CHAPTER 2

Rotation Invariant Texture Classification

The objective of the method presented in this thesis is surface rotation invariant classification of texture. This chapter survey work relevant to this goal. Definition of image texture and surface texture are reviewed, and rotation invariant classification techniques are surveyed.

2.1. What is Texture?

Texture can be seen in many images from multi-spectral remote sensed data to microscopic photography. The term of *texture* is a somewhat misleading term in computer vision, which is not the normal meaning of the word. We recognise texture when we see it but it is very difficult to describe. Despite its importance, there is no unique and precise definition of *texture* in [Pratt78], Cross and Jain [Cross83]. Each texture analysis method characterises image texture in terms of the features it extracts from the image. Therefore, it depends not only on studying the images but also on the goal for which the image texture is used and the features that are extracted from the image.

Despite the lack of a universally agreed definition, all researchers agree on two points [Jain96].

1. There is significant variation in intensity levels between nearby pixels; that is, at the limit of resolution, there is non-homogeneity.

2. Texture has a homogeneous property at some spatial scale larger than the resolution of the image.

2.1.1. Some Definitions of Texture

Texture is an important surface characteristic we use to identify and recognise objects. The texture of an image may be thought as something which describes the characteristic of the intensity surface of the image. Intensity can be measured at resolution of a single pixel, whereas texture can only be perceived from an image region which is large enough. Compared with intensity, texture is more of a *global* property.

- The Longman Dictionary

  something composed of closely interwoven elements or an organisation of constituent particles of a body or substance; and the visual or tactile surface characteristics and appearance of something (e.g. fabric).

- Haralick [Haralick79]

  The image texture we consider is non-figurative and cellular… An image texture is described by the number and types of its (tonal) primitives and the spatial organisation or layout of its (tonal) primitives…

- Faugeras and Pratt [Faugeras80]

  The basic pattern and repetition frequency of a texture sample could be perceptually invisible, although quantitatively present ... In the deterministic formulation texture is considered as a basic local pattern that is periodically or quasi-periodically repeated over some area.

- Bovik, Clarke and Geisler [Bovik90]

  an image texture may be defined as a local arrangement of image irradiances projected from a surface patch of perceptually homogeneous irradiances.

- Jain and Karu [Jain96]

  Texture is characterized not only by the grey value at a given pixel, but also by the grey value `pattern' in a neighbourhood surrounding the pixel.

For detailed discussions on what is and what is not texture, see Karu and Jain [Karu96]. For more definitions of texture, see Coggins [Coggins82], Tuceryan and Jain [Tuceryan93].

2.1.2. Texture in Visual Perception

Texture is the visual cue due to the repetition of image patterns, which may be perceived as being directional or non-directional, smooth or rough, coarse or fine, regular or irregular, etc. The following images in *Figure 2. 1* illustrate this. The objective of the problem of texture representation is to reduce the amount of raw data presented by the image, while preserving the information needed for the task.

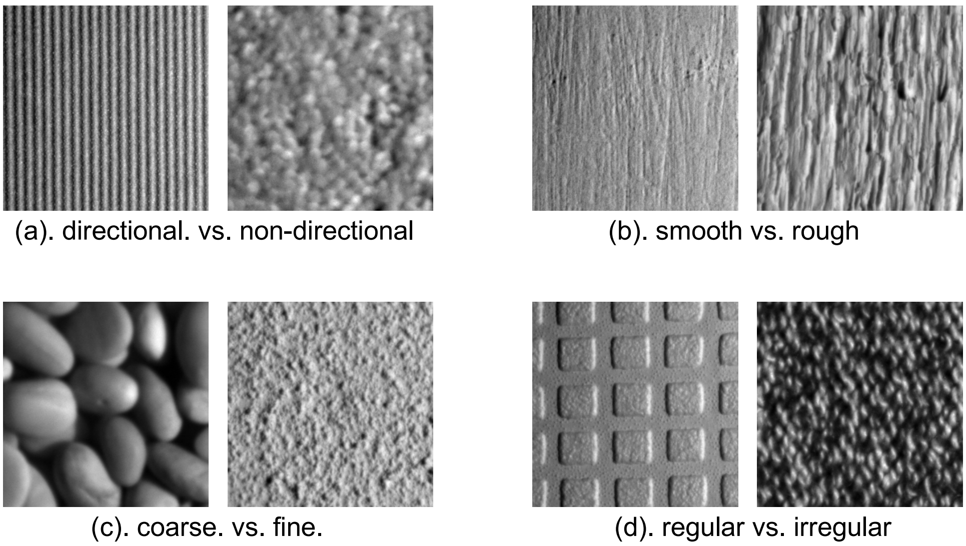

Figure 2. 1 Perception of textures. (a). directional vs. non-directional; (b). smooth vs. rough; (c). coarse vs. fine; and (d). regular vs. irregular.

2.1.3. 3D Surface Relief and Albedo

The term of *image texture*, or simply texture, usually refers to the image of a textured surface. Image texture can arise not only from surface albedo variations (2D) but also from surface height variations (3D). The distinction between 2D texture and 3D texture is explored in recent work by Dana and Nayar *et al* [Dana97], Stavridi and Koenderink [Stavridi97], Leung and Malik [Leung97]. However, there remains an absence of a clear distinction between surface relief (geometry) and surface albedo (reflectance).

Surface relief and albedo information are two important visual cues that provide a relatively large amount of information from surfaces in the scene. Although historically, they share a common role in the scenes, they have been studied separately in computer vision due to the difficulty that both properties present. To avoid any possible confusion, where applicable:

- *Surface relief* is used only to refer to the topology of a 3D physical surface in which only the surface height varies; in contrast,
- the term *surface albedo* refers to surface markings or surface reflectance.

The term *image texture* in this thesis consists of intensity variations in the image plane that are due either to surface relief or to surface albedo variation or a combination of both. An example of extracting surface relief and albedo from a 3D surface is illustrated in *Figure 2. 2*.

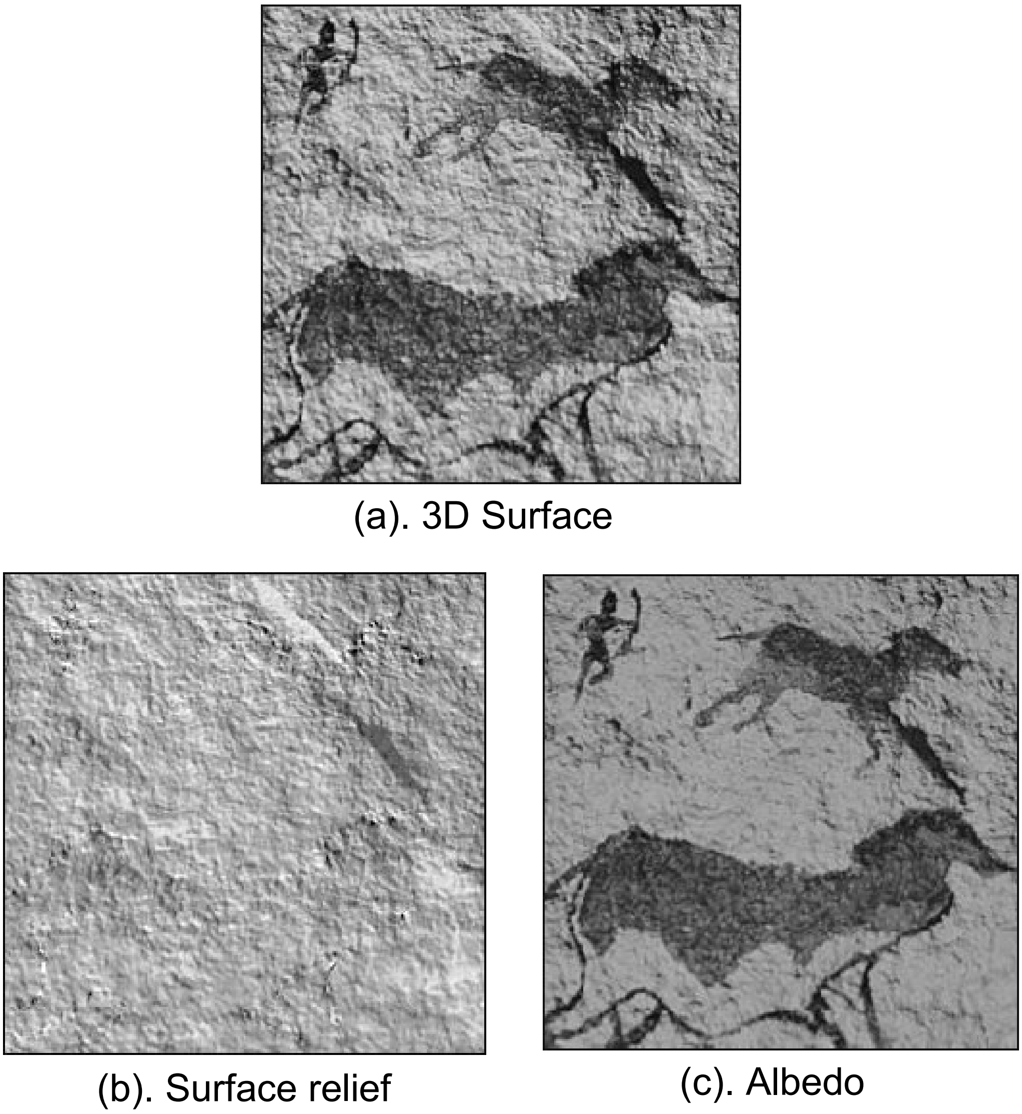

Figure 2. 2 Extracting surface relief and albedo from 3D surface

2.2. Texture Features

Texture feature extraction is the procedure of generating descriptions of a textured surface in terms of measurable parameters. The extracted features represent the relevant properties of the surface, and may be sued with a classifier. It is commonly agreed that textural features play a fundamental role in classifying textured surface and texture segmentation.

2.2.1. Three Stages of Texture Classification System

A general texture classification system can be summarised in *Figure 2. 3*.

Figure 2. 3 Texture classification system

- ***Image acquisition***

The first and arguably most important stage is that of image acquisition. The application of suitable physical constraints to the observed scene may be used to significantly reduce the complexity of subsequent stage. Careful structuring of the lighting arrangement and camera position may be used to enhance the particular features of interest.

- ***Feature extraction***

Feature extraction is concerned with the quantification of texture characteristics in terms of a collection of descriptors or quantitative feature measurements, often referred to as a feature vector. The choice of appropriate descriptive parameters will radically influence the reliability and effectiveness of subsequent feature qualification through classification [Awcock95].

Texture features and texture analysis methods can be loosely divided into two categories – *statistical* and *structural* [Haralick79].

1. *Statistical* methods define texture in terms of local grey-level statistics which are constant or slowly varying over a textured region. Different textures can be discriminated by comparing the statistics computed over different sub-regions.
2. *Structural* texture models try to determine the primitives which compose the texture. The extracted primitives and their placement rules can be utilised not only to recognise texture but also to synthesise new images with a similar texture.

- ***Texture classification***

Most natural surfaces and naturally occurring patterns exhibit texture. A texture classification system will therefore be a natural part of many computer vision systems. The problem is that, given a texture region, to decide which of a finite number of classes that it belong to?

If the classes have not been defined a priori, the task is referred to as *unsupervised texture classification*. On the other hand, if the classes have already been defined through the use of training textures, then the process is referred to as *supervised texture classification*. In this thesis, only *supervised texture classification* will be considered, and classification accuracy can refer to the percentage of correctly classified texture samples.

2.2.2. Surveys

There are several methods for defining textural features. Each method has its own way to define the features that are used in the classification problem. Many textural features proposed by researchers have been reported in the literature and are widely used in texture analysis. Haralick [Haralick79], Wechsler [Wechsler80], van Gool, Dewaele and Oosterlinck [VanGool85], Tuceryan and Jain [Tuceryan93], Reed and du Buf [Reed93] surveyed the state of the art in texture analysis.

2.2.3. Texture Feature Methods

A wide variety of methods for describing texture features have been proposed. Tuceryan and Jain [Tuceryan93] divided texture analysis methods into four major categories: *statistical*, *geometrical*, *model-based* and *signal processing* methods. The following discussion provides brief introduction to each of the four categories.

- ***Statistical method***

Statistical methods analyse the spatial distribution of grey values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. With this method, the textures are described by statistical measures. Depending on the number of pixels defining the local feature, the statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The performance of these method have been evaluated by Conner and Harlow [Conners80].

One commonly applied and referenced method is the co-occurrence method, introduced by Haralick [Haralick73]. In this method, the relative frequencies of grey level pairs of pixels separated by a distance *d* in the direction θ combined to form a relative displacement vector *(d, θ)*, which is computed and stored in a matrix, referred to as *grey level co-occurrence matrix* (GLCM) **P**. This matrix is used to extract second-order statistical texture features. Haralick suggests *14* features describing the two dimensional probability density function p_{ij}. Four of the most popular commonly used are listed in [Haralick73] [Strand94]. They are *ASM* (Angular Second Moment), *Con* (Contrast), *Cor* (Correlation) and *Ent* (Entropy):

$$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij}^{\;2} \tag{2. 1}$$

$$Con = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 p_{ij} \tag{2. 2}$$

$$Cor = \frac{1}{\sigma_x \sigma_y} \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left[(ij)p_{ij} - \mu_x \mu_y\right] \tag{2. 3}$$

$$Ent = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij} \log p_{ij} \tag{2. 4}$$

where μ_x, μ_y, σ_x, and σ_y are the means and the standard deviations of the corresponding distributions; and N is the number of grey levels.

The another most widely used statistical method is the grey level differences method (GLDM) introduced by Weszka et al. [Weszka76]. It estimates the probability density function for differences taken between picture function values.

Other statistical approaches include an autocorrelation function, which has been used for analysing the regularity and coarseness of texture by Kaizer [Kaizer55]. This function evaluates the linear spatial relationships between primitives. The set of autocorrelation coefficients shown below are used as texture features:

$$C\,(p,q) = \frac{MN}{(M-p)(N-q)} \frac{\sum_{i=1}^{M-p}\sum_{j=1}^{N-q} f(i,j) f(i+p, j+q)}{\sum_{i=1}^{M}\sum_{j=1}^{N} f^2(i,j)} \qquad (2.5)$$

where *p, q* is the positional difference in the *i, j* direction, and *M, N* are image dimensions.

Alternatively, the autocorrelation function can be determined in the frequency domain from the power spectrum method (PSM) of the Fourier transform [Castleman96]. Average values of energy of wedges or rings of Fourier spectrum can be used as features, shown in . Ring features measure coarseness or fineness, whereas wedge features measures directionality.

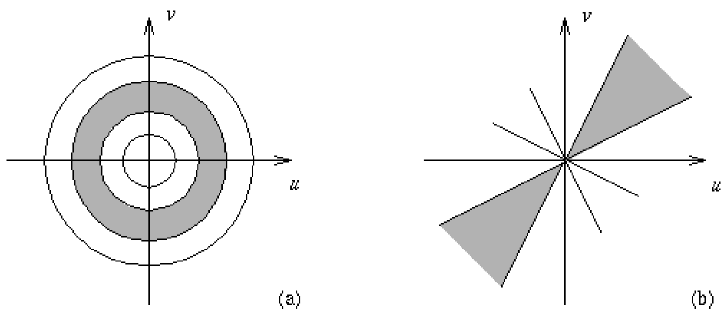

Figure 2. 4 Partitioning of Fourier Spectrum. (a). ring Filter; (b). wedgy filter.

Grey level run length features were introduced by Galloway [Galloway75], they estimate the length of identical runs where an identical run is defined as a set of connected pixels having the same grey level. The element *r(I, j|θ)* of the grey level run length matrix specifies the number of times a picture contains a run of length j for grey level i in the angle θ direction. Tang [Tang98] demonstrated that textural features extracted from a new run-length matrix can produce improved classification results over traditional run-length techniques.

- ***Geometrical model***

The geometrical models of texture are based on the view that textures are made up of primitives with geometrical properties, In these models, it is common either to compute statistical features, or to identify the placement rules that describe the texture. These structural methods model textures as consisting of primitives that appear in certain patterns. A texture is then defined by these primitives and some displacement rules [Rosenfeld70]. In general, it is difficult to extract these elements from a real textures. Structural methods may also be used for texture synthesis.

The primitives may be extracted by edge detection with a Laplacian-of-Gaussian or difference-of-Gaussian filter [Tuceryan90], by adaptive region extraction [Tomita90], or by mathematical morphology [Matheron75] [Serra73]. Once the primitives have been identified, the analysis is completed either by computing statistics of the primitives (e.g. intensity, area, elongation, and orientation) or by deciphering the placement rule of the elements [Fu82].

The structure and organisation of the primitives can also be presented using Voronoi tessellations [Tuceryan90]. Image edges are an often used primitive element. Davis et al. [Davis81] defined generalised cooccurrence matrices, which describe second-order statistics of edges. Dyer et al. [Dyer80] extended this approach by including the grey levels of the pixels near the edges into the analysis. An alternative to generalised cooccurrence matrices is to look for pairs of edge pixels, which fulfil certain conditions regarding edge magnitude and direction. Hong, Dyer and Rosenfeld [Hong80] assumed that edge pixels form a closed contour, and thus extracted primitives by searching for edge pixels with opposite directions (i.e. they are assumed to be on the opposite sides of the primitive), followed with a region growing operation. Properties of the primitives (e.g. area and average intensity) were used as texture features.

- ***Model-base methods***

Model-based texture methods try to capture the process that generated the texture. With model-based features, some image model is assumed, its parameters estimated for a subimages, and the model parameters or attributes derived from them , are used as features. There are currently three major model based methods: Markov Random Fields (MRF) by Dubes and Jain [Dubes89], fractals by Pentland [Pentland84], and The multi-resolution autoregressive (AR) features introduced by Mao and Jain [Mao92]. For detailed discussions of image models see Kashyap [Kashyap86], and Chellappa et al. [Chellappa93].

Features extracted from Markov random fields are both descriptive and generative. Thus they have been found to be very useful for texture classification, image segmentation, and other applications by Khotanzad and Kashyap [Khotanzad87]. Random field models analyze spatial variations in two dimensions. Global random field models treat the entire image as a realization of a random field, whereas local random field models assume relationships of intensities in small neighbourhoods. A widely used class of local random field models type are Markov random field models .The Markov Random Fields model for texture assumes that the texture field is stochastic and stationary and satisfied a conditional independence assumption.

The auto-regression model provides a way to use linear estimates of a pixel's grey level, given the grey levels in the neighbourhood containing it. For coarse textures, the coefficients will all be similar. For fine textures, the coefficients will vary widely. Various types of models can be obtained with different neighbourhood system. One-dimensional time-series models, autoregressive (AR), moving-average (MA), and autoregressive-moving-average (ARMA), model statistical relationships by

McCormick & Jayaramamurthy [McCormick74], and Box [Box76]. General class of 2D autoregressive models has been applied for describing textures and subsequent recognition and classification by [Sarkar97]. The power of the auto-regression linear estimator approach is that it is easy to use the estimator in a mode that synthesises texture from any initially given linear estimator. Its weakness it that the textures it can characterise are likely to consist mostly of micro textures.

Mandelbrot [Mandelbrot83] proposed describing images with fractals, a set of self-similar functions characterized by so-called fractal dimension, which is correlated to the perceived roughness of image texture [Pentland84]. In contrast to autoregressive and Markov models, fractals have high power in low frequencies, which enables them to model processes with long periodicities. An interesting property of this model is that fractal dimension is scale invariant. Several methods have been proposed for estimating the fractal dimension of an image [Keller89] [DuBuf90]. Fractal models of surfaces have been employed in image analysis where the objects are rough, irregular, and multi-scale such as cloud, trees and natural textures [Huang90] [Peli90].

- ***Signal processing***

Signal processing methods perform frequency analysis of the textures. This is achieved by using spatial filters or through filtering in the frequency domain. Randen [Randen99] presented a comparative study of filtering for texture classification. Some well known signal processing method are based on Law's Filter [Law80], Gabor filters [Bovik90] [Jain91], and pseudo-Wigner distribution [Jacobson82].

Laws [Law80] observed that certain gradient operators such as Laplacian and Sobel operators accentuated the underlying microstructure of texture within an image. This was the basis for a feature extraction scheme based on a series of pixel impulse response arrays obtained from combinations of 1-D vectors shown in *Figure 2. 5*.

Level	L5 =	[1	4	6	4	1]
Edge	E5 =	[-1	–2	0	2	1]
Spot	S5 =	[-1	0	2	0	–1]
Wave	W5 =	[-1	2	0	–2	1]
Ripple	R5 =	[1	–4	6	–4	1]

Figure 2. 5 Five 1-D arrays identifed by Laws.

For each mask, a texture feature is extracted using the following steps:

- convolve the image with the mask (i.e., position the mask at each pixel, compute the sum of products of mask elements and corresponding pixel values, and then assign the sum to the central pixel).
- compute the average of the squared values at all pixels in the convolved image (except border pixels)
- the average value is saved as the texture feature.

Law's energy filters are tested in texture classification by Pietikainen [Pietikainen82], Greenhill and Davis [Greenhill93], DuBuf [DuBuf90], et al.

Another class of spatial filters are moments, which correspond to filtering the image with a set of spatial masks. The resulting images are then used as texture features. Tuceryan [Tuceryan92] used moment-based features successfully in texture segmentation. Multi-resolution analysis, the so-called wavelet transform, is achieved by using a window function, whose width changes as the frequency. If the window function is Gaussian, the obtained transform is called the Gabor transform [Bovik87].

A two-dimensional Gabor filter is sensitive to a particular frequency and orientation. An example of a Gabor filter in spatial domains is given in *Figure 2. 6.*

Other spatial/spatial-frequency method includes the pseudo-Wigner distribution introduced by Jacobson and Wechsler [Jacobson82]. Texture description with these methods is performed by filtering the image with a bank of filters, each filter having a specific frequency (and orientation). Texture features are then extracted from the filtered images. For a detailed discussion on spatial/spatial-frequency methods see Reed and Wechsler [Reed90].

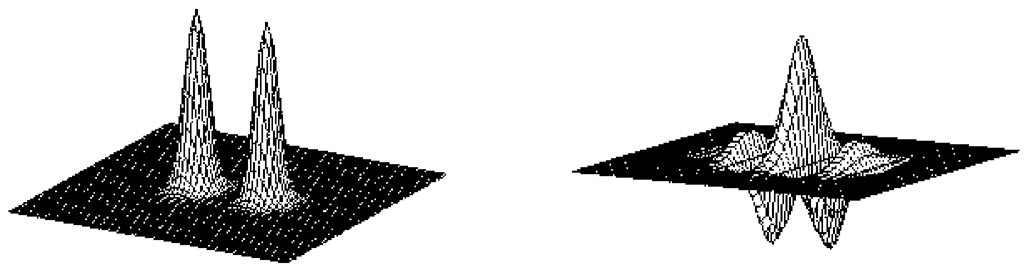

Figure 2. 6 A directional Gabor filter in the frequency (left) and spatial(right) domains

2.3. Image Rotation Invariant Features

2.3.1. Introduction

Our problem associated with texture classification is the task of identifying an isotropic or directional texture at different surface orientations. Unfortunately most techniques assume that the textures are captured from the same viewpoint. This is an unrealistic assumption in the real world. Robust rotation invariant features are the need of the day [Tan95]. In many applications, it is very difficult and impossible to ensure that surfaces captured have the same rotations between each other and such an assumption is rather restrictive in many practical applications. Therefore we consider rotation invariant texture features.

Numerous approaches have been developed that use rotation invariant texture features. A review of invariant texture features can be found on [Porter97] [Fountain98] [Zhang2002a] [Chantler94a]. As it is very difficult to include all the work in such a review of rotation invariant features. Major representative work can be divided into two categories:

- statistical methods;
- model based method and

2.3.2. Statistical Methods

With statistical methods, the stochastic properties of the spatial distribution of grey levels in an image are characterised. Many of the methods are based on the fact that the human visual system uses statistic features for texture discrimination, which are broadly classified into first-order statistics, second-order statistics, and higher-order statistics.

The simplest rotation invariant image statistics are the mean value, variance of the pixel intensities and intensity histogram. However they are very poor in performance, as there is a limited amount of textural information contained within them. More reliable rotation invariant image statistics are moment invariant firstly introduced by Hu [Hu62]. In addition, it is demonstrated by Wang and Healey [Wang98] that Zernike moments perform well in practice to obtain geometric invariance. In their method, Zernike moments of multispectral correlation functions characterise the texture. The classification accuracy rate is reported to be up to 100% for their database which contained seven textures.

The approach was adopted by Haralick [Haralick73] 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 characterisation of the directionality of the texture, whilst avoiding a dependence upon the texture orientation.

Polarogram introduced by Davis [Davis81] 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.

Rotation invariant texture classification is achieved by Alapati and Sanderson [Alapati85] by filtering input images with a set of 2D complex filters which are rotation invariant. Such filters have been known as circular harmonic function filters. The response profile of each circular harmonic filter is polar separable. The algorithm is tested on only four textures from the Brodatz database [Brodatz66] and achieves a classification accuracy of *90%.*

You and Cohen [You93] 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 [Brodatz66]*,* the amount of training to tune the masks is significant.

2.3.3. Model Based Methods

In addition to statistical rotation invariant methods, another approach to the problem is to apply a model to the texture image and then to derive a classification algorithm from the model. In most statistically oriented techniques, the image is modelled as a Markov Random Field (MRF) of pixels. In these approaches, the relationships between the intensities of neighbouring pixels are statistically characterised. These are computationally intensive compared to feature based approaches. The challenge is how to achieve rotation invariant schemes. 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. To identify the class of an arbitrarily rotated sample, the likelihood function associated with the Fourier transform of the image data is maximised 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 [Cohen91] modelled textures as Gaussian Markov random fields (GMRF) and used the maximum likelihood method to estimate the rotation and scale parameter. Their model essentially parameterises a planar texture model based on second order statistics with three-dimensional spatial parameters. Wu and Wei [Wu96] have use a 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 subbands, 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 [Cohen91] [Chen95]), 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 [Chen95].

Kashyap and Shotanzad [Kashyap86] 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 [Mao92] 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. Haley and Manjunath [Haley96] 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 [Leung92]. 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 [Greenspan94] 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. [Pietikainen00] 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. [Ojala00] showed that such an approach is much more challenging. We have therefore followed the second principle in this thesis. Recently, Pietikainen and Ojala [Pietikainen00] introduced a set of related measures, including two local centre-symmetric auto-correlation 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 presented in this section are not comparable each other, since they use different texture data as test and training set.

However, it should be noted that the above classifications are performed using image rotations rather actual physical surface rotation. The objective of this thesis is to analysis surface rotation invariant texture classification. We will discuss surface rotation invariant features in the next section.

2.4. Surface Rotation Invariant Features

Leung and Malik present a classification system which is trained on textures that are each imaged under 20 different illumination and orientation conditions [Leung99]. Their textures were obtained from the Columbia-Utrecht Reflectance and Texture Database [Dana99b]. Such natural textures arise from spatial variation of two surface attributes: (1) reflectance and (2) surface normal. The main idea is to construct a vocabulary of prototype tiny surface patches with associated local geometric and photometric properties. They call these 3D *textons*. This generalises 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 [Dana99a].

Varma and Zisserman [Varma02] [Varma02a] present a classification method which is based on the statistical distribution of filter responses in a low dimensional space. They perform their texture classification from a single image acquired with both unknown viewpoint and illumination directions. Therefore, the classification results achieved via clustering are comparable to the results achieved by using the PDF and that representing a texture by its distribution of texture elements (*textons*) is not detrimental to classification. They also demonstrate that it is possible to reliably measure a rotationally invariant co-occurrence orientation statistic.

Smith also uses 3D surface texture information directly [Smith99a]. He uses photometric stereo to acquire surface gradient information and suggests the use of features derived from the gradient space (including attitude, principal orientation, shape factor, and shape distribution) for the "quantitative analysis of repetitive surface textures". He does not go as far as applying this approach to the task of classification of rough surfaces using a conventional classifier - although it would be very interesting to see the results on the detection of surface faults. His method is summarised below in *Figure 2. 7*. We note, however, this still includes a directional filtering effect and suppression of a significant amount of surface information.

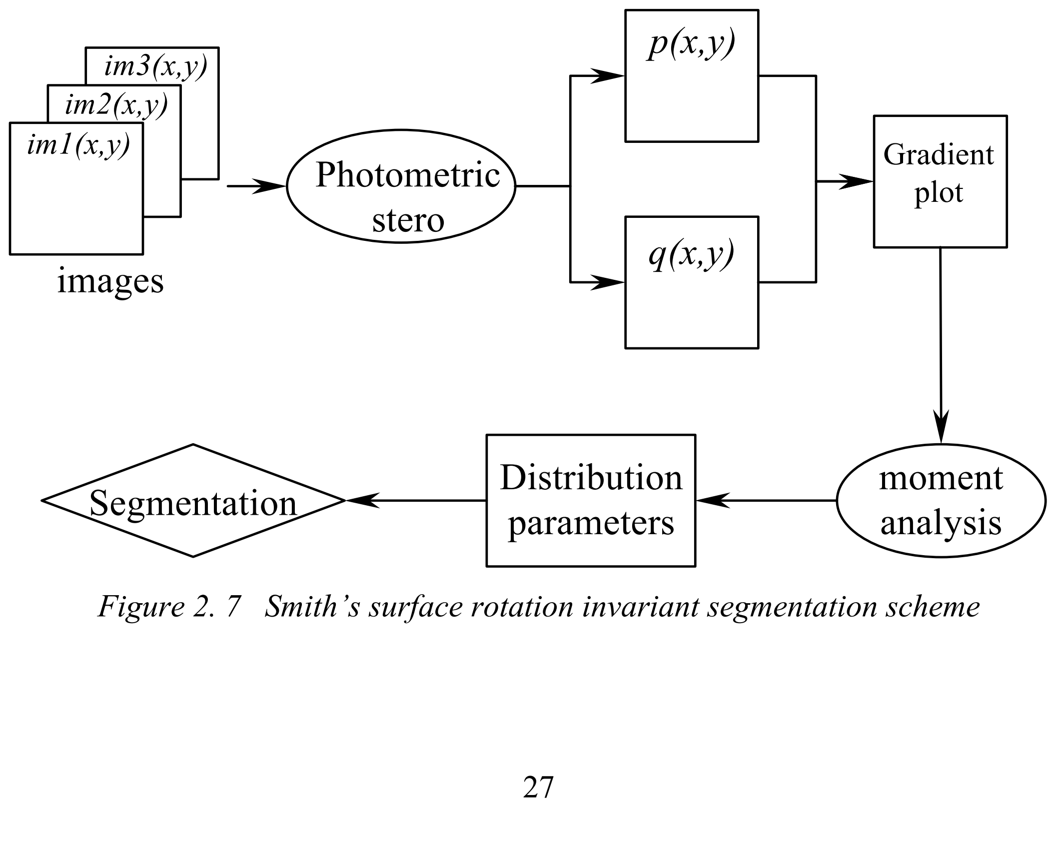

Figure 2. 7   Smith's surface rotation invariant segmentation scheme

McGunnigle and Chantler [McGunnigle97] [McGunnigle98] have developed a novel approach to classification. It uses photometric stereo to determine the surface gradients. Their work is very important as it separately verified that simple three-point photometric methods are effective at separating albedo patterns from surface gradient information. This will enable classification to be performed by comparing texture features computed directly from surface properties rather than image intensity values. Thus they can for instance compare surface relief against surface relief rather than pixel patterns against image data. The scheme was not rotation invariant. Later they proposed another photometric-based system, however, this time the gradient information was directly filtered using isotropic Gabor filters to provide a rotation insensitive scheme [McGunnigle99a].

2.5. Summary

In this chapter, the survey of rotation invariant texture classification is presented. Before we discuss the texture analysis and rotation invariant texture feature, some definitions of texture, surface relief and albedo are given.

Our problem associated with texture classification is the task of identifying an texture at its different surface orientations. Therefore, a general survey of texture feature analysis and particular rotation invariant feature analysis are given respectively. We note that most of rotation invariant feature methods are based on image rotation rather than physically surface rotation, where our main interest exists. Furthermore, most of approaches discussed above assume that images are captured in a frontal-parallel setup so that rotation only occurs around the optical axis, and there are few methods in which the effect of changing illumination conditions are taken into account.

In *Chapter 3*, the process form surface to image is presented, which enables us to estimate surface properties but image properties using photometric stereo in *Chapter 4*. Furthermore the gradient space is introduced in *Chapter 5*. Therefore we may propose a rotation invariant texture classification scheme based on the features of polar spectra on gradient spectra in *Chapter 6*.