CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In computer vision, low level segmentation is considered to be a very important step in image analysis in order to understand its content. The major methods of low level segmentation use either edge-based or region-based approaches. Region-based approaches have been analyzed with un-textured or textured regions. In un-textured images, the underlying assumption is that the intensity of the pixel is uniform over a defined region whereas real life objects like abraded, worn surfaces, satellite and medical images often exhibit non-uniform gray level variation. They are textured images. Digital images are analyzed at two stages, namely, low level analysis and high level interpretation. Edge detection and Texture analysis are used for low level image segmentation. In high level interpretation, the features computed in earlier stages are used for effective classification and identification of shapes or regions. There are many algorithms and schemes suggested and used for edge based analysis whereas very few segmentation algorithms have been used for texture analysis. The reason for this is that no unique definition exists for texture. The researchers have viewed textures from their own perspectives and proposed algorithms for specific applications.

The main objective for any research problem in texture analysis is to find or extract the features. The features extracted by most of the schemes are global in nature. That is, they extract the overall characteristics of the texture present in the entire image.

An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of the primitives. Textures could be rated as coarse, micro, macro, regular, periodic, aperiodic, directional, random, or stochastic (Richards and Polit 1974). Existing popular approaches for texture analysis have been classified into statistical, structural, and spectral approaches (Gool et al 1983). Haralick's coocurrence matrix based features (Haralick 1979), Galloway's run length matrix based features (Galloway 1975), Tuceryan's (Tuceryan 1992) moment based features, Markov Random Field-based analysis (Chen 1988), Gabor filter-based approaches (Turner 1986), Rosenfeld's Fourier descriptor-based analysis (Weszka et al 1976), Voronoi polygon method (Tuceryan and Jain 1990) and Wavelet based methods (Arivazhagan and Ganesan 2005), cross diagonal texture matrix method (Al-Janobi 2001) have been used for texture analysis. Certain gradient operators such as Laplacian and Sobel operators accentuated the underlying micro structure of texture within an image has been presented by Laws (1980). Recently, cellular automata-based schemes are also used for image analysis (Chang et al 2004; Paul L. Rosin 2006). Texture representation and image retrieval based on power spectral histograms (Wang Chong-jun et al 2004) and a sparse texture representation using affine invariant regions (Svetlana Lazebnik et al 2003) have been reported in literature. These methods provide texture description for the entire image. A complete literature survey is presented in chapter 2 of this thesis.

Sometimes it may not be necessary to find the properties for the entire image but the region of interest may be small or local. It is better if some local descriptor is defined, represented and used for further analysis.

One of the schemes thus proposed by He and Li Wang (He and Li Wang 1990) was popular and used for many texture related applications.

Texture is defined as a structure composed of a large number of, more or less ordered, similar elements or patterns. Observable textures can be characterized by the primitives and placement rules (Ehrich and Foith 1978).

The notion of texture appears to depend upon three components. They are: some local ‘order’ is repeated over a region which is large in comparison to the order’s size. The order consists of the non random arrangement of the elementary parts and these parts are roughly uniform entries having approximately the same dimensions everywhere within the textured region.

In a digital image the main goal is to extract the local texture information of a neighborhood of pixels. He and Li Wang (He and Li Wang 1990) suggested that any gray level monochrome texture images can be conveniently represented by computing the occurrences of a small unit, called texture unit. Each texture unit is defined in an image region of size 3 x 3. Representing the intensity value of the central pixel as V_0 and intensity value of each neighboring pixel as $V_i\{i = 1, 2, \ldots,8\}$, the corresponding Texture Unit (TU) can be defined as a set containing eight elements. The intensity value of a central pixel is compared with those of eight neighbors. The result of comparison, namely, equal or less or greater is coded as 0,1 or 2. The decimal equivalent of these eight digit ternary number is obtained as the quantitative descriptor called texture number. The texture numbers have been computed for the entire image and used as the global descriptor, called the texture spectrum. There are 6561 texture numbers possible and hence the feature vector length is 6561 for a texture image using this approach.

In this proposal, small texture units are not tested for the presence of texture. i.e. whatever may be the texture units under consideration, their equivalent texture numbers are computed. Sometimes, even an un-textured image or regions could also be represented with the texture numbers and are used for further analysis without knowing that they are the results of un-textured images. The texture number scheme has been experimented with images collected from the Brodatz textural album (Brodatz 1966).

This scheme suffers in two aspects, namely, (i) the number of features are 6561 which is relatively higher and (ii) it does not take care of the relative strengths of the differences in magnitude while comparing the intensities of the centre pixel with those of neighboring pixels.

Alternatively, we propose a scheme with a set of primitives as local descriptors. The distribution of the primitives over the entire image is treated as the global descriptor. The main novelty of the scheme is that they are subjected to a statistical design of experiments test for checking the presence of texture before the primitives are included for the texture description. The entire proposal has been presented in the following chapters of this thesis along with the sample results of images collected from the standard texture images of Brodatz and VisTex (Vistex 1995) databases.

The main idea of our work is from the implied suggestion offered in Julesz 1981. It is reported in literature that Texture images can be generated by a set of primitives and their placement rules. Conversely any texture image, is identified or perceived if it consists of a set of texture primitives occurring regularly or randomly. If it is possible to find out the set of primitives and how they occur or are distributed in the entire image, then we can succeed in the representation of texture in the image. The distribution of the primitives can be quantitatively obtained from the computation of the frequency of occurrences of such primitives. The success of any texture analysis scheme is inferred from the way it captures the textural features and their uniqueness. Since the textural properties of texture images carry more useful information for discrimination purposes, it is important to develop features, for texture based on suitable quantitative representation of some of these properties. The frequency of occurrences of such primitives is computed for the entire image, and the representation becomes a global descriptor.

1.2 OBJECTIVES OF THE PROPOSED WORK

The primary motivation of the research work presented in this thesis is to find a systematic way of combining both statistical and structural approaches for the representation of texture and for further analysis. This is done to make use of the benefits of both the schemes for an effective and efficient way of texture representation locally as well as globally.

The objectives of this research work are as follows.

(i) To propose a set of texture primitives as local descriptor.

(ii) To check the presence of texture in each primitive by performing a statistical design of experiments based test and to obtain the global descriptor, namely, the frequency of occurrences of primitives over the entire image; this is the primitive spectrum.

(iii) To perform supervised and un-supervised texture classification by using the texture primitive spectrum.

(iv) To perform texture segmentation using the texture primitive spectrum both for deterministic and non-deterministic texture images.

(v) To perform effective analysis of skin images affected by various degrees of burn using the features of the primitive spectrums.

1.3 TEXTURE REPRESENTATION

The presence of texture is detected by proposing a new statistical design of experiments based method for representation of micro texture. This is obtained by the computation of significant orthogonal effects due to spatial variations of gray levels. It is shown that an image region is represented by a set of orthogonal polynomial and the computed orthogonal effects are divided in to two sets. The first set is considered to contribute towards the presence of texture and the second one is for the noise. A suitable mathematical model and statistical tests for detecting the texture presence are presented in detail in Chapter 3.

A linear 2 –D image formation system is usually considered around a Cartesian coordinate separable, blurring point – spread operator in which the image results in the superposition of the point source of impulse weighted by the value of the object. Expressing the object function in terms of derivatives of the image function relative to its Cartesian coordinates is very useful for analyzing the image in order to detect textures. Since a micro texture can be detected based on the local properties of the image, it is required that a local point spread operator is to be devised such that it is a Cartesian coordinate separable and a de-blurring operator.

1.3.1 Texture Description

Texture is defined as a structure composed of a large number of more or less ordered similar elements or primitives in an image. Textures normally range from micro to macro. A small image region which is a function of two spatial co-ordinates, is represented by a set of orthogonal polynomials (Ganesan and Bhattacharyya 1995). In this representation, the image region is considered to be a linear combination of un-correlated (orthogonal) effects due to spatial variations. The un-correlated effects due to the presence of textures have been separated successfully from those due to the presence of Gaussian noise. The presence of texture in the image region under analysis is detected on the basis of the strength of the appropriate orthogonal effects.

In order to characterize texture, the set of orthogonal effects is divided into two disjoint subsets, namely, the set of effects due to the presence of Gaussian noise and the set of interaction effects due to the presence of texture. The rationale behind this separation of effects is that in the presence of texture, the two spatial coordinates depend on each other.

The criteria for the separability of orthogonal effects due to noise from the effects due to texture can be tested by using the hypothesis that in the presence of texture, the mean square variances corresponding to the orthogonal effects due to the noise are, in fact, estimates of the same noise variance and therefore can be used as an estimate of error. These can be tested by computing their divergence in the average variance. If the computed divergence in the average variance is less than the corresponding tabulated value, it is concluded that the divergence is insignificant and the hypothesis is accepted. The method of computing the divergence and the significant values for the divergence of various degrees of freedom are given in Bishop and Nair, 1939.

1.3.2 Construction of Texture Primitives

A texture primitive TP_i, is defined as a set of more than two adjacent pixels having intensities from 0 to 255 connected by an attribute (attribute for example, having small varied gray levels or within a tolerable limit). The smallest primitive is a pixel only, having only one fixed attribute. So a minimum region of size 3 x 3 is considered in our work for constructing the texture primitives. With 3 x 3 image region the intensities of the selected pixels are varied to impart the designated attribute. Thus, pixels having the same attribute (or within a tolerance limit) contribute to the formation of the texture primitive. In other words, several primitives can be formed by combining different groups of pixels satisfying the attributes within the chosen region. With 3 x 3 image regions, a set of primitives are proposed as a set of maximum primitives. These primitives are labeled from TP_1 to $TP_{92.}$ The primitives are grouped in such a way that a minimum of three pixels are used for constructing the primitives. All the primitives which can be formed within 3 x 3 pixels by connecting three pixels are grouped first, followed by grouping four pixels and so on. Each different primitive thus formed is included in the set to form the maximum set of primitives and is labeled uniquely. Thus there are 92 texture primitives. They are presented in Figure 3.5.

1.3.3 Primitive Generation and Validation

The texture primitives are generated by the grouping of pixels having gray levels ranging from 0 to 255. The line joining in the primitives is considered to be adjacent and the intensities of these pixels are more or less same or well within a tolerable limit. These primitives are tested using the divergence principle to ensure the presence of texture as depicted already. Totally there are 600 such primitives considered for the test and the results of the qualifying tests are presented. More than four or five samples (by variation in the range of gray levels used for constructing the primitives) are generated for each primitive and totally 600 primitives are included for the validation test. Almost all the sample primitives we have considered pass the tests at different levels of significance. Around 80 % of these primitives pass the test at stringent condition i.e. at 1 % significant level. Another 15 % of the primitives pass the test at somewhat relaxed significance level, namely, at 5% significance level. And the remaining 5 % of the primitives pass the tests at more than 5 % significant levels. This implies that some primitives are less textured and hence the presence of texture is realized only when the stringent conditions are relaxed.

With the above experimentation, it may be concluded that these are the primitives which can be used as local descriptor for the texture presence. Using the set of primitives proposed, texture images have been generated by filling the regions with one or more primitives in an ordered manner. The process of generation of texture images and the sample placement rules are presented in Chapter 3 of this thesis.

1.4 LOCAL AND GLOBAL DESCRIPTOR

Any texture image may be considered to have the presence of the primitives already defined, in full or in part. Different textured images look different because the primitives may occur in different proportions. That is, various compositions of occurrences of the primitives make texture images look different. The distribution of the primitives in the entire image is considered as the global descriptor which can be quantified by computing the frequency of the occurrence of these primitives. The texture images are compared for the presence of each primitive occurrences. Since images have gray level variations from 0 to 255, primitives also have these variations. 3 x 3 image regions are considered from the top-left corner of the given image. The contents of the images are compared looking for the presence of any one of the primitives already defined. If there is a match, the corresponding frequency of occurrences is incremented by one. This process is repeated for the entire image. Finally, the frequency of occurrences of all the primitives in an image constitutes the primitive spectrum, which is a global descriptor. Since the occurrence of primitives in an image is different from that of another image, the primitive spectrums are unique.

While we look for a match of gray levels, sometimes the attributes do not match perfectly. In such circumstances, the gray level tolerances are applied. For each tolerance level, the occurrences of the primitives and hence the corresponding primitive spectrums are obtained.

A set of all texture primitives has already been defined. Images from both the Brodatz and the VisTex textural album have been considered for our experimentation. These images are of size 128 x 128. The primitive spectrums for these images have been obtained. Some of the results are presented in a later portion of the thesis, in Chapter 3. Each primitive spectrum will have totally N/3 x N/3 primitives theoretically, where N x N is the image size. For each image considered, the total number of possible primitives identified are computed. The experiments are repeated for a number of images. For each image, the total number of primitives at different tolerance levels have been computed.

The texture primitive spectrums for all the images are obtained. These primitive spectrums are obtained at different tolerance levels, namely, at 10, 20 and 30. As the tolerance levels get relaxed, the frequency of the occurrences of primitives in these spectrum increases. This is because, at a lower tolerance limit, if a primitive is not occurred, the same may get occurred when the condition on attribute is relaxed.

1.5 TEXTURE CLASSIFICATION

Using the proposed primitive spectrums as textural features, both supervised and unsupervised texture classifications have been carried out. Identification of a pixel or a region into any one of the known texture classes is texture classification. The primitive spectrum for a number of texture images of size 30*30 has been obtained and used as a feature library. The primitive spectrum of any unknown texture is compared by linear distance discrimination function with the library of spectrums. A minimum distance decision criterion is used and an average correct classification of 95 % has been obtained. The experiment gets repeated for a number of images from Brodatz and Vistex images, and for various tolerance levels. As the tolerance level increases, the classification accuracy also tends to reach a maximum of 100%. The classification accuracy has been compared with He and Li Wang's texture classification which yields 84 %. Since the length of the feature vector is 6561 in the earlier scheme compared to 92 in our work, naturally, the time complexity is reduced. (as proportional to order n).

In the supervised texture classification experiment 16 images are considered, 8 from each data base. Keeping the tolerance levels at 20, the corresponding primitive spectrums are obtained and form the reference feature vector. Each 30 x 30 region considered from any image, is subjected to classification. Correct classification and misclassification have been tabulated as the confusion matrix. This leads to an average correct classification of up to 95% .The experimentation gets repeated for different tolerance levels both for the Brodatz, and the Vistex images. It is observed that as the tolerance levels get relaxed the classification efficiency is improved. This is so because, the feature vector is accurate and hence the classification tends to be more accurate.

Within a texture region, the texture properties will be more or less uniform and they will be different when the regions are from two different textures. This principle is used for unsupervised classification. No prior information about the texture classes present in the target images was considered for the experiment.

As the proposed texture descriptor, the primitive spectrum contains important textural information; the same has been used as the feature vector during classification. The reference feature vector is considered here as the primitive spectrum of the texture class. Considered from the top left corner of the target image, window of a larger width (say, 30x30 size) is slid over the target image. For each (30x30) region selected, the primitive spectrum is computed. This primitive spectrum is subjected to a minimum distance classifier as the input feature vector is computed for the previous region. The texture class, that is assigned by the classifier to the input vector is the same as that of the previous one if the differences are zero or almost zero. This process gets repeated by considering the adjacent regions of the target image. The difference is obtained by comparing the feature vector of the present window and that of the previous window. If the difference is greater than a threshold, then a new region starts to form. Finally, when the entire target image is completely scanned, it gets classified into a number of regions. Thus, the proposed primitive spectrum has been successfully used for performing un-supervised classification.

In the classification experiment, four target images are considered, collected from Brodatz data bases and the results are presented in Chapter 4 of this thesis. An average correct classification of 95 % is reported.

1.6 TEXTURE EDGE DETECTION

In the proposed method, texture image is considered to consist of different texture primitives with regular or random placement. The texture images may be deterministic or non-deterministic. In the case of deterministic textures, texture images are considered to consist of different regions, each filled uniformly with a particular primitive. The texture primitives may be present randomly in the case of non-deterministic texture images. The edge detection between different textured regions is performed by adopting suitable techniques as proposed below.

1.6.1 Edge Detection in Deterministic Textured Images

Deterministic textured images have a few texture primitives filled uniformly within each region, i.e., each textured region within the texture image is filled with a particular texture primitive. The edge detection in this image aims to detect the boundaries present between the textured regions. If the conventional edge detection operators are applied, such as Roberts or Sobel edge operators like un textured images, the micro edges within each primitive will be identified. Because of the difficulty involved in identification of the boundaries between different textured regions by using the un- textured edge detection methods, a separate method is presented here for detection of edges in textured images.

In the previous sections, a set of texture primitives have been shown and they are labeled for local descriptor. The frequency of the occurrence of the primitives represents the global descriptor. Since the textured regions are filled with only by a particular primitive, by adopting a simple conversion between the primitive by the corresponding primitive number, we have only the primitive number array. However, the dimensionality of the array size is reduced three fold when compared with the original image size. Because each 3 x 3 image region is replaced with the corresponding number, only a single digit is used in place of a primitive. This primitive array looks like an array of numbers and the conventional edge detection operators can be applied to detect the boundaries present between the textured regions. Now, the Roberts operator is conveniently applied and the edges are detected. The detected edges are also reduced in size when compared with the original image size. To overcome this problem, the detected edges are scaled up three fold, and the edges corresponding to the original image are obtained. The entire procedure for detecting the edges in deterministic texture images is given in the form of an algorithm in Chapter 5 of this thesis.

1.6.2 Edge Detection in Non Deterministic Textured Images

The edge detection scheme suggested in the case of deterministic images cannot be directly applied to the non-deterministic texture images. The reasons are (i) there is no regularity in the placement of primitives and (ii) various primitives may be present in a single region but the distribution may vary between different textured regions. Hence a separate proposal has been suggested.

The main criterion for edge detection in textured regions is that the difference in adjacent primitive spectrums of the same textured region is less compared to that of two different textured regions. Finally, the edge is detected by computing the root mean square (rms) value of the following.

$$r = \mathrm{sqrt}\,(r_1^2 + r_2^2)$$

where $r_1 = \sum |\ v_{x,y}(i) - v_{x,\,y+1}(i) + v_{x+1,\,y}(i) - v_{x+1,\,y+1}(i)\ |$ and

$r_2 = \sum |\ v_{x,y}(i) - v_{x+1,\,y}(i) + v_{x,\,y+1}(i) - v_{x+1,\,y+1}(i)\ |$

and $v_{x,\ y}$ is the primitive spectrum of the texture region of size 30 x 30, centered at x, y coordinates, i varies from 1 to 92 i.e, the primitive number. An approximate threshold T is applied on r to detect the presence of an edge. Since image windows of larger width are considered for computation of the global descriptor, the detected edges are thickened. The pattern matching thinning algorithm proposed in R T Chain et al, 1987. is applied for thinning the detected textured edges. The algorithms for texture edge detection and thinning the detected textured edges are presented in the thesis.

Edge detection of textured images is elaborately discussed in Chapter 5 of this thesis. One of the main applications of the proposed texture primitive spectrum has been shown to be effective in the analysis of skin images.

1.7 MEDICAL APPLICATIONS : SKIN IMAGE ANALYSIS

Skin diseases account for about 15 % of a general practitioner's workload. The skin is the protective interface between the potentially injurious external environment and the vulnerable organs and tissues of the body. Damage to the skin may be caused by soaps, detergents and oils that remove the essential constituents of the stratum corneum, allowing penetration into and irritation of the epidermis. Fair-skinned individuals are more susceptible to injury from irritants (Marks and Ruxburgh 2002). In this work, image - based representations of skin appearance are used in order to have descriptive capabilities without the need for prohibitively complex physics-based skin models (Oana G. Cula et al 2004). Hence the analysis of skin images is very important.

The concept of the proposed texture primitive spectrum has been applied in medical image analysis and is explained in this section and an elaborate discussion is presented in Chapter 6 of this thesis. The analysis is purely based on experimentation and its related conclusions. The concept for the known images is analyzed for which the ground truths are available. Similarly, skin images are analyzed based on the results and previous conclusions.

1.7.1 Analysis of Brodatz Images

Several Brodatz images have been used for our primary analysis and to compare the results with analogous skin images. Medical image analysis helps to use image processing techniques for many reasons. One of the main advantages is the accuracy it provides in helping the diagnosis by experts. The methods already explained in the previous section have been extended in quantifying the textural contents based on the simple mean obtained from the images and the weighted mean computed from the global texture descriptors.

The analysis is performed in two stages. In the first stage, the texture primitive spectrums have been obtained for the Brodatz images. These images are included in an order so that they vary from mild (or fine) to coarse textures. The simple mean and standard deviations have been computed for the images. These images are subjected to our proposed texture analysis, namely, obtaining the primitive spectrums. The number of primitives present in each image is obtained at different tolerance levels, namely, 3, 5, 8 and 10. The presence of texture primitives for each image at different tolerances is also presented. As the tolerance level is relaxed, the number of primitives occurrence gets improved as expected. The variations of the number of primitives occurred against various tolerance levels are presented in the form of a graph. The images are serially numbered in such a way that they have variations in primitive presence from less to more i.e. from macro to micro. The main observation from the results presented here is that, as the texture image gets more and more refined and smoother, the primitive occurrence is more and the computed statistics also exhibit the same trend. The weighted mean is computed from the primitive spectrum as follows.

$$\text{Weighted mean} = (1 / R*C) \sum_{i=1}^{92} f(x_i)x_i \tag{1.1}$$

where R * C is the image size , x_i is the i th primitive number and $f(x_i)$ is the frequency of the occurrence of the primitive number x_i.

The computed weighted mean is obtained from the primitive spectrums of the images under analysis. The weighted mean increases as the texture image type is moved from macro to micro. That is, as the image becomes smoother and smoother textured, the primitive occurrences are more and hence the weighted mean also increases. These observations have been made, based on rigorous experimentation with a number of images collected from the Brodatz textural album. These analyzed results have been extended as analogous results for medical skin images. The images are collected from the data base (Burn Images). The entire analysis based on the analogous results is presented in the following section.

1.7.2 Skin Image Analysis

Skin images are collected from the data base (Burn Images). Nine images have been used for our analysis. The main objective of this work is that the concept of texture analysis based on the primitive spectrum has been shown to be effective for the analysis of skin images. These images are textured and the ground truths are available. The images are arranged in the order of maximum severity to minimum severity caused due to a variety of burns. The skin images are also collected from various age groups and both sexes. These images as is evident from their appearance, reveal that they range from macro to micro. The statistics computed from these images are also presented. These images have the same mean and the standard deviation which are within a particular range. The simple mean or variances or standard deviations do not infer any useful information except the gray level range. Only when they are subjected to texture analysis, the extent of severity is known. The presence of texture primitives is computed. The statistical parameter, namely, the weighted mean is computed for all the nine images and is presented for analysis with the tolerance of 5. For the remaining tolerances, namely, 3,8, and 10, the weighted means are also computed and presented. This is evident from the variation that as the severity decreases the weighted mean increases. Hence the main conclusion is that, if the weighted mean is more then it implies that the severity is less. It takes lesser time to get cured or healed. This is also ascertained and confirmed by medical experts. This is quantitatively as well as qualitatively matching with the results of our analysis with the standard images, as is evident from the previous sub section. The experiments have been repeated for a number of images at different tolerance levels. In all the cases, the trend is maintained and the results are appealing. The main application of this proposal in medical image analysis especially for skin images which are affected by burns is that the extent of severity can be computed and quantified.

Various human skin diseases are considered as texture images. A skin disease database with various cases is included for the experimentation. The classification of skin diseases based on the primitive spectrum and the computed features has been successfully attempted and the results are promising. Medical image analysis using the proposed texture primitive spectrum has been elaborately discussed in Chapter 6 of this thesis.

1.8 ORGANIZATION OF THE THESIS

An overall introduction of the thesis and the problems undertaken with the framework have been discussed in the **first chapter**. It also includes the main motivation and objective of the research work and the proposal. The s**econd chapter** of the thesis concerns mainly with the review of literature under different categories like texture analysis, classification and segmentation and applications such as medical image, skin image analysis, remote sensing, inspection, document processing and image retrieval. The t**hird chapter** of the thesis describes the texture representation (local as well as global descriptor) and the properties of the descriptors. It also includes the statistical test for identifying the presence of texture. Then the supervised and unsupervised texture classification using the proposed texture descriptor has been dealt with in **Chapter 4**. Subsequently, in **Chapter 5**, texture edge detection which leads to texture segmentation has been addressed both for deterministic and non-deterministic texture images, along with experiments. One of the applications of the proposed texture descriptor, namely, the analysis of skin images affected by various degrees of burns is explained in **Chapter 6**. Finally **Chapter 7** presents the conclusion of the present work and the further scope of the work presented in the thesis.

1.9 SUMMARY

The motivation, objective and methodology have been described in this chapter. The overall work carried out has been presented in this chapter briefly. The corresponding experimentation and the results and discussions are presented in the following chapters of the thesis. The literature review related to the problems undertaken and related work are presented in the following chapter.