recognition System

Application of Facial emotion recognition can be seen in different HCI areas such as:

1. To aid autistic children
2. Robot control
3. Driver state surveillance
4. Computerized psychological counselling and therapy
5. In the detection of criminal and antisocial motives

Autistic children are found with a disorder known as, Asperger's Syndrome, an autism spectrum disease, due to which autistic children are often face problem to communicate with other people, in verbal mode [1]. As they are unable to understand verbal communication, to read people's behaviour and talks, autistic children need to be trained with non-verbal communication and facial expressions being an important cue of interaction, they must learn to read emotions. Thus, for such children, an automatic real time facial expression recognition system can be a boon during face to face interaction or even to meet their daily communication needs.

1.3 Motivation

Facial expressions are identified by position and movement of face organs such as eyes, cheeks, mouth. Thus facial expression representation is very sensitive to even slight change in face organ location or movement. The process of emotion recognition includes feature extraction and classification of extracted feature. Thus even small change in any of the face organ leads to change in emotion and also extracted feature is changed. Now, classifier should be efficient enough to monitor change in feature and map the feature to correct emotion class. There are methods available for robust feature extraction based on PCA [1], LDA [14], LBP [15], harr features [7], and more. For classification broadly used is SVM [16] because of its accuracy but at the cost of complexity and more hardware utilization. Other is based on Euclidean distance method which is less complex but shows poor results too [18]. Thus facial expression recognition system suffers either with accuracy or complexity in multi class classification part on hardware implementation.

1.4 Problem Description

Thus, the challenge is to design a classifier for multi-class classification which is less complex, very accurate and feasible for hardware implementation along with to be compatible with flow of process of facial expression recognition process.

1.5 Organization of Thesis

The thesis is organized as follows:

- Chapter 2 describes the basic process of facial expression recognition, different methods used in literature for different modules of whole emotion recognition procedure, such as pre-processing, feature extraction and classification, have been described briefly with comparison of pros and cons of each process. Also introduction to CORDIC is given in this chapter.
- Chapter 3 describes a proposed method for facial expression recognition system with detailed process of face detection based on Bayesian discriminating feature analysis, feature extraction using Gabor filters, PCA and proposed Extended Bayesian method for classification.
- Chapter 4 describes about implementation constraints which have been taken into account while implementing the proposed work. Also VHDL implementation process and its modules for classification process using CORDIC have been shown.
- Chapter 5 shows results of facial expression recognition process using proposed work and compares the result with highly accurate existing models.
- Chapter 6 concludes the work done with an insight into future scope of the work.

Chapter 2
Background

2.1 Facial Expression Recognition Process

Facial expression recognition process starts with capturing of image of desired person whom emotion has to recognize. After this, two major processes are to be followed, [5]:

- Face Detection
- Emotion Detection

Facial Expression recognition process is training based process where first some image database is developed for both face detection (having two class types, face class image and non-face class images) and emotion detection (containing images from all seven emotion classes, anger, disgust, fear, happy, neutral, sad and surprize). Training images are featured then on the basis of their property test image is featured and classified. A generalized process for both face detection and emotion detection is shown in **Error! Reference source not found.**.

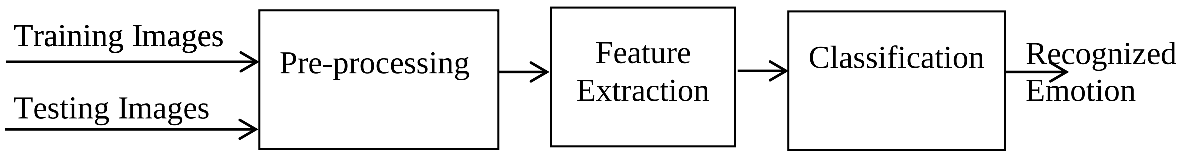


Fig. 2.1 Generalized process of face detection and emotion detection

Before applying images directly for emotion recognition process, unwanted area and noise of the image should be removed so that extracted features only have required and important values to make features robust. This purpose is solved by face detection which gives only effective part of face removing all other unnecessary things. After face detection comes the emotion detection part.

There are numerous methods existing in literature which are widely used for pre-processing, feature extraction and classification, some of them which gives high accuracy results are described next in this section.

2.2 Methods Used for Different Modules of Recognition Process

2.2.1 Pre-processing methods

When it comes to face detection system, pre-processing of an image includes the resizing, sharpening of face and non-face class images. When it comes to emotion detection, pre-processing of image means to find effective area of face contributing for feature extraction by removing background and lower face portion of body (if present). There are many methods which have been approached for face detection as face detection is being the first step of process in many applications like automatic face recognition, human computer interaction (for expression recognition, emotional state recognition), surveillance system etc. But emotion detection is an emerging topic of concern on which less effective work is done, especially when it comes to considering real time hardware implementation and it includes face detection as pre-processing step.

Some of the widely used methods for face detection are penned below along with their pros and cons in view of our requirement constraints.

- ***Skin Color Based Face Detection Algorithm***

In [19], Sanjay Kr. Singh *et al.* presents an algorithm for face detection based on skin colour. Colour is one of the important features of human faces n which basis probability of face presence can be estimated. Using human skin colour as a tool for feature for locating face in an image many advantages than other face detection methods among which most important is speed of operation and definitely colour processing is faster than any other kind of feature processing and this procedure becomes easier with the fact that colour orientation is invariant under certain lighting conditions. The coloured image under test is converted to all three colour space representation namely RGB, YCbCr and HCI and algorithms based on these three colour spaces are combined together to get a new skin colour based face detection to take the algorithm.

This method shows poor result as skin colour features are subject to change with various lightening conditions with movement of objects. Even different camera produces different colour ranges for the same person and time. Moreover this method does not work for gray-scale images.

- ***Boosted Cascade of Simple Feature Method***

In [20], Paul Viola and Michael Jones gave a method for rapid object detection. This method is outcome of three major combinations first is image representation by Harr features and termed as "Integral Image". These "integral image features" are chosen because of their very simple yet very fast calculation. For feature extraction image is divided into sub-windows then Harr features are taken for each window, by doing so there comes a huge amount of features along with some majority of available features in whole image. So, the second contribution tells to pick only small amount of data for feature with some critical features with the help of AdaBoost. Third comes the classification after feature extraction, in this method, some high response, complex classifiers are "cascaded" to increase the classification speed as cascaded classifiers look forward in some promising regions of image for face detection.

Cascaded classifier needs to be implemented in multi-layers, which becomes very complex in embedded platform with high cost.

- ***Bayesian Discriminating Feature Analysis Method***

In [7], Chengjun Liu gave this method for face detection which uses Harr like features for feature extraction but uses “difference images” unlike the previous discussed method. Along with “difference images”, amplitude projections of image and image pixels itself are combined to get robust features. For classification, this method uses statistical modelling, PCA, conditional density function and Bayes classifier. Ease of implementation with superb accuracy makes me to choose this in the project. Thus, the method is discussed in section 3.2.

2.2.2 Feature extraction Methods

For emotion recognition second step is to extract facial feature out of the face image and then to classify feature for emotion. Mainly two types of approaches are reported to extract facial features (for both face detection and emotion detection), namely, appearance-based methods and geometry-based methods. In geometric based feature extraction process, the shape, movement and location of various face organs like frowning of eyebrows, uplifting of cheeks, widening of eyes, are taken into consideration for feature extraction and for this they require accurate and reliable facial organ movement description, which is quite complex to achieve implement real time applications in hard based systems. While, in the process of appearance-based feature extraction [1], appearance changes in image are captured by applying them on image filters.

Geometric feature extraction system gives robust features but proofs to be very complex when it comes to real time hardware implementation while appearance based method is easy to implement with high accuracy. So while keeping hardware constraints in mind, we will focus on appearance based methods for pre-processing (face detection) and emotion detection. Some of the techniques used for appearance based method are:

- LDA (Linear Discriminant Analysis)
- LBP (Local Binary Pattern)
- PCA (Principal Component Analysis)
- Harr-like Features method
- Filter/ Kernel based methods

➢ ***LDA Based Method***

In [14], A. Djeradi *et al*. used a feature sub-space known as “fisher-space” to project images. This projection reduces the dimensionality of the data matrix while preserving the unique feature set. Training images are projected to this “fisher-space” for feature extraction then test images are projected to LDA training space. Class information extracted from fisher space is used to find unique vector set which minimizing the intra-class scatters while maximizing the inter-class scatter.

Classification accuracy of LDA based method is affected by the "small sample size" (SSS) problem.

➢ ***LBP Based Method***

In [15], Caifeng Shan *et al.* studied a method for face detection based on facial local statical features which was earlier done for texture recognition. In this method feature is extracted by considering 3×3 neighbour pixel of each pixel and then taking threshold value of each neighbouring pixel with respect to centre pixel, formulating a binary number belonging that block and finally take a 256 bit bin histogram as feature descriptor.

Small neighbouring size loses some dominant features when applied on large scale images which limit its effectiveness of operation.

- ***PCA Based Method***

Similar to LDA method, this PCA method uses “Eigen-space” for dimensionality reduction and feature extraction. It uses eigen values and eigen vectors of the input data matrix for calculation of principal component and later some significant principal components are taken as feature descriptor. This method suffers from loss of data due to dimensionality reduction and feature extraction can’t bear data loss which makes it yield less accurate result along with implementation ease [1].

- ***Harr-like Features Method***

Harr-features provides a promising feature extraction method by taking sub-portion of image and calculating “integral images” or “difference images”. This method provides very robust features but with repetition of features as integral or difference images are linked to forth and back window of image. The robustness comes with redundant data. The process is shown in [7] and [18].

- ***Filter/Kernel Based Method***

A kernel or filter bank is created with varying parameters and image under test is convolved with the filter bank to map its feature with kernel. Such an approach is shown in by Vitomir Struc and Nikola Pavesi C. in [11] which makes Gabor filter bank varying with orientation and frequencies and image is mapped to this kernel. It provides flexibility to choose size and robustness of feature by limiting number of scale and orientation variation. This property is taken into advantage of this project and detailed in section 3.3.1.

2.2.3 Classification Methods

- ***Support Vector Machine (SVM)***

SVMs are based on supervised learning methods, first model learns with the help of training then perform pattern recognition on test images. SVM is a non-probabilistic binary classification method where classes are separated by boundary and patterns are shown as points in space. Binary SVM can be extended to multi-class but high degree of complexity as shown in [16]. Above methods result best with SVM (support vector machine) classification but SVM makes it complex to be implemented on embedded platform hardware especially when it comes to multi-class classification.

- ***KNN Classifier***

KNN classifier as shown in [18], is based on Euclidean distance. Point to point space distance is calculated from training to testing feature and the minimum is distance, maximum is the similarity. This is the very basic and simplest method to classification but suffers inaccuracy due to no cross point measures.

- ***Bayes Classifier***

Bayes classifier is for binary class classification, uses statistical model for measuring parameter by calculating likelihoods of test image with classes [7]. The accuracy and simplicity of implementation makes it useful for face detection which needs binary class classifier and so detailed in section 3.2.

2.3 CORDIC and Its Applications

Many DSP and pattern recognition algorithms use elementary functions like logarithmic, trigonometric, hyperbolic, exponential, division and multiplication. There are two ways of implementing these functions, first by using lookup table method and second is through polynomial expansions. The above mentioned methods require large number of multiplications/divisions and additions/subtractions. Hardware implementation is done in embedded platform environment which uses development boards such as Spartan, Virtex etc. These are bounded by number of input-output pins, area, slices, flip-flops and multiplication/division uses further excess adders/subtracts which is not feasible as it crosses the source limitations.

2.3.1 What is CORDIC?

COordinate **R**otation **DI**gital **C**omputer (CORDIC) is a special purpose computer useful to compute many non-linear and transcendental functions, was proposed by Volder in 1959 and generalized by Walther later [22]. It is useful when there is no hardware multiplier are provided and computation is done on additions/subtractions only. The CORDIC core architecture is shown in fig 2.2, where all trigonometric, logarithmic and other non-linear functions are computed using only shifts, additions and subtractions. The functions that can be computed using a CORDIC computer include trigonometric, logarithmic, exponential, hyperbolic, multiplication, division, square root, etc. [22].

Though it initially served the purpose of navigation systems, it later became a popular tool to implement several digital systems especially in the areas of digital signal processing, communications, computer graphics, etc. The simplicity of CORDIC is that it can compute any of the above mentioned functions using shifts and additions which are of the form ($x \pm 2^{-i} * y$). The operating mode and the coordinate system chosen are two

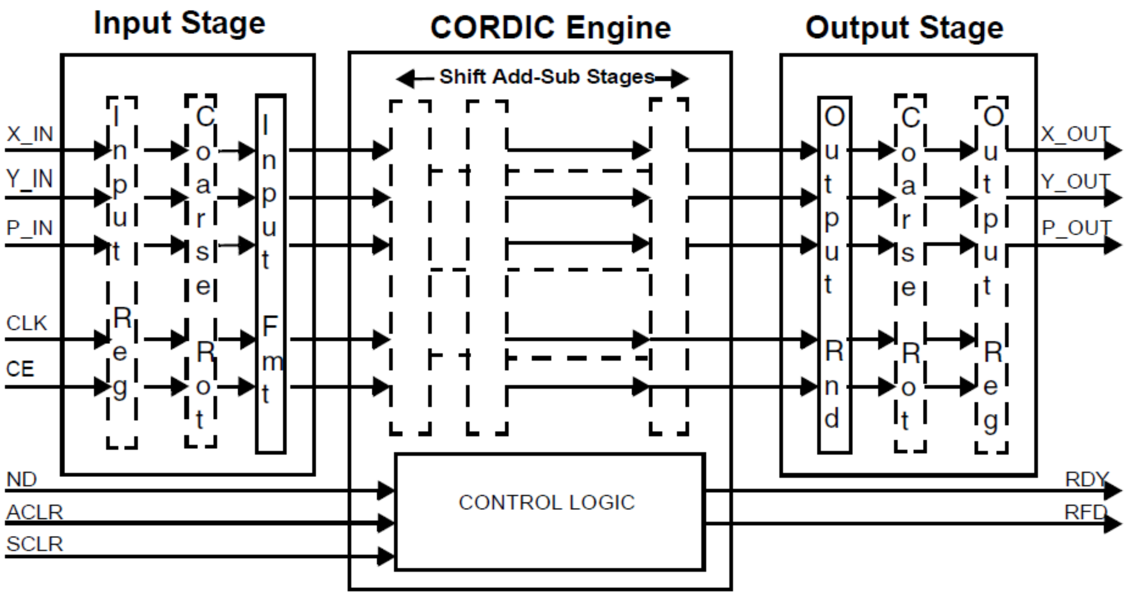


Fig. 2.2 The Cordic core architecture

key factors to compute the desired functions in the CORDIC. Many signal processing and communication systems operate CORDIC in circular coordinate system and in either of rotation or vectoring modes.

2.3.2 Functional Description of CORDIC

Main functional blocks of CORDIC are:

- Conversion (polar to rectangular and vice versa)
- Trigonometric function (Sin and Cos)
- Hyperbolic functions (Sinh and Cosh)
- Inverse trigonometric functions (arctan and arctanh)
- Logarithmic
- Other non-linear functions such as square root, multiplication, division etc.

CORDIC operates on rotation of coordinate system with prefixed angles until the rotation angle reaches to zero from a defined angle, this process is shown in fig.2.3, which shows 2D coordinate circular rotation system. The trigonometric and other arithmetic functions are executed by solving eqs.(2.3.1) with some predefined set of conditions. In equations X_{new}, Y_{new} are new coordinate value of X_{old} , Y_{old} vectors after rotating with angle Θ.

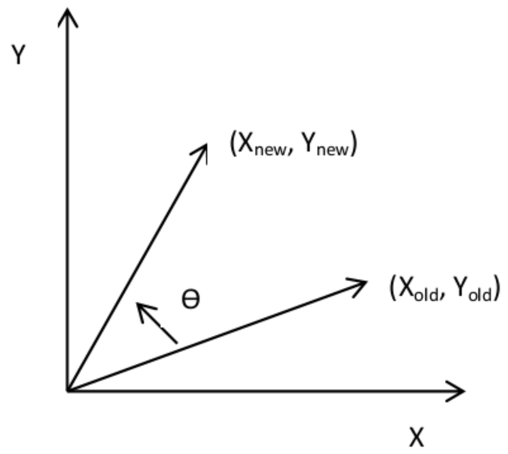


Fig. 2.3 2D circular rotation of a vector by an angle in coordinate system

$$\left.\begin{array}{c} X_{new} = K(X_{old}\cos\theta - Y_{old}\sin\theta) \\ Y_{new} = K(X_{old}\sin\theta + Y_{old}\cos\theta) \\ \text{Or} \\ R = K\sqrt{X_{old}^2 + Y_{old}^2} \\ \theta = \tan^{-1}\dfrac{Y_{old}}{X_{old}} \end{array}\right\} \quad (2.3.1)$$

K is invariable constant in above equations.

➢ ***Input/Output Data Representation***

Fig 2.3 shows CORDIC core block where X_IN, Y_IN are input data signals and X_OUT, Y_OUT are output data signals while p_in and p_out denotes phase input and output signals. Clk, ce, ND, ACLR, SCLR are input control signals with two output signals RFD and RDY. There is separate format for reading data signals and phase signals.

- **XQN Number Format**

  This number format is used to represent signed values in 2's complement format. This format is described as XQN => 1 sign bit + X bits for integer + N bits for mantissa (fraction). So if 'w' is word width then N = w − (X+1) bits will represent fractional part of the value. This is also represented as Fix (N+X+1)_N using system generator fixed format.

- **Data Signal Representation**

  - Input data signals (signed) should lie in the range from -1 to +1, outside which CORDIC core gives unpredictable results. So to present maximum integer of value '1' one bit is required with an additional bit for sign representation. Thus input data signals are represented in 1QN format where N= word_width – 2. It can also be represented as Fix(N+2)_N format.

    Example: If word width is 10bit then signed data signal will be represented by 1Q8 format.

    "0011000000" => 00.11000000 => +0.75

    "1101000000" => 11.01000000 => −0.75

  - When data signal set to unsigned fraction, value can be ranged 0 <= X_in < +2 and integer is represented by 1 bit allowing it to represent as UFix(N+1)_N format. N = word_width – 1.

    Example:

    "0011000000" => 0.011000000 => 0.375

  - For unsigned integer, data signal range varies from 0 <= X_IN < 2**Input Width.

Example:

"0011000000" => 192

- **Phase Signal Representation**

Input phase signals (signed) should lay in the range from −∏ to +∏, outside which CORDIC core gives unpredictable results. So to present maximum integer of value '3', two integer bits are required with an additional bit for sign representation. Thus input phase signals are represented in 2QN format where N= (word_width – 3). It can also be represented as Fix(N+3)_N format. Phase is represented in radians in CORDIC core.

Example: If word width is 10bit then phase signal will be represented by 2Q7 format.

"0011000000" => 001.1000000 => +1.5 radians

"1101000000" => 110.1000000 => −1.5 radians

2.3.3 Applications

CORDIC applications are mainly figured in following areas of development:

- Matrix decomposition
- Image processing
- Digital signal processing
- Communications implementations
- Computer graphics
- Robotics and many more.

With the base of this literature review and defined processes, further work is done.

Chapter 3

Proposed Algorithm for Facial Expression Recognition

3.1 Overview

Facial expression recognition system has been designed by following the procedure as shown in section 2.1 and the flow of proposed method is shown in fig 3.1. A set of database containing numerous images showing all seven basic facial expressions (anger, disgust, fear, happy, neutral, sad and surprize), with equal prior probabilities, is taken and used for training of the system. All the training images are first pre-processed to find the effective face area out of the image, which is useful for feature extraction. Also the test image is pre-processed before it is used for future feature extraction and classification. A pre-existing Bayesian discriminating feature analysis method [7], is used for pre-processing, which is described in detail in section 3.2. This particular method is used for pre-processing because of its simple implementation and robust and speedy classification and as here classification is only between two classes, face class which contains effective face portion of the human reducing all other noises and other is non-face class which includes images from rest of the world, binary based Bayesian classification shows the best result.

After pre-processing of training images, images belonging to same emotion class are grouped together and combining features of each image of same emotion group, class feature is generated which collectively represents an emotion feature. Since emotions are represented by very minute details of face organs digitally, it becomes necessary to extract very robust features for accurate classification which contains various aspects of face appearance. To cover maximum available features Gabor filters, its wavelets and generated features are used for feature extraction and described in section 3.2 in detail [11]. Since Gabor wavelets can be generated depends on various frequencies and scales, higher the frequency and scale, robust will be the feature with hardware cost. So there comes a trade-off between feature robustness and hardware cost and one can choose depending on high priority. Test image features are is also extracted using this method.

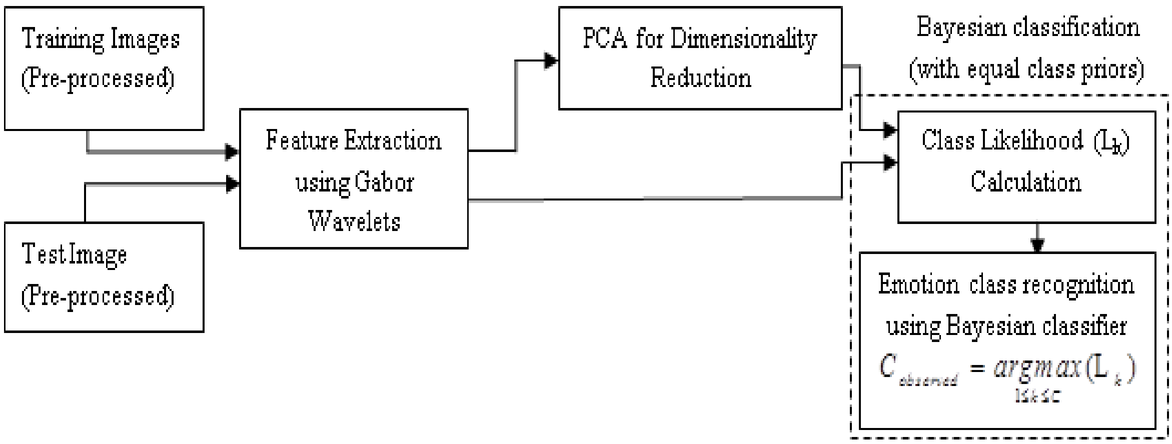


Fig. 3.1 Proposed Method for Facial Expression Recognition System

As Gabor features are of very high dimensionality, to reduce its computational complexity PCA is used. By calculating eigen values and eigen vectors of feature matrix, principal components of the feature vector is estimated. Section 3.3 shows how PCA is used for dimensionality reduction.

Reduced dimensionality class features are modelled with test image feature. Here modelling means to estimate the similarity between class feature and test image feature and classification is based on measure of similarity. For this conditional density function is used with its logarithm value, it shows the likelihood amount of one category to other, shown in section 3.4.1. Since here multi-class classification is required an **Extended Bayes classifier** is proposed contrary to binary Bayes classifier, detailed in section 3.4.2. Extended Bayes classifier gives very high accuracy rate and is far easier for embedded platform implementation as compared to support vector machine (SVM) which is widely used for classification but loses implement ability for multi class classification.

3.2 Pre-processing

An image or portion of image (window) may belong to face class or non-face class (rest of the world). To identify face in an image, we check in window in varying size of image whether that particular portion belongs to face class or non-face class. For this, training is done with both face class images and non-face class images. For window under test of test image, discriminating feature vector for feature extraction is applied then log likelihood of conditional density function of extracted feature with respect to both face class and non-face class is calculated and to identify to whether there is face or not, Bayes classification rule is applied on calculated log likelihood.

3.2.1 Discriminating Feature Analysis

An enhanced and simple feature is estimated in discriminating feature analysis by combining Harr features and amplitude projections to give high discriminating power of features [7], graphically shown in fig.3.2. If image $A(i,j) \in R^{m \times n}$ then discriminating feature vector of image, Y, is calculated by combining :

a) Image A

b) 1D Harr representation of image A

c) Amplitude projection of image A

1D Harr representation includes calculation of horizontal difference image and vertical difference image of image A(i, j), $A_h(i, j) \in R^{(m-1) \times n}$ and $A_v(i, j) \in R^{m\times (n-1)}$ respectively.

$$A_h(i, j) = A(i+1,j) - A(i, j) \quad 1\leq i <m, 1\leq j \leq n \tag{3.2.1}$$

$$A_v(i, j) = A(i,j+1) - A(i, j) \quad 1\leq i \leq m, 1\leq j<n \tag{3.2.2}$$

Amplitude projections, row and column projections, denoted as X_r and X_c respectively gives vertical symmetry and horizontal characteristics of image.

$$X_r(i) = \sum_{j=1}^{n} A(i, j)\ ,\ 1 \leq I \leq m\ , \quad X_r \in R^m \tag{3.2.3}$$

$$X_c(j) = \sum_{i=1}^{m} A(i, j)\ ,\ 1 \leq j \leq n\ , \quad X_c \in R^n \tag{3.2.4}$$

A new discriminating feature vector is formed by combining normalized values of vectors X, Xh, Xv, Xr and Xc, in order to make data redundant for ease of calculation. Normalization of a vector is done by subtracting vector with the mean of its components then dividing the subtracted result by their standard deviations. Say X1, Xh1, Xv1, Xr1, and Xc1 represents the new normalized vectors then discriminating feature vector $Y1 \in R^N$ is formed by concatenating above normalized vectors, given as:

$$Y1 = (X1, Xh1, Xv1, Xr1, Xc1)^t \tag{3.2.5}$$

Again Y1 is normalized to form final discriminating vector, Y also the normalization process can be viewed by the equation (3.2.6):

$$Y = \frac{Y1 - \mu}{\sigma} \tag{3.2.6}$$

where μ shows mean and σ shows standard deviation of Y1. Size of the resulting discriminating feature vector will of range, $Y \in R^N$ with $N = 3 \times m \times n$.

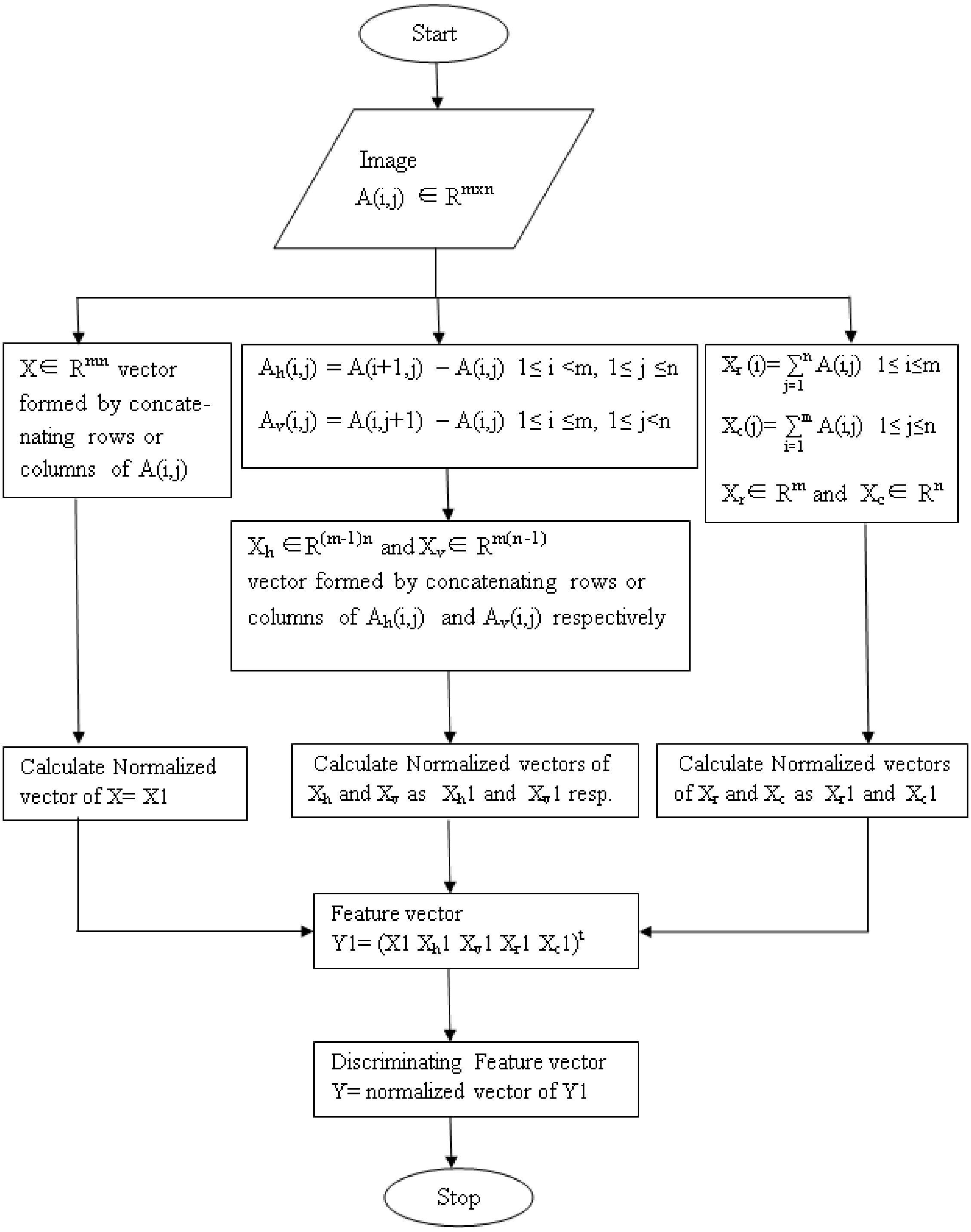


Fig. 3.2 Process to find feature vector using Discriminating Feature Analysis

3.2.2 Statistical Modelling

Statistical modelling estimates the conditional probability density functions, of any class for test image using multivariate normal distribution will be used later for classification for feature.

Let w is feature matrix representing particular class, M is mean of class feature (w) and $\sum$ is covariance matrix then multivariate normal distribution of w is represented as

$$w = N(M, \sum) \tag{3.2.7}$$

Since, multivariate normal distribution is of high dimensionality so to make it ease with computation, an important property, optimal signal reconstruction, of principal component analysis (PCA) is used for dimensionality reduction. Only a part of original signal can be used to represent the whole signal as, PCA uses minimum mean square error for reconstruction of signal [6]. If eigen vector space and eigen values of covariance matrix are denoted by ϕ and λ respectively and Y is test image feature vector then principal component of deviation of test image with particular class can be calculated by eq.(3.2.8)

$$Z= \phi^t (Y -M) \tag{3.2.8}$$

With the use of PCA above property, inspite of using all principal components, only first Mn, (Mn << N) components are used to formulate the conditional density function and impact of other principal components can be included by adopting Moghaddam and Pentland model [21], that calculates eigen value equivalent for the rest (N –Mn) eigen values, by the averaging them:

$$\rho = \frac{1}{N-M} \sum_{K=Mn+1}^{Mn} \lambda_k \tag{3.2.9}$$

Logarithmic of conditional density function (δ) of class (w) for image having discriminating feature vector (Y) can be given as

$$\delta = \ln[p(Y|w)] = -\frac{1}{2}\{ \sum_{i-1}^{M} \frac{z_i^2}{\lambda_i^2} + \frac{||Y-M||^2 - \sum_{i-1}^{M} Z_i^2}{\rho} + \ln(\prod_{i-1}^{M} \lambda_i) + (N-M)\ln\rho + N\ln(2\pi)\} \quad (3.2.10)$$

Discriminating feature vector of each training image of face class and non-face class is determined and combined to get face class features wf and wn respectively. Also a feature of test image window is estimated with the above defined process.

With the defined procedure of statistical modelling, log likelihood of CDF with respect to face class and non-face class, for test portion is calculated and denoted by δf and δn respectively.

3.2.3 Bayes classifier

Binary Bayes classifier is used for classification on the basis of likelihood between two classes [10]. Here, in face detection likelihood of test window is calculated for both face class and non-face class and whatever likelihood is greater test window belongs to that particular class, mathematically

$$Y \in \begin{cases} \mathrm{wf} & , \text{if } \delta f > \delta n \\ \mathrm{wn} & , \text{otherwise} \end{cases} \quad (3.2.11)$$

If Y belongs to face class then save it and process it for expression recognition otherwise slide the window further and repeat the process to find face. Summarized process of face detection is shown in flow chart of fig 3.3.

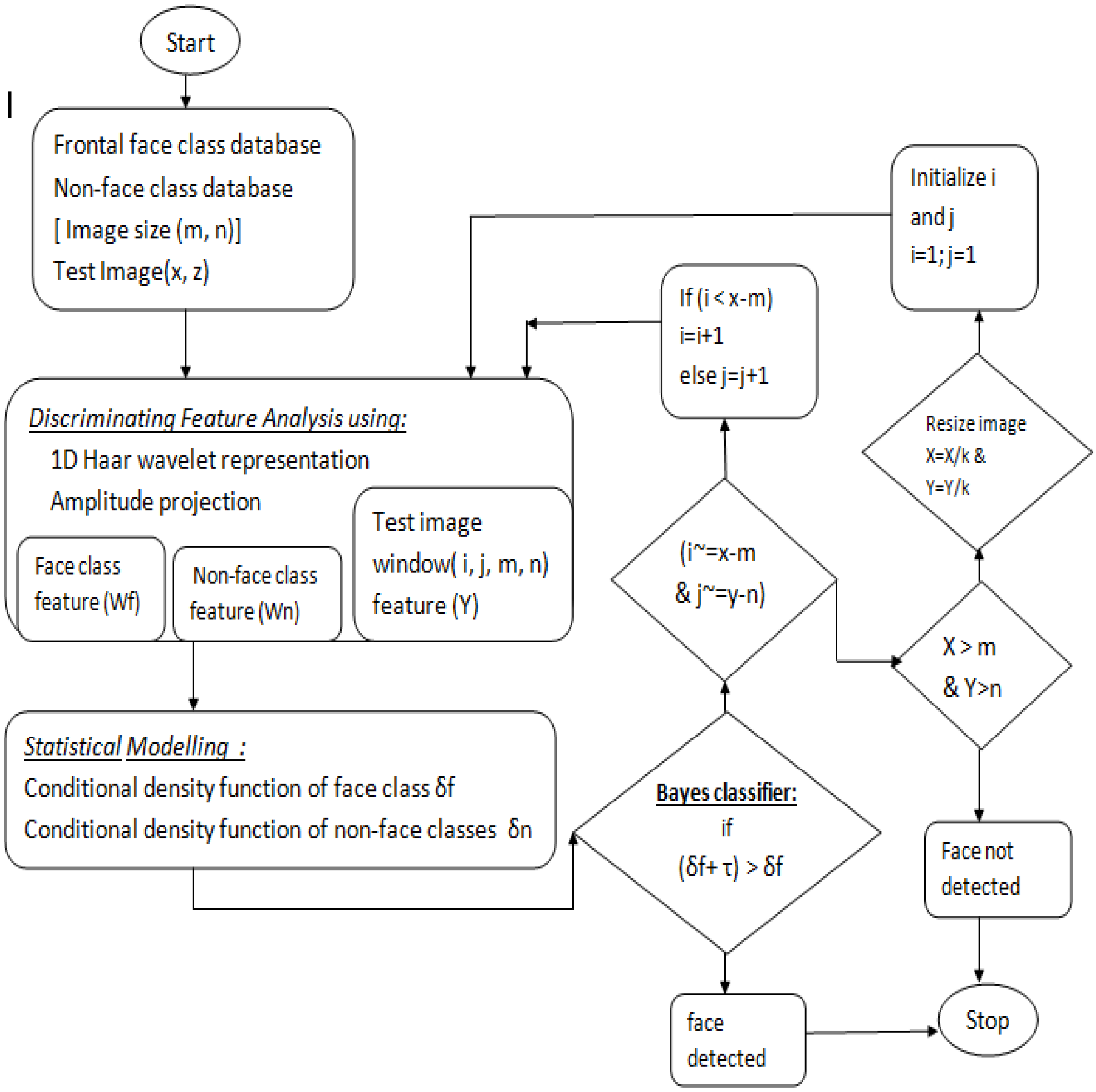


Fig. 3.3 Detailed process of Face Detection

3.3 Feature extraction using Gabor Wavelets

3.3.1 Gabor Wavelet Representation

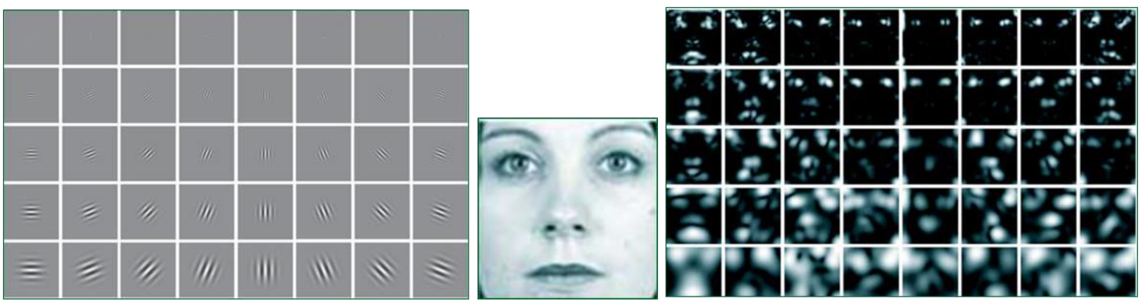
For 2D data, Gabor wavelet is given by [11],

$$\left.\begin{aligned} \psi_{\Pi}(f,\theta,\gamma,\eta) &= \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x_t^2+\frac{f^2}{\eta^2}y_t^2\right)} e^{j2\pi f x_t} \\ x_t &= x\cos\theta + y\sin\theta \\ y_t &= -x\sin\theta + y\cos\theta \end{aligned}\right\} \quad (3.3.1)$$

Here, f is sinusoidal frequency, θ is wavelet orientation, γ is the spatial width along the sinusoidal plane wave, η represents spatial width of wavelet which is perpendicular to the wave and x,y represents the coordinates of pixels. By varying the scale (f) and orientation (θ), a filter bank is created. The scale and orientation are changed according to equations given by eq. (3.3.2) :

$$\left.\begin{aligned} f_g &= f_{\max} / \left(\sqrt{2}\right)^g, \\ \theta_h &= \frac{h}{8}\pi, \\ \psi_{g,h}(x,y) &= \psi_{\Pi}(f_g,\theta_h,\gamma,\eta) \end{aligned}\right\} \quad (3.3.2)$$

The value of parameters in Eq.(2) are given by $\gamma = \eta = \sqrt{2}$, $f_{max} = 0.25$ with $g \in \{0,\ldots,3\}$, $h \in \{0,\ldots,7\}$, generally. In the current work both scale and orientation are taken as $(g,h) \in \{0,\ldots,7\}$, to extract more discriminating features.



(a) (b) (c)

Fig. 3.4. (a) Gabor wavelet, (b) an image and (c) convolved image with Gabor wavelet

3.3.2 Feature Extraction from Gabor Wavelets

Each component of the 2-D Gabor wavelet (at different scales with different orientations) is convolved with image (A) and given by Eq. Down sampling is performed by a factor of 4 in rows and columns of the absolute value of the filtered image. The feature vector is obtained by rearranging the down sampled value.

$$O_{g,h}(x,y) = A(x,y) * \psi_{g,h}(x,y) \tag{3.3.3}$$

The vector F, is normalized to have unit variance and zero mean. If $o_{g,h}$ denotes the feature vector from the filtered image at scale *g* and orientation *h*, then final feature (*F*) value in R^d is given by Eq.(4)[11]. For m×n image, the size of feature space dimension,

$$d = m \times n \times g \times h/(d1 \times d2) \tag{3.3.4}$$

Where ‘g’ is number of frequency scale and ‘h’ is number of orientations taken into account to create Gabor filter bank.

The feature extraction method is performed using a Gabor filter bank of scales and orientations both equal to 8. The pixel coordinates *x*, *y* (in Eq.(1)) is taken as 39, 39 as in [12], and the final feature vector is given by eq.(3.3.4).

3.4 Principal component analysis

PCA is used for dimensionality reduction as dimensionality reduction gives a compact, effective and low-dimensional feature for a given high-dimensional data set. In an *N* dimensional space, if PCA is applied then it aims to find a linear subspace with lower dimensionality say *D* where (D << N) while maintaining almost all variability of *N* dimensional data. Eq.(3.4.1)-(3.4.5) shows the how to calculate the principal components using eigen values and eigen vectors. First *D* principal components, associated with *D* largest eigen values are considered to represent reduced dimensionality vector [1].

Let A_i is featuring vector of an image after feature extraction using Gabor wavelets. All the feature vectors of image belonging to same emotion class are grouped together to form class feature matrix. Let say 'A' represents class feature matrix then process to calculate principal components of it is as follows:

$$A = [A_1, A_2, A_3 \ldots\ldots\ldots A_n] \tag{3.4.1}$$

where 'i' is number of images belonging to same class. Mean ($A_{n,mean}$) of all 'n' images is calculated and deviation of image by mean is calculated and represented by Ã.

$$\tilde{A}_n = A_n - A_{n,mean} \tag{3.4.2}$$

To find principal component of a matrix its eigen values and eigen vectors are required and for this Covariance matrix is used because use of its symmetry property makes calculation overhead half of the actual. Let '*cov*' represents covariance matrix of A then it can be calculated as;

$$cov = \frac{1}{n-1}\sum_{q=1}^{n} (\tilde{A}_q^{'} * \tilde{A}_q) \tag{3.4.3}$$

Covariance matrix '*cov*' comes out to be a n×n matrix. The process of finding eigen values and eigen vectors of this matrix is by Jacobi Algorithm, as follows:

Step 1.Start with an identity matrix *U* and covariance matrix *cov.*

Step 2. Find out the off diagonal element with largest absolute value, cov_{ij} then take out corresponding diagonal elements cov_{ii} and cov_{jj} using to calculate rotation angle 'α' using eq.(3.4.4),

$$\alpha = \frac{1}{2} tan^{-1}\left(\frac{2*cov_{ij}}{cov_{jj}-cov_{ii}}\right) \tag{3.4.4}$$

Step 3.Take an identity matrix *V* except for $V_{ii} = V_{jj} = cos\ \alpha$, $V_{ji} = -sin\ \alpha$, and $V_{ij} = sin\ \alpha$.

Step 4. Compute the matric products C'' and U'' such that C''_{ij} becomes zero and other elements of matrix changes.

$$C'' = V' \times cov \times V \qquad \text{and} \qquad U'' = U \times V \tag{3.4.5}$$

Step 5. Compare maximum absolute value of off diagonal element (cov_{ij}) with threshold value, if cov_{ij} is greater repeat steps from step 2 to step 5 until convergence with C'' as *cov* and U'' *as U. Upon convergence* C'' *diagonal elements contains eigen values and* U'' *contains eigen vectors.* U'' and C'' both are of size n×n.

Eigen vector associated with highest eigen value gives principal component and so on effectiveness of components decreases with decreasing eigen values. If X is (m×n) size data which is projected to eigen space $Z = XU''$, principal components are in order of U''.

3.5 Extended Bayesian classifier for classification

3.5.1 Modelling

Feature vector of training images, belonging to same emotion class, is estimated using eqs.(3.3.1)– (3.3.4), and are grouped together to form particular class feature vector. If emotions are categorized in ‘C’ number of classes, class feature vectors, w_k, for each class (k=1 to C) are obtained to get covariance matrix of size (d×d), where d is given in eq(3.3.4). These covariance matrix features are undergo dimensionality reduction by using PCA. For PCA, eigen values and eigen vectors of covariance matrix are calculated and PCA is applied as shown in section 3.2.2. Similarly feature vector (Y) of test image is estimated using eqs.(3.3.1)– (3.3.4) . Conditional density function and its logarithm using PCA is shown in eq.(3.5.1)-(3.5.2) below [7],

$$p(Y|w) = \frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}} \; exp\left\{\frac{-1}{2}(Y-M)^t \Sigma_f^{-1}(Y-M)\right\} \tag{3.5.1}$$

$$\mathrm{L} = \ln[p(Y|w)] = -\frac{1}{2}\{ \sum_{i-1}^{M} \frac{z_i^2}{\lambda_i^2} + \frac{\left||\mathrm{Y}-\mathrm{M}|\right|^2 - \sum_{\mathrm{i}-1}^{\mathrm{M}} \mathrm{Z}_{\mathrm{i}}^2}{\rho} + \ln(\prod_{\mathrm{i}-1}^{\mathrm{M}} \lambda_{\mathrm{i}}) + (\mathrm{N}-\mathrm{M})\ln\rho + \mathrm{N}\ln(2\pi) \} \quad (3.5.2)$$

where M and $\sum$ are mean and covariance of class feature vector 'w' and 'L' shows likelihood of test image with respect to class w.

3.5.2 Classification

If there are 'k' number of classes (k = 1 to C) then for each 'k' emotion class (k = 1 to C), likelihood of test image 'L_k' is estimated using eq.(3.5.3). To classify the estimated likelihoods, L_k, (k = 1 to C), proposed method extends the binary Bayes classifier to multi-class classifier (having equal class priors), such that class 'k' having the maximum value of logarithmic of conditional density function, shows maximum similarity of that class feature to test image feature thus test image is categorized under 'k'th emotion class, mathematical shown in eq.(3.5.3)

$$C_{observed} = \underset{1\le k\le C}{argmax}(\mathrm{L}_k) \quad (3.5.3)$$

Eq.(9) recognizes the emotion class '$C_{observed}$' as the emotion label of the test image. Prior probabilities of each emotion class are equal, as equal number of training images in each class has been taken.

This proposed method has been implemented and tested in the subsequent sections.

Chapter 4
Implementation

4.1 MATLAB Implementation

The proposed method is implemented following the process described in chapter 3. The pre-processing of images is done by Bayesian discriminating feature analysis method with (M = 10) principal components taking into account for modelling by using eqs. (3.2.1) to (3.2.11) using MATLAB.

Pre-processed images are undergoing for feature extraction as per section 3.3 using Gabor wavelets. Table 4-1 shows the parameters taken while designing Gabor wavelets and also for feature extraction using wavelets. The features are extracted using eqs. (3.3.1) to (3.3.3). Eq.(3.3.4) gives the size of the feature of an images. With the defined parameters size of the feature comes out to be (1024×1) since ($d = 16\times16\times8\times8/(4\times4) = 1024$).

Table 4-1

Parameters for Gabor Wavelets generation

Gabor wavelets	
No. Of frequencies (g)	8
Orientations (h)	8
No. of rows in 2-D Gabor filter	39
No. of columns in 2-D Gabor filter	39
Gabor features extraction	
Factor of down sampling along rows (d1)	4
Factor of down sampling along columns (d2)	4

Each class feature is computed by combining similar class images. Since size of the feature is very large, PCA is applied on class features using eqs.(3.4.1) to (3.4.5) for dimensionality reduction and effective first 10 principal components (M=10), are considered for modelling using eqs.(3.5.1) and (3.5.2) and likelihood is calculated for each training class, anger, disgust, fear, happy, sad, surprize and neutral. Now calculated likelihoods for each class are compared with each other to find which class shares maximum similarity with the test image and the class with max likelihood is recognized as recognized emotion class for given test image.

4.2 FPGA Implementation of Post Feature Extraction Process

After pre-processing and feature extraction of using MATLAB, the dimensionality reduction and modelling part is implemented in FPGA using Xilinx 10.1. The computational block diagram which is designed by following Jacobi Algorithm, as in section 3.4, is shown in fig. 4.1.

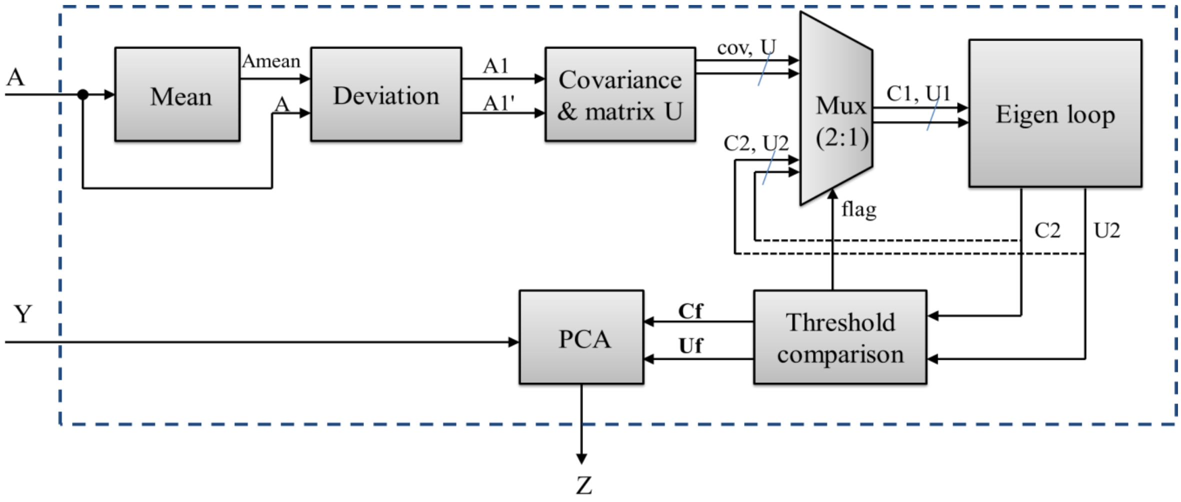


Fig. 4.1 Block diagram for Dimensionality Reduction process of Classification

Let say 'A' is feature matrix of representing any class and Y is feature of test image after Gabor feature extraction. Since class feature is accumulation of various images, covariance of class feature is calculated to take the measure of difference among images. Covariance is a symmetric matrix where diagonal elements shows variance of an image with its different components while off diagonal elements shows difference between different images. Taking advantage of symmetry property of covariance matrix, while calculation; only upper triangular off-diagonal elements are calculated and lower half are assigned copying the upper triangular elements, it saves hardware utilization.

Covariance is calculated using eq.(3.4.3) where deviation of feature (A1), with its mean (Amean), is need to be calculated. The mean is calculated as shown in fig. 4.2. If each column represents an image in class then column wise mean is calculated and subtracted with its respective column to find deviation. Since feature is of (1024×1) size, division operation for mean is calculated using right shift property of HDL, and to divide by 1024 times, vector is right shifted 10 bits ($1024 = 2^{10}$). Deviation A1 and its transpose A1' are calculated and fed to Covariance block, fig. 4.3, which calculates upper triangular elements by adding and multiplying elements logically then divided by using CORDIC divider.

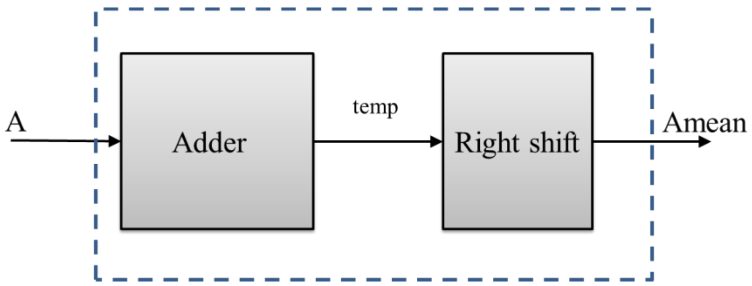


Fig. 4.2 Block diagram for mean calculation

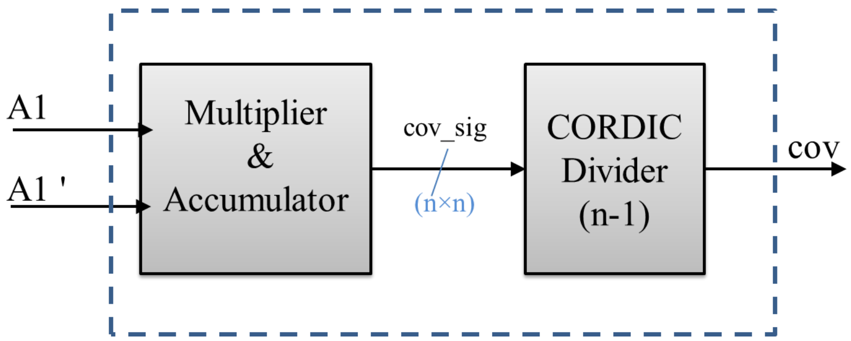


Fig. 4.3 Block diagram for Covariance module

As per the steps of Jacobi Algorithm of section 3.4, eigen values and eigen vectors are calculated iteratively using covariance matrix *cov*, With covariance block an identity matrix U is also formed. Using Eigen loop block, fig. 4.4, each iterative value of C2 and U2 is calculated until threshold is reached. Here in this particular implementation threshold is set to ‘2’. Mux is used in top block, fig.4.1 to make iterations according to threshold. Max value and indices block calculates max value among absolute values of off-diagonal elements of C1, along with the indices, max value index and its symmetric part index (max_index and symm_max_index), its corresponding diagonal elements index (diag_i and diag_j) are calculated. (Cos α, sin α) block is implemented to fulfil steps 3 followed by matrix V and (C2,U2) block of step 4. Threshold comparator of fig. 4.1, compares the max_element and threshold, which is set to ‘2’ to generate a flag of condition satisfaction, and this flag works as select line for mux.

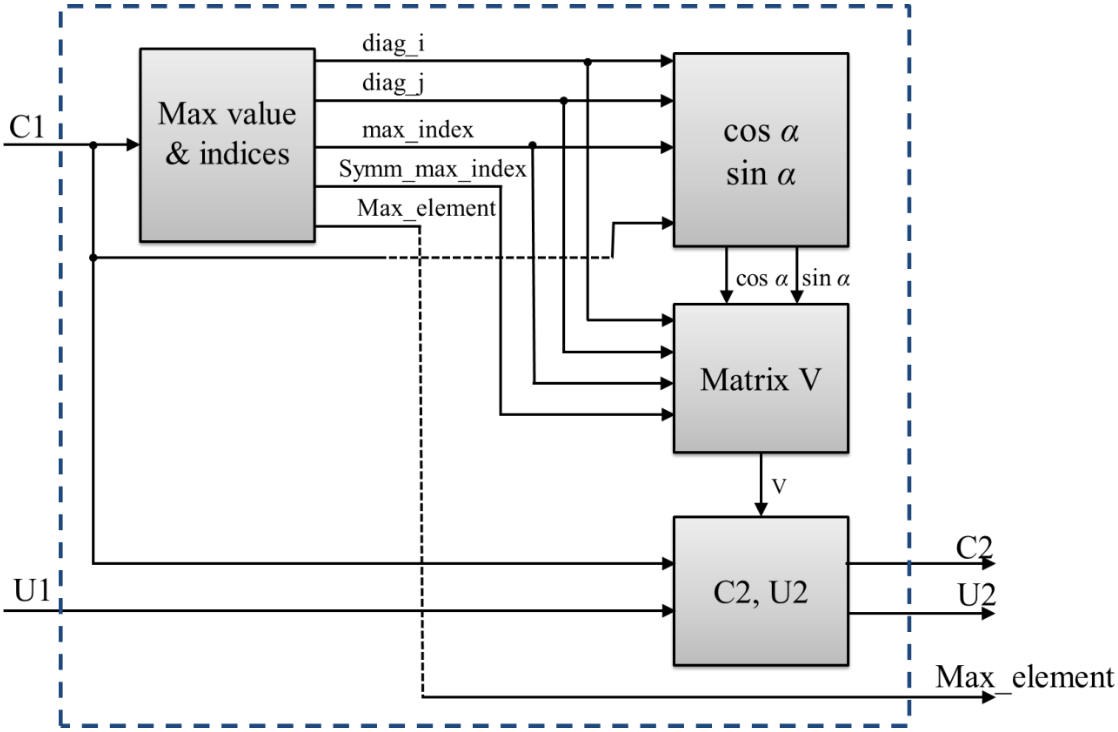


Fig. 4.4 Block diagram for Eigen Loop

Fig. 4.5 shows implementation of block used to generate cos α and sin α signals. Alpha angle is calculated using eq.(3.4.4) which uses tan inverse function. Tan inverse function and cos and sin functions are implemented using CORDIC ip core 4.0. The CORDIC cos, sin values are read using XQN format as described in section 2.3.2.

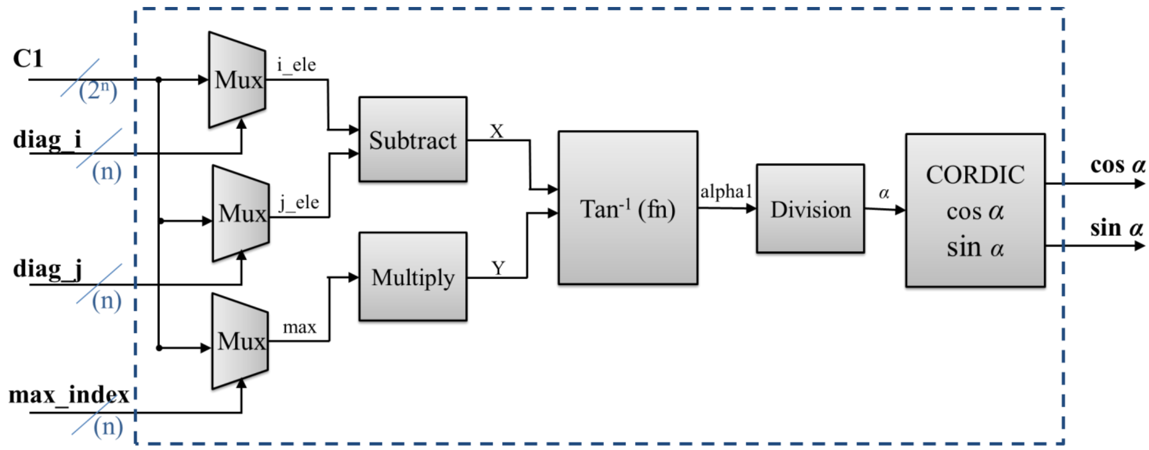


Fig. 4.5 Block diagram for (cos α, sin α) module using CORDIC

To implement tan inverse function there is an arctan function available in CORDIC but that gives phase angle correctly when values of tangents (X and Y) are subjected to first quadrant (i.e. both positive) only, otherwise it gives garbage as its output phase limitation is upto (-pi/4 to +pi/4). So to realize an arctan function which is suitable for all four quadrants some functionality has to be added with CORDIC block as shown in fig. 4.6. As we know, if phase_out is tan inverse angle when tangents lie in first quadrant then angle for rest quadrants can be calculated as :

sel => 00 => angle <= phase_out (Ist quadrant)

sel => 10 => angle <= pi - phase_out (IInd quadrant)

sel => 01 => angle <= − (phase_out) (IIIrd quadrant)

sel => 11 => angle <= − pi + phase_out (IVth quadrant)

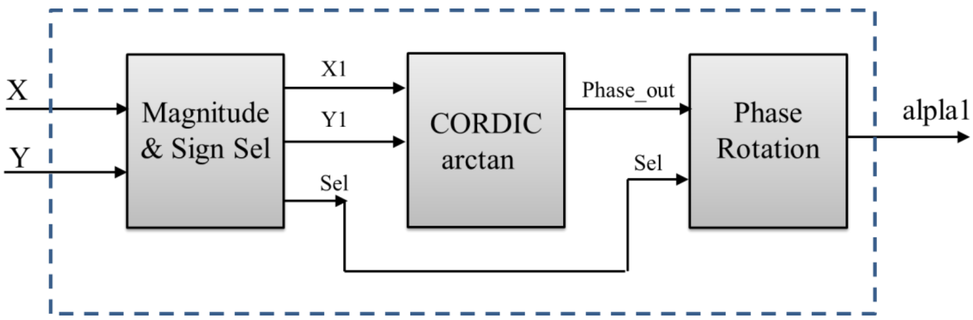


Fig. 4.6 Block diagram for Arctan function using CORDIC

In fig. 4.6, (magnitude and sign sel) block store the magnitudes and signs of inputs (X and Y) and according to signs generates *sel* signal. On magnitude values tan inverse function is operated and then according to *sel* signal angle is rotated using Phase rotation having above functionality, which gives the correct tan inverse angle.

After calculating eigen values and eigen vectors from fig. 4.1 and intermediate blocks, fig.4.7 shows the process of calculating principal components using eq. (3.2.8).

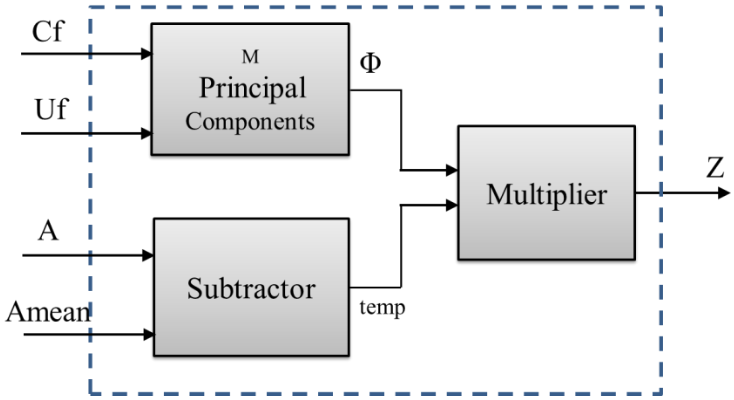


Fig. 4.7 Block diagram for Principal component calculation

Here first block selects the M principal components corresponding to M maximum eigen values and gives eigen vector matrix Φ. Second block finds the deviated feature matrix and fed to multiplier. Multiplier multiplies the transpose of matrix Φ and temp matrix signal to generate principal components Z. These principal components are further used in eq.(3.5.1) to (3.5.3) to model and classification.

➢ Delay Path Model for FPGA Implementation

While designing for hardware implementation, one of the most important aspects is the synchronization between different modules of design. Since clock is the measure of latency in HDL design, inputs to particular module should reach at same time to avoid cross calculation of data. To maintain the synchronization latencies if blocks are calculated pre-hand and delay wherever required are given as shown in fig. 4.8.

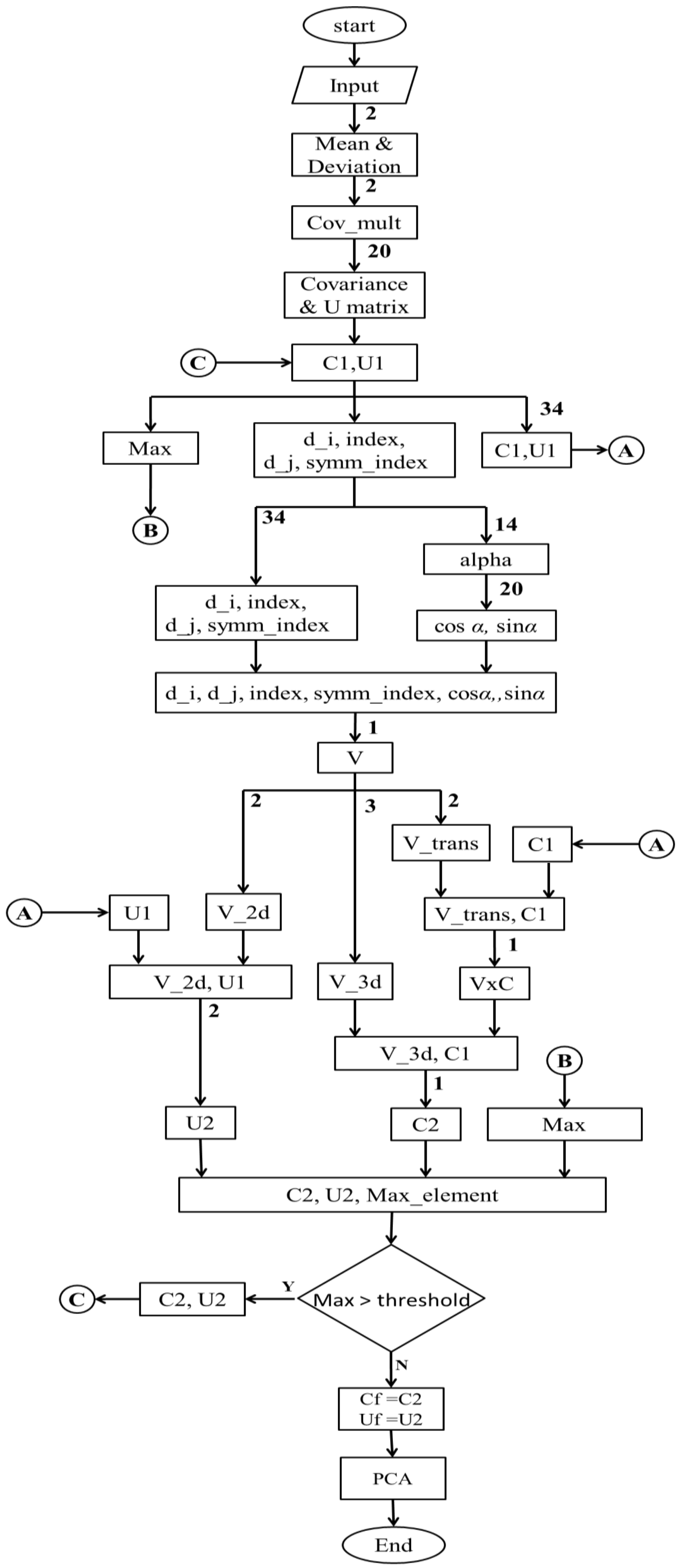


Fig. 4.8 Delay path model for FPGA implementation

In flow graph, number with arrow shows the delay required to provide to input of successive signal or block to maintain the synchronization in output of that particular block, in such manner full design is synchronized. For an example, in the above design, tan inverse function has latency of 14 clock cycles and further (sine, cosine) block has latency of 20 clock cycle, since for calculation of matrix V output of (sine, cosine) block and all the indices are required so to make these in sync, delay of 34 clock cycles (14 + 20 =34) is given to indices signals. In the similar way whole design is synchronized.

Chapter 5

Results and Analysis

5.1 Simulation Results

Both face detection and emotion detection processes are implemented using constraints defined in chapter 4. Since both face detection and emotion detection are supervised learning method, first system is modelled and trained using training images (from both face-class and non-face class in case of face detection and images from all seven emotion classes in case of emotion detection) then test images are subjected to the system to be classified.

The pre-processing steps i.e. face detection method is implemented with (M=10) principal components and trained using 2400 face class images and 4500 non-face class images from variance face class database and variance non-face class database respectively. Since non-face class images may contain images from rest of the world except face image, so there is hell number of images belonging to this class but for training, images with similar variance to face class are taken into account. The examples of face class and non-face class variance images are shown in fig.(5.1) and fig.(5.2) respectively.

Fig. 5.1 Example of Variance face class images

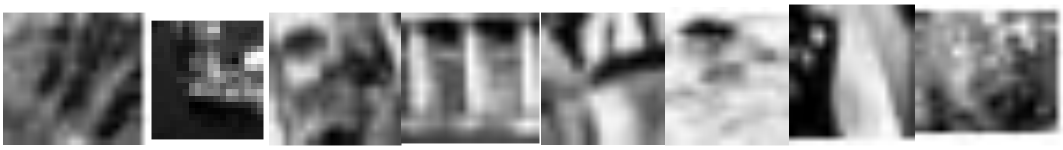


Fig. 5.2 Example of Variance non-face class images

Facial expression recognition algorithm is tested on JAFFE database so JAFFE database is first pre-processed (face detection) then used in emotion recognition part for both training and testing.

- **JAFFE Database:** JAFFE is an acronym for Japanese Female Facial Expresion. JAFFE database provides 213 images posed by 10 Japanese females showing all the seven basic emotions (Anger, Disgust, Fear, Happy, Sad, Surprise and Neutral) [10]. The database was planned and assembled by Michael Lyons, Miyuki Kamachi, and Jiro Gyoba. These images were taken when these females were subjected to sudden feel of any of the above described emotions. The example of images from JAFFE database is shown below in fig. 5.3.

Fig.5.3 Example of images from JAFFE Database showing various emotions

Images from JAFFE database have been pre-processed, the accuracy of pre-processing and resized to 16×16 for training as well as testing has been shown in Table 5-1below and fig.5.4 shows example of pre-processed images.

Table 5-1
Accuracy of Face Detection using Bayesian Discriminating Feature Analysis Method

Set	**Sources**	**Number of Images**	**Detected face**	**Undetected face**	**Accuracy**
Set1	JAFFE Database	213	205	8	96.244%

Fig. 5.4 Example of pre-processed images of JAFFE Database

JAFFE database have 210 images of frontal face showing seven emotions posed by 10 Japanese female models. Each emotion class has 30 images. Out of 30 images in each class, 20 have been used for training and rest of 10 images for testing the accuracy. In three different rounds, different training and test sets have been used. The principal components taken is 10 (i.e., M=10). Performance result of proposed emotion recognition method is shown in table 5-2. The columns represent the classified emotion for the desired emotion in corresponding rows. Anger is classified with 100 % accuracy. The lowest accuracy is obtained in case of fear class.

Table 5-2

Percentage of Correct and Erroneous Emotion Recognition With Training Database and Test Images from JAFFE Database

Desired Emotion	**Recognized Emotion**						
	Anger	Disgust	Fear	Happy	Neutral	Sad	Surprize
Anger	100	0	0	0	0	0	0
Disgust	0	96.77	3.22	0	0	0	0
Fear	0	3.22	93.54	0	0	3.22	0
Happy	0	3.22	0	96.77	0	0	0
Neutral	0	0	0	0	96.77	0	3.22
Sad	0	3.22	0	0	0	96.66	0
Surprize	0	0	3.22	0	0	0	96.77
Overall Accuracy	96.73%						

5.2 FPGA Implementation Results

The design shown in fig. 4.1 for classification is implemented and simulated using Xilinx ISE 10.1 tool on board of VirtexIIP family with device XC2VP30 and package being FF896. The simulated waveform output is shown in fig. 5.5.

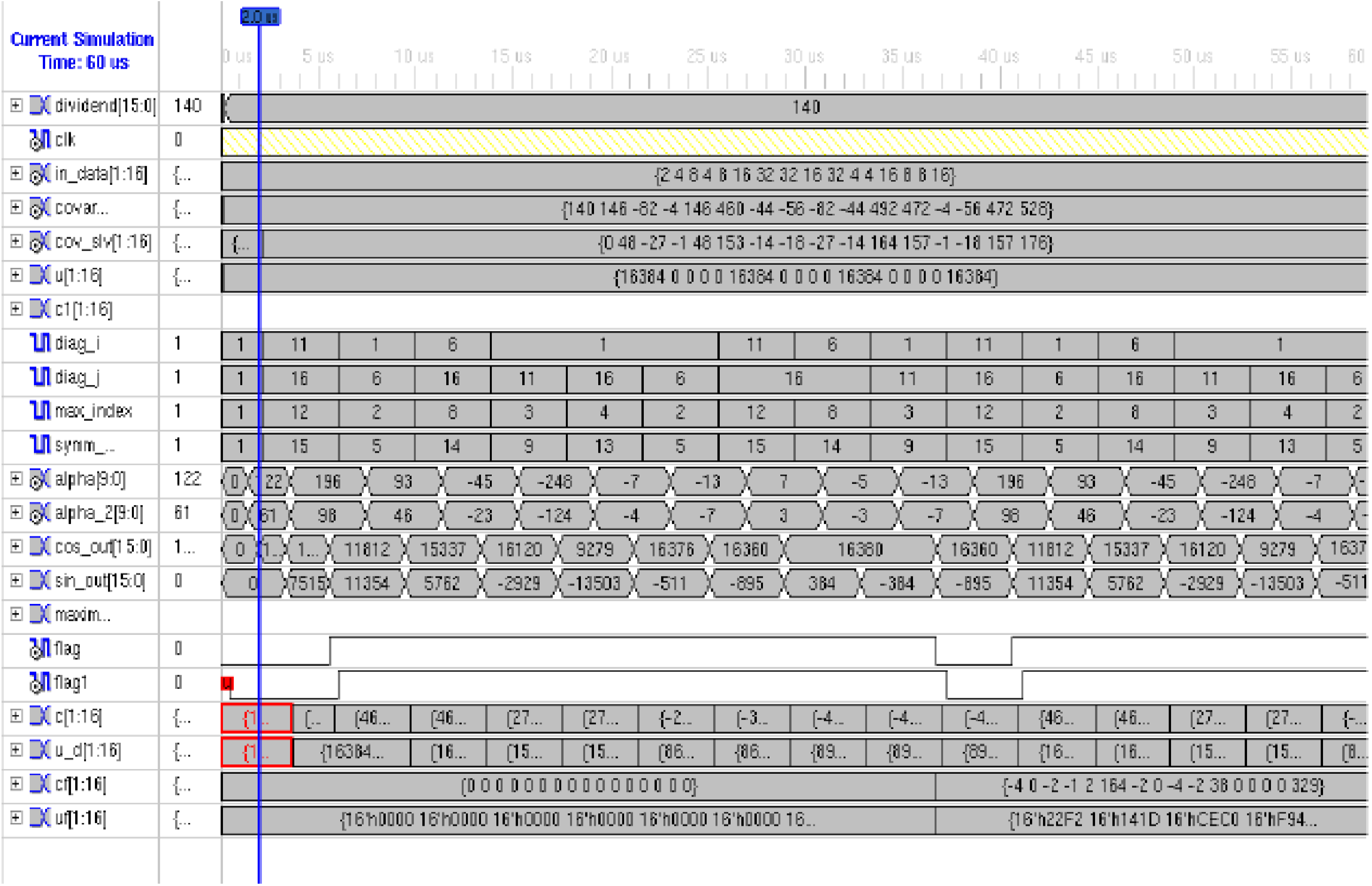


Fig. 5.5 Simulation waveform of FPGA implemented model

5.3 Comparison

The performance of proposed method is compared with existing highly accurate facial emotion recognition models listed below and comparison chart is shown in fig.5.6.

- The method proposed in [2], based on fuzzy relational approach shows overall 88.2 % accuracy when tested on Set, containing images of 100 Indian male showing 6 emotions (except neutral). It shows 92.2 % accuracy when tested on Set2, contains images of 100 Indian female showing 6 emotion (except neutral).
- The method proposed in [4], which is based on facial movement analysis, shows 92.92 % accuracy when tested on Set1 containing 180 images from JAFFE database showing 6 emotions (except neutral) and 93.14 % accuracy when tested on Set2, containing 800 images from Cohn-Kanade database showing 6 emotions.
- Method proposed in [5] based on local directional number pattern, shows 96.68 % accuracy when tested on Set1, contains images from Cohn-Kanade database showing all seven emotions.
- In [6], 94 % accuracy is obtained by using Hidden Markov Model method for recognition.
- Facial action units based method in [8], which is, shows 87.43% accuracy when tested on Set1, contains images from Cohn-Kanade database showing 6 emotions (except neutral).

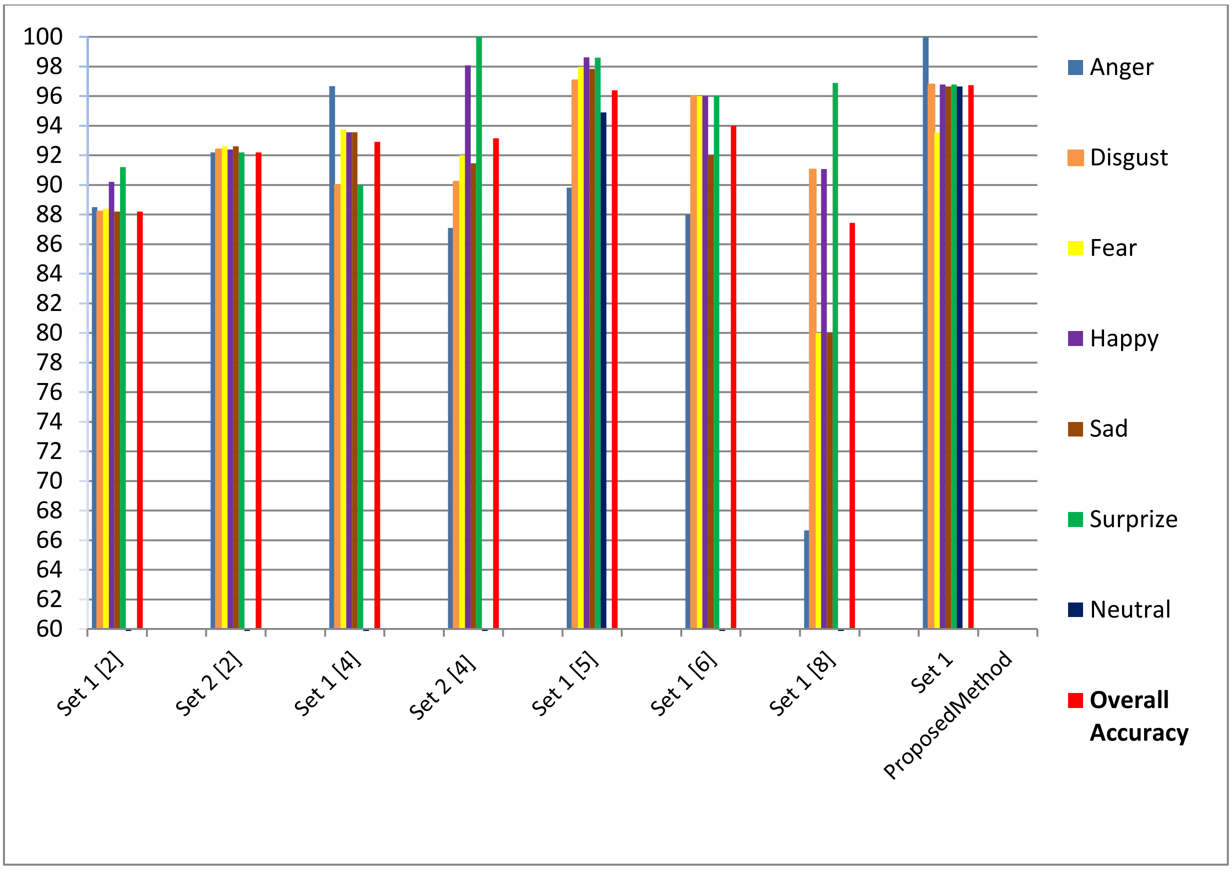


Fig. 5.6 Chart comparing performance of proposed method with that of existing methods

The comparison chart shows that the proposed method of facial expression recognition has highest accuracy when tested on JAFFE database and anger emotion class has 100 % accuracy, which is also highest among other methods.

Chapter 6
Conclusion

6.1 Conclusion

A method for facial emotion recognition based on Gabor wavelet based feature and extended Bayesian classifier for multi class classification is proposed. The proposed method shows overall accuracy of **96.73%** for JAFFE database, when implemented on MATLAB which is higher than that of highly accurate existing facial emotion recognition methods. Also existing method for Face detection based on Bayesian discriminating feature analysis is implemented successfully with accuracy of **98.59%** when tested on JAFFE database. The simple extended Bayesian classifier is suitable for real time implementation and is implemented on FPGA VirtexIIpro using Xilinx ISE 10.1 simulator with CORDIC IP Core. The ease of implementation and hardware efficiency of CORDIC IP core makes the FPGA implementation area efficient and faster. The intellectual properties of CORDIC core have been used significantly for calculation of logarithm, sin, cos, tan and arctan functions.

6.2 Scope for Future Work

- To implement the remaining existing modules of feature extraction and face detection in HDL and to perform full FPGA implementation of algorithm in hardware.
- Real time implementation of the proposed algorithm for facial expression recognition.
- Realization and implementation of second parameter of HCI that is gesture recognition.
- ASIC implementation for HCI including both emotion and gesture recognition.

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