Rotational Invariant Local Features for Texture Classification, A Comparative Study

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DECLARATION

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بسم الله الرحمن الرحيم

This thesis is dedicated to my parents and my supervisors

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Abstract

This thesis presents a comparative study of different rotation invariant local features for texture classification where classification accuracy of local features is examined and then compared with each other. Experiments are conducted on Outex datasets using Nearest Neighbor classifier. Thesis includes comparison of Local Features like absolute local difference, gray level of center pixels, standard deviation, mean, local binary pattern, and different combination of these features. All the methods are compared in terms of accuracy. Results of experiment have shown that although individually some local features may give poor result in classification but they can give enhanced results when used in combination with other local features. This study has helped us to conclude that gray level of center pixel when used in combination with absolute local difference and local binary pattern enhances the classification rate by adding information about center pixels which is not present in both of them individually. Combined feature of gray level, with local binary pattern and absolute local difference are compared with other techniques as well e.g. with invariant feature of local textures (IFLT) and gabor wavelets methods. It has been observed that our combined features give better results as compared to these techniques.

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Chapter 1

Introduction

1.1 Introduction

Texture Classification is an important task in many applications of machine automation e.g. checking of defects and disease nutrients in industries, ground classification and segmentation of satellite images, segmentation in document analysis and content based analysis in image databases [1]

Research on the texture classification methods has been active for many years. Texture analysis methods should ideally be invariant to viewpoint in such applications. Obtaining truly viewpoint invariant texture features is a non trivial task [2]. Rotation (e.g. due to skew angles) and scale (e.g. change in focal length) invariance are important aspects of the general viewpoint invariance problem.

Rotation invariant texture classification can be accomplished either via learning and compensating [3] for such rotation inconsistencies during preprocessing phase or through the extraction of rotation invariant features from the input textures[4][5]. Model based [6], statistical [7] and Fourier methods [8] [9] have been applied to extract features.

A lot of things can be described as texture, the physical appearance of a material due to its size, shape and pattern, the structure and self similarity present within either synthetic and natural materials or local spatial interactions. Texture is therefore a very broad area and hence covers a huge range of concepts. However within this thesis we will discuss textures created in objects, we will not be looking as to how texture is created. Synthetic as well as artificial textures are abundant within the real world and so it is essential that computer vision systems be able to deal with textural information present in images and hence provide vision to machines. Research in this area is important within the vision community as any application which deals with image information will inevitably contain a significant amount of textural information.

Within this thesis the main problem addressed is the comparison between rotation invariant local features for texture classification in terms of better classification accuracy. Feature extraction is one of the main areas of current texture research, other major areas being segmentation, synthesis and classification of texture. The general texture classification problem can be defined as follows; a set of features is generated from a set of training images of which the texture classes are known. The system is then presented with an image containing textural information; it is then to correctly identify the class of this texture. This is in contrast to segmentation where the aim is to divide the image up into regions of separate textures but the actual texture class itself is unknown, all that is required is to divide the image into textured regions.

Texture synthesis aims to replicate the look of the original texture onto areas which do not contain texture or may partially contain it. To assess the effectiveness of synthesis the most common approach is to present the results to a human observer and see if they can identify the synthesized image or image regions from the original, much like an image based version of the Turing test [10]. The aim of texture methods is to identify shape cues present within textural information and use them to gain geometric information about the underlying structure. An example would be when trying to find out the curvature of a round shape object using the illumination variations caused by the texture on the surface to determine that it indeed has a spherical structure. Although texture research can be partitioned into multiple areas [11, 12, and 13], in reality the areas share much in common, particularly with their approaches to texture modeling and many models [11, 12, and 13] are used within multiple areas.

1.2 Motivation and Background

Texture analysis plays an important role in many image analysis applications. Even though color is an important feature in interpreting images, there are situations where color measurements just are not enough nor even applicable. In industrial visual inspection, texture information can be used in enhancing the accuracy of color measurements. In some applications for example in textile industry, quality control can be done by texture analysis of fabric. Texture measures can also deal better with varying conditions caused by rotation and illumination effects of surroundings e.g. day timings and weather. Therefore, textures can be useful for analysis of objects in varying conditions of surroundings. Other application where texture methods can be used include content extraction from images, writing analysis in printed documents, textile industry, coding of images based on different models and a lot of other applications as well.

Since many decades, a lot of research has been done on texture analysis methods and techniques but unfortunately very few improvements have been made to these methods. A lot of areas have room for further enhancement in these techniques. The methods that have been developed so far are rarely used in real world classification problems. Analysis of real world textures is very difficult because of problems caused by rotations, illumination effect, size, and homogeneity of textures. In most of the real time applications, texture analysis should be done using very few resources e.g. in real time visual application few computations should be done in order to get results in real time. More over feature extracted for texture classification should not be of large size so that they could be manipulated and stored easily. Often, the Gabor filtering method [9] is credited as being the most suitable in texture classification. This method has given enhanced performance in most of the comparative studies. The strength of the method can be measured by different attributes like its incorporation in analysis of spatial frequencies as well as local image information. This tends to be very demanding with respect to computations normally when larger masks are used. Performance of Gabor filter is also affected by varying illumination conditions.

For most of the real-world applications it is desired to have texture features which should be less computational and robust against variation in size, illumination, and rotation. These variations are caused by uneven illumination, different viewing angles, shadows and resolution etc. So texture operators must be invariant to illumination changes, rotation, scaling, viewpoint and distortions. The invariance of an operator still cannot ensure 100 percent accuracy.

We can design an operator that is invariant against everything i-e rotation, size etc, but this doesn’t necessarily ensure that this will be good operator.

A lot of classification techniques are present in literature, which are invariant to image rotation. Some of them extract their features from a single image and are tested using rotated images while other uses original image as well as images rotated at several angles. If the image texture results solely from variation rather that surface relief or if the illumination is not directional or immediately overhead, then these schemes are surface-rotation invariant as well. However, 3D surface textures are often illuminated from one side when they are photographed in order to enhance their image texture, e.g. Brodatz data set. Such images acts as a directional filter of the 3D surface texture. [14]

1.3 Applications

There are a lot of applications that have been developed from texture classification methods. Most popular among these application are image retrieval applications [15, 16, 17, 18], where images are classified by their similarity to a training image of some description. These images are presented to the retrieval system and then system is expected to search images that are similar to them or contains part of test image within database. Same technique is used for remote sensing applications where images are classified on basis of containing certain type of desired information. Information such as the terrain type [19, 20] or actual objects, such as vehicles from traffic images are extracted from image. In a related application of biomedical, texture has been used to trace cancerous cells within mammographic images [21, 22]. This application is classification based where images are classified as containing cancerous cells or having no cancerous cells present. Texture analysis has also been used for the image restoration purposes [23] where areas are generated to overcome discontinuities in the original image. Synthesis has been widely used in computer graphics to automate generation of large textures [24]. This helped in reducing storage requirement for storage of raw textured images. Instead of storing raw textured image it stores compact texture models which can be used to generate textures as required.

1.4 Contributions

In this comparative study different local features for texture classification are examined in term of classification accuracy and then compared with each other. Experiments are conducted on Outex datasets using Nearest Neighbor classifier. Local Features including absolute local difference, gray level of center pixels, standard deviation, variance, mean, local binary pattern, and different combination of these features are examined to compare their accuracy. This comparison lead us to conclude that gray level of centre pixel, being very poor feature for classification, when used in combination with other features that have less information about centre pixel gives far better classification results. Results obtained by these combined features are also compared with results by different researchers.

1.5 Outline of the thesis

In Chapter 1 we have discussed importance of rotation invariant features in texture classification, its applications and contributions and. Motivation of the topic is the fact to meet the requirements of real-world applications, texture operators should be computationally cheap and robust against variations in the appearance of a texture. These variations may be caused by uneven illumination, different viewing positions, shadows etc. Depending on the application, texture operators should thus be invariant against illumination changes, rotation, scaling, viewpoint, or even affine transformations including perspective distortions. The invariance of an operator cannot however be increased to the exclusion of discrimination accuracy.

In chapter 2 we will discuss literature review done during this thesis work. An introduction to the terms used in thesis will be provided. More over chapter will cover details regarding textures, features, texture classification methods and the work that already has been done in the field regarding feature extraction.

In chapter 3 all details about setup of experiments and result are given. The chapter provides details regarding what methods are implemented. Results obtained are then compared with each other and with the results of other authors in the literature.

Chapter 4 contains the conclusion of whole research work. This chapter summarizes our work and findings based on the results. This chapter also proposes some future work that could be done to further enhance and justify the results based on the conclusion made by this comparative study.

Chapter 2

Literature Review

The objective of the comparison presented in this thesis is to identify rotation invariant local features that give good results in classification of texture. Here we will briefly discuss about features, textures, classification methods and datasets.

2.1 Texture

Textures are present in all images either in form of some visible pattern or some microscopic repeating properties. Term “Texture” is very complex in computer vision as for having different definitions as described in next subsection. We can easily recognize repeating pattern (textures) while seeing an image but defining it is a hard task. Despite of importance of textures in pattern recognition, we don’t have a précised single definition of texture. Every texture analysis method characterizes textures of images in term of extracted features of that image. Therefore, definition of texture doesn’t depends only on studying the images but also on the features that have been extracted from the image for goal of study.

2.1.1 Some Definitions of Texture

Texture can be defined as an important characteristic that can be used to identify objects that are our point of prime interest. The texture of an image can be considered as characteristic of the intensity of the image. Intensity is normally computed every pixel, while texture is obtained from a large image region. Texture is a global property while intensity is local. Here we will mention some definition of textures according to different researchers.

- We can consider image textures as symbolic and cellular. Texture can be described by its primitive and the spatial association or layout of its primitives [24].

- The basic prototype and recurrence of a texture sample can be invisible, although present in large amount. In the deterministic formulation texture is considered as a basic local pattern that is periodically or quasi-periodically repeated over some area
- *“An image texture may be defined as a local arrangement of image irradiances projected from a surface patch of perceptually homogeneous irradiances”* [26].

- *“Texture is characterized not only by the grey value at a given pixel, but also by the grey value `pattern' in a neighborhood surrounding the pixel”* [27].

2.2 Three Stages of Texture Classification System

In a texture classification system first of all an image is acquired on which classification is done. After acquiring the image some preprocessing is required to reduce illumination, resolution and rotation effects .after acquisition and pre processing features are extracted from images .Features to be extracted are selected on the basis of requirement of classification system. Factors, on which feature selection is dependent, includes computational complexity and accuracy. After features are extracted some classification mechanism is required to classify image on basis of extracted features.

A number of classifiers can be used for classification purpose .Mostly used classifier are nn-classifier and Gaussian Bayes classifier. Nearest neighbor classifier being the simplest one Is mostly used for classification purposes.

A general texture classification system can be summarized in *Figure 2.1*

Figure 2.1 Texture classification system

2.2.1 Image acquisition

The first and most important step in texture classification process is image acquisition. During image acquisition there are number of things that should be cared about for taking image. These includes illumination intensity, resolution and view angle. These constraints can be changed in order to get desired object in focus. In most of the real time scenarios these constraints are less controllable. So, some pre-processing is required to remove impact of these constraints on the image.

2.2.2 Feature extraction

Feature extraction means extracting descriptors or features that best describe the image and can be used to classify other images of same type, multiple features are extracted for a single image and set of these features is called a feature vector. Selection of appropriate descriptive parameters influences the reliability of feature during classification and hence influences their effectiveness.

Feature extraction reduces the amount of information required to describe an image accurately. The major problem that arises during analysis of large amount of data having a large amount of variables is that it requires large amount of memory, high computational power or a classifier that might not be able to give good generalisation. Feature extraction can be described as method of constructing new variables to represent information accurately with less data.

Best results of classification can be achieved by extracting application specific feature sets. If application specific features could not be extracted then alternatively general dimension reduction techniques could be used at cost of relatively less accuracy

There are two main categories of texture feature extraction methods, statistical and structural [24].

1. Statistical methods define texture in terms of local grey-level attributes that vary slowly over a texture region. Different textures can be distinguished by comparing the statistics computed over different sub-regions. Most common statistical methods include Fourier transforms, convolution, co-occurrence matrices and autocorrelation.

2. Structural texture model use approach of determining the primitives of which a texture is composed of. The main benefit of structural texture model is that beside texture classification it can also be used to synthesize new images having same texture

2.2.3 Texture classification

Every surfaces and naturally occurring patterns exhibit a certain texture. So Texture classification system is main part of computer vision that plays important role in giving vision sense to machine. If we have to classify a texture to which class it belongs and the classes are not pre-defined, the process of classification will be called *unsupervised texture classification*. While on the other hand, if the classes are pre-defined through the process of training textures, then it is known as supervised *texture classification*. In this study we will discuss about supervised learning only.

The general goal of classification is to classify an unknown object in a category that best describes it, given a set of known categories. As some times it is impossible to accurately classify a texture in a single category so we might classify that texture in a group of closely matching categories. An alternative way is to create an additional reject class for the objects that cannot be accurately classified to single category [29]. The objects are presented with feature vectors that describe their characteristics with numbers.

Normally Supervised classifiers can further be divided in to two categories: parametric and non-parametric. Parametric classifiers e.g. like Bayesian classifiers, make certain assumptions about the distribution of features. Non-parametric classifiers, like the k-NN classifier, can be used with arbitrary feature distributions. Some prior knowledge of data is required for both parametric and non-parametric classifiers in form of either training samples or parameters of the assumed feature distributions. This is the reason for calling them supervised techniques. A supervised classification process involves two phases. First, the classifier must be presented with known training samples or other knowledge of feature distributions. Only after that can the classifier be used in recognizing unknown samples. Prior to the training and the recognition, the samples must be processed with a texture analysis method to get a feature vector. Any method, for example those presented in next section, can be used for this purpose.

With non-supervised techniques, classes are to be found without any prior knowledge of data. This process is also known as clustering. Examples of such methods include vector quantization, utilized in texture classification. Different unsupervised classification techniques are discussed by Theodoridis [30].

2.3 Texture Features

Texture feature extraction is the procedure of generating descriptions of texture that best describes maximum information of texture using less data. The extracted features represent the original texture, and may be used with a classifier. Textural features play a fundamental role in classification of textures in to some class.

2.3.1. Texture Feature Methods

A large of number of method has been proposed for textural features extraction. Tuceryan and Jain [31] divided texture analysis methods into four major categories: *statistical*, *geometrical*, *model-based* and *signal processing* methods.

2.4 Image Rotation Invariant Features

2.4.1. Introduction

One of the main issues related to texture classification is the identification of an isotropic texture at different angle of rotations. Most of the techniques present in literature assume that the textures under observation are rotation invariant i.e. taken from same viewpoint. But this is not true in real world and this assumption leads to misclassification. Rotation invariant features are important in real world for correct classification of textures. In most of the daily life applications, ensuring that surfaces captured have the same rotations between each other is not quite possible. Therefore we consider rotation invariant texture features because of their importance in daily life.

Numerous approaches have been developed that use rotation invariant texture features.

Major work that has been done on rotation invariant features till date can be divided into two categories:

- Statistical methods
- Model based method

2.4.2. Statistical Methods

Statistical methods define texture in terms of local grey-level attributes that vary slowly over a texture region. Different textures can be distinguished by comparing the statistics computed over different sub-regions. Most common statistical methods include Fourier transforms, convolution, co-occurrence matrices and autocorrelation.

Statistical methods are used to characterize the properties of the spatial distribution of grey levels in an image. Mostly statistical methods are based on the fact that the human eyes uses statistic features to distinguish textures, which are further classified into first-order statistics, second-order statistics, third order and higher-order statistics depending upon number of pixels in neighbor.

The simplest rotation invariant image statistics features are the mean value, variance, standard deviation, Local Binary Patterns, absolute local difference and histograms. However they do not give good performance, because of limited information contained by them. But when used as combined feature they sometimes give better results. More reliable rotation invariant image statistics are moment invariant. In addition, it is demonstrated by Wang and Healey [36] that Zernike moments perform well in practice to obtain geometric invariance. In their method, Zernike moments of multispectral correlation functions characterize the texture. The classification accuracy rate is reported to be up to 100% for their database which contained seven textures but they have disadvantage of computation complexity.

One different was adopted by Haralick [24] who suggested that the values of grey-level co-occurrence matrix features should be averaged over all directions. The problem with this approach lies that directionality, an important characteristic of the texture, is lost when an isotropic feature is considered. Some work had also been made to extract rotation invariant features from different textures. A better technique would be one which would enable a characterization of the directionality of the texture, whilst avoiding a dependence upon the texture orientation.

Polarogram introduced by Davis [32] is a polar plot of texture features as a function of orientation. When the image is rotated, the corresponding polarogram is translated by that angle. However the shape and moment features of the polarogram are invariant to rotation. A flat polarogram indicates a texture which is isotropic with respect to the underlying texture feature. In his experiment by using image rotation, the correct classification rate is obtained up to 90%. Unfortunately Davis does not however consider the effects of illumination or physical surface rotation in his experiment.

Alapati and Sanderson [28] achieved rotation invariant texture classification by filtering input images with a set of 2D complex filters that are rotation invariant. Such filters have been known as circular harmonic function filters. The response of each circular harmonic filter is polar separable. The algorithm designed in [28] was tested on only four textures from the Brodatz database and achieves a classification accuracy of 90% but reduces when more textures are used. You and Cohen [37] extend Laws' scheme for rotated and scaled textured images. The method uses standard deviation of pixel grey scale within a specified window computed after convolution with a texture "tuned" mask. Texture energy is a useful measure of texture features, but varies with orientation of the image. A tuned mask on samples overcomes this problem over a range of ration changes to produce a high clustering texture energy term. Although the classification accuracy achieved is 91% using the Brodatz textures, the amount of training to tune the masks is significant.

2.4.3. Model Based Methods

In addition to statistical rotation invariant methods, another approach for rotation invariant texture classification is to apply a model to the texture image and then to derive a classification algorithm from the model. In most statistical model based methods, the image is modeled as a Markov Random Field (MRF) of pixels. In these approaches, the relationships between the intensities of neighboring pixels are statistically characterized. These methods are rarely used for the reason that they are computationally complex when compared to feature based techniques. The main challenge is to achieve rotation invariant schemes that give good results. Rotation invariance can be achieved in one of two ways, either by extracting rotation-invariant features or by the appropriate training of the classifier to make it learn invariant properties. Since general MRF models are inherently dependant on rotation, several methods were introduced to obtain rotation invariance. For class identification of class for an arbitrarily rotated sample, the likelihood function associated with the Fourier transform of the image data is maximized with respect to the rotation parameters. This determines the class of the sample as well as the rotation angle the test sample has undergone.

Cohen, Fan and Patel [37] modeled textures into Gaussian Markov random fields and used the maximum likelihood method to estimate the rotation and scale parameter. Their model has three-dimensional spatial parameters and is based on second order statistics. Wu and Wei [39] have use classical dyadic wavelet decomposition on spiral resampling lattice, the phase and therefore the rotation of the spiral is removed in the decomposition thus enabling rotationally invariant measures to be produced from the resulting sub bands where rotation invariance was achieved by translation invariance. The correct classification rate of 95.1% is obtained. They explicitly do not consider topological texture or illuminant effects. In addition, the problem of these approaches to rotation invariant texture analysis is their computational complexity (e.g. in [37] [3]), which may render them impractical. Finally, using a large number of features to describe each texture can lead to an unmanageable size of feature space.

Kashyap and Shotanzad [6] proposed a circular symmetric auto-regressive (CSAR) model for extraction of rotation invariant texture features. Spatial interaction models such as this represent the grey level values at a pixel as a linear combination of its neighbours plus a noise component. This method is tested on differently oriented textures and a 80- 90% classification accuracy was achieved. However, this method is computationally inefficient. On the basis of this model Mao and Jain [38] developed a multivariate rotation invariant simultaneous autoregressive (RISAR) model and extended it to a multi-resolution (MR-RISAR) model. However, the training sets in those experiments contain samples of different orientations. The performance of those features, when applied to samples with different scaling and orientation than those in the training set, is not clear.

A multi-channel filtering technique based on Gabor filters in the frequency domain is used to acquire rotation invariant texture features. Healey and Manjunath [40] propose an isotropic form of the 2D Gabor function. Here the Gabor function is extended in a 2D form in the frequency domain, it is the product of a set of 1D analytic function of radial frequency and a Gaussian function of orientation θ provide a set of filter. Using these features the classification performance is tested on a set of 13 Brodatz textures, and achieved a 96.4% correct classification rate. In other techniques, features based on Gabor filters are extracted, that allow the formulation of a rotation invariant model [23]. The central step of their approach is to identify the rotation angle of the test sample with respect to a reference orientation, and then transforming the test sample to the reference orientation before classification.

Greenspan et al [41] employed a set of oriented filters which are complex exponential functions modulated by Gaussian filter acting on the Laplacian pyramid. Feature vectors are formed from the outputs of the oriented filters, describing the local characteristics of the original images. A DFT of the feature vector in orientation dimension is insensitive to this circular shift of points. This provides the rotation invariant features used in the study. A set of thirty textures from Brodatz is used for validation and the best classification accuracy is 91.5% for K-nearest classifier.

In the earlier studies, the testing was done in such a way that rotated samples of the textures were included in both the training and the classification stage. Recently, Pietikainen et al. [42] suggest that the rotation-invariant algorithm should be able to classify the texture classes even if the training procedure is to run on the texture samples for only one rotation. Ojala et al. [42] showed that such an approach is much more challenging. We have therefore followed the second principle in this thesis. Pietikainen and Ojala [42] also introduced a set of related measures, including two local centre-symmetric auto-correlations. Measures, with linear (SAC) and rank-order versions (SRAC), together with a related covariance measure (SCOV). A distribution-base classification approach is applied to rotation invariant texture classification. A difficult classification problem of fifteen different Brodatz textures and seven rotation angles is used in experiments. It was reported that the best results were achieved with distributions of joint pairs of features.

Note that the accuracy of classification methods presented in this section is not comparable with each other, since they use different texture data as test and training set

2.5 Surface Rotation Invariant Features

Natural textures that are extracted from spatial variation of two surface attributes: reflectance and surface normal are known as surface rotation invariant features. Basic idea is to construct a database of surface patches associated with geometric properties that are local to the surface. These features are known as 3-D textons.Leung and Malik [23] presented a classification system which is trained on textures that are each imaged under 20 different illumination and orientation conditions [23]. Their textures were obtained from the Columbia-Utrecht Reflectance and Texture Database [43]. This generalizes the classifier but does not use explicit 3D surface texture information directly. Dana and Nayar describe a correlation model for 3D surface texture and suggest how this might be used to provide a 3D surface texture feature, correlation length. They present a model which uses surface statistical parameters to predict the change in the correlation length with illumination directions. They do not, however, use this for texture classification purposes [43].

2.6 Local Features

Local features are among simplest features. Most common local features are the mean value, variance, standard deviation, Local Binary Patterns, absolute local difference and gray level of centre pixels. However they do not give good performance when directly extracted. Preprocessing of image is required to bring invariance to these features. Normally these features provide accuracy of more than 80 percent. Basic reason for their low efficiency is limited information contained by them. When used as combined feature they sometimes give better results than individuals. Rotation and illumination invariance can be brought to these features after some preprocessing.

Here we will provide basic information regarding all local features.

2.6.1 Standard Deviation

Standard deviation is a widely used measure of variability or diversity used in statistics and probability theory. It shows how much variation or "dispersion" exists from the average (mean, or expected value).

In order to make standard deviation a rotation invariant feature we need to find points of image in true circular symmetry using following equation

$$X_i = \left(Rcos\frac{2\pi i}{P}, Rsin\frac{2\pi i}{P}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.1)}$$

X_i gives location of pixel on circular symmetry. After finding all pixel values in circular symmetry we calculate gradient intensity in all directions with reference to the centre pixel, taking Ic as the intensity of the centre pixel, gradient components which are approximately intensity Invariant are computed. The gradient intensities around the centre pixel can be written as a 1D vector, I, as

$$I = [I_c - I_0, I_c - I_1, I_c - I_2, \ldots \ldots, I_c - I_{P-1}] \ldots\ldots\ldots\ldots\ldots \text{(2.2)}$$

It can be noted that any rotational effects result in linear shifts in the 1D vector of Eq 2.2. That is, rotations in image space correspond to linear shifts in the transformed space.

The discrete wavelet transforms (DWT) of a signal I is calculated by passing it through a series of filters whose coefficients are given in

$$h = \left[\frac{1}{\sqrt{2}}, \frac{-1}{\sqrt{2}}\right],\ g = \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right] \text{...} (2.3)$$

where h is coefficient for high pass filter and g is coefficient for low pass filter. As rotation in image causes linear shift in transform space so standard deviation coefficient is rotation invariant

2.6.2 Mean

In statistics, mean has two related meanings:

- the arithmetic mean (and is distinguished from the geometric mean or).
- the expected value of a random variable, which is also called the population mean.

Mean is also extracted by following the same procedure which is used by standard deviation in previous topic.

2.6.3 Local Binary Pattern

Although being simple, Local Binary Pattern (LBP) [48] is still very efficient texture operator as compared to other local features which labels the pixels of an image by thresh holding the neighborhood of each pixel and considers the result as a binary number. Due to its distinguishable power and minimal computational complexity, Local binary pattern has become a popular feature for a number of applications.

LBP can be considered as a unifying approach to the structural texture analysis methods.

The most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, and for this property it is used in many of real time application. Normally binary representation of sign of local difference is considered as local binary pattern and is represented by following formula:

$$LBP_{P,R} = \sum_{P=0}^{P-1} S(g_p - g_c)2^P \,, S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad \text{(2.4)}$$

Here LBP represents the local binary pattern. While g_p and g_c are gray level values of neighbor pixel and centre pixel respectively. S(x) gives information of sign of the difference between centre pixel and neighbor in m x n window. This equation gives binary equivalent of signs of gradient.

2.6.4 Gray level of center pixels

Gray level of center pixel can also be considered as feature as it also contains some information regarding image but gray level gives very small accuracy as they contain information only about gray level of centre pixel. When used in combination with other local features that contain more information about textures it can give better results.

2.6.5 Absolute local difference

Beside local binary pattern, absolute local difference is another important feature in texture classification. In absolute local difference simply absolute difference of neighbor is calculated. This feature stores the amplitude of difference of neighbor pixels with center pixel in contrast to Local binary pattern which uses sign of local difference as information of texture.

2.7 Datasets

A number of datasets are available for experimental purpose of texture classification. Most common of these datasets are OUTEX,Boradtz and CUReT. Among these datasets outex has the largest number of images.

The Brodatz's dataset is a well-known benchmark database used for texture classifications by many researchers. It contains 111 different texture classes and each class has one image at 9 different rotations. So this dataset consists of 999 images in total. All images have dimensions of 215 x 215.

CUReT dataset is another common dataset used in texture classification. This dataset consists of 61 different textures which are taking at different rotation angles and illumination intensities. Each class contains a total of 92 texture images which are used by the classifier.

Outex is only dataset that is used for both texture classification and segmentation algorithms. It is most widely used data set. It contains large image database. The image database includes a large number of textures, both in form of surface textures and natural scenes. The collection of surface textures exhibits well defined variations to a given reference in terms of illumination, rotation and spatial resolution. Reliable manual segmentation of natural scenes is included in the ground truth data. Dataset is divided into a number of sets on basis of pre-defined problem statement e.g. TC00010 is used for texture classification of rotation invariant features.

2.8 Texture Classification Techniques

Many texture classification schemes have been presented that are invariant to image rotation so far. The major existing approaches include image rotation invariant statistical features, moment invariants, polarogram features, Hough transform features, iso-energy directional signatures in 2D Fourier spectra, autoregressive models, Gaussian Markov random field models, multi-channel filtering and wavelet transforms

Image rotation invariant classifiers normally derive their features directly from a single image and are tested using rotated images. If the image texture results solely from variation rather that surface relief or if the illumination is not directional or immediately overhead, then these schemes are surface-rotation invariant as well. However, in many cases rotation of a textured surface produces images that differ radically from those provided by pure image rotation. These images show that rotation of a 3D surface texture does not result in a simple rotation of the image texture. This is mainly due to the directional filtering effect of imaging using side-lighting [44]. Such changes in appearance can cause significant failures in image-base texture classifiers. For instance a rotation of *90°* of the illuminant tilt angle can cause the mis-classification rate of a texture classifier to change from *4-5%* to nearly *100%* [44]. In another way, rotation of the physical texture surface under fixed illumination conditions can also cause significant changes to its appearance. It causes failure of classifiers designed to cope with image rotation as well [45]. Among the various methods of supervised statistical pattern recognition, the Nearest Neighbor rule achieves consistently high performance, without any prior assumption about the distributions from which the training examples are drawn. It involves a training set. A new sample is classified by calculating the distance to the nearest training case; the sign of that point then determines the classification of the sample. In this study all test images are classified using nearest neighbor classifier. More over accuracy is measured in term of number of correctly classified images divided by total number of test images.

Distance matrix of test images after being calculated using chi-square distance is forwarded to NN classifier for classification. NN classifier looks for the minimum distance of test image with all training images and assigns class to test image that of training image which has minimum dissimilarity it.

Class assigned to a test image is then compared with actual class of test image provided with dataset and correct classification is considered if both classes match.

2.9 Summary

In this chapter, the literature, which has been reviewed for this study, is discussed in detail. Survey of texture feature measurements and rotation invariant texture classification has been done in this chapter. Chapter starts with definition of texture. After basic definitions of textures, Features are discussed in detail. Chapter also includes texture classification system. This chapter contains details regarding type of textures classification methods, types of features, and different datasets. After describing texture classification system, chapter proceeds with discussion on different types of textures and features. Chapter contains detail of local feature which are prime focus of our thesis. After the detailed description of features and texture, information regarding dataset is provided focusing Outex Dataset.

Chapter 3

Implementation and Experimental results

During this comparative study the focus was on local features i-e standard deviation and mean of high pass and low pass filters respectively. Comparison is done between the following features.

1 Magnitude of local difference
2 Sign of local difference
3 Gray level of center Pixel
4 Local binary Pattern variance
5 Gray level of center pixel and absolute local difference
6 Gray level of center pixel and Local binary pattern
7 Absolute local distance and Local binary pattern.

All implementation is done in Matlab and different functions from PRtools are used in the implementation of some of the algorithms. The texture images have been taken from the Outex dataset.

3.1 Implementation

3.1.1 Pre Processing

Before feature extraction, pre-processing of images is done to remove rotation variance from these images and hence making features rotation invariant.

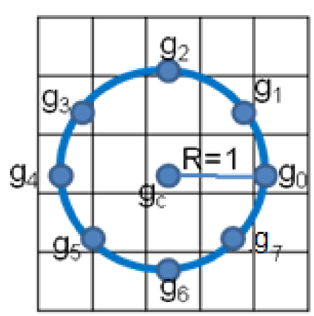

Figure 3.1. Neighbour pixel in circular symmetry of radius 1

Circular symmetry is achieved by recalculating pixel intensities at coordinates given by:

$$X_i = \left(Rcos\frac{2\pi i}{P}, Rsin\frac{2\pi i}{P}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where P is number of neighbours of central pixel, X_i is the equivalent position of the ith of P-1 pixels in circular symmetry around centre pixel with radius R. The grey values of neighbours, which do not fall exactly on integral pixels, are estimated by interpolation. Eight neighbours of a pixel are shown in fig 3.1.

3.1.2 Feature Extraction

After calculating gray level values of pixels in circular symmetry, local features are extracted from image. Following features are extracted and then compared with each other.

3.1.4.1 Local Binary Pattern

Local Binary Pattern (LBP) [48] is the simplest among the features but still an efficient texture operator. In LBP the pixels of an image are labeled by thresholding the neighborhood of each pixel and consider the result as a binary number. For its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings. Normally binary representation of sign of local difference is considered as local binary pattern and is represented by following formula:

$$LBP_{P,R} = \sum_{P=0}^{P-1} S(g_p - g_c)2^P \,, S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

Here $LBP_{P,R}$ is local binary pattern for P neighbors. g_c is gray level of centre pixel while g_p is gray level of Pth pixel in circular symmetry of radius R.

Fig 3.2 shows an image classification system using local binary pattern as a feature.First of All local difference of m x n neighbours with center pixel is calculated .Once local difference is calculated then sign of binary is calculated by thresholding which is followed by calculation of histogram and then classification is done by using different classification techniques already discussed in previous chapter

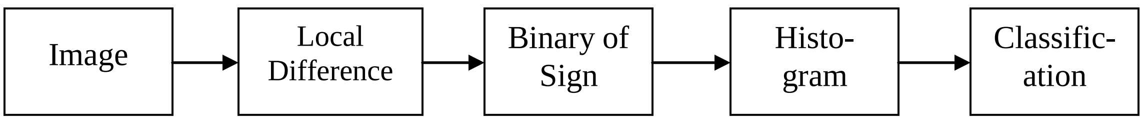

Figure 3.2 Basic steps of local binary patterns.

Figure 3.3 shows a simple example of calculation of local binary pattern. In figure 3.3(a) a sample block of image is given. First of all local difference is calculated i-e difference of all pixels with centre pixel is calculated as shown in figure 3.3 (b). Once difference is calculated thresholding of local difference is done in order to extract sign factor (fig 3.3(c) & 3.3 (d)). Local binary pattern is binary representation of sign of local difference.

10	30	05
10	20	20
60	50	10

(a) 3X3 sample block

-10	10	-15
-10		0
40	30	-10

(b) local difference

0	1	0
0		1
1	1	0

(c) f(x)

8	4	2
16	0	1
32	64	128

(d) weight of locations

LBP= 1+4+32+64 =101 => 01100101

Figure 3.3 Example of Local Binary Pattern

3.1.4.2 Gray level of center pixels

Gray level of center pixel [49] is considered as feature as it also contains some information regarding image but gray level gives very small accuracy .When used in combination with other local features like absolute local difference it can give better results. Following formula can be used to extract centre pixel feature.

$$f(g_c, T) = \begin{cases} 1, x \geq T \\ 0, x < T \end{cases} \quad \ldots\ldots\ldots\ldots \quad (3.3)$$

In this formula thresholding is used where threshold value T can be global average of gray level of pixels in image. This thresholding is done for the purpose of representing gray level feature in a format that is compatible with Local binary Pattern when used in combination.

3.1.4.3 Absolute Local Difference.

Absolute local difference (ALD) [49] is used as a feature. First of all distance vector is computed which can be represented as:

$$\left[d_0, d_1, \ldots\ldots\ldots d_{p-1}\right] \quad \ldots\ldots\ldots\ldots \quad (3.4)$$

Here

$$\mathrm{d_p} = \left| \ \mathrm{g_p} - \mathrm{g_c} \ \right| \quad \ldots\ldots\ldots\ldots \quad (3.5)$$

In above formula d_p represent absolute local difference, g_p is gray level value of p neighbour and g_c is gray level of centre pixel.

As in case of gray level of centre pixel, absolute local difference also needs to be represented in binary so that it could be used with local binary pattern as a combined feature. Following equation could be used to represent ALD in binary.

$$ALD = \sum_{P=0}^{P-1} f(d_p, T) 2^P \ , f(x, t) = \begin{cases} 1, x \geq T \\ 0, x < T \end{cases} \quad \ldots\ldots\ldots \quad (3.6)$$

Where d_p, is absolute difference of pixel “p” with centre pixel and T is threshold value which is set to be average gray level of whole image.

Figure 3.4 shows an example of implementation of above equation. In this example, a sample block of size 3X3 pixel is used. First of all absolute local difference is computed and then values are compared with threshold value which is set to be average gray level value of whole image. In the end, weight of location is applied to represent the result in binary format.

10	30	05
10	20	20
60	50	40

(a) 3X3 sample block

10	10	15
10	0	0
40	30	20

(b) Absolute local difference

0	1	0
0	0	0
1	1	0

(c) $f(d_p, T)$ assuming T =30

8	4	2
16		1
32	64	128

(d) binary weights

ALD = 4+32+64 = 100=> 01100100

Figure 3.4 Example of Absolute Local Difference

Once features are extracted then their histograms are calculated .Basic advantage of using histograms is representation of features with less amount of data and hence usage of less memory. When histogram of a feature is calculated it is represented in 10 bins by default .So histogram of single feature of each of 3000 test images having size of 126 X 126 pixels each can be represented in a matrix of 3000 X 10 dimensions.

3.1.4.4 Local Binary Pattern Variance

Local binary pattern variance is a feature that was suggested by [48]. This feature is same as LBP. The only difference among two is that LBP of a given subset of image is replaced with variance at that point if LBP is greater than a given threshold value. Following equation[48] describes the procedure.

$$LBPV(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} f(LBP(i,j),k), k \in [0,K]$$
$$f(LBP(i,j),k) = \left\{ \begin{array}{r} VAR(i,j), LBP(i,j) = k \\ 0, otherwise \end{array} \right\} \qquad \ldots\ldots\ (3.7)$$

This helps out to retrieve information of intensity at a given point, as variance is measure of change in intensity at a given area.

3.1.4.5 Combined Features

Individual features that are extracted for classification purpose can also be used in combination with each other to further enhance their individual performance. There are two methods to combine the features. Simplest one is to concatenate both feature matrices and then calculate the histogram of resultant matrix. Second one includes concatenation of histograms of individual features. We have used first method in our research work because of its simplicity. Following combination of local features were tested on outex TC00010 dataset using nearest neighbor method.

1. Gray level of center pixel and absolute local difference
2. Gray level of center pixel and Local binary pattern
3. Absolute local difference and Local binary pattern.

Feature matrices of gray level of centre pixel and absolute local difference are concatenated and then histogram resultant matrix is calculated. Same procedure is used to calculate combined feature histogram of all the combinations that have been mentioned above.

3.1.3 Outex Dataset

In this research work Outex dataset is used. Among this dataset TC00010 test suit is used for feature extraction and classification. Training set contains 480 images while test set has 3840 images. All images are of 128x128 resolutions. Among different qualities, a few are mentioned below.

This database contains a large collection of textures, both in form of surface textures and natural scenes. The collection of surface textures exhibits well defined variations in terms of illumination, rotation and resolution.

A large collection of texture classification and segmentation problems, both supervised and unsupervised, is constructed using the image database. The diversity of the surface textures provides a rich foundation for texture classification problems. In addition to standard texture classification, problems of illumination/rotation/resolution invariant texture classification, or their combinations, are also available.

Problems are encapsulated into well defined test suites having precise specifications of input and output data. Specifications are provided in form of general purpose text and image files; hence the user of the framework is not constrained to any given programming environment. Test suites are delivered as individual zip files, which expand to a standardized directory and file structure.

Figure 3.5 shows some images from Outex dataset. Outex dataset includes images of canvas, tiles, paper and carpet.

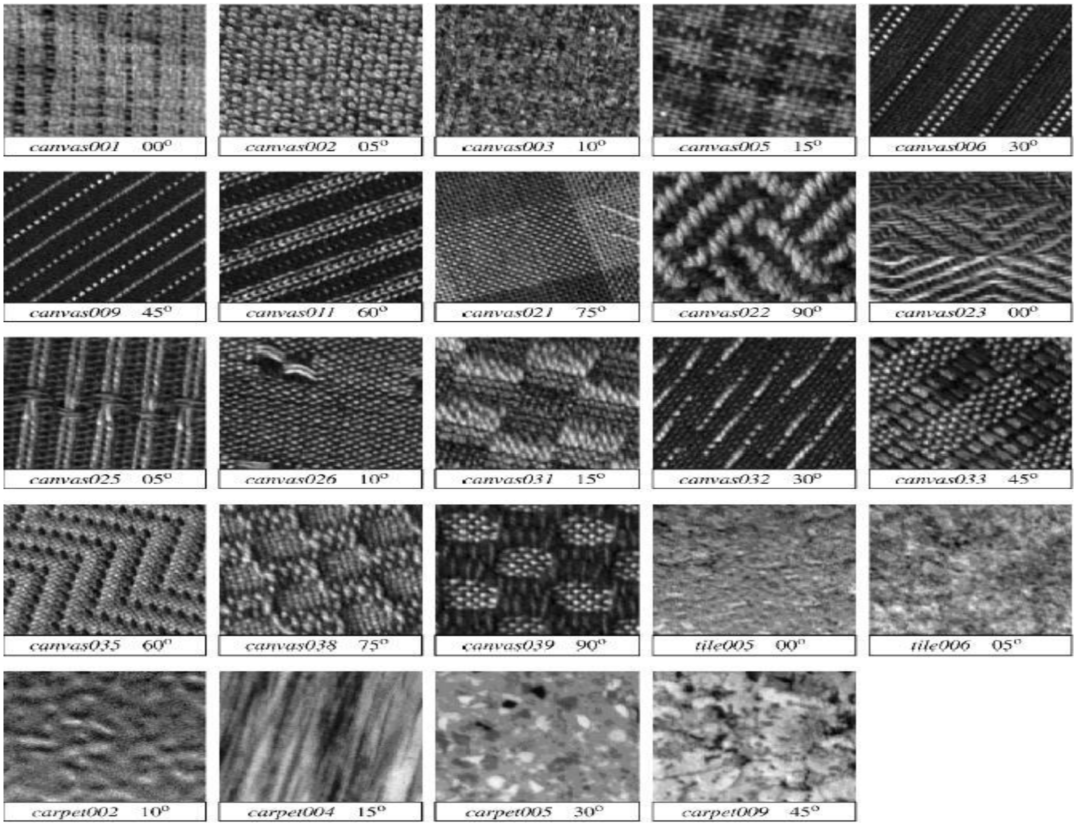

Figure 3.5 Images from Outex TC 00010 test suit[47]

3.1.4 Classification

Among the various methods of supervised statistical pattern recognition, the Nearest Neighbor rule achieves consistently high performance, without any prior assumption about the distributions from which the training examples are drawn. It involves a training set. A new sample is classified by calculating the distance to the nearest training sample, the class of that sample then determines the classification of the test sample. In this study all test images are classified using nearest neighbor classifier. More over accuracy is measured in terms of number of correctly classified images divided by total number of test images.

3.1.4.1 Distance Metric

Once histogram is calculated for each test image then distance matrix is calculated for each test image with every training image. Different techniques can be used to find distance matrix. Mostly used techniques include Euclidian distance and chi-square distance. Chi-square distance measures the dissimilarity between feature matrices of test and train image.

We have used chi-square distance for calculation distance vector. It is calculated using Equation (3.8).

$$x^2 = \sum_{x=1}^{X} (Test_x - Train_x)^2 \big/ (Test_x + Train_x) \quad \ldots\ldots \quad (3.8)$$

here X represents number of bins.

Once distance vector is calculated for each test image it is then passed to a classifier for assigning a class to that image. Classes to test images are assigned on the basis of minimum dissimilarity with a training image.

Distance matrix of test images after being calculated using chi-square distance is forwarded to NN classifier for classification. NN classifier looks for the minimum distance of test image with all training images and assigns class to test image of that training image which has minimum dissimilarity with it.

Class assigned to a test image is then compared with actual class of test image provided with dataset and correct classification is considered if both classes match. After classification, accuracy is measured on the basis of following equation:

$$\text{Accuracy} = \frac{\text{correctly classified images}}{\text{Total test images}} \times 100 \quad \ldots\ldots \quad (3.9)$$

3.2 Results

Each of the local features extracted from training dataset images is used to classify the test texture images using nearest neighbor classifier.

All features are used individually as well as in combination for classification. First of all, gray level of center pixel is used as a feature for classification purposes. Gray level of centre pixel feature is computed for 3840 test images as well as 480 training image. After histogram calculation distance vector of each of test sample is computed with every training image feature histogram. Once chi-square distance vector is computed for all 3840 test images, classification is done by measuring least difference of test sample with training sample and class of training sample, that gives minimum distance value with test image, is assigned to test image. This classification is then verified by comparing with actual class of test image provided with data set.

Table 3.1 Classification accuracy (%) of Gray level of centre pixel

P,R	Classification Accuracy
1,8	18.69
2,16	17.5
3,24	18.0990

Table 3.1 shows that gray level of center pixel give the worst classification rate. Results in Table 3.2 gives detail of classification accuracy of all individual features that have been used in this study. These results show that Local binary Pattern variance gives the best classification results but at the expense of more computations. From the table, it is also obvious that gray level of centre pixel when used individually gives poor performance. Moreover we can observe that greater the value of P and R i-e, the radius, greater is the accuracy.

Table 3.2 Classification accuracy (%) of individual features

Features	P = 1, R=8	P=2, R=16	P=3, R=24
Gray Level of center Pixel	18.69	17.5	18.0990
Absolute Local Difference	81.74	93.6719	95.5208
Local Binary Pattern	85	89.329	95.0781
LBP Variance	91.4583	92.1354	95.1563

Gray level of center pixel (GCP) gives least accuracy as compared to Local Binary Pattern (LBP) and Absolute Local difference (ALD). Results of absolute local difference are a bit better than LBP but at the expense of computational complexity. Whereas LBP gives high accuracy while using simple computations.

After investigating invariant features individually, these features are used in combination.

Table 3.3 shows the results of combined features. From Table 3.3, it can be seen that combined features give far better results than individual features. In this table, results for invariant feature of local texture (IFLT) [47] are also mentioned for comparison purpose. This table clearly shows that when gray level of centre pixel is used with LBP or absolute local difference as combined feature, it gives better results as compared to mean and standard deviation which needs computation for wavelet transform and then mean and standard deviation of low pass and high pass filters. Similarly IFLT also need complex computations [47]

Table 3.3 Classification accuracy (%) of combined features

	Features	P = 1,R=8	P=2 ,R=16	P=3 ,R=24
Own Results	GCP+ ALD	90.3646%	97.4479%	98.0208%
	GCP + LBP	95.2865%	97.0313%	97.9948%
	ALD + LBP	94.6875%	97.8385%	99.2969%
Results from Literature	IFLT	86.8%	89%	90%

Besides these techniques many other techniques including Gabor wavelets, Circular shift Technique (CST) [50], Adoptive circular orientation normalization (ACON) [51] and Elastic Cross-Frequency Searching [51] can also be used for rotation invariant texture classification.

Table 3.4 Classification accuracy (%) of Gabor Filter Techniques

Features	Accuracy
Gabor wavelets	46.6
Gabor wavelet + Circular shift Technique (CST)	76.1
Intensity values	78.1
Gabor Wavelet +Adoptive circular orientation normalization(ACON)	74.5
Gabor Wavelet + ACON + intensity values	93.1
Gabor Wavelet + intensity values+ Elastic Cross-Frequency Searching	75.2

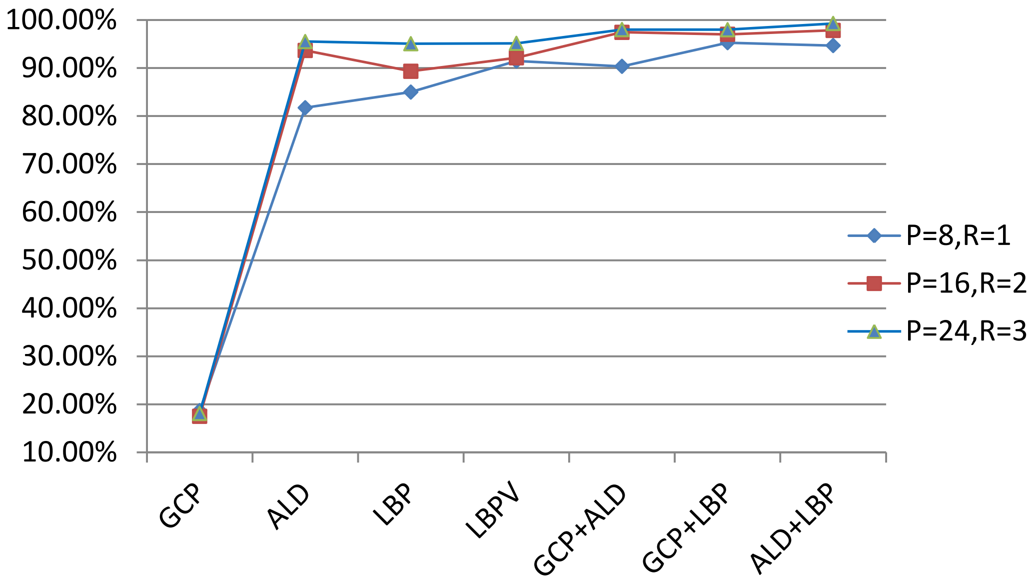

Figure 3.6 Graphical Representation of classification results of different techniques

Figure 3.6 shows graph of classification accuracy of all the techniques implemented in this thesis. Graph is plotted for 8, 16 and 24 neighbour pixels. Plotted Values are taken from Table 3.2 and Table 3.3

From the results, we can conclude that Gray level of center pixel can be used as combined feature along with Local binary pattern and absolute local difference as it gives better results if used individually, as obvious from results shown in tables.

3.2 Summary

In this chapter we have discussed implementation of different methods and then their results are compared with each other and with other techniques in the literature that are mostly used for texture classification. From these observations, we conclude that gray level of centre pixel when used with local binary patterns or absolute local difference as combined feature gives high classification accuracy.

Chapter 4

Conclusion

In this thesis, the main problem addressed is the comparison between rotation invariant features for texture classification in terms of better performance. Feature extraction is one of the main areas of current texture research, other major areas being segmentation, synthesis and classification of texture.

This thesis provides a detailed comparison between different individual as well as combined local features. We have concluded from this research that combined feature pair of gray level of centre pixel with local binary pattern and absolute local difference gives better results as compared to other combined and individual local features.

Observation and Conclusion

We have investigated different individual as well as combined local features. Experiments are conducted using NN classifier with chi-square distance metric on Outex test suit. From results, it is obvious that gray scale level of center pixel gives least accurate results. From comparison, it has been figured out that combined features give better classification accuracy as compared to individual features. Classification success rate of combined features increases to more than 90 percent which is sufficient for a large number of applications. Among combined features, absolute difference and local binary pattern gives high accuracy of about 99 percent whereas LBP combined with gray level of center pixel and Absolute local difference combined with gray level of center pixel gives accuracy up to 98 % but uses less information than Local binary pattern and absolute local difference pair of combined features. From these results, it is obvious that gray level of center pixel gives least accuracy but when used in combination with LBP or absolute local difference, it gives enhanced accuracy as compared to individual LBP or absolute local difference. This knowledge can be further implemented on different datasets and using different classifiers to check the impacts of these features on classification accuracy, obtained by combined feature pair of gray level of center pixel with either Local binary pair or absolute local difference.

4.1 Recommendations and Future Work

This study leads us to conclude that a lot of enhancement can be done in local feature extraction methods using combined features that do not overlap each other's information. Gray level of centre pixel can be used to enhance accuracy of classification by using them in pair with other features which do not have information about centre pixels.

Scope of this research can be further enhanced by trying these combined features over different datasets like brodatz, CUReT etc. More over different classifiers can be used for classification purpose. Beside local features, geometric features and model based methods can also be used to extract different features which can then be used in combination to get better results of classification.

Scope of the studies can be increased by combining more than two local features. Similarly pair of local features can be formed with geometric and model based features like DWT etc.

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