6.0 Introduction

Texture is a basic cue for Human Visual System (HVS) to recognize many kinds of objects. The previous chapter proposed a foundational idea for decamouflaging through texture analysis using line masks. The chapter elaborated on the design of line masks for capturing different linear orientations present in the underlying texture. The design process clearly portrayed the complexity involved in generating line mask kernels for all orientations. As the orientation requirement becomes finer, the size of the kernel thoroughly increases. This increase in size of the kernel leads to higher computational complexity. Apart from the complexity the variation in the size of the kernel in accordance to the orientation poses a limitation on generalization.

Recently Pradeepkumar and Nagabhushan (2006) elaborately analyzed the process of knowledge extraction at multiple resolutions and showed that when a data is explored at multiple scales/resolutions tremendous amount of information or knowledge could be extracted. This chapter attempts at adopting these proposed views on multiresolution analysis. Thus the chapter converges to extract texture descriptors at multiple resolutions in addition to the orientation information which was dealt in the previous chapter. The crucial aspects of this extension would be the following:

* Some parts of the material in this chapter appear in the following research paper: Decamouflaging using Gabor-Histogram features, (Under the Process of Communication)
1. Extraction of good features for texture discrimination.
2. Smoothing the feature space using the multichannel anisotropic flow\(^1\).
3. Multiresolution analysis by studying non-linear multiscale\(^*\) feature spaces.
4. Dealing with vast amount of resolutions and orientations.

In recent times Gabor filter has been used for texture analysis and it is supposed to possess most of the above characteristics. This chapter proposes to represent the texture characteristics through descriptors extracted from Gabor coefficients. Although Gabor based approaches for texture analysis is very common and found in many literatures, the mystery behind dealing with the vast amount of Gabor bands is still unexplored. In most cases, a single energy descriptor is extracted from each band which is an over summarized component to characterize the texture information present in the bands. These over summarized energy descriptors would perform poorly when it comes to applications like decamouflaging which requires finer and deeper analysis. Although certain literatures propose to characterize the Gabor bands with histogram descriptors the amount of computation involved with histogram data structure had always limited them to few number of bands with constrained number of scales and angles. Once the number of bands is limited, the dramatic advantage provided by Gabor filters cannot be exploited to the fullest extent. In this chapter, it is proposed to characterize the Gabor coefficients of each band with a histogram and then apply histogram principal component analysis for reducing the dimensionality of the histogram feature set. The experimental analysis portrays that the information gathered in huge number of Gabor bands can be characterized by few number of principal component histograms. These few number of principal component histograms can be then used for decamouflaging through clustering approaches. As discussed earlier, it is a two class problem with one set of samples belonging to camouflage group and the remaining set to non-camouflaged group.

\(^1\) Direction dependent flow based on multiple features
\(^*\) Features extracted at different scales
The rest of the chapter organized as follows. In section 6.1, we introduced the Gabor filter. In section 6.2, we portray the Gabor filter for texture analysis: state of the art. Section 6.3 discussed the proposed model through histogram and PCA. In section 6.4 experimentation analysis is illustrated. Chapter concludes in section 6.5.

6.1 Gabor Filters: A Brief Introduction

The Gabor function can be implemented as a multi-channel, wavelet-like filter, which leads to:

$$W_r(a, \theta, x_0) = a^{-1} \int \int f(x) \Psi_\theta(\frac{a^-1(x-x_0)}) \, dx$$

where ‘a’ is the dilatation parameter, $x_0$ the spatial translation parameters and $\theta$ the orientation parameter of the wavelet.

Fig 6.1: An ensemble of Gabor wavelets; the spatial frequency plane (left); half peak magnitude of the filter response (right).

A particular Gabor elementary function can be used as the mother wavelet to generate a whole family of Gabor wavelets.

The examples of a particular class of 2D Gabor wavelets are presented in Fig 6.1. Using this 2D Gabor-wavelet transform, images are decomposed into several channel outputs. For a given image $I(x,y)$, the decomposed image at scale $m$ and orientation $n$:

$$W_{mn}(x,y) = \int I(x,y) \cdot \Psi_{m,n}(x-x_1, y-y_1) * dx_1 dy_1$$

where * indicates the complex conjugate.
6.2 Gabor for Texture Analysis: State of the Art

Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. One immediate application of image texture is the exploration of image regions for existence of camouflaged objects using texture properties. Texture is the most important visual cue in identifying these types of homogeneous regions. This is called texture classification. The goal of texture classification then is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs to. We could also find the texture boundaries even if we could not classify these textured surfaces. This is then the second type of problem which attempts to solve texture segmentation. This section reviews a vast amount of literatures that has dealt with texture analysis using Gabor filters.

Inspired by the multi-channel operation of the Human Visual System for interpreting texture, research has been focused on using a multi-channel approach based on Gabor filtering to mimic the operation of HVS for identifying different texture regions. Hammouda and Jemigan (2000) attempt to employ this multi-channel approach in order to gain insight into the ability of this methodology in solving the texture segmentation problem.

Kruizinga et.al (2002) extract features based on the local spectrum which is obtained by a bank of Gabor filters. They evaluate the performance of a number of texture feature operators using a quantitative method which is based on Fisher's criterion. It is shown that, in general, the discrimination effectiveness of the features increases with the amount of post-Gabor processing.

De Bonet and Viola (1998), describe a technique for using the joint occurrence of local features at multiple resolutions to measure the similarity between texture images. Though superficially similar to a number of “Gabor” style techniques, which recognize textures through the extraction of multi-scale feature vectors, their approach is derived
from an accurate generative model of texture, which is explicitly multiscale and non-parametric. The resulting recognition procedure is similarly non-parametric, and can model complex non-homogeneous textures.

It is generally agreed that the conventional Trans-Rectal Ultrasound (TRUS) examination is an important, cost-effective and useful technique for imaging the prostate (De-Bonet and Viola, 1998). TRUS is used in the interpretation of the prostate-specific antigen (PSA) test, for monitoring response to non-surgical and surgical therapy, and for providing image guidance during some minimally invasive procedures. By processing the TRUS images using multiple resolution techniques, the image is decomposed into appropriate texture features that can be used to classify the textures accordingly.

Chen et al (2004), widely used Gabor filters to extract texture features from images for image retrieval. A number of parameters (number of scales and orientations and filter mask size) were used in the Gabor Filter. In their paper, they investigate the effects of different Gabor filter parameters on texture retrieval.

Dennis (1992) devised a new, more effective, more rigorously based method for determining Gabor-filter parameters. The method is based on an exhaustive, but efficient, search of Gabor-filter parameter space and on a detection-theory formulation of a Gabor filter's output. They provide qualitative arguments and experimental results indicating that their method is more effective than other methods in producing suitable filter parameters.

Boutros (1993) in his dissertation developed effective algorithms for texture characterization, segmentation and labeling. These representations are an analog of the spatial frequency tuning characteristics of the visual cortex cells. The Gabor function, of all spatial/spectral signal representations, provided optimal resolution between both domains. A discussion of spatial/spectral representations focused on the Gabor function and the biological analog that exists between it and the simple cells of cortex. George demonstrates a simulation generated examples of the use of the Gabor filter as a line detector with synthetic data.
The ability to segment a textured image into separate regions (texture segmentation) continues to be a challenging problem in computer vision. Many texture-segmentation schemes are based on a filter-bank model, where the filters (henceforth referred to as Gabor Filters) are derived from Gabor elementary functions. The goal of these methods is to transform texture differences into detectable filter-output discontinuities at texture boundaries. Then, one can segment the image into differently textured regions. Distinct discontinuities occur, however, only if the parameters defining the Gabor filters are suitably chosen.

Gabor filters have been successfully employed by Weldon et al (1994), in texture segmentation problem. They first present a multichannel paradigm that provides a mathematical framework for the design of filters. The paradigm establishes a relationship between the predicted texture-segmentation error, the power spectrum of the texture, the parameters of the Gabor filters, the parameters of subsequent Gaussian post filters, and the predicted vector output statistics of multiple filter channels. Using these mathematical relationships, they develop a Gabor filter design procedure based on selecting the set of filters associated with the lowest predicted texture-segmentation error. They also include a classifier design and post processing methods to provide a complete texture segmentation system.

Most investigators used bank of Gabor filters, where the filter parameters were predetermined adhoc and not necessarily optimized for particular task. Other investigations have proposed using filters turned to dominant components in the FFT of constituent textures. Weldon et al (1994) propose the design of a single Gabor filter to segment multiple textures based on Rician distributions (Karlsen et al, 1999) at two different scales of the Gabor filter envelope.

Puzicha et al (1999), introduced a novel statistical mixture model for probabilistic grouping of distributional (histogram) data. Adopting the Bayesian framework, they propose to perform annealed maximum a posterior estimation to compute optimal clustering solutions. In order to accelerate the optimization process an efficient multiscale formulation is developed. They present a prototypical application of this
method for the unsupervised segmentation of textured images based on the local distributions of Gabor coefficients.

Haley and Manjunath(1995) proposed a method of rotation invariant texture classification based on a joint space-frequency model. Multiresolution filters, based on a truly analytic form of a polar 2-D Gabor (1946) wavelet, are used to compute spatial frequency-specific but spatially localized microfeatures. These microfeatures constitute an approximate basis set for the representation of the texture sample. The essential characteristics of a texture sample, its macrofeatures, are derived from the statistics of its microfeatures. A texture is modeled as a multivariate Gaussian distribution of macrofeatures. Classification is based on a rotation invariant subset of macrofeatures.

In the paper of Tsai et.al(2005), a Gabor filtering approach for the automatic inspection of defects in coloured texture surfaces is proposed. They propose an approach to simultaneously measure both chromatic and textural anomalies in an image. Two chromatic features derived from the CIE-L*a*b* colour space were used to form a complex number for colour pixel representation. The proposed method was based on the energy response from the convolution of a Gabor filter with the colour image characterized by two chromatic features in the form of a complex number. The Gabor filtering process converts the difficult defect detection in a coloured texture image into simple threshold segmentation in the filtered image.

Clausi and Deng(2005) proposed a design-based method to fuse Gabor filter and grey level co-occurrence probability (GLCP) features for improved texture recognition. The fused feature set utilizes both the Gabor filter's capability of accurately capturing lower and mid-frequency texture information and the GLCP's capability in texture information relevant to higher frequency components. The fused feature sets are demonstrated to produce higher feature space separations, as well as higher segmentation accuracies relative to the individual feature sets.

The foundational work that was carried out in the previous chapter for designing the line masks and the vast survey of Gabor literatures for texture analysis laid a strong motivation to use Gabor filters for decamouflaging based on texture discrimination. As
Decamouflaging requires ample amount of finer information, the Gabor coefficients were modeled as distribution type features in order to minimize the information loss during characterization. The following section broadly discusses the proposed model for decamouflaging using these distributional features.

6.3 Proposed Model

At first, the proposed model makes use of the inferences that were derived in previous Chapters 2, 3 etc, which emphasized the need for finer analysis of the image for decamouflaging. It can be recollected that the image was fragmented into smaller non-overlapping blocks before performing further analysis. Then the image blocks were subjected to feature extraction and were analyzed for classification into camouflaged or non-camouflaged blocks. Even in this proposed model the image is initially fragmented into smaller blocks for finer analysis.

The LxL image blocks obtained after image fragmentation are then passed through a bank of Gabor filters as portrayed in the block diagram shown in figure 6.2. The output of each filter bank is a filtered image consisting of coefficients corresponding to certain scale and orientational parameters of Gabor filter. These filtered image blocks are then characterized using histograms. If the Gabor filter consists of N number of banks, then each block will be characterized by N number of histogram features.

As discussed earlier Gabor filters have the ability to extract the texture information at various orientations and scale. Thus the increase in the number of orientations and scales would correspondingly result in the increase of the number of bands. This would increase the number of histogram features.

The earlier chapters emphasized that decamouflaging requires finer analysis of textures for detecting the presence of obscured objects. The finer analysis demands for investigation of textures with large number of orientations and scales. This results in massive number of filtered image blocks and correspondingly histogram features. As mentioned before, extraction of single valued features (like energy descriptor) from each band would result in loss of information which is not fine with a decamouflaging
application. This is the reason behind choosing histogram features so that maximum amount of information present in the filtered image blocks can be characterized. The real challenge in dealing with such a situation is because each of these blocks are characterized by huge number of histogram features. It is here we propose to use the recently introduced histogram principal component analysis for reducing the dimensionality of histogram features.

A thorough analysis has been performed on histogram PCA and Gabor outputs with the image shown in figure 6.3 (a) for illustration. The image was split into 16 blocks as shown in figure 6.3(b) and passed through Gabor filter banks at scales 2, 4, 8, 16, 32 and orientations $0^\circ$, $45^\circ$, $90^\circ$, $135^\circ$ and $180^\circ$. The filtered outputs at different scales and orientations are shown in figure 6.3(c) to (z) and (a1) to (h1) for different blocks along with their corresponding histograms.
Decamouflaging using Gabor-Histogram Features

Fig 6.2 Gabor-Histogram feature based proposed model
Decamouflaging using Gabor-Histogram Features

Fig 6.3 (a) Sample Image

(b) Image split into 4x4 blocks

c) Block-1 Gabor output, (d) Gabor Histogram features

e) Block-2 Gabor output, (f) Gabor Histogram features
Decamouflaging using Gabor-Histogram Features

(g) Block-3 Gabor output, (h) Gabor Histogram features

(i) Block-4 Gabor output, (j) Gabor Histogram features

(k) Block-5 Gabor output, (l) Gabor Histogram features

(m) Block-6 Gabor output, (n) Gabor Histogram features
Decamouflaging using Gabor-Histogram Features

o) Block-7 Gabor output, (p) Gabor Histogram features

q) Block-8 Gabor output, (r) Gabor Histogram features

s) Block-9 Gabor output, (t) Gabor Histogram features

u) Block-10 Gabor output, (v) Gabor Histogram features
Decamouflaging using Gabor-Histogram Features

w) Block-11 Gabor output, (x) Gabor Histogram features

y) Block-12 Gabor output, (z) Gabor Histogram features

a1) Block-13 Gabor output, (b1) Gabor Histogram features

c1) Block-14 Gabor output, (d1) Gabor Histogram features
Thus the image sample shown in figure 6.3(a) has been fragmented into 16 blocks and each block is characterized by 25 histograms corresponding to 25 Gabor bands (5 scales and 5 angles). Analyzing such high dimensional feature is computationally non-trivial. Thus the histogram feature set needs to be subjected to dimensionality reduction. This model proposes to make use of histogram principal component analysis for dimensionality reduction of histogram features. Before proceeding further with the discussion of Histogram PCA results, the theory behind histogram PCA is introduced briefly (Nagabhushan and Pradeep Kumar, 2006). The details of arithmetic available in the work of Pradeep Kumar and Nagabhushan (2006).
6.3.1 Histogram PCA†

Problem Statement

There are m samples in n-dimensional space. Each feature $f_i$ of sample $j$ is of histogram type (symbolic distribution type), i.e., $f_{ij} = H$ where $1 \leq j \leq m$ and $1 \leq i \leq n$. It is required to transform the given n-d histogram features $f_{ij}$ to n-d histogram features $F_{ij}$ where $F = T(f)$. Here $T$ represents a feature transformation function which generates the principal components. Each histogram feature is constituted with $B$ number of bins.

Computational Aspect

For describing the computational details of principal component method on histogram data set let us consider an original space of 2-d data set $D$.

$$f_1 \quad f_2$$

Let $D = S_1 \quad H_{11} \quad H_{12}$

$S_2 \quad H_{21} \quad H_{22}$

where $S_1$ and $S_2$ are the samples and $f_1$ and $f_2$ are the histogram features.

And let the resultant principal component data set scores be given as

$$F_1 \quad F_2$$

PCA Scores = $S_1 \quad H_{11}^* \quad H_{12}^*$

$S_2 \quad H_{21}^* \quad H_{22}^*$

where $S_1$ and $S_2$ are the samples and $F_1$ and $F_2$ are the principal component histogram feature.

† I would like to express my sincere thanks to Mr R Pradeep Kumar and Dr P Nagabhsuahn for their kind co-operation and oblige to make use of the Histogram arithmetic concept which was developed by them. To understand this I had spent some time with Mr R Pradeep Kumar. In this context I would like to thank Dr A Shanmugam, Principal, BIT, Sathyamangalam India, for kindly allowing me to stay in the campus and interact with his colleague Pradeep Kumar, Assistant Professor, Department of Information Technology during the preparation of the manuscript of the thesis.
The variance and covariance of the 2-d data set are computed. Let matrix $A$, be the variance – covariance matrix. The covariance function is defined as

$$A = \text{VarCov}(D) = \begin{bmatrix} E[(H_{11} - \mu_1)(H_{12} - \mu_2)] & E[(H_{12} - \mu_1)(H_{12} - \mu_2)] \\ E[(H_{21} - \mu_1)(H_{21} - \mu_2)] & E[(H_{22} - \mu_1)(H_{22} - \mu_2)] \end{bmatrix}$$

where $E$ is the expectation, $\mu_1$ and $\mu_2$ are mean histograms of $f_1$ and $f_2$ respectively.

$$\mu_1 = \frac{1}{2} * [H_{11} + H_{21}] \text{ and } \mu_2 = \frac{1}{2} * [H_{12} + H_{22}]$$

Let $X$ be a column histo matrix of eigenvectors and $\lambda$ be its corresponding histo vector of eigen values.

$$[A] [X] = \lambda [X]$$

Equation (6.3) can be rewritten as

$$[A - \lambda I] [X] = 0$$

where $I$ is an identity histo matrix of the size that of $A$. The solution of equation 6.4 can be obtained as follows:

$$\text{DET}(A - \lambda I) = 0$$

Since we are considering a 2-d data set, i.e. $A$ is 2 x 2 matrix, equation 6.3 gives $B$ (number of histogram bins) number of quadratic equations in $\lambda$. Let the roots of this quadratic equations be $\lambda_{1i}$ and $\lambda_{2i}$ corresponding to $i^{th}$ bin of histogram. Thus we obtain $B$ sets of ($\lambda_{1i}, \lambda_{2i}$).

Now corresponding to $i^{th}$ bin substituting $\lambda_{1i}$ in equation 6.4 and solving it gives eigen vectors of the form $V1 = a_{11}^{i} x1(i) + a_{12}^{i} x2(i)$ where $a_{11}^{i}, a_{12}^{i}$ are coefficients of the eigen vector of dimension 1 ($F1$) corresponding to $i^{th}$ bin.

Similarly corresponding to $i^{th}$ bin substituting $\lambda_{2i}$ in equation 6.2 and solving it gives eigen vectors of the form $V2 = a_{21}^{i} x1(i) + a_{22}^{i} x2(i)$ where $a_{21}^{i}, a_{22}^{i}$ are coefficients of the eigen vector of dimension 2 ($F2$) corresponding to $i^{th}$ bin.
Now corresponding to $i^{th}$ bin, if the first coefficient of the eigen vector $V_1$ is multiplied with the feature values of dimension 1, second coefficient with the feature values of dimension 2 and combination of the two gives the feature values in dimension 1 of the rotated co-ordinate system.

$$H_{11}^* = a_{11}^i H_{11}(i) + a_{12}^i H_{12}(i)$$
$$H_{12}^* = a_{21}^i H_{11}(i) + a_{22}^i H_{12}(i)$$

Similarly corresponding to $i^{th}$ bin, if the first coefficient of the eigen vector $V_2$ is multiplied with the feature values of dimension 1, second coefficient with the feature values of dimension 2 and combination of the two gives the feature values in dimension 2 of the rotated co-ordinate system.

$$H_{21}^* = a_{11}^i H_{21}(i) + a_{12}^i H_{22}(i)$$
$$H_{22}^* = a_{21}^i H_{21}(i) + a_{22}^i H_{22}(i)$$

For $n$ dimensional data the first principal component histograms represent the large percentage of the total scene variance and the succeeding components ($pc-2, pc-3,...pc-n$) contains a decreasing percentage of the scene variance. Furthermore, because successive components are chosen to be orthogonal to all previous ones, the data are uncorrelated. Most times, the first few principal components are good enough for classification, thus resulting in dimensionality reduction.

The dimensionality reduction that is achieved is demonstrated through the results shown in figure 6.4 (a) and (b).
Figure 6.4(a) and (b) show the variance histogram of principal component histograms of the histogram feature set extracted from the 25 bands. Both the figures try to portray the same inference with the axis value of figure 6.4(a) set to constant for all principal component variance histograms whereas in figure 6.4(b) the axis value is automatically
set in accordance to the values of the individual histograms. It can be clearly observed that the variance of the entire histogram feature set is accumulated in the first principal component histogram and the variances in the remaining principal component histograms are highly negligible. Thus with the first principal component histogram itself a good classification of the blocks into camouflaged and uncamouflaged categories could be achieved. Figure 6.5(a) shows the plot of the summed up variances of the variance histograms i.e. the individual variances of the bins in a histogram are summed up to obtain a single value. It can be noted that the variance of the principal component histograms reduces drastically from PCH1 to PCH25. The corresponding classification result obtained from the first 3 principal component histogram is shown in figure 6.5(b). It could be observed from the input image that the top left corner of the image had been purposefully camouflaged with a minute change in the texture and the dendrogram shown in figure 6.5(b) portray the decamouflaging of block 1 which corresponds to the camouflaged block.
Further in-depth analysis has been carried out on the performance evaluation of histogram principal component analysis with higher number of Gabor bands through experimentations. It can be observed in figure 6.6 that with the number of Gabor bands as high as 185 and correspondingly 185 histograms, the camouflaged block could be uncovered through the first few principal component histograms. The results presented in figure 6.6, table 6.1 and bar chart in figure 6.7 portray the effectiveness of the proposed model to characterize and deal with huge number of Gabor bands.

This model breaks the hurdle that was in place all these years to deal with larger orientational information and multiresolution information that Gabor was capable of producing. The distance matrix for hierarchical clustering was generated using piecewise histogram distance measure proposed in Chapter 2. As discussed in chapter 2, the regression based histogram distance measure drastically reduces the complexity of histogram distance computation.

Fig 6.5(b) Dendrogram for sample image
Decamouflaging using Gabor-Histogram Features

**Fig 6.6(a)** Scales: 1-5; Angles 0, 180; No of Bands: 10; Classification using first 3 PCH's of 10 PCH's

**Fig 6.6(b)** Scales: 1-5; Angles 0, 90, 180; No of Bands: 15; Classification using first 3 PCH's of 15 PCH's

**Fig 6.6(c)** Scales: 1-5; Angles 0, 45, 90, 135, 180; No of Bands: 25; Classification using first 5 PCH's of 25 PCH's
Decamouflaging using Gabor-Histogram Features

Fig 6.6(d) Scales: 1-5; Angles 0,30,60,90,120,150,180; No of Bands: 35; Classification using first 10 PCH's of 35 PCH's

Fig 6.6(e) Scales: 1-5; Angles 0,15,30,45,60,75,90,105,120,135,150,165,180; No of Bands: 65; Classification using first 10 PCH's of 65 PCH's

Fig 6.6(f) Scales: 1-5; Angles 0,10,20,30,40,50,60,70,80,90,100,110,120,130,140,150,160,170,180; No of Bands: 95; Classification using first 10 PCH's of 95 PCH's
Table 6.1 Summary of the results portrayed in Fig 6.6

<table>
<thead>
<tr>
<th>Orientation interval with 5 scale</th>
<th>#of Gabor bands</th>
<th>Dominant PCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 180</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>2 90</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>3 45</td>
<td>26</td>
<td>16</td>
</tr>
<tr>
<td>4 30</td>
<td>35</td>
<td>16</td>
</tr>
<tr>
<td>5 15</td>
<td>65</td>
<td>16</td>
</tr>
<tr>
<td>6 10</td>
<td>95</td>
<td>16</td>
</tr>
<tr>
<td>7 5</td>
<td>185</td>
<td>16</td>
</tr>
</tbody>
</table>

Fig 6.7 Summarized visualization of the results portrayed in Fig 6.6
6.4 Experimentation Results

Experiment 1: In this experiment a synthetic data set shown in Fig. 6.8(a) is considered. In Fig 6.8, V elements are camouflaged in U texture. The image is of size 256x256. It is decomposed into 4x4 blocks, each of size 64x64. The dendrogram obtained by using Ward's clustering algorithm is shown in Fig 6.8(c) for Gabor histogram features obtained from 25 bands and using 3 PCH’s. The defective blocks are 4 and 13. Each defective block is subjected to Quad-tree based segmentation and Fig 6.8(d) shows the camouflaged segment.

Fig 6.8 (a) UV Image, b) Decomposed into 4x4 blocks, (c) Dendrogram and (d) Segmented portion
Experiment 2: This experiment makes use of one more synthetic data set similar to the one presented in Fig. 6.8(a). The image is shown in Fig 6.9(a) with 1 (lower case L) elements camouflaged in 1 (numeral one) texture. The image is of size 128x128. It is decomposed into 4x4 blocks, each of size 32x32. The dendrogram obtained by the application of complete clustering algorithm is shown in Fig 6.9(c) for Gabor histogram features obtained from 35 bands and using 5 PCH’s. The defective blocks are 4, 7, 10, 11, 13 and 14. Each defective block is subject to Quad-tree based segmentation and Fig 6.9(d) shows the portion which is camouflaged.

Fig 6.9 (a) l(lower case L) and 1(one) Image, b) Decomposed into 4x4 blocks, (c) Dendrogram and (d) Segmented portion
**Experiment 3:** In this experiment, a pragmatic case study of a ceramic plate containing defect which was studied in (Boukouvalas et al. 1998, Song et al. 1996) has been considered. We have employed the Gabor model to successfully trace the defective region. The Image is decomposed into 4x4 blocks as shown in Fig 6.10(b). Each block is of size 50x50. For an image frame of size 200x200 shown in Fig. 6.10(a), 4x4 fragmented image blocks are generated. The Gabor principal components histogram feature set is obtained for 16 blocks using 35 Gabor bands. With the first 5 PCH's the samples were subjected to classification which resulted in two classes which shows 4 blocks in defective class and 9 blocks in normal class. The dendrogram in Fig. 6.10(c) shows that 6, 7, 8 and 9 are defective blocks. To trace the actual extent of defect, we have performed Quad-tree based segmentation (Gonzalez and Woods 2005) process on defective blocks. The Stretch of defect is mapped in Fig.6.10 (c).
Fig. 6.10(a) defective ceramic tiles with undulation, b) Decomposed into 4x4 blocks, c) Segmentation of Camouflaged portion and d) Dendrogram

**Experiment 4:** In this experiment, an interesting image frame which is a modified version of the image available in (John 1999) containing a boy face has been considered for analysis. The sample image is shown in Fig. 6.11(a). The image of size 256x256 is decomposed into 4x4 blocks each of size 64x64. The histogram feature set was obtained for all of these 16 blocks using 35 Gabor bands. The Ward linkage hierarchical clustering algorithm produced the dendrogram shown in Fig 6.11(c) only with the first principal component histogram. The defective block is the 11th one and the defect in this block is due to variations in shading patterns.
Fig. 6.11(a) Boy face Image, b) Decomposed into 4x4 blocks, c) Dendrogram and d) Segmentation of Camouflage portion

**Experiment 5:** In this experiment, an image consisting of an array of match boxes with two duplicate match boxes in 7\textsuperscript{th} and 9\textsuperscript{th} places (marked on image) was considered. The sample image is shown in Fig 6.12(c). The image decomposed into array of 16 blocks is shown in Fig 6.12(b). The decamouflaged output is portrayed through the dendrogram presented in Fig 6.12(a).
6.5 Conclusion

This chapter proposed an interesting approach to detect camouflaged/defective regions through texture analysis. The obscured camouflaged/defective portions were determined through Gabor filter which holds the multi resolution and multi orientation properties.
These properties of Gabor filters help in capturing the texture information at multiple bands. This chapter makes an important contribution by proposing a model through which an image/image blocks could be analyzed at huge number of orientations and scales. Characterizing huge number of Gabor bands without much information loss has been a great challenge all these days. This chapter proposed to make use of histogram principal component analysis technique for holding the entire set of information in few principal component histograms. The finer discriminatory features that are required for decamouflaging can be captured by analyzing the image/image blocks with Gabor filters designed with higher number of orientations. The experimentation results emphasize the potential of the proposed approach for decamouflaging.

Chapter 2 and 3 proposed models where the features/descriptors like mean, variance, histograms, higher order moments and zemike moments were capable of discriminating the camouflaged blocks based on gray level characterization. Then chapter 4 and 5 provided foundational methods using GLCM and Line Masks respectively for finer analysis of texture information. This chapter provided a means to accumulate the huge amount of finer information with few number of principal component histograms. It is clearly understood from the computational procedure of PCA that the eigen values and eigen vectors are important parameters to obtain the principal components. Thus in the next chapter we make an attempt to characterize these texture information through eigen features.