Four Way Local Binary Pattern for Gender Classification Using Periocular Images

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Abstract

Human face can represent such information that would be difficult to express using thousands of words. For this reason, human face has always been an active field of research in Computer Vision and Image Processing. Face carries vital information such as identity, gender, mood etc. of an individual. The power of discrimination and recognition come naturally to human being while machine does not have this trait. Machine cannot extract information from face with such ease like human being. Lots of painstaking efforts are required to make machine a strong competitor to human being. To make the machine performing close to human being we need to extract the discriminating features very efficiently. Several image descriptors have been proposed for facial image description. But they are not robust in all aspects. For an image descriptor to be a good one it should have some quality of robustness against different challenging environments such as pose variation, illumination change, rotation, noise, scaling etc. So, finding a good image descriptor is a challenging task in Image Processing applications. To extract features from a face image, several descriptors such as global and local are proposed. Global descriptors such as Principal Component Analysis, Linear Discriminant Analysis, etc. adopt a holistic approach for representing the face image which does not encode local information and it degrades the performance of the algorithms. To encounter these problems, many local texture based approaches have been proposed such as Local Binary Pattern (LBP) which encodes the local texture information of an image and represents them globally. But, performance of LBP degrades in presence of noise, rotation and non-monotonic gray scale changes. These image descriptors are used in various Computer Vision applications such as face recognition, facial expression recognition, age estimation

and gender classification etc. Among these, gender classification is a recent field of research that has grown interest among the researchers. Automatic gender classification can improve the performance of many computer vision applications such as security, surveillance, human interaction etc. Many facial image based gender classification techniques have been proposed by the researchers. They use the full face for gender classification. Most of them use Global or Local feature extractors for extracting the image features and then give them to machine learning algorithms such as Support Vector Machine, Nearest Neighbor Classifier, Neural Network for classifying gender. Following a full face based approach degrades the classification accuracy when the face is occluded. Occlusion is a natural phenomenon that is very common in real world. Full face image may not be available all the time for classification. So, the performance drops drastically. Moreover, the proposed approaches use the existing feature extractors. So, they incorporate all the drawbacks of these algorithms which is another performance degrading factor. Periocular region is attracting much interest recently due to the occlusion factor. Periocular region refers to an area in immediate vicinity of eye. Due to the availability of periocular images over full face image, researchers have used this for different classification purpose. Considering all this limitations of gender classification from facial images, we propose a novel image descriptor, the Four Way Local Binary Pattern (FWLBP) for classifying gender from periocular images. This proposed method generates a binary bit pattern called FWLBP code by thresholding the image pixels of a 3 x 3 neighborhood in four ways (top, left, right, bottom) with respect to three horizontally and vertically centered pixels. This gives a better representation of edges in four ways which is a much more robust information than intensity information. The proposed method's efficiency is tested on publicly available FERET database. Periocular images were extracted from facial images and FWLBP was used to extract the features which were given to Support Vector Machine for classifying gender. From experimental results, it is seen that our proposed method gives better classification accuracy than the traditional LBP method both in general circumstances and in different challenging factors such as rotation, out of focus etc.

Dedication

Dedicated to my father who passed away few days ago of this dissertation and to my mother who bore the utmost pain to raise me up.

-Md. Siyam Sajeeb Khan

Dedicated to my beloved parents without whom none of my success would be possible.

-Rifat Mehreen Amin

Declaration

We, Md. Siyam Sajeeb Khan and Rifat Mehreen Amin, declare that this thesis titled, " Four Way Local Binary Pattern for Gender Classification Using Periocular Images" and the work presented in it are our own. We confirm that:

- This work was done wholly or mainly while in candidature for an undergraduate degree at this University.
- No part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution.
- Where we have consulted the published work of others or not this is always clearly attributed.
- Where we have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely our own work.
- We have acknowledged all main sources of help.
- Where the thesis is based on work done by ourselves jointly with others. we have made clear exactly what was done by others and what we have contributed ourselves.

Sign:

Letter Of Acceptance

I hereby declare that, this thesis is the student's own work and best effort of mine. All other sources of information used have been acknowledged. This thesis has been submitted with my approval.

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"Ever tried. Ever failed. No matter. Try again. Fail again. Fail better"

Samuel Beckett, *Worstward Ho*

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Chapter 1

Introduction

For an automatic system, covering a larger population defines a complex class border, making the process of classification more difficult. Due to the open challenges, gender classification is a current field of research in computer vision, with different application scenarios that include demographics, direct marketing surveillance and forensics among others [1]. Gender of a person is actually one of the soft biometric traits. Classification of this biometric trait is an important task which can enhance the performance of a wide range of applications which include human-computer interaction, access control and authentication [2]. With the development of image processing techniques, human face recognition techniques have been applied so broadly. Meanwhile, the gender identification technique based on human face images has become one of mode recognition research focuses. Gender Identification of human face images means that computers process human face images, extracts the features of images, then identifies the gender by using classification. Gender classification has broad research prospects. It can easily identify and control the scenes where there are requirements for gender [3]. But there exists some challenges in this field.

The major challenge in gender classification is twofold:

1. To find discriminant features which is feature extraction.

2. To distinguish male and female classes which is using classifier [4].

1.1 Background

The face is the most widely used biometric trait. Every day and even without noticing it, we all use facial information to recognize each other. Not only that, it becomes one of the most successful applications of image analysis and understanding [5]. Previously face was used for gender classification. The face is the most expressive part of the human body and from face one can determine a number of attributes or characteristics of a person. For example the face conveys identity, lineage, sex, race, ethnicity, mood, feelings, etc. The face is powerfully expressive, and hence, it can be challenging to extract information in a robust and efficient way. Over the years the face has provided unique challenges to the biometrics community [6]. A number of studies suggest that gender can be robustly estimated from face images with relatively high accuracies [7] and then again, only a limited number of studies have investigated the estimation of gender information from fingerprint and eye images. Enrique *et al.* have worked on large databases for gender classification, they worked with the MORPH database and achieved a very high accuracy [1].

Face recognition performance from the Good, the Bad, and the Ugly problem [8] indicate that more work is needed for face recognition to address the non-ideal, or PIE, scenarios. Face verification research in the literature [9, 10, 11] has shown that the verification performance decreases with an increase in the age span between the match pairs, and that the main–anecdotally derived–causes are due to large facial shape and texture changes.

1.2 Motivation

Due to increasing concern on security and safety of modern societies, biometrics have emerged in the last decade as a major domain of knowledge and has been motivating significant research efforts. The periocular region has recently emerged as a promising trait for unconstrained biometric recognition, especially on cases where neither the iris nor a full facial image can be obtained [5].

The terms "periocular region" refer to the area around the eye- the area of the face that includes the eyelids, eyelashes, eyebrows and the skin surrounding the eye. Sometimes, the definition can correspond to several interpretations of how much information is available around the eye [12]. Periocular Biometric is such a field which grabbed a lot of attention as an emerging field of biometric. Periocular is the region of the face at immediate vicinity of the eye [13]. Capturing an eye or face automatically captures the periocular image.

As no external help of the subject is needed, therefore, this gives the facility of recognizing an individual using the periocular data along with iris data without extra storage or acquisition cost. Study suggests that, the first facial features, the brow and eyes, precisely define the scope of the periocular region and this region contains sufficient and primary information for reliably identifying gender [14].

Some of the highly considered approaches in this area include working with basic LBP and SVM on FRGC dataset. Lyle *et al.* showed [15] soft biometric classification approach using appearance based periocular features. In [7] the authors have evaluated gender recognition from ocular images captured in mobile environment. Realizing the face as most expressive part Gayathri *et al.* have worked on a unique scenario of recognizing individuals across gender transformation using periocular images [6]. The authors had used ICA for feature extraction and made very favorable advancement in using only 25% data of whole face image and obtained very high accuracy [4]. Markow *et al.* [16] showed that at least 85% classification rate can be obtained using the periocular region with a database of 936 low resolution images collected from the web. Using 11,000 images of the UBIRIS v2 database Bhardwaj *et al.* made promising results which showed that using periocular region can be very effective for recognition when the information of iris does not contain subtle details [17]. Park *et al.* worked with periocular biometric trait and gained a rank-one recognition accuracy of 87.32% using 1136 probe and 1136 gallery periocular images. [13] In past, there had been enormous progress made in ocular biometrics but still some challenges remained in those traits.

And the challenges addressed by periocular biometrics are:

1. **Size of Iris:** The size of iris is very small compared to that of a face. So, face images acquired with low resolution sensors or large standoff distances offer very little or no information about iris texture [4].

2. **Iris is a moving object:** Reliably localizing the iris in eye images obtained at a distance in unconstrained environment can be difficult [18].

3. **Closed eye of the subject:** If by any chance the subject closes his/her eye, the iris information cannot be retained.

4. **Information extraction with subject cooperation:**The subject needs to give the image information or the permission of using his/her images. Much effort is needed in this case.

5. **Occlusion of portions of the face:**The portions of the face pertaining to the mouth and nose are often occluded due to various reasons. Therefore, the information of the whole face cannot be retrieved descriptively [4].

LBP operator which is Local Binary Pattern is one of the best performing texture descriptors and it has proven to be highly discriminative and its key advantages namely, its invariance to monotonic gray level changes and computational efficiency, make it suitable for demanding image analysis task [19]. LBP is such an extractor that assigns a label to every pixel of an image by thresholding the neighborhood of each pixel based on the center pixel value and converting the resultant binary number to a decimal value. Then histograms are computed from tessellated blocks and concatenated to form a descriptor [20]. Maximum recent works on periocular images have used Local Binary Pattern as their feature extractor. Such as, using VISOB database the authors evaluated gender recognition from ocular images captured in mobile environment [7]. In [17], authors have used CLBP (Circular Local Binary Pattern) which motivates to capture the discriminating texture features from the periocular region. Their result was promising in the fact of using periocular region for recognition when the information is not sufficient for iris recognition. Multiscale bandlet and LBP based method for gender recognition from face images is proposed in [21]. Gudla *et al.* in their paper presented a variant of Local Binary Patterns for gender classification which can discriminate the facial textures efficiently. They used a new neighborhood shape for obtaining LBP [22]. LBP with SVM had also been used by Fei *et al.* and they used SVM as low order polynomial which are better than Gauss-kernel function [3]. Enrique *et al.* also got high accuracy by using Local Binary Pattern in large databases [1] and they proved that success of the method is not database independent. Mahalingam *et al.* had used TPLBP (Three-patch Local Binary Pattern). While the LBP and HOG are pixel based feature descriptors, the TPLBP is a patch based feature descriptor that extracts features from local patches around a central patch [6].

1.3 Objective of the Research

Textures in the real world are often not uniform due to variations in orientation, scale, or other visual appearance [20]. Although LBP efficiently captures the local structure, it is not rotation invariant. For an image with rotation or small gesture, the performance of traditional LBP is not very good [23]. The main objective of the research is to develop such a feature extractor which gives high performance in gender classification using periocular images. Which will be rotation invariant to address the problem of traditional Local Binary Pattern.

1.4 Contributions of the Thesis

The contributions of the thesis lie in two folds:

1. **New feature extractor:** We propose an efficient approach named Four Way Local Binary Pattern (FWLBP) which considers the local information of the textures in micro-level using four way line symmetry.

2. **Gender classification from periocular images:** Gender Classification using only the periocular region, is reliable, even when testing is performed on images with a high degree of variability, including illumination and focal length. Even under unpredictable environments or acquisition conditions, periocular gender classification can be proven to perform only a small percentage lower than with more controlled data using full facial information [16]. Recently, gender classification using facial features has attracted researchers' attention. Gender classification using texture features of faces exhibited promising improvement over other facial features [22].

So, We carefully addressed the challenges of extracting features and use of classifier. Our proposed method is working on gender classification from periocular images achieving a maximum accuracy rate of 94.67%. This approach gives a very good performance during rotation than traditional LBP (Local Binary Pattern) enhancing the gender classification rate using the textural properties of the periocular regions.

Chapter 2

Background Study

2.1 Overview

Analysis and classification of object in images and videos have received much attention in the research of computer vision and pattern recognition recently. As stated in Chapter 1, this task is really challenging but at the same time promising and it has many potential applications. This chapter makes some literature review on the related works and some background theories in classification, from feature extraction and emphasis will be placed on the techniques that have been chosen for analyzing periocular images which is main objective of this thesis work. Some previous works on feature representation methods of objects will be describes.

For classification, the image features should carry enough information of the region of interests (ROI) and image should not contain any irrelevant and redundant knowledge from the extraction. They should be easy to compute in order to make the approach feasible for a large collection of images ad rapid extraction. The image features should also provide invariance to changes in illumination, background, etc. To achieve these goals, rather than directly applying raw image intensities or gradients, one often uses some form of more advanced local image feature descriptors. Such features can be based on points, blobs, intensities, gradients, color or their combinations. In a word, the final feature descriptor needs to represent the image sufficiently well for the detection and classification tasks. There are various kinds of approaches for image feature representation. These include model-based approaches, shape-based approaches, and appearance-based models. Model-based approaches try to represent (approximate) the object as a collection of three dimensional, geometric primitives (boxes, spheres, cones, cylinders, surface of revolution). Shape-based methods represent an object by its shape/contour. In Appearance-based models only the appearance is used, which is usually captured by different two dimensional views of the object-of-interest.

2.2 Classification of Image Feature

The image feature can be classified based on the area of image from where relevant image properties are extracted. Accordingly features can be divided into two classes, i.e, global image descriptor and local image descriptor.

2.2.1 Global Image Descriptor

Global features try to cover the information content of the whole image or patch, i.e., all pixels are regarded. This varies from simple statistical measures (e.g., mean values or histograms of features) to more sophisticated dimensionality reduction techniques, i.e., subspace methods, such as principle component analysis (PCA) [24], independent component analysis (ICA) [25], or non negative matrix factorization (NMF) [26]. The main idea of all of these methods is to project the original data onto a subspace, which represents the data optimally according to a predefined criterion: minimized variance (PCA), independence of the data (ICA), non-negative, i.e., additive components (NMF).

Principal Component Analysis:

Principal Component Analysis (PCA) also known as Karhunen-Loeve transformation (KLT) is a well known and widely used technique in statistics. It was first introduced by Pearson and was independently rediscovered by Hotelling. The main idea is to reduce the dimensionality of data while retaining as much information as possible. This is assured by a projection that maximizes the variance but minimizes the mean squared reconstruction error at the same time. Due to its properties PCA can be considered as a prototype for subspace methods.

Independent Component Analysis:
Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive sub-components supposing the mutual statistical independence of the non-Gaussian source signals. It became widely known and popular method when it was introduced in signal processing for blind source separation, i.e., separation of mixed audio signals [27, 28]. This problem is often described by the task of identifying a single speaker in a group of speakers ("Cocktail-party problem").

2.2.2 Local Image Descriptor

A local feature is a property of an image (object) located on a single point or small region. It is a single piece of information describing a rather simple, but ideally distinctive property of the object's projection to the camera (image of the object). Examples for local features of an object are, e.g., the color, (mean) gradiant or (mean) gray value pixel or small region. For object recognition tasks the local feature should be invariant to illumination changes, noise, scale changes and changes in viewing direction, but, in general, this cannot be reached due to the simplicity of the features itself. Thus, several features of a single point or distinguished region in various forms are combined and a more complex description of the image usually referred to as descriptor is obtained. A distinguished region is a connected part of an image showing a significant and interesting image property. It is usually determined by the application of a region of interest detector to the image.

Since the whole data is represented global methods allow reconstructing the original image and thus providing, in contrast to local approaches, robustness to some extent. Contrary, due to the local representation local methods can cope with partly occluded objects considerably better. Feature descriptors describe the region or its local neighborhood already identified by the detectors by certain invariance properties. Invariance means, that the descriptors should be robust against various image variations such as affine distortions, scale changes, illumination changes or compression artifacts (e.g., JPEG). It is obvious that the descriptors performance strongly depends on the power of the region detectors. Wrong detections of the region's location or shape will dramatically change the appearance of the descriptor. Nevertheless, robustness against such (rather small) location or shape detection errors is also an important property of efficient region descriptors. Some Local descriptors are:

- Scale invariant feature transform (SIFT) [29], [30]
- PCA-SIFT (Gradiant PCA) [31]
- Gradient location-orientation histograms (GLOH) [32]
- Spin Images [33]
- Shape context [34]
- Local Binary pattern [35]

PCA-SIFT:

Ke and Sukthankar [31] modified the DoG/SIFT – key approach by reducing the dimensionality of the descriptor. Instead of gradient histograms on DOG-point, the authors applied Principal Component Analysis (PCA) to the scale-normalized gradient patches obtained by the DoG detector. In principle they folloy Lowe's approach for key-point detection They extract a 41×41 patch at the given scale centered on a key-point, but instead of a histogram they describe the patch of local gradient orientations with a PCA representation of the most significant eigenvectors. In contrast to SIFT-keys, the dimensionality of the descriptor can be reduced by a factor about 8, which is the main advantage of this approach, Evaluation of matching examples show that PCA-SIFT performs slightly worse than standard SIFT-keys[9].

Gradient Location-orientation Histogram (GLOH):

Gradient location-orientation histograms are an extension of SIFT-keys to obtain higher robustness and distinctiveness, Instead of dividing the patch around the key-points into a 4×4 regular grid, Schmid *et al.* dicided the patch into a radial and angular grid [32], in particular 3 radial and 8 angular sub-patches leading to 17 location patches. Gradient orientation of those patches are quantized to 16 bin histograms, which in fact results in a 272 dimensional descriptor. This high dimensional descriptor is reduced by applying PCA and the 128 largest eigenvalues are taken for description.

Local Binary Patterns:

Local binary patterns (LBP) are a very simple texture descriptor approach initially proposed by Ojala *et al.* [35]. They have been used in a lot of applications [36, 37, 38, 24, 25, 25, 26, 27, 28, 39, 40, 41, 29, 30, 31, 33, 34, 42, 43] and are based on a very simple binary coding of thresholded intensity values. In their simplest form they work on a 3×3 pixel neighborhood. The rest about LBP is discussed in Chapter 3.

Chapter 3

Local Binary Pattern (LBP)

3.1 Introduction

Extracting the features from an image and representing them efficiently is always a challenging task in the field of Image Processing. Different holistic approaches such as Principal Component Analysis (PCA) [44], Linear Discriminant Analysis (LDA) [45] and 2D PCA [46] have been adopted. But, the problems with the global descriptors are, they are not efficient enough to capture the local information of an image such as pose and illumination changes which are vital for classification problems. Local descriptors have attracted much attention due to their robustness against pose and illumination changes. Among different local image descriptors, Local Binary Pattern (LBP) is one of the most powerful means of texture analysis. The original LBP operator was first introduced by Ojala *et al.* [35, 47]. Since its introduction, it has remained as a strong and robust texture descriptor for facial images and proven to be highly discriminative. One of the main reasons behind LBP's strength and robustness is its tolerance against illumination changes. Another important feature is the simplicity of the calculation process and computational efficiency which makes it highly demanding for facing the challenges of real-time image analysis. LBP alone and combined with its variants have been used in numerous applications including visual inspection, image retrieval, remote sensing, biomedical image analysis, face image analysis, gender classification, motion analysis, environment modeling, outdoor scene analysis etc. A list of some applications of LBP in different sectors can be found in [36, 37, 38, 24, 25, 25, 26, 27, 28, 39, 40, 41, 29, 30, 31, 33, 34, 42, 43].

3.2 Generation Scheme of LBP Features

Generation of LBP feature values is very simple and easy. In its simplest form, the LBP operator works on a 3 x 3 pixel neighborhood (p) by thresholding the intensity of every pixel of the 3 x 3 neighborhood $I(p_1 - p_8)$ with respect to the intensity of the center pixel $I(p_c)$ and assigns them to S:

$$S(p_c,\ p_i) = \begin{cases} 1, & I(p_i) \geq I(p_c) \\ 0, & I\left(p_i\right) < I(p_c) \end{cases} \tag{3.1}$$

After that an LBP code is generated by summing up the signs of S which are weighted by a power of 2:

$$LBP\left(p_c\right) = \sum_{i=1}^{i=8} S_i * W_i \tag{3.2}$$

where W is the weight matrix and W_i is the weight assigned to S_i. Figure 3.1(a) illustrates the process of thresholding the neighborhood pixels with respect to the center pixel and 3.1(b) depicts how the LBP code is generated. LBP values are then combined in a LBP-histogram to form a distinctive region descriptor. A histogram of the encoded image $f_l(x, y)$can be described as

$$H_i = \sum_{x,\ y} I\left\{f_l\left(x, y\right) = i\right\},\ i = 0, 1, \ldots\ldots\ldots n - 1 \tag{3.3}$$

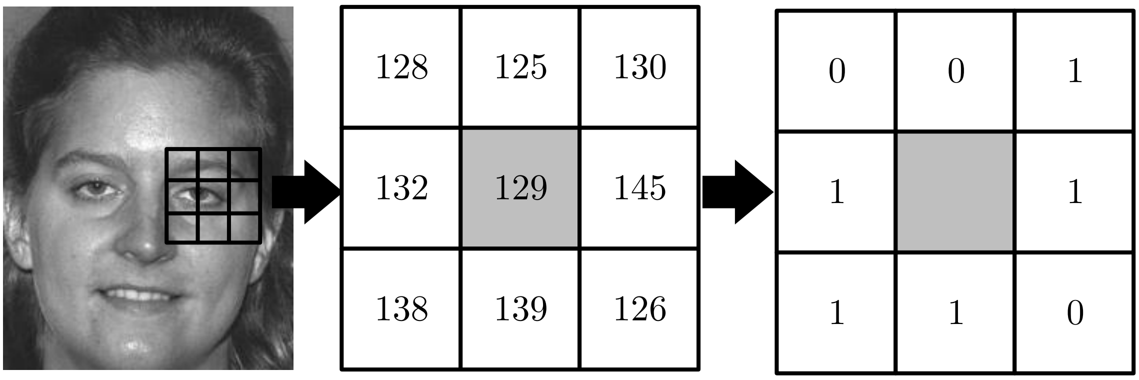
in which n is the number of different labels produced by the LBP operator and

$$I(A) = \begin{cases} 1, & A\, is\, true \\ 0, & A\, is\, false \end{cases} \tag{3.4}$$

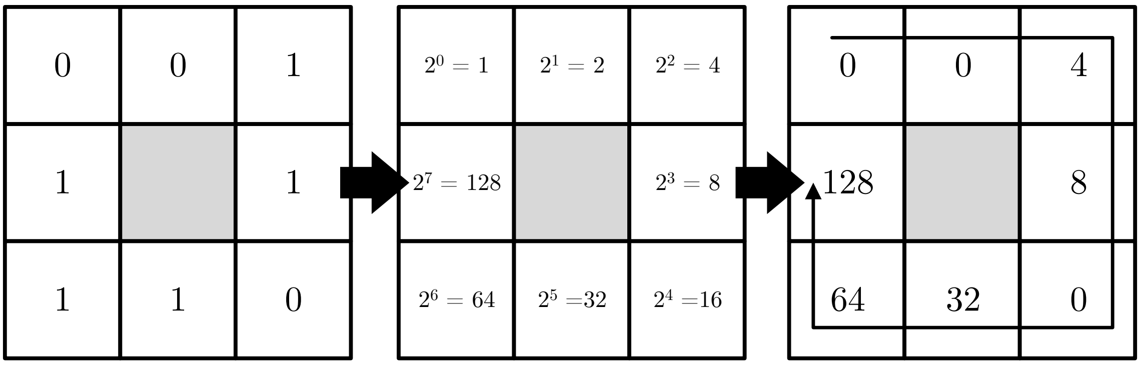
This histogram contains information about the distribution of the local micro patterns, such as edges, spots and flat areas, over the whole image. For efficient representation of face spatial information should be captured. For this purpose, the facial image is divided into small regions and the basic histogram is extended into a spatially enhanced histogram [19] [48]. The face image is divided into m regions numbering from $I_0, I_1, I_2 \ldots \ \ldots \ \ldots \ I_m - 1$ and histograms of each division are calculated independently. All these histograms are then concatenated to form the *spatially enhanced histogram* of size $m \times n$ where m is the total number of regions and n is the size of independently calculated LBP histogram. The *spatially enhanced histogram* can be defined as

$$H_{i,\,j} = \sum_{x,\,y} I\left\{ f_l\left(x,y\right) = i\right\}\ I\{(x,y)\,\epsilon R_j\},\ i = 0,1,\ldots n-1,\ j = 0,\ 1,\ \ldots,\ m-1 \tag{3.5}$$

The *spatially enhanced histogram* contains effective information on three different levels of locality: The LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level, and the regional histograms are concatenated to build a global description of the face. Figure 3.2 illustrates the whole process.



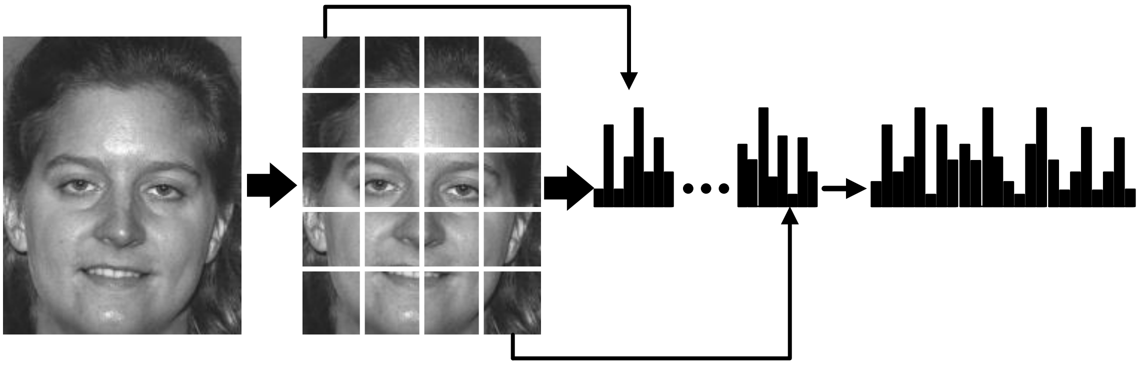
(a) Thresholding the pixels of 3×3 neighborhood p against the center pixel



(b) Generating LBP code from S using the weight matrix W

Figure 3.1: Generating original LBP code

$$\text{LBP code} = 0 + 0 + 4 + 8 + 0 + 32 + 64 + 128 = 236$$



(a) Face image (b)Face image divided into blocks (c) Histogram concatenation

Figure 3.2: Example of an LBP based facial representation

Although the original LBP operator works on 8 neighboring pixels situated at a radius of 1 from the center pixel, it can easily be extended to include all circular neighborhoods of any radius with any number of pixels using bi-linear interpolation of the pixel intensity [20]. Figure 3.3 shows some of the examples of the extension of original LBP operator to multiple neighborhoods. This process can be generalized as follows:

$$LBP_{(N,\, R)}\left(p_c\right) = \sum_{i=1}^{i=N-1} S\left(p_i - p_c\right) * 2^i \tag{3.6}$$

where $LBP(N, R)$ means the LBP code with N neighbors and radius R, p_c - corresponds to the intensity value of the center pixel and p_i corresponds to the intensity value of the N neighborhood pixels. Here $S(x)$ is defined as:

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{3.7}$$

Another extension of the original LBP operator is so called uniform patterns [20]. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. For example, the patterns 00000000 (0 transitions), 10000001 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 10101000 (5 transitions) and 01000010 (4 transitions) are not. While computing LBP histogram uniform patterns are used so that there is a separate bin assigned for each of the uniform pattern and all the non-uniform patterns are assigned to a single bin in the histogram. While experimenting with texture images, Ojala *et al.* noticed that uniform patterns account for 90% of all the patterns found using (8,1) neighborhood and 70% using (16, 2) neighborhood. To express uniform LBP with different neighborhood and radius we use the notation $LBP^{u2}(N, R)$ where N is the number of pixels in the neighborhood described by radius R. Uniform LBP can be very useful in reducing the size of feature vectors it assigns all the non-uniform patterns into a single bin instead of separate bins and provides rotation invariance mechanism [27].

3.3 Some Variants of LBP

LBP has brought revolutionary improvement in the field of Computer Vision and Image Processing. Since its great success in numerous fields, a number of variants of it have been proposed by many research groups. Some of these proposed methods are described as follows:

Local Directional Pattern (LDP): The Local Directional Pattern (LDP) introduced by Jabid *et al.* [28] is a variant of LBP which computes the edge response values in all eight directions (M_0~M_7) using Kirsch masks at each pixel position and generates a code from the relative strength magnitude. These masks are shown in Figure 3.4.
After applying these eight masks eight edge response values $m_0, m_1, \dots \dots m_7$ are obtained which represent edge significance in their respective directions. The response values do not bear equal significance in all directions. It is seen that presence of edge or corner show high response values in particular directions. From all the 8 directions k most prominent directions are taken in order to generate LDP code. Hence, top k values are found and set to 1 while the rest of the $(8 - k)$ bits of the LDP pattern are set to 0. The code generation process can be expressed as follows:

$$LDP_k = \sum_{i=0}^{i=7} s\left(m_i - m_k\right) \times 2^i \tag{3.8}$$

where m_k is the k-th most significant response and $s(x)$ is defined as

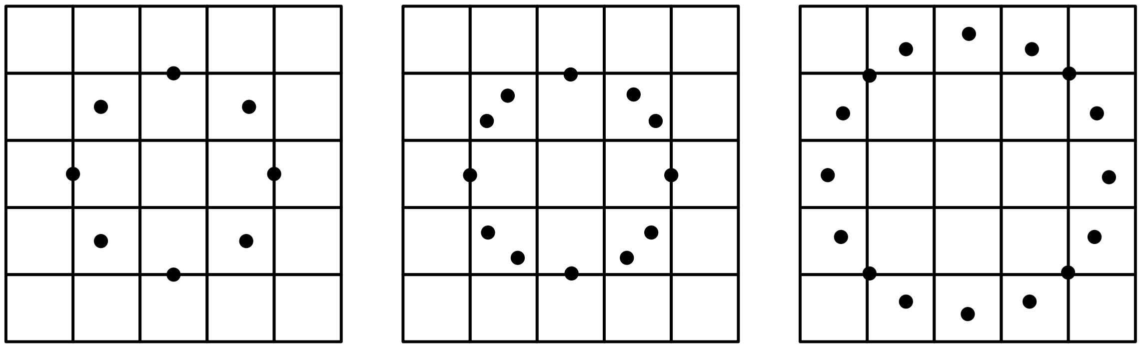
$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{3.9}$$

LDP is more robust in response to noise and produces more stable pattern than LBP. Performance of LDP is tested in different problems including face recognition [28], facial expression recognition [29] and gender classification [49] with excellent results.

Local Ternary Pattern (LTP): Local Ternary Pattern (LTP) introduced by Tan *et al.* [31] is an extension of LBP to 3-valued codes. LBP thresholds the gray level pixels of a neighborhood exactly at the center pixel p_c but LTP sets a threshold level $\pm t$ around p_c and quantizes the pixels to 0 that are in a zone of width $\pm t$ around p_c, to +1 that are above this and to -1 those are below the defined level. The following equation describes the process:

$$s\left(u,\ p_c,\ t\right) = \begin{cases} 1, & u \geq p_c + t \\ 0\,, & \left|u - p_c\right| < t \\ -1, & u \leq p_c - t \end{cases} \tag{3.10}$$

LTP code is calculated by splitting the values of s into two binary patterns named as upper and lower patterns considering its positive and negative components as illustrated in Figure 3.5 where t = 5 was used as threshold value.
LBP is resistant to illumination change but it becomes vulnerable to noise as it thresholds only respect to the center pixel. As LTP combines a user defined threshold value t along with the center pixel for quantizing a gray level neighborhood, it provides more resistance to noise.



(a) r = 1.0, N = 8 (b) r = 1.5, N = 12 (c) r = 2.0, N = 16

Figure 3.3: Some examples of LBP with extended neighborhoods

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East M_o North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

Figure 3.4: Kirsch edge response masks in eight directions

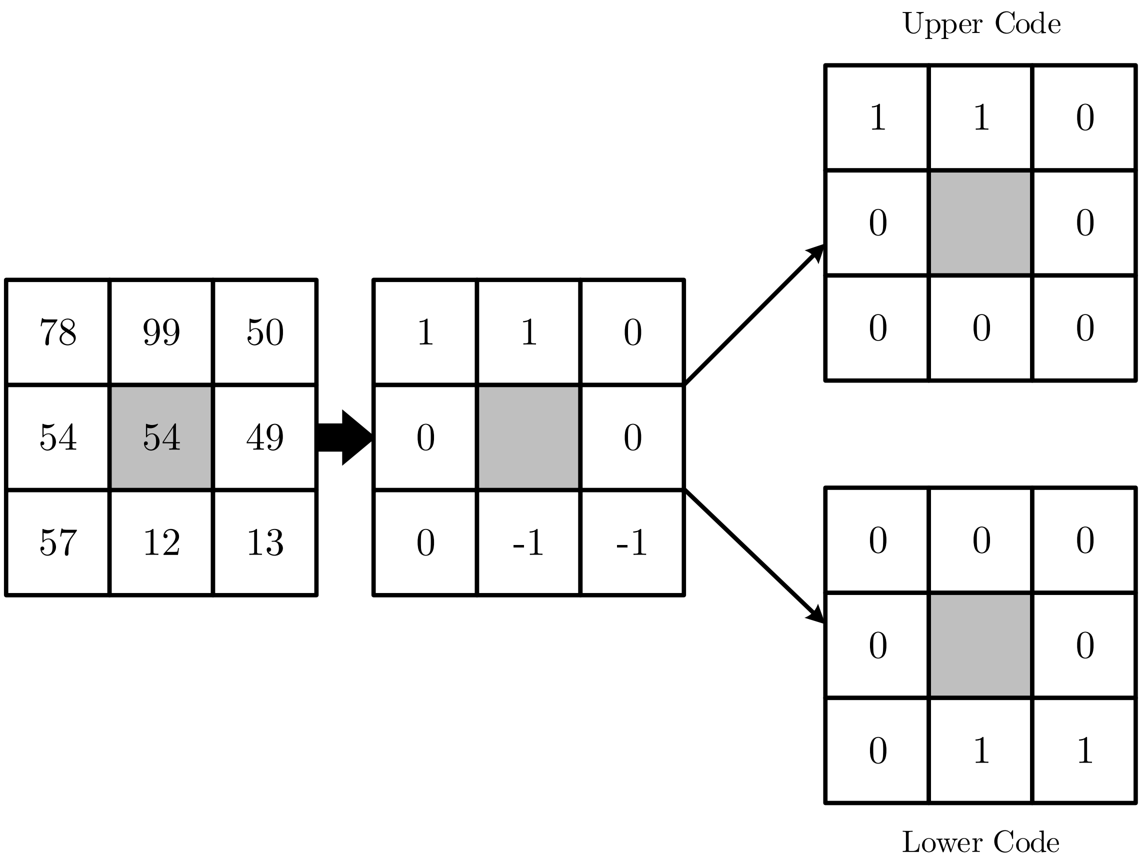


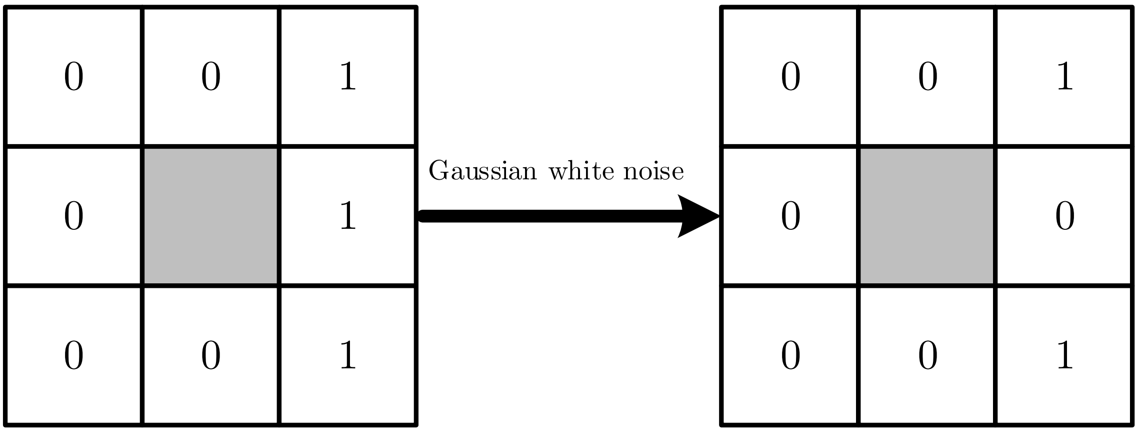
Figure 3.5: LTP code generation using a threshold value t=5

Improved Local Binary Pattern (ILBP): Improved Local Binary Pattern (ILBP) [32] is another variant of LBP which compares intensity of the neighborhood pixels values with respect to the local mean pixel intensity instead of the center pixel's intensity like LBP. This is done to reduce the effect of noise. However, it raises a tradeoff between less noise sensitivity and description capability. Jabid *et al.* showed that description capability is reduced significantly while trying to make it less sensitive to noise [28].

Dominant Local Binary Pattern (DLBP): This approach is introduced to effectively capture the dominant patterns in texture images. DLBP proposes a new approach of computing the occurrence frequencies of all the rotation invariant patterns defined in the LBP groups instead of just exploiting the uniform patterns like LBP. These patterns are then sorted in descending order. The first several most frequently occurring patterns should contain the most dominating patterns of an image and, therefore, are the most dominant patterns. DLBP is more reliable in representing the most dominant patterns in a texture image.
Although DLBP captures more textural information than the traditional LBP features, distant pixel interactions remain out of its consideration. The reason behind is that the binary patterns are extracted in the proximity of local pixels. So, the pixel interactions that are out of the scope of this locality remain unconsidered both in LBP and DLBP.

3.4 Limitations of LBP

LBP is a very powerful local texture descriptor. Multiple properties like robustness to pose and illumination change, rotation invariance etc. have contributed to its vast use in numerous applications in the field of Computer Vision and Image Processing. Still, it is vulnerable to some aspects. One of the major performance degrading factors of LBP is its sensitivity to noise. The concept of uniform LBP patterns is greatly affected by the presence of noise in the dataset. Figure 3.6 shows an example of how LBP code loses its uniformity with the presence of noise in data.



(a) intensity values of a 3x3 pixel before adding noise

(b) changed intensity values after adding noise

Figure 3.6: Sensitivity of LBP to noise

We apply Gaussian white noise on a 3 x 3 pixel region. Before the introduction of noise the computed LBP binary code was 00111000 which is a uniform LBP code. But, after applying noise the code was changed to 00101000 which is no longer a uniform LBP code. This is an example of LBP's sensitivity to noise. Presence of noise degrades the performance of LBP operator.

Chapter 4

Four Way Local Binary Pattern (FWLBP)

4.1 Introduction

To encounter the challenge of effective feature extraction and texture analysis from facial images, a number of image descriptors have been proposed by different research groups. Some of these were mentioned in chapter 2. These descriptors are diverse in nature because of their varied approaches. Some of these descriptors try to capitalize the concept of image gradient of each pixel or gradient from a local patch for describing an image. Image gradients can provide much stable information in presence of noise or with different imaging conditions. However, gradient based approaches have various problems. Firstly, gradients provide information of an instant time. Information of surrounding area does not fall under its consideration. So, there may be situation where two gradients are same but they correspond to two completely different local structures. Thus, it will not be able to discriminate between those two different local structures. Local texture based appearance descriptors outperforms gradient based appearance descriptors totally as they consider the change of intensity in a locality unlike the gradient based approaches which makes them more discriminating.

Secondly, in real world, the target object may not appear in a favorable environment. Most of the cases, it appears in a cluttered environment where appearance of unexpected noise is a common phenomenon. This can drastically degrade the performance of gradient based methods.

One of the pioneer approaches of local texture based descriptor is known as Local Binary Pattern (LBP). One of the variants of LBP named as *Uniform LBP* can handle the case of outliers by collecting all the outliers in a single bin. But, performance of LBP can be affected by noise which can hamper the concept of uniform pattern greatly. Motivated by the success of LBP operator, many researchers have tried to adopt similar ideas to encode the micro-level information of images such as edges, spots etc. Many methods were adopted using the concept of LBP's thresholding around the center pixel of a certain region. One of the problems of LBP is, it thresholds the neighboring pixel just at the center pixel's intensity and does not consider the difference with the center pixel which can encode useful information. It is not robust enough to encounter noise in data and also cannot produce code in presence of non-monotonic illumination variation. Local Ternary Pattern (LTP) showed thresholding the neighboring pixels along with a user defined threshold value can improve the performance notably. However, it maintains two histograms which makes the feature dimension larger. Another problem is selecting the correct threshold point on which the performance of the algorithm depends greatly.

Another method named Local Directional Pattern (LDP) was proposed by Jabid *et al.* which computes the edge response values in different directions and use them to encode the image texture. Considering the relative edge response values in different directions the proposed LDP feature encode the local neighborhood property of image pixel with a binary bit string like LBP. It presents a more consistent texture representation in presence of noise and non-monotonic illumination variation. But, problem with LDP is that it selects k most prominent edge response values to represent the texture of an image pixel. Performance of LDP depends largely on optimal selection of this k value which makes it computationally costly costly because of the use of eight directional mask.

Considering all of these drawbacks of existing LBP and its variants, we propose a new local image feature descriptor Four Way Local Binary Pattern (FWLBP) which computes the edge response in four ways of horizontal and vertical direction using the line symmetry of the three horizontally and vertically situated centering pixels. Instead of just only comparing with one centering pixel's intensity, it considers the intensity of three horizontally and vertically centered pixels to encode the change in illumination more precisely. Moreover, using a line symmetry to compare how the intensity is changing with respect to a line gives a better representation of edges. This can lead to better discriminating capability than the intensity information. Performance of intensity based methods can degrade with sharp change in the intensity values whereas adopting an edge based methodology provides more robust information. Intensity value of the pixels around the edge changes drastically which corresponds to discontinuities in depth, discontinuities in surface orientation and changes in material properties and variations in scene illumination. In presence of noise, rotation and other challenges edge response exhibits more stable information [50]. So, our method extracts the edge information considering a four way approach. After thresholding the neighborhood pixels in above mentioned way, it generates a bit sequence like LBP to encode the local neighborhood property of an image which we call FWLBP code. While producing the FWLBP code it follows clockwise and anticlockwise approaches which gives the operator an inherent robustness against rotation. Thereafter, it accumulates the occurrence of FWLBP code or feature over the whole image (or image region) with a histogram called FWLBP histogram which acts as an image descriptor for representing the image (or image region). This histogram's information are then given to the classifier.

4.2 Generation Scheme of FWLBP Features

The proposed FWLBP approach works on a 3×3 neighborhood (p) and produces a twelve bit binary number by thresholding the neighboring pixels in four ways (Top, Right, Bottom and Left). Thresholding with respect to just one pixel may not provide a good idea about the change of intensity in a certain locality. That's why we have adopted a four way approach to have a better representation of the texture of a certain neighborhood. We call the four directions Top (top 3 pixels, p_{top}), Right (right 3 pixels, p_{right}), Bottom (bottom 3 pixels, p_{bottom}) and Left (left 3 pixels, p_{left}). We calculate separate codes for each of these four directions. Among the four directional codes, Top and Bottom codes are calculated by thresholding the intensity of top and bottom pixels with respect to the intensity of three horizontally centered pixels (p_h) whereas Right and Left directional codes are generated by thresholding with respect to the intensity of three vertically centered pixels (p_v). We follow a scheme of assigning 1 to S_i where $i\epsilon$*{Top, Left, Right, Bottom}*, if the intensity of the pixels are greater than or equal to the centered pixels and otherwise 0.

After that we merge the bits of Top and Left code together in anti-clockwise direction to produce a 6 bit binary number whom we call $FWLBP_{top-left}$. We also merge the codes of Right and Bottom code together in clockwise direction to get another 6 bit binary number named $FWLBP_{right-bottom}$. These 6 bit binary numbers are then weighted by a power of 2 to produce FWLBP code for top-left and right-bottom direction. The whole code generation process is described by the following equations:

$$S_{top} = I\left(p_{top}\right) - I\left(p_h\right) \tag{4.1}$$

$$S_{left} = I\left(p_{left}\right) - I\left(p_v\right) \tag{4.2}$$

$$S_{right} = I\left(p_{right}\right) - I\left(p_v\right) \tag{4.3}$$

$$S_{bottom} = I\left(p_{bottom}\right) - I\left(p_h\right) \tag{4.4}$$

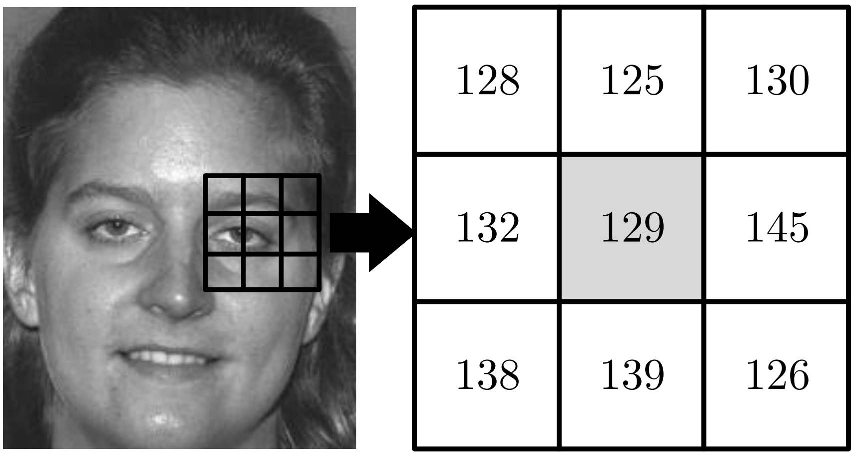
where $S(x)$ is defined as:

$$S(x) = \begin{cases} 1, & I(p) \geq I\left(p_h\right), \quad I(p) \geq I\left(p_v\right) \\ & 0, \quad otherwise \end{cases} \tag{4.5}$$

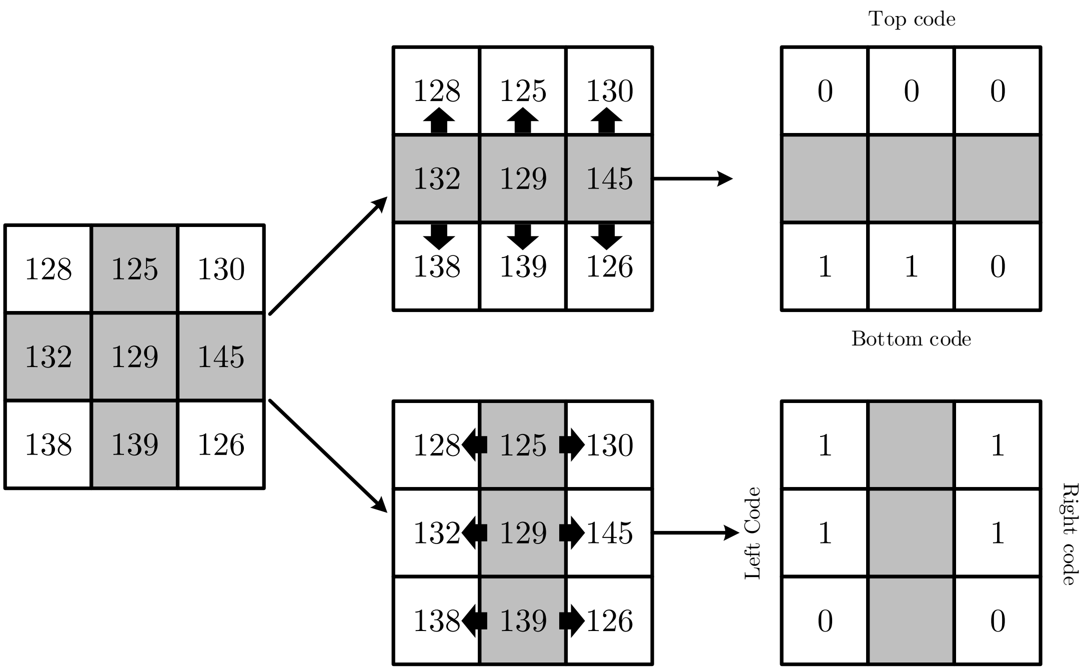
$$FWLBP_{top-left} = \sum_{i=0}^{5} \bigcup \left(s_{top},\ s_{left}\right) * 2^i \tag{4.6}$$

$$FWLBP_{right-bottom} = \sum_{i=0}^{5} \bigcup \left(s_{right},\ s_{bottom}\right) * 2^i \tag{4.7}$$

Here $I(p)$ represents the pixel values of top, left, right or bottom 3 pixels. Calculating the $FWLBP_{top-left}$ code anti-clockwise and $FWLBP_{right-bottom}$ code clockwise gives the operator robustness against rotation. Figure 4.1 and 4.2 describes the process of FWLBP code generation.

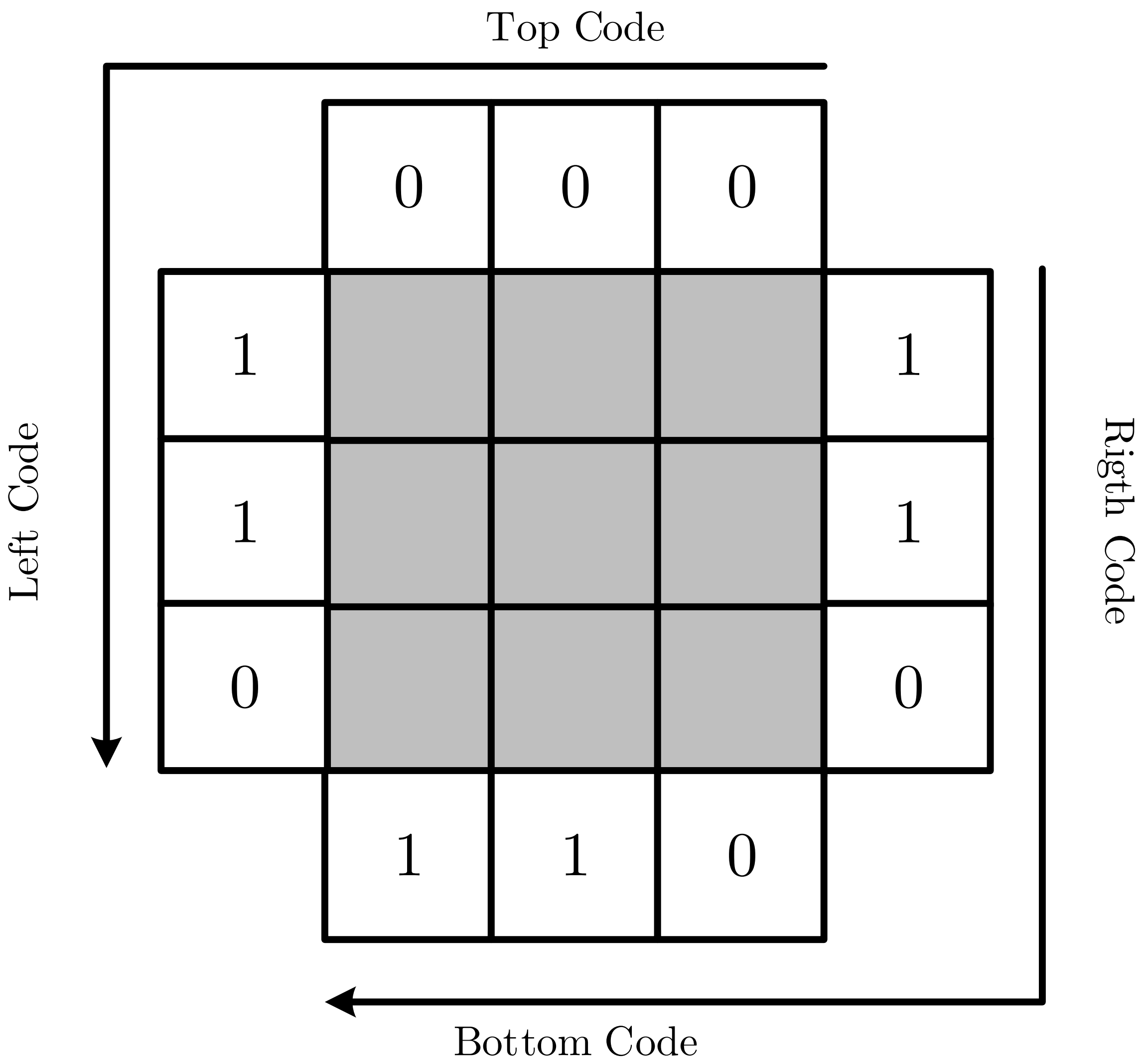


(a) A 3×3 patch collected from the face image



(b) Generation of 4 way image code

Figure 4.1: FWLBP code generation



Top-left code = 000110 = 6
Right-bottom code = 110011 = 51

Figure 4.2: Generation of Top-left and Right-bottom image code

4.3 FWLBP Descriptor

There are various ways to represent the features of an image. Color histogram approach of Swain and Ballard [51] identifies an object in an image by matching a color histogram from a region of the image with a color histogram from a sample of the subject. Their technique has been proven remarkably robust against changes in object's orientation, changes in scale of the object, partial occlusion or changes of viewing position. Even changes in the shape of an object do not necessarily degrade the performance of their method.

Due to its simplicity, speed and robustness, the color histogram approach is an attractive method for object recognition but its reliance on object's color and light source's intensity makes it inappropriate for many recognition problems. Our focus has been on developing a similar technique using local descriptions of an object's shape provided by a feature that encodes the local texture pattern. For Swain and Ballard algorithm, it can be seen that robustness to scale and rotation are provided by the use of color. Robustness to changes in viewing angle and to partial occlusion are due to the use of histogram matching. As face images can be seen as a composition of micro-patterns, it is natural to exploit the power of histogram matching to perform classification based on histograms of the proposed Four Way Local Binary Pattern. After generating FWLBP coded image (shown in figure 4.3), we need to devise a method to generate image descriptors for the FWLBP coded image.

(a) original face image (b) FWLBP top-left image (c) FWLBP right-bottom image

Figure 4.3: FWLBP coded image

In this regard histogram of the FWLBP image is used to represent, analyze and characterize images. Main reasons behind using histogram based descriptor are its computational efficiency, significant data reduction, robustness to noise and local transformations. Recent researchers have proposed histogram based descriptors for widely used algorithms like LBP where histograms are used to describe a LBP coded image [52]. The histogram of a FWLBP coded image can be computed in the same way that was used for the intensity images or color images. For a FWLBP coded image of size $M \times N$ the FWLBP histogram H can be expressed as the equation:

$$H_i = \sum_{x,\, y} I\left\{f_l\left(x, y\right) = i\right\},\ i = 0, 1, \ldots\ldots\ldots n-1 \tag{4.8}$$

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

$$I(A) = \begin{cases} 1, & A\, is\, true \\ 0, & A\, is\, false \end{cases} \tag{4.9}$$

Figure 4.4 illustrates the generation process of FWLBP histogram from a FWLBP coded image. However, a histogram computed over a whole face encodes only the appearance of micro-patterns without any indication about their locations. To also consider shape information of faces, face images can be divided into smaller regions. Extracting the histograms of each regions and concatenating them can be a good way to represent the micro level information of smaller regions of a face image. The extracted feature histogram is a good spatial representation of the local texture and global shape of face images [1-3]. The following equation explains the process of creating this spatially enhanced histogram of an image divided into m regions:

$$H_{i,\,j} = \sum_{x,\,y} I\left\{f_l\left(x,y\right) = i\right\}\; I\{(x,y)\,\epsilon R_j\},\; i = 0,1,\ldots n-1,\; j = 0,\; 1,\; \ldots,\; m-1 \tag{4.10}$$

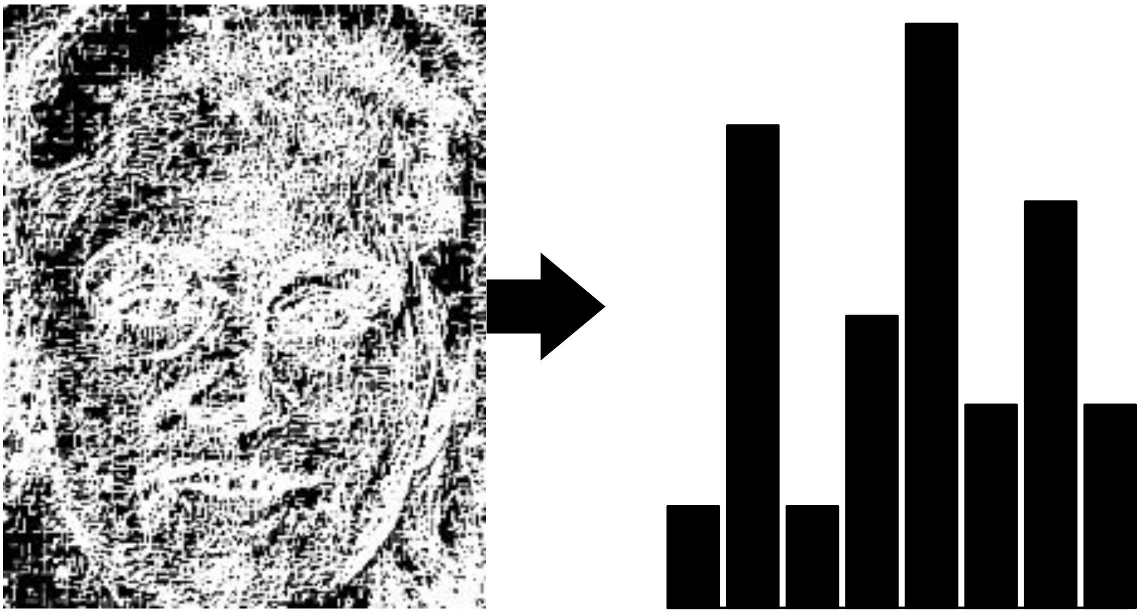


Figure 4.4: Full face histogram of FWLBP coded image

Each bin of the histogram contains information about different aspects of texture image such as spots, edges etc. Selection of number of bins is also important. If the number of bins representing the features is too large it will not give a proper idea of the distribution. So, keeping the bin numbers to a reasonable range is also an important criterion. In our proposed FWLBP method, the produced FWLBP code represents a 12 bit binary number which makes the bin numbers of FWLBP histogram equals to $2^{12} = 4096$ which is very large. To reduce the size of the feature vectors we then divide this twelve bit binary number into two equal parts of top-left and right-bottom code with six bits assigned to each of them. This reduces the number of the histogram bins notably to $2^6 + 2^6 = 128$ bins. Figure 4.5 depicts the process of histogram concatenation. Advantage of using a histogram based approach can further be described as neither segmentation nor an explicit geometric model of an object. An object class is described by the histogram of its local characteristics.

4.4 Descriptor's Discriminating Ability

In this section we will show the discriminating ability of our proposed FWLBP features in presence of rotation, scaling and noise. We present a comparison of the discriminating capability between FWLBP and LBP with rotation, scaling and presence of noise in the image.We have used images of periocular region to show this comparison as our interest is based on this. To show robustness of any sample image under certain condition, we compute histogram-based FWLBP representation and compare it with the histogram-based LBP representation. For measuring histogram similarity different techniques such as log-likelihood (eqn. 4.11), quadratic distance, Chi-square distance (eqn. 4.13) and histogram intersection (eqn. 4.12) exist [53]. Log-likelihood performs poorly on small windows whereas chi-square performs slightly better than histogram intersection. So, Chi-square statistic is used in this paper. Equations of different histogram similarity measurement process of two histograms are as follows:

Log-likelihood statistics:

$$L\left(H_1,\ H_2\right) = -\sum_i H_1^i log H_2^i \tag{4.11}$$

Histogram Intersection:

$$D\left(H_1,\ H_2\right) = \sum_i \min(H_1^i, H_2^i) \tag{4.12}$$

Chi-square statistics:

$$X^2(H_1,\ H_2) = \sum_i \frac{(H_1^i -\ H_2^i)^2}{(H_1^i +\ H_2^i)} \tag{4.13}$$

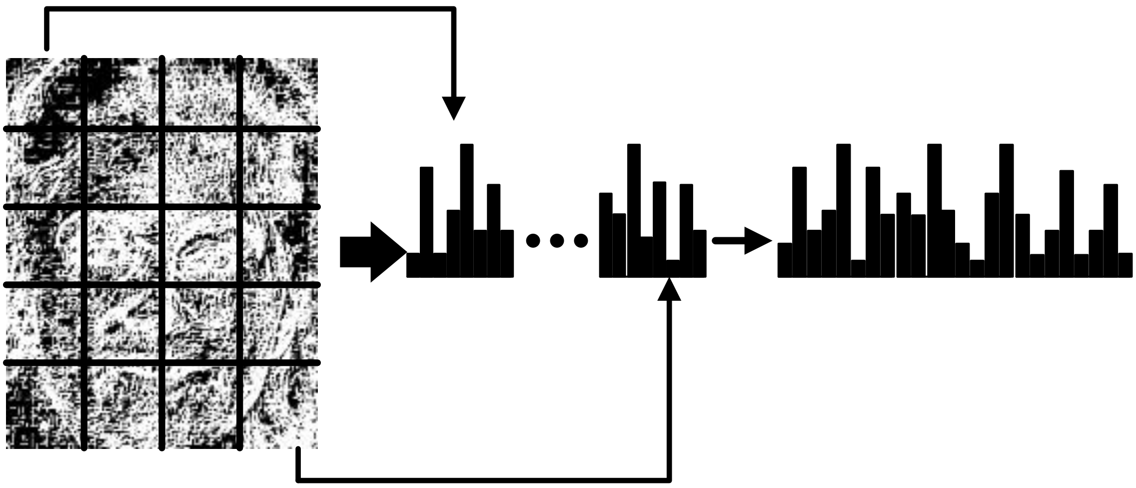
where H_1, H_2 are two histograms and i indicates the i^{th} bins in the histograms.

Robustness to Rotation:

We mentioned earlier that our proposed method has inherent rotation invariance property because of the generation process of the FWLBP codes. This works very well to represent rotated texture images. FWLBP shows better result than LBP to represent images with in-plane rotation. To investigate the sensitivity of FWLBP and LBP to in-plane rotation, we rotate the images with different angles ($\theta = 5°, 10°$,... ... , $25°$) in clockwise and anti-clockwise direction and compare histogram similarity values with the original image's histogram and rotated image's histogram. Table 4.1 and 4.2 exhibits that the FWLBP histograms are much closer to the original image's histograms in comparison with LBP operator. The main reason behind the robustness of FWLBP is that it can omit the effect of rotation because of its code generation policy. The results suggest that up to $20°$ rotation, FWLBP can provide almost 90% similar texture pattern.

Robustness to Out of Focus Images:

To test the robustness of FWLBP in case of out of focus face images an experiment is conducted where Gaussian filter of different standard deviations were applied on face images to get an effect of out of focus images. It was seen that, FWLBP gives better similarity rate compared to LBP in most of the cases.Table 4.3 exhibits a comparison of the similarity of LBP and FWLBP histograms.



(a) Face image divided into 5x4 regions

(b) Histogram Concatenation

Figure 4.5: Histogram concatenation of FWLBP image

Rotation Angle	Histogram Similarity Score	
	LBP	FWLBP
5°	0.996	0.998
10°	0.989	0.997
15°	0.982	0.994
20°	0.974	0.988

Table 4.1: Comparison of histogram similarity of LBP and FWLBP on anti-clockwise rotated images

Rotation Angle	Histogram Similarity Score	
	LBP	FWLBP
5°	0.996	0.999
10°	0.990	0.997
15°	0.983	0.994
20°	0.976	0.989

Table 4.2: Comparison of histogram similarity of LBP and FWLBP on clockwise rotated images

	Histogram Similarity Score	
Standard Deviation	LBP	FWLBP
0.5	0.996	0.996
1.0	0.986	0.978
1.5	0.978	0.966
2.0	0.975	0.958
2.5	0.973	0.954

Table 4.3: Comparison of histogram similarity of LBP and FWLBP on out of focus images

Chapter 5

Gender Classification from Periocular Images

5.1 Introduction

Facial image has always been an attractive field for the researchers of image processing and computer vision due to its multidimensional use in numerous fields. Faces play one of the most important roles while communicating with people. While talking with people our attitude consciously or subconsciously varies with the facial expression of the person with whom we are talking. Faces carry information about a person's identity in a subtle manner. Automatic processing and interpretation of facial images has attracted much attention in the last decades due to the amount of information it carries. Application of face lies in many folds. The most important one is undoubtedly automatic face recognition because of its necessity in various applications such as security systems, Human Computer Interaction, commercial systems and in many other fields. Besides face recognition face image has been exploited in detecting human expression, age, mood etc. Gender classification using face images is a recently explored field of research. Gender is a soft biometric trait of a person which has become an important feature in many applications recently. Accurate prediction of gender is a pre-requisite of many applications in computer vision. Examples of these applications include visual surveillance, marketing, intelligent user interfaces, demographic studies, etc. Some works on gender classification from face images can be found in [54, 55].

However, automatic gender classification based on facial image offers with lots of challenges. Human being can easily discriminate between a male and a female in a blink of an eye with God gifted power. Discriminative features are caught by the human eyes very fast. But, enabling a machine for doing this task automatically is not an easy thing to do. Problems with gender classification consist of several challenges. Most of the gender classification works are based on two steps. Firstly, extracting the features from the face image and secondly using binary classifiers like SVM, NN, KNN and Neural Network to classify gender with the extracted features. Mostly, two approaches for feature classification are used. One is the appearance based approach and the other one is geometric feature based approach [56]. In appearance based methods, the whole image is considered rather than the local features corresponding to different parts of the face. While, in geometric based methods, the geometric features like distance between eyes face length and width, etc., are considered. This geometric feature requires extra computation prior to feature extraction to localize face components and also any error while localization may lead to significant performance drops. In appearance based method the micro level information are not encoded efficiently which may contain important discriminating features. Recently more local appearance based approaches are being proposed which takes local information of a texture image under consideration and divides the image into smaller regions and extracts the features from it. Ahonen *et al.* [19] recently proposed Local Binary Pattern (LBP) which was later on applied to analyze face image in different application including gender classification using face image [57], [58]. This method became much popular due to its robustness in environmental change and also its independent nature from the location of facial components. LBP provides an invariant description in presence of monotonic illumination variation on face image, however, suffers much in non-monotonic illumination variation, random noise, and change in pose, age, expression.

5.2 Background

Although, there has been a notable number of works with gender classification from face image still there are chances of improvements due to many challenges offered by different circumstances. One of the biggest challenges of classification problem is efficient extraction of features on which performance of the classifier algorithms depend on greatly. If the features are not good enough the classification rate drops drastically. Feature extraction itself has many difficulties. Any facial feature extractor must meet some constraints to be considered as an efficient one. In short, a good facial feature should have properties like – (a) it can discriminate different class while tolerating within class variation (b) it can be easily extracted from raw face image to ensure fast processing and (c) it can be described in a low dimensional feature space to ensure computational speed during classification step. It is not that obvious to find features that concurrently meet all the demands because the appearance of face may encounter a large number of variations due to variation in pose, lighting condition, facial expression etc. Different global descriptors like PCA, LDA have been used for extracting the features considering the image at a whole. But, using a holistic approach does not encode the local information and thus many discriminative feature lying in the spatial domains get neglected by these operators. To encode the micro level information many local descriptors such as LBP have been proposed but they are not robust in all conditions.

Challenges with the feature extraction algorithms affect the field of gender classification also. Beside the obstacles with feature extraction algorithms another challenge regarding gender classification is that most of the gender classification studies have utilized face images captured in controlled conditions which are very rare in real world. Many variations may appear in the image of a person's face. These variations may affect the ability of the computer vision system to estimate the gender accurately. They are due to many factors which can be divided into: human factors (race, facial expression etc.) and capture process factors (pose, illumination, quality etc.) [6]. These factors hinders the accuracy of the classification algorithm by a great deal.

Another major problem of adopting a full face based approach for gender classification is occlusion due to many natural events which drastically decreases the performance of the proposed methods. In real world, full face may not always be available for classification. Occlusion may hide important features of the face images. For example, people wearing masks, helmets, women wearing niqab etc. covers large part of the face and hides many important features of the face image. Figure 5.1 shows some of the examples of occluded face images where adopting a full face based approach may not give a good result.

Alternatives to the face image are being searched and one alternative can be iris information. Iris information is used for different recognition problems and it can be used in gender classification also [59], [60]. But problems of the iris based detection approach are strongly showed bt Park et al [61]. Gender classification from mascara has also been proposed by Kuehlkamp *et al.* [62].

Due to the drawbacks of full face based approach and iris based recognition, researchers have adopted alternative approaches of gender detection. Among different approaches, periocular biometrics is recently an emerging field of researchers. Park *et al.* has discussed about the feasibility of periocular biometric in one of the pioneer papers in the field of periocular biometrics. Different research groups are using periocular biometrics for different purposes. The term periocular region refers to the area of a face image in immediate vicinity of eye that includes eyebrows, eyelashes and other areas close to eyes. It is found that many significant information can be extracted from this region. It is gaining popularity as an independent field of recognition or complement to face and iris modalities under non-ideal conditions [63, 64]. A survey on periocular biometrics can be found in [65]. This has been used in number of applications including human identification, face recognition, expression recognition etc. [66, 67, 5, 17, 68, 15].

Recently, discriminative power of periocular regions have been explored in the field of gender classification also. In real life, while looking at a person the most prominent features catch our eye first and our decision is influenced by these fea-

Figure 5.1: Example of some occluded facial images of real world

tures. Periocular region is one of the most prominent features. So, it has been used for classifying gender recently by many researchers. Dong *et al.* used eyebrow shape-based features for classifying gender [69]. Santanaa *et al.* experimented with different feature extractors like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Local Ternary Patterns (LTP), Weber Local Descriptor (WLD) and Local Oriented Statistics Information Booster for classifying gender in the wild [70]. Sunita *et al.* classified gender using Independent Component Analysis (ICA) for poor quality images [4].

Main reason behind choosing periocular region is its availability under difficult circumstances like occluded faces. People cannot cover their eye regions except for some extreme cases. The availability of the periocular information is much more guaranteed than the availability of full face image. Moreover, using only the periocular region doesn't degrade the classification accuracy that much compared to full face, showed by Park *et al.*

After considering all the drawbacks of full face based gender classification and the used feature extractor algorithms, we propose a novel local appearance based descriptor Four Way Local Binary Pattern (FWLBP) that encodes the texture information of periocular images using four way line symmetry. This encodes the edge information of the periocular region more precisely which carries significant discriminative information. After calculating the FWLBP code for the whole periocular image, it accumulates the occurrence of FWLBP codes with a histogram which we call FWLBP histogram. This histogram acts as a feature descriptor for representing the whole periocular image. The effectiveness of FWLBP based periocular gender classification is demonstrated with a gain of increased accuracy in classifying gender compared to the most popular feature extractor LBP.

5.3 Periocular Image Representation using FWLBP

We use a three step approach to represent the low resolution periocular image using FWLBP features. Firstly, the FWLBP operator is applied on the periocular image to get two FWLBP coded top-left and right-bottom images. Secondly, histogram is extracted from each local region of FWLBP image to build the local representation of the periocular region image. Thirdly, all the histograms of the local regions are concatenated together to form a feature vector which exhibits the global representation of the image.

5.3.1 Generating FWLBP periocular image

At the beginning FWLBP operator is applied on the raw periocular face image. FWLBP generates a 12-bit binary value using four ways: top, left, right, bottom by comparing the top, left, right and bottom pixels' intensity with respect to the three horizontally and vertically centered pixel values. After that top and left codes are merged together in anti-clockwise direction to form $FWLBP_{top-left}$ code whereas merging right and bottom codes in clockwise direction produces $FWLBP_{right-bottom}$ code. From these two codes we get two FWLBP images named as $FWLBP_{top-left}$ image and $FWLBP_{right-bottom}$ image. Figure 5.2 shows the FWLBP coded images.

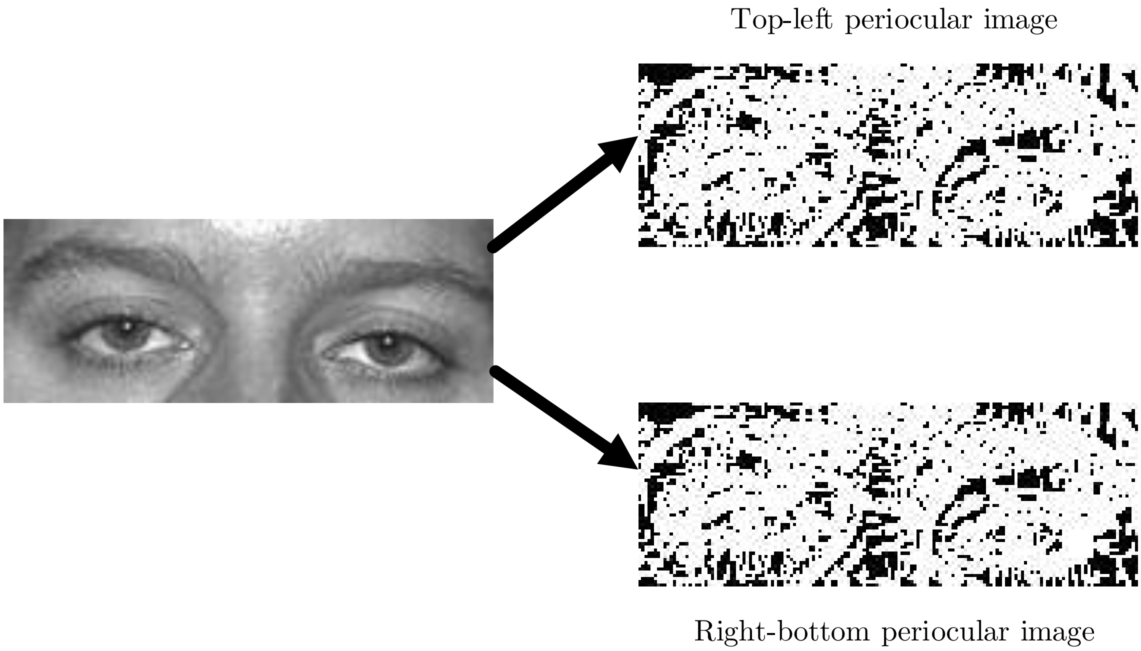


Figure 5.2: Periocular image generation

5.3.2 Histogram of FWLBP

After generating two FWLBP coded images we represent them using histogram. Let $f_l(x, y)$ be $FWLBP_{top-left}$ image. We represent it using a 128 bin histogram which can be expressed by the following equation:

$$H_i = \sum_{x,\ y} I\left\{f_l\left(x, y\right) = i\right\},\ i = 0, 1, \dots\dots\dots n - 1 \tag{5.1}$$

in which n is the number of different labels produced by the FWLBP operator and

$$I(A) = \begin{cases} 1, & A\, is\, true \\ 0, & A\, is\, false \end{cases} \tag{5.2}$$

Same process is repeated for $FWLBP_{right-bottom}$ image and the histograms are extracted. Figure 5.3 illustrates the process of histogram generation.

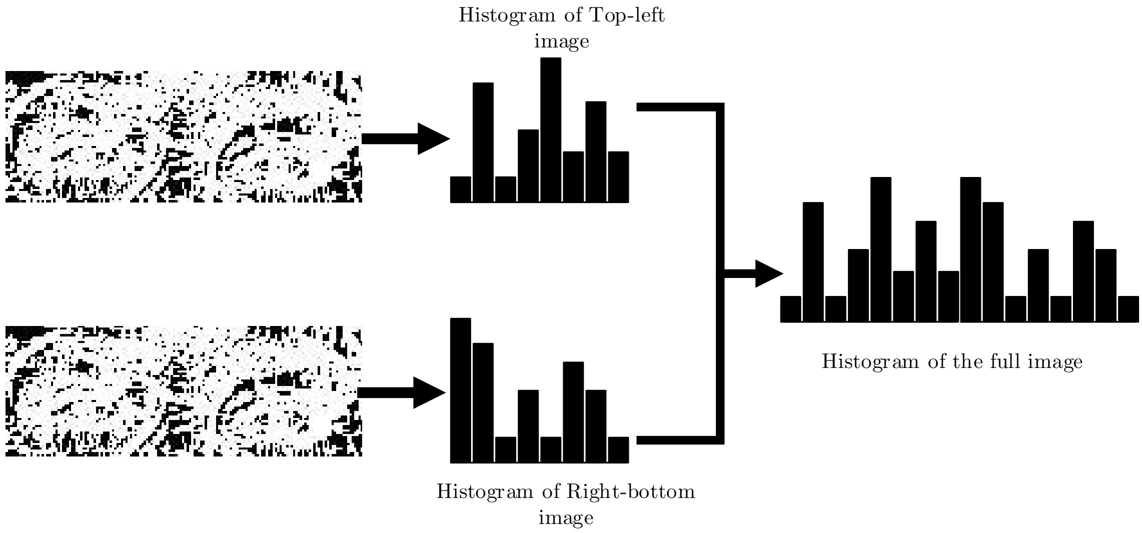


Figure 5.3: Histogram generation of periocular images

5.3.3 Concatenated FWLBP Histogram

To capture the spatial information, the periocular face image is divided into m regions numbering from $I_0, I_1, I_2 \ldots \ \ldots \ \ldots \ I_{m-1}$ and histograms of each division are calculated independently. All these histograms are then concatenated to form the spatially enhanced histogram of size $m \times n$ where m is the total number of regions and n is the size of independently calculated FWLBP histogram. Process of histogram concatenation is expressed as follows:

$$H_{i,\,j} = \sum_{x,\,y} I\left\{f_l\left(x,y\right) = i\right\}\ I\{(x,y)\,\epsilon R_j\},\ i = 0,1,\ldots n-1,\ j = 0,\ 1,\ \ldots,\ m-1 \tag{5.3}$$

In the same way we concatenate the $FWLBP_{top-left}$ and $FWLBP_{right-bottom}$ image histograms and concatenate these two histograms to form a 128 bin sized histogram for feature representation. The whole process of histogram concatenation is shown in figure 5.4.

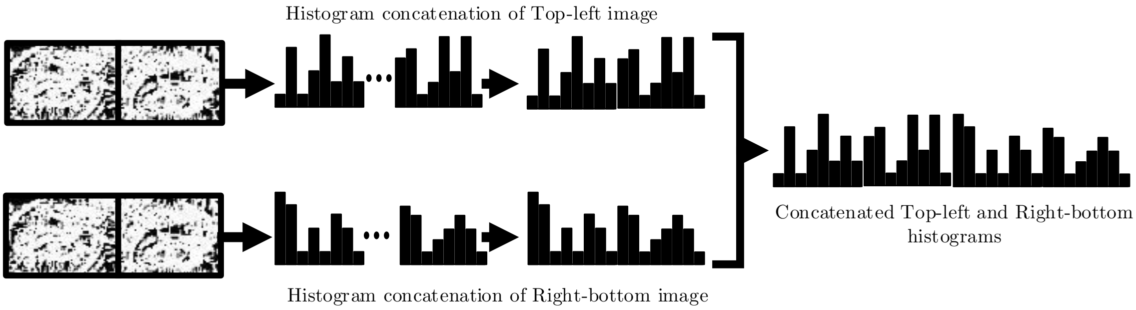


Figure 5.4: Histogram concatenation of FWLBP periocular images

5.4 Gender Classification from Periocular Images using FWLBP

There are several classifiers such as Support Vector Machine, Nearest Neighbor Classifier etc. are used for classification purpose. Among the different classifiers SVM performs well under varying circumstances. SVM is a binary classifier and our problem consists of binary class. So we used SVM with grid search technique to classify gender from image features.

5.4.1 Support Vector Machine

SVM is a well-founded statistical learning theory that has been successfully applied in various classification tasks in computer vision. SVM performs an implicit mapping of data into higher dimensional feature space and finds a linearly separating hyperplane with maximal margin to separate the data in this higher dimensional space. Given a training set of labeled examples $T = \{(s_i, l_i), i = 1, 2, \ldots \ldots, L\}$ where $S_i \epsilon R_p$ and $l_i \epsilon -1, 1$, a new test data x is classified by

$$f(x) = sign(\sum_{i=1}^{L} a_i l_i K(x_i,\ x) + b) \tag{5.4}$$

where a_i are Lagrange multipliers of dual optimization problem, b is a basis bias or threshold parameter, and K is a kernel function. The training sample x_i with $a_i > 0$ is called the support vectors and the separating hyper-plane maximizes the margin with respect to these support vectors. Given a non-linear mapping function that transforms the input data to the higher dimensional space, kernels have the form of $K(xi, xj) =< (xi), (xj) >$. Among the various kernels found in literature, linear, polynomial and radial basis function (RBF) kernels are the most frequently used ones. SVM makes binary decisions, which we use for classifying gender. We carried out grid-search on the hyper parameters in a 5-fold cross-validation approach for selecting the optimal parameters, as suggested in. The parameter setting producing the best cross-validation accuracy was picked.

5.5 Experimental Setup and Dataset Description

We used the widely used FERET face database to test the performance of our proposed method. The FERET database consists of a total 14,051 images representing 1,199 individuals. The images contain variations in lighting, facial expressions, pose angle, aging effects etc. In this work we mainly focus on showing applicability of our work in biometric recognition systems. In biometric recognition systems it is expected to extract user information without that much of user interaction. For this reason, only frontal face images are considered with different lighting conditions with different aging effects on the face image. After choosing the face images, we then crop them for getting images of only periocular regions using the positions of two eyes, mouth and nose. After bringing all the images down to equal aspect ratio we then resized them into 160×60 pixels. In FERET database, the ground-truth data of eye, mouth and nose are provided. For automatically detecting the periocular region of the facial image we used the horizontal distance between two eyes (termed as dx) and vertical distance between eye and mouth (termed as dy). A distance of $\frac{2}{5}dx$ between the boundaries and both eyes has been maintained. The upper and lower boundary has maintained a $\frac{1}{4}dy$ distance from the eyes. Some examples of cropped periocular images of male and female subjects are shown in Figure 5.5.

(a) Female subjects

(b) Male subjects

Figure 5.5: Male and female periocular images

Here we used 300 periocular images of two subjects male and female. We used 150 male and 150 female images for our experiment. In our experimental set up every image is partitioned into $M \times N$ sub-regions. The classification result is achieved through the Support Vector Machine classifier. We used grid search technique for selecting optimal SVM parameters for better classification accuracy.

5.6 Result and Discussion

The optimal parameter values obtained from grid search are used for classifying gender from periocular images which were processed from FERET database. A better recognition rate than traditional LBP confirms the efficiency of the proposed FWLBP method. SVM is a well devised machine learning technique that provides better classification accuracy in pattern recognition. Therefore, we conduct the recognition using SVM with RBF kernel and grid search technique to classify gender. We achieved a maximum of 95% accuracy dividing the periocular image into different regions which gives better result than traditional LBP. Figure 5.6 shows the comparison between the performances of LBP and FWLBP on periocular images. Classification accuracy can vary due to the number of blocks in which the image is divided into. Figure 5.7 shows that using different blocks for dividing our image doesn't change the recognition accuracy that much.

Rotation is a common phenomena that occurs in the real world scenarios. It is very difficult to get the images without any rotation. So, the image features should produce good results in terms of rotation. Our proposed FWLBP method exhibits better recognition rate than the traditional LBP in terms of rotated image to different degrees. Table 5.1 and 5.2 show the comparison between LBP and FWLBP on anti-clock and clockwise rotated images.

Our analysis of FWLBP feature demonstrates that the proposed descriptor performs robustly over original periocular images and it exhibits stable result in terms of rotation. Our experimental result shows that the proposed FWLBP method performs better than LBP in gender classification. It can be used in real world scenarios and where rotation appears more often.

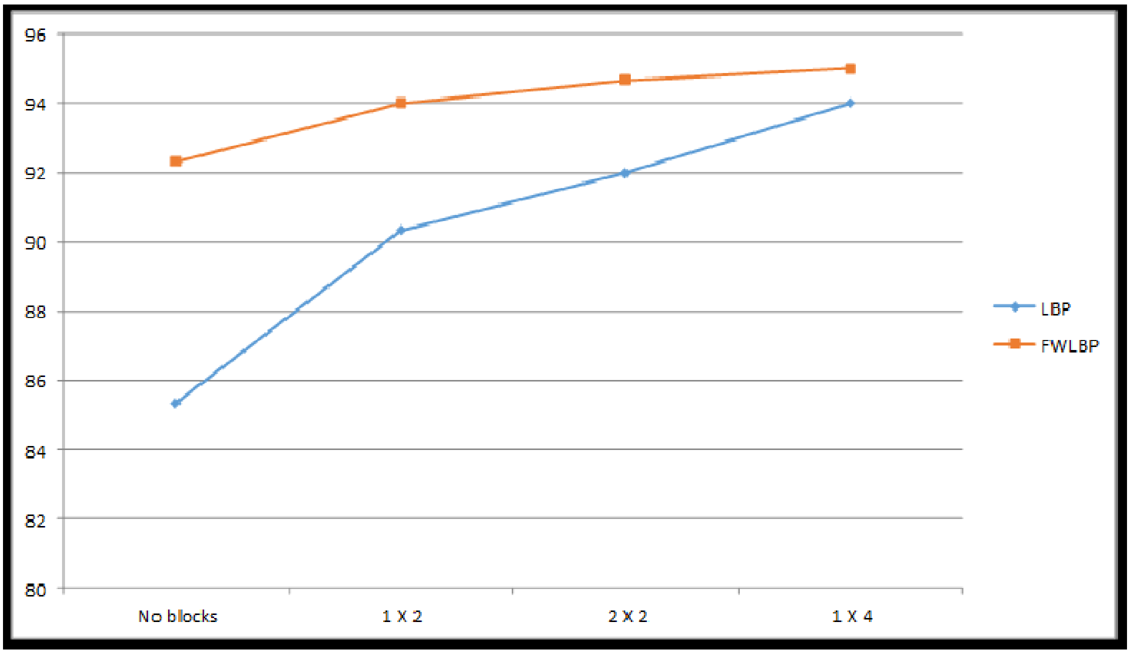


Figure 5.6: Performance comparison of LBP and FWLBP

5.7 Concluding Remarks

The chapter describes how the proposed local facial based descriptor FWLBP codes are applied for gender classification problem. The FWLBP codes contain the local information encoding the texture and the descriptor contains the global information. Extensive experiments justify that FWLBP are effective for gender classification from periocular images in presence of rotation. It exhibits a better recognition rate than traditional LBP. Gender classification plays a significant role in different computer vision applications such as security, surveillance, customer interactions and so on. A gender classification algorithm with high accuracy can improve the performance of different algorithms whose pre-requisite lies on efficient gender classification. Our proposed method can be used to serve this purpose. Principal Component Analysis can reduce the feature dimensionality hence improves the accuracy rate. In future, we plan to incorporate PCA with our proposed method to classify gender more efficiently.

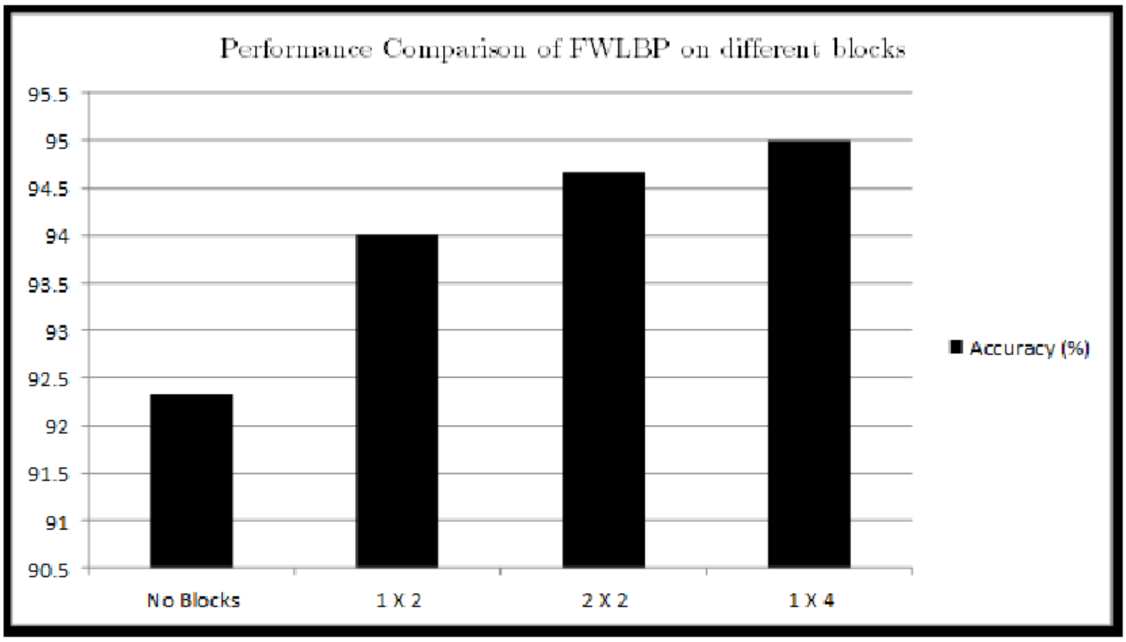


Figure 5.7: Performance comparison of FWLBP on different blocks

	Classification Accuracy (%)	
Rotation Angle	LBP	FWLBP
5°	93.33	94.67
10°	89.67	93.33
15°	92.33	93.67
20°	91.0	92.33

Table 5.1: Comparison of Classification accuracy of LBP and FWLBP on anti-clockwise rotated images

	Classification Accuracy (%)	
Rotation Angle	LBP	FWLBP
5°	93.33	95.0
10°	90.67	94.33
15°	89.0	93.0
20°	88.33	90.33

Table 5.2: Comparison of Classification accuracy of LBP and FWLBP on clockwise rotated images

Chapter 6

Conclusion

In this chapter we summarize the research works presented in this dissertation and make final concluding remarks with few directions for future works and improvements.

6.1 Summary of Research

The goal of this dissertation is to investigate the challenging issues related in gender classification and designing a robust image descriptor for classifying gender under difficult circumstances like occlusion, rotation etc. The main focus of the thesis is to propose a new image descriptor Four Way Local Binary Pattern (FWLBP) that can encode the local texture information from periocular images by analyzing the presence of edges computed using a four way line symmetry approach. This produces a binary bit pattern which then converted into decimal number for encoding the texture information of a certain image area. These calculated codes are then statistically used as feature vectors for classifying genders.

In Chapter 1, necessity of gender classification and its use in various applications are discussed. Challenges of automatic gender classification from facial images are addressed and the limitations of the adopted feature extractor algorithms are explained along with the motivation of this dissertation. The contributions of the thesis are also discussed in this chapter.

In Chapter 2, we presented some background study on the state-of-the-art global and local image descriptors to understand their mechanism and address the limitations.

In Chapter 3, we represent a brief idea about widely used Local Binary Pattern algorithm. We discussed its working mechanism, its strength in describing an image robustly in presence of illumination variations. We also pointed out the weaknesses that LBP exhibits in presence of different challenging environments such as noise, illumination variation, rotation etc. We also presented some of the variants of LBP such as uniform LBP, LDP, LTP, WLD etc. that were inspired by the success of LBP.

In Chapter 4, we introduce a new local appearance based facial image descriptor Four Way Local Binary Pattern (FWLBP) and we discuss its working mechanism. The effectiveness of FWLBP image descriptor′s discriminating ability was tested by chi-square statistics using different challenging factors such as rotation, out of focus image set etc.

In Chapter 5, we empirically address the advantage of periocular region based image classification over full face classification and shows how different obstacles like occlusion can degrade the performance of full face based approaches. We also addressed of challenges of gender classification from full faces under occlusion and discussed how periocular image can overcome that problem. We then tested our proposed descriptor FWLBP's performance on FERET database under different circumstances and showed that FWLBP gives better classification accuracy generally and under rotation than the traditional LBP method.

Finally, in this thesis we showed that, gender classification from periocular images using the proposed image descriptor produces encouraging results which can counter the problems with gender classification form occluded face images. Moreover, the proposed descriptor shows much robustness against different photometric changes like rotation, image blurring etc. Different experiments were conducted to justify the effectiveness of the FWLBP descriptor on periocular images for classifying gender.

6.2 Scope for Future Works

The researches in this dissertation have opened up many scopes for future works. The contribution of this thesis lies in two folds. It not only contributed to the works of gender classification but also proposed a new image feature descriptor for classifying gender from periocular images. This may encourage other research groups to use this descriptor for solving other problems or incorporating the idea to improve the existing feature descriptors.

In future, we plan to test our algorithm's effectiveness on different problems such as face recognition, facial expression recognition etc. There is also scope for analyzing the performance of this algorithm with other global and local based approaches.

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