SHAPE AND TEXTURE IN QUARTZ SAND GRAINS:

A QUANTITATIVE ASSESSMENT

BY

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Beati monoculi in regione caecorum !

ABSTRACT

Thirty years of microtextural study of quartz grain form has revealed many different textural types and shapes. In conjunction with other sedimentological methods, surface textures and shapes have been assigned to quartz grains from a variety of depositional settings. Many different methods have been devised to semi-quantify these variables and identify sedimentologically meaningful surface features. However, ambiguity and controversy about feature recognition has questioned the method's credibility. Recent attention has turned to new methods of texture and shape analysis using computer image processing techniques. This approach was suggested as a framework for eliminating human subjectivity, to speed up processing time and provide quantitative methods of analysis which were reproducable and available to a wide variety of researchers.

Quartz grain images from a Scanning Electron Microscope were 'frame grabbed' and converted into digital images using a P.C. based image analysis system. The use of digital imagery allowed a number of pre-existing textural and shape algorithms to be applied for the first time. Three differing quartz grain textural types were used (Beach, Desert and Crushed Quartz), employing three hundred grains per sample. A new quantitative method for describing quartz grain shape using Fourier Descriptors removed problems inherent in earlier Fourier implementations, particularly the difficulty in dealing with re-entrant values generated by irregular shaped grains. In addition, a variety of textural algorithms (Autocorrelation, 2-D Fourier Transforms, Textural Units, Edge textures and Single Gray level Dependency Matrices) were applied to quartz grain surfaces. While all algorithms were successful in separating different textural types, edge textures proved to be the most discriminating and potentially the best individual method of analysis.

This departure from established methods has provided exciting new methodologies for quantitative analysis of quartz grain form. Statistical analysis confirmed that textural quantification was possible and when several textural methods were used in conjunction with shape analysis, provided a powerful environment for the study of quartz grain morphology. Discriminant analysis was able to separate grain types, with an average 80% success rate. The use of a neural network, employing a back propagation paradigm, proved successful as a method for automatic quartz grain texture recognition .

CERTIFICATION OF RESEARCH

This is to certify that except where specific reference is made, the work described in this thesis is the result of the candidate. Neither this thesis nor any part of it has been presented or is currently submitted in candidature for any degree at any other University or Polytechnic.

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INDEX

LIST OF FIGURES

LIST OF TABLES

LIST OF PLATES

CHAPTER 1

INTRODUCTION

1. INTRODUCTION.

'Complex aspects of particle morphology are potentially capable of being included in particle characterization once we are able to digitally map the surface of the particle by automatic methods .' (Telford et al, 1987, p. 281) .

'There has, as yet, been no really satisfactory amalgamation of Fourier Descriptors and S.E.M. surface textures.' (Whalley, 1985, p. 185).

1.1 RESUME

Use of Scanning Electron Microscope (S.E.M.) imagery in the analysis of quartz sand grain form has revealed important aspects concerning the relationship between surface texture, grain shape and physical forces which act upon grains in the natural environment. While detailed investigation has assigned many grain attributes to specific sedimentary environments (see Margolis and Krinsley, 1974; Prusak and Mazzullo, 1987), when interactions between the particle and its physical environment are complex many of the established methods of form analysis fail. This is particularly true in microtextural research where lack of complexity in the quantitative models and an inability to process and resolve overwhelming amounts of information contained on quartz grain surfaces often fail to quantify grain 'signatures'. Textures developed on sedimentary particles which have diffused along complex transport pathways, often appear chaotic and previous understanding and analysis has included a degree of semi-quantitative judgement. This problem is further compounded by a lack of standard analysis methods. Therefore, the requirement for methods which are reproducable, have rigid methods of application and produce results which are optimal for 'between sample' discrimination is desirable. In addition, workers within the quartz grain analysis field have rarely appraised the more esoteric nature of *'texture'* within their own field (see Section 2.2.1). As Whalley and Orford (1983), and Telford, et al (1987), pointed out the need is to remove operator variance in surface texture studies and to resolve semantic problems concerning the basic concepts that define particle morphology. This work presents a more involved analysis of grain form using integrated mathematical models of grain texture and shape, implemented within an image processing and pattern recognition environment, (see Figure 1). As both shape and texture studies have deficiences, amalgamation of the two within this framework offers an enhanced tool in the overall quest for sensitive quartz grain discrimination and provides some solutions to the inherent problems. The motivation for this project was to investigate quartz grain shape and surface texture within a quantitative environment, using mathematical models for description , and in the process evaluating their use in this particular application.

Two major aspects of quartz grain form were investigated within the above framework :

a) **Surface texture analysis.**

b) **Shape analysis.**

Of the two disciplines, the study of surface texture has developed a contradictory nature despite the 'Krinsley school's' extensive exploration of characteristic assemblages (e.g. Krinsley and Doornkamp, 1973), while mathematical study of particle shape, particularly through use of Fourier analysis, primarily under the influence of R. Ehrlich has produced significant results (see Section 2.3). Recent integration of surface texture and shape analysis has made significant contributions, however both approaches are time consuming and computationally expensive. Some degree of automation has been included, particularly in Fourier Transform implementation, but little use has been made of image processing hardware and software as 'tools' from which rapid and quantitative analysis of all aspects of grain form can be achieved. For this thesis, 'form' is the term used to include all aspects of external morphology including shape and surface texture, denoted by the relationship :

Form = f (shape, sphericity, angularity, roundness and texture). *(Whalley 1972)*

Barrett (1980), considered form, roundness and surface texture as independent properties of shape because one can vary widely without necessarily affecting the other two. 'There exists a set of relationships between the morphology of a particle and the texture. The texture describes the internal chemical and structural detail of the particle and the morphology describes the size shape characteristics', (Beddow and Meloy, 1977, p. 74).

The rapid development of image processing technology has brought several benefits to grain morphology studies. While previous work has used binary images of quartz grains (light and dark) , increased sophistication permits possible manipulation of all 256 gray levels and allows more intricate models to be created. As an example of this progress Clark (1987), cited the infrequent use of the Fourier Transform in particle studies as the result of the involved methods of collecting boundary points and conversion to polar coordinates. Reference to Section 3.4.2 shows how increased computation power has made this task easier.

1.2 DIGITAL IMAGES

Digital image processing and pattern recognition are two major disciplines used to analyse a wide range of image databases including Landsat imagery, medical micrographs etc. An image is a two dimensional light intensity function f(x,y) where x and y denote spatial coordinates and f is proportional to the brightness value at that point. Image processing refers to representation, enhancement, restoration and general manipulation of an image. Pattern recognition attempts to extract information from that image to allow automated scene matching and understanding, and may be defined as 'the categorization of input data into identifiable classes via the extraction of significant features or attributes of the data from a background of irrelevant detail', (Gonzalez and Tou, 1974, p. 174). Understanding of pattern recognition and image processing requires knowledge of a wide range of disciplines including probability and statistics, computer science, calculus, cognitive science and engineering principles, (James, 1987). It is not the intention to provide 'in depth' descriptions of these areas but to deal only with relevent aspects when required. Many of the algorithms used are readily available incorporated in low cost image processing software packages. Again a veneer of theory is presented but not actual computer code.

Images can be represented in digital form, from which computer manipulations can be used to extract useful information. This extraction can either be used in harness with visual systems or to enhance them. As an example, light from an image source may be captured using a *'charge couple device'* camera (CCD) which consists of a M x N array of photosensitive elements each of which produces an analogue output proportional to the amount of light incident on it. The process of converting an image into an array of integers is 'digitization'. Spatial quantization refers to sampling image brightness at a number of points, usually a rectangular grid which produces an array approximate to the original image. Obviously the more sampling points the better the image. Sampling can be on a point basis or averaged over a sample size. Gray level quantisation restricts brightness values to a finite set of integers to conserve storage space. Two hundred and fifty six gray levels are commonly used because this number reduces the effect of contouring, the appearance of false edges in an image due to the inability of gray levels to change smoothly from one value to another, (James, 1987). The camera output is 'Frame grabbed' and digitized into discrete picture elements commonly referred to as 'pixels'. The use of a regular grid system allows each pixel to be located at an x,y coordinate. Each image used here is composed of 512 x 512 grid points , using 262144 pixels. Such large numbers of points usually restricts memory allocation, an important consideration when applying image processing algorithms.

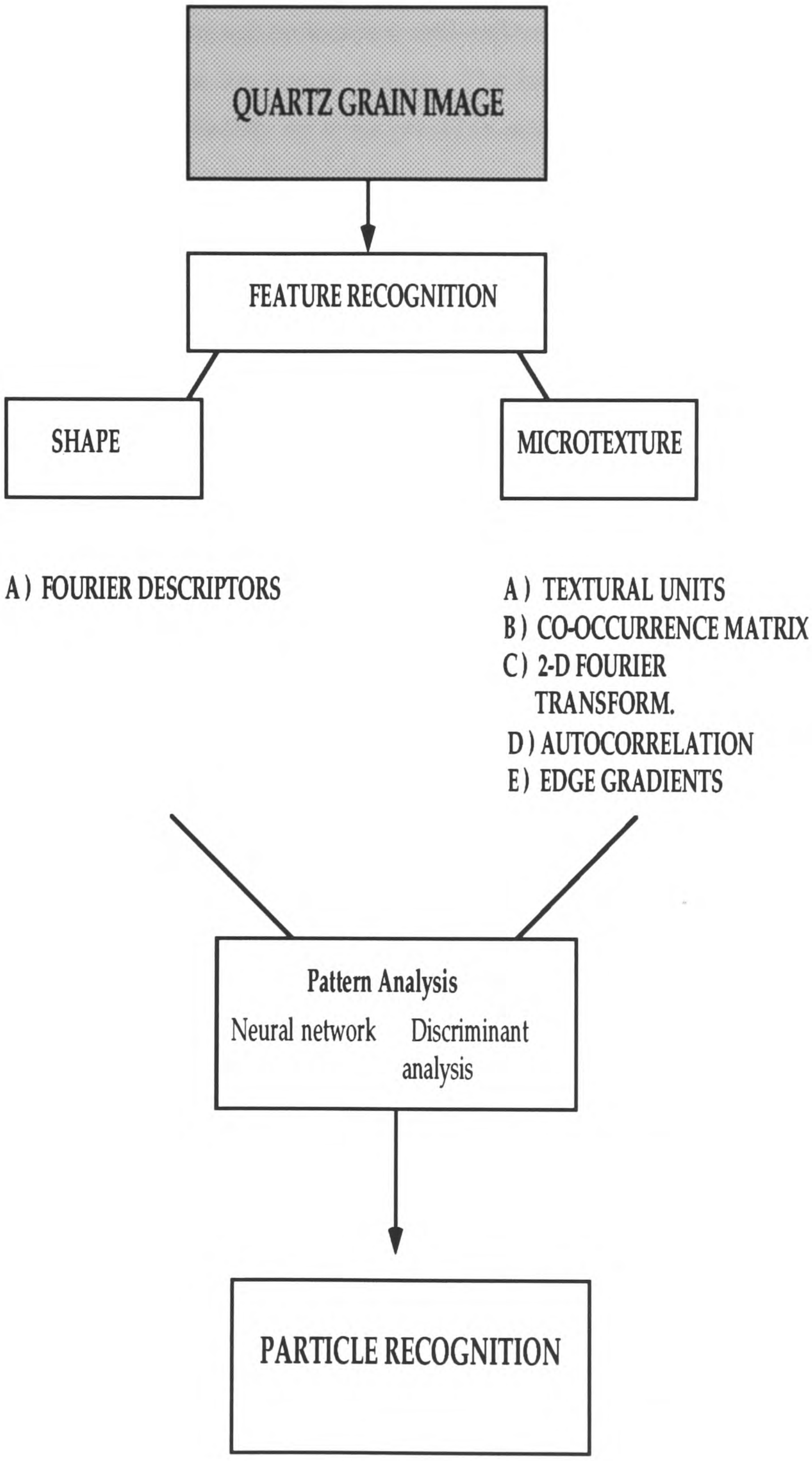


Figure 1 - Major components of the quartz grain image pattern recognition system.

Images are rarely presented in ideal format as shown in Section 3.2.2. This is frequently due to the presence of 'noise', or areas of importance not being apparent. Solutions to these problems come under the banner of image restoration and enhancement. Normally these methods either operate within the spatial or frequency domain. The former refers to the aggregate of pixels in an image, using operators directly on these pixels at each point , defined as :

$$g(x,y) = h[f(x,y)]$$

where $f(x,y)$ is the input image, $g(x,y)$ is the resulting image and h is an operator on f , defined over some subsection of the whole image. In the frequency domain, images are decomposed into a series of periodic functions. High spatial frequencies correspond to rapidly changing detail while low frequencies correspond to slowly changing brightness, (James, 1987). Both approaches are used here, 2-D Fourier analysis representing the frequency method and textural and edge analysis, the spatial domain. (Section 3.4 onwards gives a more involved account of these techniques).

1.3 QUARTZ GRAIN MICROTEXTURAL ANALYSIS

'Certain surface features of quartz grains caused either by mechanical or chemical agencies are diagnostic of a particular set of energy conditions. Those energy conditions were characteristic of particular environments and when certain combinations of these surface features were present in statistically significant percentages, they became highly diagnostic of that environment .' (Bull , 1976 , p. 7).

Throughout the history of sedimentology, the study of grain form has occupied a prominant place within the discipline. With the advent of improved technology i.e. S.E.M.'s and computer image processing software and hardware more subtle aspects of grain form can be revealed. This is particularly true for shape and surface texture analysis. The latter has evolved over the last three decades from being a purely qualitative descriptor, through a semi-quantitative stage and finally integration into the more rigorous methods of shape analysis. Section 2.1 identifies the contribution that the principal 'mover' in this field, D. Krinsley has contributed to this metamorphosis. However a decline in interest in the subject as an independent method of analysis has occurred due to ambiguities in results, a lack of methodology and an inability to process the overwhelming amounts of information contained on a grain's surface. In addition a feeling grew questioning what exactly the textures represented and whether a particular set of textural features were diagnostic of a unique sedimentary environment. The sole use of surface textures in determining previous depositional histories is still hampered by the similarity in abrasion features from a wide range of environments and an inability to quantify these intricate patterns, (Mazzullo, et al, 1986). The paucity of experimental production of surface textures particularly relationships to hydrodynamic parameters such as flow conditions, shear stresses and transport stage, remains a large obstacle and few papers have experimentally produced textures under strict laboratory conditions, (Linde and Mycielska - Dowgiallo, 1980). An example of the techniques shortcomings was highlighted by Williams and Thomas (1989a), who semi-quantitatively analysed five Barrier Island sediment types (Beach, Dune, Flood Tidal Delta, Inlet and Overwash). Using a checklist approach, an attempt was made to discriminate on the basis of surface texture. While subtle differences between samples was evident statistical analysis failed to separate them.

1.4 QUARTZ GRAIN SHAPE

The study of particle shape has a long history in the sedimentological arena. The almost 'Victorian' preoccupation with description of a grains shape extended up to the 1960's and beyond. As the importance of grain surface microtextural analysis in reconstructing depositional environments began to be questioned, retrospective work questioned what exactly a grain's shape told the researcher about its depositional history. The answer to this was commonly 'not a lot', due to previous methodologies being so qualitative in aspect. Even the introduction of the Powers' scale (1953) did little to improve matters. As with surface texture analysis, the technique was acceptable when separating discrete environments but when analysing complex populations the techniques proved time consuming and produced ambiguous results. The introduction of mathematical methods of grain shape description particularly the use of Fourier Transforms removed many problems allowing shapes within grain populations to be modelled accurately and shape trends within a population resolved. Initially this technique promised much, particularly for standardizing the methodology. However, problems of implementation , lack of mathematical awareness of this complex application and time cost of analysis all conspired to keep the most intensive work within the 'Ehrlich' sphere of influence (see Section 2.3). These problems stiffled new work exploring the strengths and weaknesses of the method. Indeed once the technique became embedded in the literature in the 1970's and 80's few papers appeared which improved or questioned the techniques application to sedimentological problems. A discussion of grain shape and Fourier Descriptors is presented in Section 5.4.

1.5 TEXTURAL STUDIES

Textural analysis of digital images has been primarily investigated by one worker, R. Haralick, who has played a similar role to Krinsley and Ehrlich in the discipline's development.

A fundamental problem underlying the approach outlined in Section 1.1 was actually pinpointing what texture was and once a definition was established, how best to describe and analyse it. The problem of understanding the hierarchical nature of texture, illustrated in Section 2.2.1 and Section 5.6 is one of the main causes for the confused nature of S.E.M. studies. A major problem with texture description is that it has local as well as global properties. The former considers structural form of a single texture element while global properties deal with the arrangement of a multiplicity of texture elements. In addition, textures display large frequency content compared to it's actual information content and this tends to slow down computation processing, (Granlund, 1980). An example of this is given in Section 3.8 which outlines the problems encountered using autocorrelation as a textural measure.

In keeping with other work in pattern recognition studies the approach to textural analysis of sand grain surfaces has been 'ad hoc', employing techniques which best described the texture and crucially provided the best discrimination between samples. While the field is too vast to explore and implement many of the techniques in use, the addition of a selection of mathematical textural models of quartz grains in tandem with shape studies is shown to be a powerful method of analysis, (see Section 5.4). The main issues in texture analysis may be divided into three groups :

1) *Given a textured region, determine to which of a finite number of classes does the region belong .*
2) *Given a textured region, determine a description or model for it.*
3) *Given an image having many textured areas determine the boundaries between the differently textured regions.*

This work is firmly rooted in group two, with use made of six methods. Autocorrelation is a classical approach to textural analysis but has rarely been applied to textures as complex as quartz grain surfaces. Co-occurrence matrices have developed in many forms dependent on the application and have proved to be a useful indicator of structure within texture. Edges are an important cognitive trait in all texture so any measure of frequency and development is a crucial area in resolving distinctive textures, (see Section 5.6). Textural units, Fourier Descriptors and 2-D Fourier transforms are new implementations to quartz grain study. The ability of each method to discriminate sand grain surface texture was appraised individually and in combination with each other. This posed two important questions. What was the efficiency of the textural algorithm for analysing complex texture and how satisfactory did the algorithm analyse quartz grain surface texture? In addition, an evaluation was made of the efficiency of using integrated frequency and spatial domain techniques to model texture. The Discussion section (5.7 and 5.8) expands on these questions and poses new ones for future work.

1.6 PATTERN RECOGNITION AND CLASSIFICATION

'In pattern recognition the situation is special in that we are at liberty to select from an almost limitless range of possible measurements that will be used in the classification rule.' (James, 1987, p. 30).

'Pattern recognition is concerned with the investigation of adaptive and analytic techniques for processing large amounts of data, the extraction of useful information to reduce the data and the classification of the data as required.' (Viglione, 1970, p. 115).

An initial stage in any pattern recognition task, eg. automatic recognition of a quartz grain microtextural surface, is the selection of features to select and ways to measure them, (James, 1987). In this case, both shape and surface texture information were extracted. The resultant variables were then passed to the classification process whose ultimate goal was to separate and assign quartz grains into identifiable groups using multivariate analysis. Five classification methods have been commonly used :

i) Distance functions
ii) Likeli-hood functions
iii) Trainable classifiers - deterministic methods
iv) Trainable classifiers - statistical methods
v) Syntactic methods.

Distance functions involve the use of a distance criterion. The item to be classified is incorporated in the pattern space along with previously established training pattern classes. Likeli-hood functions require knowledge of the probability of occurrence of a particular pattern class. Deterministic pattern classifiers make no assumption regarding the statistical properties of the pattern class, while statistical pattern classifiers minimize the probability of error (Beddow and Meloy, 1977). The method principally employed here is Discriminant Analysis.

The aim of Discriminant Analysis is to examine the extent to which it is possible to distinguish between members of various populations based upon the observations made upon them. The observations used here are the texture and shape values obtained by the various algorithms. Discriminant Analysis has been widely use in the geological and geomorphological arena, (Williams and Thomas, 1989a; El-Ella and Coleman, 1985). Davis (1986), provides a detailed review of it's implementation. Further discussion is given in Section 3.9.2.
This technique generates a logic unit or feature detection and assigns the patterns into the

subspace using an optimum discriminant function. Patterns falling on one side of the resulting surface are associated with one pattern class, those on the other side with another.

The multivariate nature of grain morphology studies has been stressed by many workers, (eg. Telford, et al, 1987; Culver, et al, 1983) and therefore the use of multivariate statistical analysis was an obvious method for analysing the results. Discriminant analysis has been applied to many pattern recognition and sedimentological problems, (see Williams and Thomas, 1989, a and b; El-Ella and Coleman, 1985; Morgan, 1990). Its use in analysing Fourier Descriptors was a departure from established methods of analysis which used the frequency distributions of individual harmonics from grain populations as the basis for separation (see Ehrlich, 1977). The ultimate goal of pattern recognition is to train a pattern classifier to classify an unknown texture. Since the success of texture recognition is measured by the researcher's own judgement the ultimate goal of textural modelling is to achieve human level performance. The advantages of using this approach are discussed in Section 5.7.

1.6.1 NEURAL NETS

'You could describe neural networks as humanity's attempt to create an artificial brain.' (Tazelaar, 1989, p. 214).

'Most of today's so-called 'intelligent' computer systems would qualify as brain damaged if they were people.' (Forsyth, 1989, p. 3)

While multivariate discriminant analysis was one method of separating grain samples, an innovative approach to the discrimination problem made use of a 'Neural Network'. Neural networks, or parallel distributed processing (PDP's), are software engineered models of the physical operations of the brain, developed with the aid of neurophysiologists, cognitive scientists, computer scientists and mathematicians. Neural modelling began in the 1940's but disappeared in the 1960's. The 1980's has seen an upsurge in their popularity due to a realization of the digital computer's limitations and an increasing sophistication in technology able to model the neural nets. Applications vary from areas of data compression, image recognition, to multivariate statistical modelling. So what are 'neural networks'? In simplest terms, they are models of the brain and thinking processes which may be implemented on either a hardware or software environment. The models are based on the neuron or brain cells, with each cell (10 - 100 billion) connected to approximately 10,000 others.

A neuron consists of a cell body (soma), branching extensions called dendrites for receiving input and an axon that carries the neuron output to the dendrites of other neurons. Interconnections between an axon and a dendrite is called a synapse. The neuron performs a summation of inputs which, if received in sufficient quantity, it activates. Some inputs are inhibitory and some excitory. Psychological testing has indicated that the brain can respond to a visual stimulus within 500 ms. The neurons are a slow device and take 5 ms to fire and propagate through the axon to the next synapse. Therefore only 100 steps are required for difficult problems such as visual recognition. The same process would take a conventional computer billions of steps, (if it were a solvable problem on a Van Neuman computer). The reason for the brain performance is that its' steps consists of massively parallel operations. It is the summation of inputs which is the key to implementation of this system within a computer environment. A generalized neuron consists of inputs into a process element containing combining and threshold functions and output. There are a number of different transfer functions used to convert inputs (via the weights) to output, (see Figure 16). Some of the models are close to the biological reality of the brain while others are far removed from it.

Artificial neural networks are composed of elements based on guesses as to the transfer functions involved in the brain. Their most interesting feature from a pattern recognition viewpoint is an ability to learn a function from training data. In a sense, they have the capability to program themselves.

While neural networks can be trained to recognise patterns by letting the data define the structure within it, in reality, they display only minimal intelligence, (Openshaw, et al, 1990). There are a variety of neural nets as shown in Figure 16, but there is no standardization in methodology and as Openshaw, et al (1990 p.797), stated, 'they represent the ultimate in currently available black box technology'. Section 3.9.3 outlines the paradigm used and implementation. The question must be asked, what is their use in quartz grain shape and texture recognition ? As the ultimate aim of this research is automatic recognition of quartz grain form, the use of neural networks removes the human decision making process from quartz grain discrimination. As neural nets become more efficient, their place in automatic pattern recognition problems, such as here, will become increasingly relevant, (see Section 5.8).

1.7 SUMMARY

The proceeding subsections highlight the use of mathematical models of quartz grain texture and shape within a 'PC based environment' to achieve a quantitative definition of quartz grain form. Emphasis is placed on integration of various techniques and not isolated study of one set of parameters. As quartz sand grain morphology is the result of complex interactions between physical forces in the environment and the grains themselves, an integrated approach to it's study more closely follows the 'nature of the beast'. This integrated approach is reflected in the need to understand a variety of disciplines ranging from statistics to computer programming. With this in mind, subsequent chapters are written with a geomorphologist, or earth scientist's outlook and irrelevant details concerning a method or it's application are excluded.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

This section reviews the :

i) Historical development of S.E.M. analysis of quartz grain microtexture
ii) Quantitative quartz grain shape analysis
iii) General development of textural analysis within an image processing context.

All three disciplines of shape analysis, microtextural study and image processing have developed along parallel lines and only recently are the strands converging to form a powerful paradigmatical structure for quartz grain form studies. A comprehensive review of all three areas would be an immense task, well beyond the scope of this work. With this as a guide it was decided to focus and highlight areas of research pertinent to this particular study.

2.1 QUARTZ GRAIN MICROTEXTURAL STUDY

'The state of the art should have advanced in the realm of feature origin occurrence and a whole host of other areas .' (Krinsley and Marshall, 1987, p. 17).

'Surface texture will not be considered further, as numerical parameters are yet to be devised.' (Barratt, 1980, p.2).

Increasing sophistication in microtextural research in the last thirty years has followed the technological advances made in the field of electron microscopy. Briefly mentioned in the Introduction, the technique has undergone fluctuating fortunes due partially to misconceptions about its ability to unravel sedimentological histories without reference to other lines of evidence. Sceptism has and still does remain and will continue until the discipline leaves the qualitative domain.

From the early investigations of Sorby (1880), and Cailleaux (1943), textural analysis evolved in the 1960's, coinciding with the appearance of the Transmitting Electron Microscope (T.E.M.). Biederman (1961), Porter (1962), and Krinsley and Takahashi (1962), all recorded detailed studies of grain textures from a variety of sedimentary environments. However the complicated procedures involved in grain preparation and viewing limited T.E.M. studies. In addition, the lack of a unifying nomenclature or standardized methods of analysis had already become apparent. This legacy was to 'dog' the subject for the next thirty years.

Early studies attempted to quantify the relationship between microtextures and the physical environment. Krinsley, et al (1964), studying sediments derived from the headland section in Eastern Long Island observed that mechanical V-pit densities were low or absent on grains from Montauk Point till, but increased from 0.5 per μ to 3/ μ 20 miles to the west. They surmised that previous glacially derived textures were obliterated, and replaced by beach textural inprints.

A compendium of previous work was produced towards the end of the 60's. Krinsley and Donahue (1968), updated and catalogued the results published during the decade, emphasing the importance of understanding the multicycle nature of quartz grain textures. Many feature combinations were related to discrete sedimentary environments and used as environmental indices.

At the decade's close new workers in the field were already faced with a bewildering amount of textural information. Few papers related textures to their physical environment, nor had satisfactory methods of analysis been implemented. The advent of the Scanning Electron Microscope (S.E.M.) brought rapid scanning of large numbers of grains and with it a dramatic increase in the amount of information that needed to be processed. Many grains could be viewed quickly using the deeper field of focus and increased contrast. This improvement in surface scanning allowed the development of a semi-quantitative approach, the *checklist*, to record surface microtextures. Many different forms were used and became the major method of analysis in S.E.M. study, (Bull, 1981). Krinsley and Margolis (1969), attempted to update existing S.E.M. procedures, and introduced new textural assemblages. These were used by many workers to interpret sediments, (Krinsley and Donahue, 1968; Margolis and Kellner, 1969; Coch and Krinsley, 1971). The origin of one feature, chattermarks, was to later become the object of debate, illustrating the problem of feature recognition within the subject. To combat these problems, attempts were made to concentrate on original first cycle textures displayed on granitic source rocks, to provide a benchmark for multicycle textural assemblages.

Margolis and Krinsley (1971), studied submicroscopic frosting on aeolian and subaqueous sand grains. Upturned plates, an expression of quartz cleavage, were introduced as an important diagnostic texture of aeolian transport. Frosted subaqueous grains were interpreted as a product of abrasion and chemical sea solution.

The possible existence of quartz cleavage was investigated by several researchers (Berry 1974; Hoffer 1974; Smalley and Krinsley 1973), and brought S.E.M. workers in conflict with mineralologists. The latter pointed to several directions of weakness in the atomic lattice as responsible for the apparent cleavage. Moss, et al (1973), argued that quartz grains in sedimentary environments were rarely perfect and contained many defects derived from processes exerted during rock forming processes.

S.E.M. analysis was now used to look at Pleistocene derived sands, particularly those found in coastal environments. (Margolis and Kennett, 1971; Hey, et al, 1971; Nordstom and Margolis, 1972). Margolis and Kennett (1971)In an attempt to understand the Cenozoic palaeoglacial history of Antarctica studied deep sea cores. Margolis and Kennett (1971), noted the presence of 22 features, occurring on more than 10%of the grain surface. Percentages of total sample grains were calculated and shown diagrammatically as variability plots.

Krinsley (1972), and Krinsley, et al (1973), studied microtexture from glacial environments, noting that no single feature could be used as a valid diagnostic index. The need for a more quantitative approach was becoming apparent. Setlow and Karpovich (1972), measured the degree of development or dominance and area of development (density) of surface textures were assigned values in ranking order ranging from dominant (9 - 10) to absent (0). However the method was time consuming, and operator variance in estimating the overall development was considerable (Williams, et al, 1985). This method and it's drawback is discussed in Section 5.6.

The publication of *'The Atlas of Quartz Grain Sand Surface Textures'* (Krinsley and Doornkamp, 1973), provided a much needed reference point for potential and existing researchers. Grain preparation, quartz grain surface texture recognition and interpretation were all outlined and are still referred to in present studies. An important paper clarifying textural assemblages from a number of environments was produced by Margolis and Krinsley, (1974). Using 22 surface textures, 12 environments were described, based on varying texture frequency. Conchoidal fracture was interpreted as cup shaped surfaces produced by compressional stresses applied during grain shattering. Grain size was also related to cleavage derived textures. V-shaped grooves and rounded grain edges were cited as textures produced during grain to grain collision in an aqueous medium. The spatial development of mechanical 'v' pits, (MV's) was related to energy conditions. Low energy beach environments created shallow widely spaced V pits due to low pressure rubbing and splintering as grain's slid over each other. Increasing energy produced cracking and greater V pit densities leading to conchoidal fracture at high impacts. This subdivision was artificial as no account was taken of the effect of low frequency high energy events such as hurricanes and North Easters in low energy environments.

The mid 1970's produced new workers who strove for a more quantitative approach. New sedimentary environments were sampled including caves (Bull 1978), and soils (Bull and Bridges, 1978), Whalley's edited publication (1978), provided a timely boost to a *'flagging horse'*. Twenty nine papers addressed a variety of aspects including rock particles (Walker 1978), diagenetic studies and weathering (Waugh, 1978).

In the European theatre, Le Ribault (1978) produced intricate descriptions and analysis of complex textures. Grains were grouped into original quartz grains, quartz from soils, aeolian quartz, continental aqueous environments, marine derived and multitextural quartz. Amorphous silica and quartz undersaturation in sea water was considered a critical factor in textural control in marine environments. A number of sedimentological complex environments were analysed for the first time, including infra and intertidal environments.

Baker (1976), introduced the first 'sceptical' comments on the technique and its methods. Using a simple presence or absence approach of 10 textural features for twenty grains sample, an attempt was made to discriminate between marine and aeolian grains. It was concluded that it was possible to define subaqueous and aeolian textures statistically but noted that some 'diagnostic' textural assemblages would be applied to other sedimentary environments, a point reiterated by Mazzullo, et al (1986).

Attention turned to studying glacially derived microtextures in an attempt to reconstruct paleoclimates, (Krinsley and McCoy, 1977; Margolis, 1975; Culver, et al 1978; Eyles, 1978). Many workers divided grain surface textures into either mechanical and/or chemical, the latter normally occurring during syn-depositional chemical processes, or diagenesis and weathering, (Krinsley and Margolis 1969). Krinsley and Donahue (1968), described four main classes of diagenetic texture, crystal surfaces, solution surfaces, pressure solution striations and fracture surfaces. Krinsley and Doornkamp (1973), noted that the dominant effect of solution was to reduce relief and mask projecting areas. Rapid precipitation produced an undulating smoothed topography as displayed on aeolian grains. Slow precipitation produced a fine coating reflecting the underlying topography in detail. Tankard and Krinsley (1975), divided solution features into crystallographically controlled and those independent of internal symmetry. Slow solution at high pH values produced orientated triangular etch pits, solution along cleavage planes produced parallel steps. Several other studies (Friedman, et al, 1976; Waugh, 1970; Whalley, 1978), assessed the effects and proposed mechanisms for production of various solution/precipitation features. However it is evident that each operator has used different approaches and many questions are left unanswered, such as how do you tell the difference between solution and precipitation features? The answer to this problem is one of the main attractions of using mathematical models which do not need to include this confusing and often contradictory background, (see Section 5.7).

Bull's involvement in the late 1970's, early 1980's improved the technique in several ways. A quantitative approach was stressed and adopted, (i.e. the checklist) and multivariate statistics included in analysis. Cluster analysis and linear discriminant analysis were applied to checklist results to appraise the statistical difference between various cave sediments (Bull, 1978a). He stated that "The generalisations achieved by quantitiative analyses do not substitiute in any way the necessary descriptive analyses that identify the sequence of events upon a sand grain", (Bull, 1978, p. 220). This may be the case but where the identification of a sequence of events is based on a series of conflicting observations then this statement becomes debatable.

A notable piece of quantitative work in the early 1980's was performed by Krinsley and Wellendorf (1980). Using an aeolian simulation paddle device they simulated Martian wind conditions. The tentative relationship between wind velocity and the spatial arrangement of the plates indicated that within very short time spans (minutes to hours) sustained high wind velocities produced new plate spacing. The publication of this article in '*Nature*' provided a high point in the discipline.

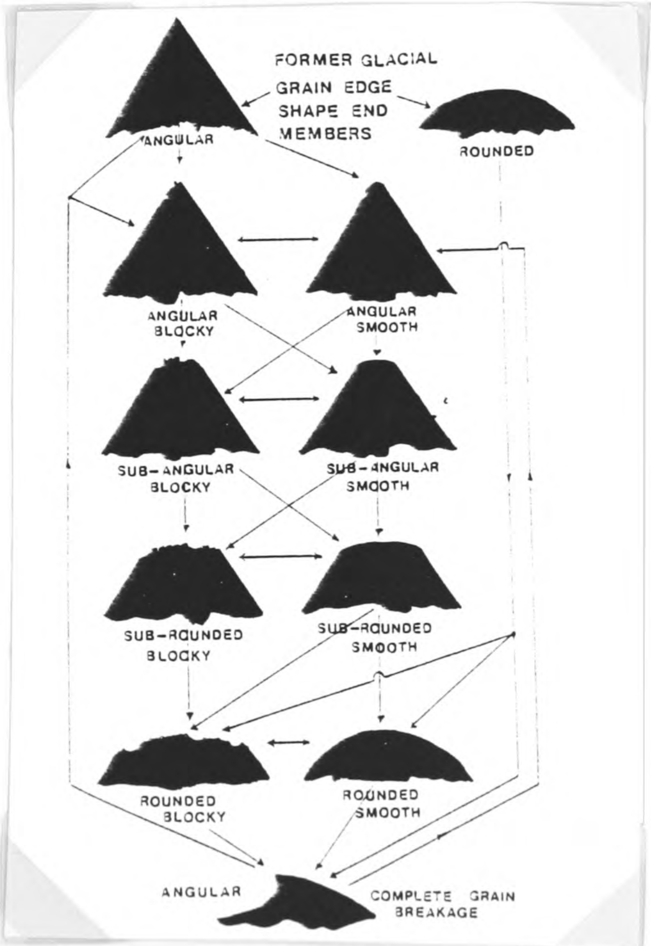
Bull's contributions to the subject's development acted as a catalyst for new ideas particularly in the area of quantification. However these developments were based on a subject whose 'qualitative legacy' refused to be shaken off. Johnson, et al (1989), Grutzeck (1989), Folk (1978) all posed questions regarding feature identification research. The past 20 years had developed a catalogue of features. but the lack of agreement on feature identification and methodology created few papers of note in the mid 1980's. The checklist approach continued. Cater (1984), used a checklist of 22 features supported by texture superimposition indices and feature abundances. The checklist was produced from previous workers checklists but contained features and combinations not described before. Goudie and Bull (1984), used thirty four surface features in a study of colluvial samples from Swaziland. Progressive edge abrasion was used as a major discriminating feature in separating samples. Culver, et al (1983), attempted to validate the use of a multifeature checklist approach. Five S.E.M. operators studied eight coded samples using 32 grain surface features. While canonical variate analysis was able to discriminate between all samples, no single feature was able to achieve a satisfactory discrimination. Operator variance was considerable during scanning but strict operational procedures overcame this problem. Williams and Thomas (1989a), in a precursor to Morgan's (1990), work used thirty six features to discriminate between five Long Island sedimentary environments; Washover Fan, Inlet, Beach, Flood tidal delta and Aeolian environments. Samples from a buried offshore palaeodrainage channel and adjacent offshore sediments were included to establish on-shore transport pathways.

The late 1980's produced increasing numbers of papers combining grain shape and surface texture studies, (Mazzullo and Magenheimer, 1987; Haines and Mazzullo, 1988). The publication of '*Clastic Particles*' edited by Marshall (1987), provided the best review of the discipline. Many aspects of grain form from a variety of sediments were considered, with emphasis on a variety of approaches not just using textural or shape analysis in isolation. These areas are considered in Section 2.3.

Morgan (1990), undertook an exhaustive S.E.M. examination of the nearshore sediments from Long Island in an attempt to compare known sources at Montauk Point with sediments from buried palaeodrainage channels and spatially adjacent offshore samples, and to examine the degree to which they may be linked to south shore beaches. Using a checklist approach, à la Bull, quantitative results comparing individual quartz grain 'surface feature variability' with transport distance west of Montauk Point, divided the south shore into three sections :

1) The glacial deposits of the Ronkonkama moraines at Montauk Point,
2) Headlands section beaches
3) Fire Island beaches.

Surface feature variability plots and between sample variability plots revealed a more complex pattern of surface feature development, which suggested additional sediment input from an offshore source. An interesting aspect to this work was the comprehensive examination of edge abrasion, edge shape and internal surface edges work. Varying levels of abrasion were shown on selected micrographs. These edges varied widely from very angular shapes, modified by medium and large breakages. A continuum visual chart was constructed from which edge type description was attempted, (Figure 2).



Edge shapes were introduced as a 'refinement backup'. Angular edges were assumed to be associated with grains which had suffered high energy breakages and had crystallographically controlled faces intersecting at sharp angles. Rounded edges were connected with advanced surf abrasion or extensive solution precipitation, (Morgan, 1990). Internal edges per se were not studied but the micro topography of adjacent regions was examined. Angular edges decreased from a maximum of 48% at Montauk Cliff to a 'fluctuating' low of 4% - 8% on Fire Island with edge roundness increasing. Progressive grain edge rounding was 'smoother' and persistent westward of Montauk Cliff. Edge results indicated that the moraine samples at Montauk Point were different from barred channel lobes deposits offshore, confirming Reister, et al's (1982), and Williams and Thomas (1989a), earlier observations.

Hodel, et al (1988), used S.E.M. analysis in conjunction with existing hydrological, climatic and depositional environment information in an attempt to delineate the history of surface deposits on the Alaskan North Slope and shelf. Two grain types from two different drainage basins of the Alaskan North slope, the Colville and Sagavanirktok rivers were studied. Their underlying assumption proposed that more angular grains may be found upstream while exposure to prolonged abrasional transport down stream created rounder grains. The formation of chemical surface features on exposed river sediments were also expected to be minimal in the cold, dry climate. Eight gradational grain types were identified ranging from type 1 grains which were sharp and angular in outline, had high relief and displayed a variety of mechanical micro features ranging from conchoidal fracture patterns to block breakage, to type 8 grains which were well rounded, with high sphericity and a high degree of chemical weathering. This latter finding was surprising but was explained by the result of long periods of inactivity due to river and innershelf freeze up and refreezing of the active layer of permafrost ground allowing for slow chemical processes to take place. In conclusion, Hodel, et al (1988, p. 26), stated ' although some scepticism within the scientific community remains concerning this popular S.E.M. method, the authors believe that subsequent studies, as well as our own research, have shown that S.E.M. analysis of surface textures when used in conjunction with other geologic research .... can help shed light on depositional histories.'

SUMMARY

Thirty years of microtextural research has produced fascinating glimpses into the effect of the natural environment on quartz grain surfaces. Extensive descriptions of microtextural forms provided new researchers with a considerable amount of information. However causal links between process and form remained elusive and the hierarchical nature of texture, its ability to alter radically with changing magnification, has presented many problems. The lack of a strict methodology or quantitative methods of analysis has generated many sceptics. While this deficiency appears to signal the deathrows of the discipline, it may be the birth of a more interesting, quantitative and rigorous discipline, the integrated study of *quartz grain form*, (see Section 5.4).

2.2 TEXTURAL ANALYSIS IN IMAGE PROCESSING

The Introduction (Section 1.5) has indicated the problems that existed for researchers when they attempted to interface the humanistic view of texture with the practicalities of computer implementation.

Early work, concerned itself with the meaning and nature of texture. An insightful understanding of texture was produced by Pickett (1970, p. 289), who stated that 'the basic requirement for an optical pattern to be seen as a texture is that there will be a large number of elements, each to some degree visible and on the whole densely and evenly arrayed over the field of view'. Pickett's (1970), review considered two kinds of subjective textural analysis, *deliberate* and *impressionistic*. In the latter, the visual system automatically and unconsciously performs basic tests on the optical data which give immediate impressions about the data. In the former, the observer makes a deliberate attempt to separate textures. Factors which the visual system measured included size, shape, shading, orientation of various elements, number and density of elements and the pattern of elements. Empirical studies showed that the resolution of texture was done best using element size or shape as oppposed to variations in density or arrangement, (Pickett, 1970).

Hawkins (1970) considered texture to contain three ingredients :

1) some local order repeated over a region which is large compared to the orders size
2) the order consists in the non-random arrangement of elementary parts
3) the parts are roughly uniform entities having approximately the same dimensions everywhere within the textured region.

While Hawkins (1970), recognised that these definitions were fine for regular man made patterns, natural patterns showed more irregular patterns varying in spatial periodicity and displaying increasing irregularity, as discussed in Section 5.7. This idea of texture being made up of patterns or 'primitives' was investigated by later researchers. Van Gool, et al (1985, p. 2), defined texture as a 'structure composed of a large number of more or less ordered similar elements or patterns without one of these drawing special attention'. Where texture was composed of identical subpatterns, the texture was described as deterministic, ie. it could be described by characteristics of one subpattern and the placement rules of one such primitive. Where a texture had a 'statistical' definition, a texture was described as stochastic and primitives were heavily disturbed, Ballard and Brown (1982), showed that creativity was required in defining primitives. From Brodatz (1966), textures generated by weaving could be described either by the vertical and horizontal 'struts' or by the shapes they bounded i.e. squares. However certain materials, ie. paper, did not display such patterns so bumps and creases were used as primitives in classification.

The separation of textures into deterministic and stochastic has played a major role in the approaches used to characterize texture. The two major approaches are structural and statistical. The structural model regards primitives as forming a repeating pattern and generates rules for their placement and work best for textures with a great deal of regularity. The statistical model describes texture by statistical rules affecting the distribution and relation of gray levels, (Ballard and Brown, 1982). This latter approach is employed in this thesis, (see Section 3.3 onwards). While separation into statistical and structural methods has been widely used, some workers, e.g. Ahuja and Rosenfeld (1982), have proposed that this division is not useful if either the structural model is not statistical i.e. the image it describes is too regular to be of interest, or the statistical model cannot reveal the basic structure. Their division produced two distinct models; pixel based and region based.

2.2.1 'TEXTURE' AND QUARTZ GRAINS

'The human perceiver exhibits weaknesses that would not be tolerated in a machine perceiving system, for instance gross lapses of metric accuracy and limited abilities for error correction, backup and top-down control. These weaknesses, taken together with the obvious success of the human perceiver, suggest that the human visual system employs tactics quite different from those of most machine systems.' (Perkins, 1983, p. 341)

The Introduction and Literature Survey sections highlight the extensive research produced to unravel the intricacies of texture and human vision. Previous qualitative and semi-qualitative methods of quartz microtextural analysis have employed many methods of analysis ranging from the ubiquitous checklist to the proportional evaluation of Setlow and Karpovich (1972). However, work on texture per se has many implications for the microtextural analyist, particularly in the cognitive analysis of texture.

Early workers in the microtextural field primarily relied upon their human vision system to evaluate surface texture. While subsequent introduction of 'checklist analysis' aided in interpretation, the S.E.M. analyst was still fundamentally responsible for recognising textural features and describing them in terms that could be understood by other workers.

Perkins' (1983), reference to the 'human perceiver' as a 'bad machine' highlights areas where the human perceiver is highly competent, particularly in it's superior recognition abilities recognising objects from partly visible or distorted images. This human superiority over existing shape and pattern recognition algorithms is highlighted by the inability of Fourier Descriptors to produce accurate shape information when quartz grain edge boundaries are missing or noisy. Further discussion of this problem is given in Section 3.4 .

Sketchy representation is another area where the human perceiver excels, producing a sketchy outline of everyday scenes. *Need to know* infers that we do not need to develop a detailed representation of portions of a scene unless there is a motive for such a representation. The human perceiver depends upon high resolution input to a very rapid and flexible pattern recognition and inference making system using the principles of :

a) need to know - proceed beyond a sketchy representation only on a need to know basis

b) reliable steps - construct a representation of the stimulus through a series of reliable recognitions and inferences.

c) avoid search - rarely explore deeply alternative representations (Perkins, 1983).

What relationship does sketchy representation have on quartz grain microtextural analysis ? Initially, the S.E.M. analyst attempts to capture basic spatial regularly, identifying coherent regions such as large flat areas, edges, symmetrics ie. conchoidal fractures, and produce a mental sketch. The importance of edges, highlighted by Goudie and Bull (1984), is very valuable in forming an early sketch of a quartz grain surface. Many computer vision systems rely on edges and the surfaces which they enclose. With three main stages :

a) first locate edges

b) construct a sketch

c) construct a sketch independent of the observer, (Perkins, 1983).

The first stage was termed a primal sketch, a primitive but rich descriptor of an image used to determine the reflectance and illuminance of each visible surface and it's orientation and distance from the viewer by locating all of the visual edges. The second stage requires construction of the position, orientation and discontinuity of each surface relative to the observer through use of stereopsis, occlusion, shading, lighting and importantly here, texture. Stage three creates a 3-D image sketch. So the first impression of a quartz grain's surface produces a primal sketch of edge types dependent on lighting sources. Microtexture is then used as a depth and orientation indicator.

When quartz grain analysts study grain surfaces at increasing magnifications, it becomes more difficult to produce a primitive sketch which is meaningful and this may be the clue to Bull's (Pers Comm), conjecture that high magnifications of quartz grains should be avoided. Possibly our immediate impression of a quartz grain shape and surface is the best method for recognising it's population class. The weakness of the human visual system in judging proportions is an obvious reason why techniques which rely on estimation of a quartz grain surface, ie. Setlow and Karpovich (1972), have failed to gain acceptance, (Williams, et al, 1985). Reference to the vast literature on texture and the limitations of the visual system may have saved time and effort for workers employing Setlow and Karpovich's techniques, (see Section 5.7)!

2.2.2. STATISTICAL MODELS

'On the statistical level we regard a texture as defined by a set of statistics extracted from a large ensemble of local picture properties.' (Van Gool, et al , 1985, p. 337)

Many statistical models of texture have developed, but there has been distinct polarization towards certain models.
Haralick (1982), reported eight statistical approaches :

a) Autocorrelation
b) Optical transforms
c) Digital transforms
d) Texture edgeness
e) Structural elements
f) Spatial gray level dependence matrices (SGLDM)
g) Gray tone run lengths
h) Autoregressive models

In this thesis only autocorrelation, SGLDM's, edge texture and a new method of texture analysis, the textural unit, were used and are considered below, (see Section 3.3 onwards).

2.2.2 a) AUTOCORRELATION

Most texts and reviews cite the autocorrelation (of an image gray level array) as a classical approach to textural analysis, (Rosenfeld, 1969; Rosenfeld & Weszka 1976; Haralick, 1979; Chen & Pavlidis, 1979; Rosenfeld, 1982). General reference to its application relate to the optical work of Kaizer (1955). (See Haralick, et al, 1973; Haralick & Shanmugan, 1974;

Haralick, 1979; Van Gool, et al, 1985). Kaizer's (1955), methods, employing measurements of the transmittance of light through two copies of a transparency offset by given amounts, apparently gave fairly poor resolution of textural features. The method appears to have taken a 'backseat' in textural studies with development of more intricate analyses using first and second order statistics and use of various texture elements and primitives, (e.g. Rosenfeld 1982).

Surprisingly, little work has used digital methods to determine the autocorrelation functions of textural patterns numerically from discrete pixel data. However, this is routinely done for gray scale co-occurrence matrices and other statistical methods used in texture analysis (e.g. Haralick, et al, 1973; Galloway, 1975; Chen & Pavlidis, 1979). Most work involving autocorrelation in this way has been applied in the separate area of image simulation and particularly 'radar clutter' reconstruction, using the calculated autocorrelation as a constraint on pixel values (e.g. Gagalowicz and De Ma, 1982 ; Oliver, 1988).

One reason for the lack of applications may be the prevailing opinion that spatial frequency methods and by inference the autocorrelation function, since it is the Fourier transform of the power spectrum (Blackman & Tukey, 1958), perform less well than co-occurrence or structural techniques (see Weszka, et al, 1976). In addition, Haralick (1979), pointed out that the autocorrelation can be written as a function of the co-occurrence matrix elements at the same lag. Thus co-occurrence matrices certainly do contain more information than the autocorrelation, though the question then arises as to the useful interpretation of this information when dealing with non simple textures. In practice, a multiplicity of possible functions or combinations of the co-occurrence matrix elements are actually used, rather than any direct analysis of the matrix itself (see Haralick, et al, 1973).

Despite real or imagined drawbacks (e.g. Lin, 1982), autocorrelation methods (and their discrete analogues) have had great success in describing spatial distributions in many areas of science, particularly plasma physics, the physics of fluids, and non ideal gases (e.g. Montgomery & Tidman, 1964; Ichimaru, 1973), astronomy and cosmology (Phillipps, 1979; Peebles, 1980; Barcons & Fabian, 1989), and surface physics and thin films (Raether, 1977 ; Rasigni, et al, 1982).

In all these areas autocorrelation methods have proved to be far more amenable to analytic study and to have much more direct connections to physical theory than other (possibly mathematically superior) means of describing spatial distributions. For example, the distribution of galaxies in space has been shown to have a power law autocorrelation function whose behaviour and evolution with time is related to the physical development of structure in the universe through the growth of gravitational instabilities (Peebles, 1980 ; Maddox, et al, 1990). In addition to its relationship to the physical processes governing spatial distributions, a major advantage of the autocorrelation function is it's relative ease of interpretation in terms of visually perceived structures (see Section 3.8), which are especially beneficial when applied to more irregular and complex situations. However reference to Section 4.3.2 shows the drawbacks of the method, when applied to complex textures such as quartz grain surfaces.

2.2.2 b) SPATIAL GRAY LEVEL DEPENDENCE MATRICES (SGLDM's)

'***Our initial assumption in characterizing image texture is that all the texture information is contained in the gray tone spatial dependence matrices.' (Haralick et al, 1973, p. 611).***

This method and it's many variations have been one of the most widely used methods of textural analysis. They have been called by a variety of terms from simply co-occurrence matrices to gray tone co-occurrence matrices to spatial gray-level dependence matrices. Here they are referred to as spatial gray level dependence matrices, (SGLDM).

As the name implies this method is a measure of the spatial relationships of pixels to each other over a variety of distances. As such it is a second order of texture, i.e. it does not operate on pixels directly but on a matrix derived from the window pixels, and is essentially a two dimensional histogram of the number of times that pairs of intensity values occur in a given spatial relationship, (Zucker and Terzopoulos, 1980). In more formal language, the matrix evolves from consideration of the joint probability density function of two pixel locations. The first stage in the process is construction of a new matrix where each element is filled by the number of times that pixels with certain intensities occur next to one another in the original image. Figure 8 illustrates the construction of this matrix. From an image window, it is possible to construct four matrices representing the major angles, 0, 45, 90 and 135 degrees. These matrices are called angular nearest-neighbour gray tone spatial dependence matrices. Not only is it possible to measure the occurrence of pixel i against its nearest neighbour j, but it is possible to use a distance measure ∂, (Haralick, et al, 1971). Symmetric co-occurrence matrices are generated by summing the angular matrices, (see Methodology section). Usually the co-occurrence matrix is normalized so that they approximate discrete joint probability densities of co-occurring gray levels. Haralick, et al (1973), proposed 14 measures derived from the matrix, some relating to specific textural characteristics of the image such as homogeneity, contrast and organized structure within the image. It was added that even though these features contain information about the textural characteristic it is hard to identify which specific textural characteristic is represented by each of these features, (Haralick et al, 1973). A full description of some of these measures, (Contrast, Entropy, Correlation and Homogeneity) is given in Section 3.3.2.

While Julesz (1962), was the first to use co-occurrence statistics in his innovative human texture discrimination experiments, Rosenfeld and Troy (1970) , Haralick (1971), and Haralick, et al (1973), employed the matrix approach with varying success. The latter research computed textural features for three different kinds of image data; Photomicrographs of five types of sandstones, 1:20000 aerial photographs of eight different land uses and Earth Resources Technology satellite imagery. Piecewise Linear Discriminant analysis was used as a pattern recognition technique to correctly assign the images to their true groups. Identification accuracy was 89% for the photomicrographs, 82% for the aerial photographs and 83% for the satellite imagery. The distance used in all 3 data sets was 1 pixel.

Weszka, et al (1976), compared the Fourier power spectra, second order gray level statistics and first order gray level differences. Contrast, Angular second moment, Entropy and correlation measures were computed for varying distances d. Using Landsat data, an attempt was made to demarcate a set of distinctive lithological regions; Mississippian limestone and shale, Lower Pennsylvanian shale and Pennsylvanian sandstone and shale. Using Fisher classification, they concluded that small distances of ∂ performed best, Fourier features did not do as well and all the 'Haralick' statistical features did equally well with a classification of 75%-93%. A geologist and a 'naive' subject attempted to classify the 180 samples according to class type. The geologist correctly classified 143 out of 180 while the naive subject scored 145 correct , (not much of a geologist!). This was a poorer performance than even the worst textural feature type, i.e. Fourier Pairs. They also showed that the discriminatory power for the SGLDM improved when several intersample spacing distances were used, (see Section 3.3.2 and Section 5.8).

Chen and Pavlidis (1979), used the co-occurrence matrix in conjunction with a split and merge algorithm to segment texture into distinct regions. Using the symmetrical form of the matrix, they observed that this loses directional information which was not very important. Connors and Harlow (1980), theoretically compared four commonly used methods; SGLDM, the gray level run method (GLRM), the gray level difference method (GLDM) and the power spectral method (PSM). Their results indicated that the SGLDM was the most powerful algorithm with the PSM worst.

Haralick, et al (1973), used SGLDM to analyse pore structure of petroleum bearing reservoir rock. Applied to 243 photomicrograph images from seven sandstone samples, they were able to achieve 89% correct classification. They concluded that the high accuracy of classification indicated that the textural features were useful for describing the pore geometry of natural porous materials. In addition they implied that better classification accuracy could be achieved by using additional features. This conclusion is investigated in this thesis where a number of features are used to improve classification success, (see Section 4.3.7). Use of the SGLDM methods have been widely used in analysis of medical images (Haralick and Shanmugan, 1973), pulmonary radiographs (Chien and Fu, 1974), and cervical cells (Pressman, 1976). In the diagnosis of *'oesteogenesis imperfecta'*, Terzopoulos and Zucker (1982), combined SGLDM features with edge co-occurrence features and produced a 13% increase in diagnostic acccuracy.

A novel application of the SGLDM was undertaken by Siew, et al (1988), in an analysis of carpet wear. Appearance changes in carpets during wear had previously been judged selectively during quality control experiments. Discrepancies in qualitative analysis prompted the requirement for an automated method. Carpet samples were exposed to a controlled wear treatment. Using a variety of co-occurrence matrix types and features selected from them, it was possible to develop a model of carpet texture change over a given time period. They concluded that the image processing approach using statistical textural analysis was superior to a panel of 'expert' judges. Is this an indication of its likely performance in sand grain microtextural analysis?

Vickers and Modestino (1982), argued for the use of the co-occurrence matrix as a pattern classifier and not *Haralick* textural measures derived from it. Using this method better than 95% correct identification accuracy was obtained when distinguishing tree bark, calf leather, wool, beach sand, pigskin, etc. Their optimal distance, ∂ was 5. However a glance through previous correct classification percentages in the literature and those obtained here (see Section 4.3.6), indicate a high correct classification percent can be achieved without the need for additional computation time handling large co-occurrence matrices.

Variations of the SGLDM are common in the literature because each worker has been presented with different problems in their individual data sets, hence the 'application specific' and image nature of the implementations. As an example, Galloway's (1975), 'short note' is often cited. She used 'gray level run lengths' as the basis for texture analysis. The length was a 'set of consecutive, collinear picture points' having the same gray level, (Galloway, 1975, p. 172). A gray level run length matrix was constructed, the matrix element (i,j) specifying the number of times that the picture contains a run of length j in a given direction. Numerical texture measures analogous to the 'Haralick' measures were computed. These included short and long run emphasis, gray level nonuniformity and run length nonuniformity. Fifty four terrain samples from nine category land covers including orchards, woods, urban, suburb, lake, marsh, swamp, railroad and scrub. Good separation was obtained when one feature was plotted against another but no discriminant classification was attempted, as in previous studies.

Generalized co-occurrence matrices (GCM's) describe spatial distributions of local features such as edges and lines rather than spatial distributions of intensity (Van Gool, et al 1985). Dyer, et al (1980) and Davis, et al (1981) calculated co-occurrence features using edge strength maxima and edge direction relationships using pixels located near edges.

2.2.2 c) **2-D FOURIER ANALYSIS**

The Methodology section gives an indepth view of this technique. In brief, it is possible to decompose any motion into a series of simple periodic motions of varying frequencies. The Fourier transform uses sine waves. Increasing the number of sine waves in the sum creates a waveform more and more like the original wave, (James, 1987). The discrete implementation treats the input picture f(x,y) as periodic. If a texture is spatially periodic or directional, it's power spectrum will tend to have peaks for different spatial frequencies. The peaks can be used as a basis for pattern recognition discriminators (see Section 3.6). Bajcsy and Lieberman (1976), defined features by 'searching' the Fourier space directly by expressing the power spectrum in a polar coordinate system of radius versus angle. Directional textures tended to have peaks in the power spectrum along lines orthogonal to direction of texture. Blob textures had peaks in the spectrum at radii corresponding with blob size.

The Fourier space can be partitioned into bins using either radial or angular bias or a combination. Angular rings produce a measure for texture coarseness while wedges contain directional information. A coarse texture has high values concentrated near the origin while fine textures have values more distributed. A texture with many edges in a direction θ will have values concentrated around the perpendicular direction. Weszka, et al (1976), analysing terrain images used intersections of rings and wedges. Classification results indicated that wedges did substantially worse than rings, indicating coarseness was more important than directionality. They noted that the Fourier transform treated a picture as periodic even if it was not, it produced spurious high values in horizontal and vertical directions, degrading the Fourier features.

Generally workers have found that Fourier measures performed less well than SGLDM statistics, a conclusion supported here and elsewhere (see Section 4.3.3; Weszka, et al 1976). D'Astous and Jernigan (1984), argued that this poor performance was due to the use of rings and wedges. They suggested the use of discriminating information taken directly from the power spectrum such as regularity, directionality, linearity and coarseness. Peak features yield greater interclass difference than the co-occurrence features and yielded uniformly greater interclass distances than the summed Fourier energy features.

2.2.2 d) **OTHERS**

Wang and He (1990), proposed a new statistical approach for texture analysis. They used *texture units*, the smallest complete unit which best characterized the local texture aspect. Using the distribution of texture units within an image, a texture spectrum was developed. Applying their method to 'Brodatz' textures, and airborne synthetic Aperture radar imagery, they were able to discriminate different textures. Their method has been applied to quartz grain microtextures and is described in detail in Section 3.7.1.

2.2.3 STRUCTURAL MODELS

'The structural approach to texture analysis consists of the extraction of meaningful textural primitives, ... and the description of the primitives in terms of their attributes and spatial interrelations.' (Hong et al, 1980, p. 520)

Structural models of texture presume that textures consist of primitives which appear in quasi-periodic spatial arrangements, (Haralick, 1982). As such, a texture is considered to be defined by elements which occur repeatedly according to placement rules and may be used to discriminate between textural types. A primitive may be defined as a connected set of resolution cells characterized by a list of attributes, (Haralick, 1982). The simplest primitive is the pixel, the more complex forms created by connected sets of pixels all having the same grey level on edge detection. Other primitive attributes include shape and homogeneity. Once primitives are known, topographical relationships can be formed such as adjacency or nearness, counting how many primitives occur in a specified spatial relationship. As a technique, structural models are much more theoretically complex, difficult to implement, and their classification is difficult. The only method used in this thesis is a variation of the edges per unit area, (see Section 3.5.2).

Rosenfeld and Troy (1970), and Rosenfeld and Thurston (1971), suggested the amount of edge per unit area as a texture measure using the individual pixel as a primitive. The gradient was calculated using the Robert's gradient neighbourhood operator. Using a specified window size centered on a given pixel, the distribution of gradient magnitudes were calculated. The use of edge based techniques has been supported because workers have noted that Julesz (1970), concluded that colour line terminators and edge segments were all good cognitive features used by the human visual systems. Sutton and Hall (1972), extended Rosenfeld and Thurston's (1971), work by considering the gradient as a function of the distance between pixels. Applying these methods to a pulmonary disease identification task, they were able to achieve accuracies of up to 80% between normal and abnormal lungs. The role of edges in quartz grain microtexture recognition is discussed in Section 2.2.4.

Edge detection has often been used to segment images into homogeneous regions. Lumia, et al (1983), studied the potential of textural segments for analysing aerial photographs. Using a gradient operator, they were able to segment different textural areas. However deficiencies in the edge detection techniques, particularly degeneracy in edges, caused problems in classification.

Hong, et al (1980), addressed the texture primitive extraction problem using an edge based technique. Primitives were defined as areas which were enclosed by edges. Initially, an edge detection operator found the edges and weak edges were removed. A set of 3 x 3 masks were applied at each edge point to determine it's response, ie. it's angle from 0 to 315 degrees. A threshold, E, was used to reduce the number of points. Using antiparallel points, a primitive was developed. Using first order statistics of the primitives ie. area, perimeter, dispersedness, elongatedness, eccentricity, they classified 'Brodatz' and Terrain textures.

2.2.4 EDGE MORPHOLOGY IN QUARTZ MICROTEXTURES

The Introduction has indicated that many of the mathematical textural models employed here do not have 'cognitive correlates', and features, such as, mechanical V's and microblock development are totally unrecognisable in the processed data. However, one set of pattern descriptors, edge features or gradients can be measured and gradient images of sand grains can be produced, (see Section 3.5 and Section 5.7).

The study of edge development on quartz grain surfaces has been the subject of many research articles. Exterior edge abrasion is a result of grain to grain collisions during turbulent or high energy transport modes. Recently, Morgan (1990), has introduced the idea of edge quantification through the idea of edge shapes, (Figure 2). Angular edges were associated with high energy breakage, or crystallographically controlled forces intersecting at sharp angles. Edge shape study revealed two contrasting edge families, blocky edges and smooth edges. Morgan (1990, p. 167), also commented that 'higher magnifications would tend to increase apparent edge roundness by flattening out the edge horizon'. This has important considerations for the Fourier Descriptor analysis and this relationship has been quantified in Section 3.4.

Grain surface relief represents the macrotopography of grain surfaces. Glacial grains have displayed very high and varied relief compared with grains from littoral and aeolian environments. Bull (1984), suggested conchoidal fracture and breakage block development as initiating mechanisms. Provenance was also cited as important and has been described in several works, (Goudie and Bull, 1984; Williams and Thomas, 1989a).

Features which have considerable appeal as a textural feature are conchoidal fractures. They appear in a variety of morphologies but may be described as concave upward, curved fracture surfaces with an accurate fan shape. Margolis and Krinsley (1974), thought that an ideal form contained dish shaped concavities created by the collision of two particles with uniformly distributed concentrated pressures. The size of fracture varies between grain types. Beach conchoidal fractures were generally smaller and more uniform than their glacial equivalents. A bi-product of conchoidal development are meandering ridges, created by the intersection of small scale blocks and conchoidal fractures.

Blocky development is related to high energy fractures associated with glacial grinding, subaqueous and aeolian transport. Krinsley and Wellendorf (1980), defined them as angular positive areas ranging from 6μ to 20μ and bounded by small conchoidal fractures and flat surfaces on aeolian grains. A relationship to cleavage faces was also suggested.

Steps have been described from a number of grain types. While Goudie and Bull (1984), distinguished straight steps, accurate steps and imbricate grinding, Krinsley and Margolis (1969), considered that all three graded into one another. The validity of using chemically produced step textures have been discussed by a number of workers particularly Bull (1981). Tankard and Krinsley (1975), detailed a three stage cycle in solution surface development :

1) Rounded forms and surfaces
2) Irregular pit development
3) Deeply etched terrains produced by extreme etching.

In an 'etching' environment, two types were identified :

1) Crystallographically controlled orientated triangular and rhombohedral pits and cleavage solution steps and grooves.
2) Solution surfaces independent of internal symmetry.

Analysis of chemical surfaces presented considerable problems to previous methodologies. There is great variation in form and spatial development on a quartz grain, therefore quantification of a *chemical surface* by previous analysis is almost impossible. However, some of the mathematical models, such as the SGLDM approach, have considerable potential in describing a surface which has undergone chemical modification, (see Section 5.7).

SUMMARY

From this review of the major textural algorithms, several points can be made:

1) The spatial textural methods, particularly the SGLDM have proved a very popular and successful method.
2) In general, statistical methods, appear to be simpler to implement than the structural models.
3) The structural models are more complex and beyond the guidelines of this thesis.
4) Some algorithms perform markedly better than others, ie. SGLDM vs Fourier Transforms.
5) Textural algorithms have evolved to meet the criteria of the *user* for analysis of specific problems for a wide range of image database. While the methods may be ad hoc, they have generally been applied to standard images such as 'Brodatz' textures. Few complex textures, such as quartz grain surfaces have been analysed.

2.3 PARTICLE SHAPE ANALYSIS

'The relative merits of alternative shape measurements have been argued with some heat, and perhaps still provide a fruitful area for a master's thesis or two.' (Davis 1986, p. 343).

'Shape is the composite effect of curvature; it is a property of a curve independent of scale and orientation, and refers to the manner in which the curve deviates from some norm." (Freeman 1977, p. 159)

'Shape-data collection systems are that and only that:Data acquisition devices. The procedures they employ for edge extraction are ad hoc solutions to the problem and they do not mimic the human process of visual perception.' (Hills , 1988, p. 487)

In the sedimentological arena, grain shape analysis has always been a popular method of study, generating a variety of methods. This divergence is due to the difficulty in measuring or defining 'shape' in precise terms. In the last two decades, increasing sophistication in technology has made it possible to 'investigate the relationships between environment and sediment morphological response on ever-decreasing scales.' (Telford, et al, 1987, p. 281). Reflecting these changes, this section will deal with research which has harnessed new methods and technologies and will not dwell on previous 'visual subjective assessment or quasi-objective chart comparisons', (eg. Powers, 1953, p. 118; Williams and Thomas, in press). The survey will begin at the *'Fourier Age'*, circa 1968.

In the late 1960's and 1970's, several workers independently implemented the idea that a 'dimensionless description of the profile of a fine particle could be obtained from a Fourier analysis of a wave form representing the profile', (Kaye, 1981, p. 355). Schwarcz and Shane (1969), and Ehrlich and Weinberg (1970), were early workers who implemented Fourier techniques to grain shape analysis. The latter's methodology paper recognised that previous research had failed to characterize such an obviously important variable as shape. This failure was ascribed to the lack of methods which separated shape characteristics of different magnitude, ie. either gross (sphericity) shape and smaller scale directional changes (roundness and angularity). They went on to describe implementation of the Fourier method, where grain shape was estimated by an expansion of the periphery radius as a function of angle about the grain's centre of gravity by a Fourier series. Co-ordinates of points on the grain periphery had to be calculated. Digitization of the boundary was achieved by projecting the grain on a grid and manually recording the intercepts, or using an automatic digitizer. Boundary co-ordinates were converted to polar co-ordinates and two coefficients, (harmonic amplitude and phase angle) for each harmonic was calculated.

Much of the early Fourier work was performed at the Department of Geology, University of South Carolina, under the auspices of R. Ehrlich. Their research objects were :

1) to understand the fundamental reasons for quartz shape variation
2) to develop numerical statistical techniques to extract shape information
3) to demonstrate the usefulness of particle shape analysis in sedimentology, (Ehrlich et al, 1980).

With these goals in mind, the group and other workers embarked on a series of studies using methodologies which have become standards in the discipline. As such, many papers simply described the same methodologies producing a large amount of redundancy in an incestuous literature, (compare Mazzullo and Ehrlich, 1983 and Prusak and Mazzullo, 1987). This repetition may be a result of the apparently limited number of workers who have explored the field, (Ehrlich, et al, 1980; Mazzullo and Magenheimer, 1987; Prusak and Mazzullo, 1987). Few workers have tried to apply other methodologies, (see Whalley and Orford, 1983). Improvements to the methodology have come through technological advances, ie. automation of the grain shape analysis system or improvements in statistical analysis, ie. Q-mode factor analysis or incorporation of other techniques, ie. S.E.M. analysis to aid interpretation.

Early implementations relied on semi-automatic digitization of a grain's periphery, (Full and Ehrlich, 1982). Development of the 'Arthur II' system, a micro-processor controlled scanning system consisting of a microscope-mounted videoscanner feeding a fast video-digitizer controlled by a Cromenco microcomputer, allowed digitization of 200 sand sized particles in less than 10 minutes. This rapid digitization allowed large scale studies to be attempted. However, as Ehrlich, et al (1980), discussed, the digitization was the easy part, the difficulty arose determining the most appropriate numerical statistical technique to extract information. However if the digitization was the easy part why did not more sedimentologists implement the technique ?

The following delve into the literature will not be in chronological order because there appear to be no chronological 'threads' to the subject. Instead, priority will be given to the more expansive studies.

Yarus (1978), analysed shape variation of sand sized quartz in the Eastern Gulf of Alaska. Two principal sand populations in the Eastern Gulf were resolved. The first was characterized by quartz grains with irregular profiles derived from crystalline and glacial sources, while the second population consisted of smooth profiled quartz grains. Mid and Outer shelf regions were dominated by smoother grains conjectured to be grains which had undergone a complex cycle of abrasion and reworking. Analysis of nearshore sand bodies revealed that grains from the shore face sand wedge contained dominantly irregular profile grains, while grains from seawards of the first consisted of smooth 'super mature' quartz grains. Yarus (1978 p.56), used these differences to 'support two important conjectures of Swift (1975), ie. that recently derived sand could not bypass the littoral zone without a major transgression and major sediment movement on shelves tended to be landwards during transgressive events. Yarus (1978), used Q mode factor analysis on chi square values to determine proportionate contributions of end-members to samples, concluding that smooth grains originated on the mid and outer shelf and moved shoreward during transgressive events, accumulating on the inner shelf. Williams and Thomas (1989a), semi-qualitatively discovered the same scenario on the Long Island island barrier system. It was concluded that irregularly shaped grains were found to derive from relict offshore glacial lobes while rounder, smoother grains were found in interfluvial areas. It is interesting to note that they were able to semi-qualitatively separate the two populations using only 100 grains per population and without the need for complicated shape analysis!

Mazzullo and Ehrlich (1983), analysing quartz grains from the St Peter sandstone, Southern Minnesota, found two grain-roundness types mixed in varying proportions. Type 1 had a population of smooth, well rounded grains while type 2 had irregular, angular grains. Additional information provided by S.E.M. textural analysis indicated that type 1 grains were generated during aeolian transport, and abrasion type 2 roundness types were conjectured in less abrasive fluvial environments with little residence time in subaerial environments. The two grain types varied in a 'nonrandom manner' related to alternating units of abraded sand rich and unabraded sand rich beds. It is interesting to note this combination of the two techniques. It may be surmised that while shape analysis was generally efficient in separating populations, it did not tell anything about the mechanisms of shape modification, and as indicated earlier, S.E.M. analysis was just as efficient, if not better, in semi-qualitiatively separating grains types compared to Fourier analysis, (see Williams and Thomas, 1989a).

In a rare non 'Ehrlich' study, Dowdeswell (1982), used S.E.M. micrographs of 158 quartz sand grains representing subglacial transport and subaerial weathering in cold environments. The small number of grains analysed contrasts markedly with the thousands used in Ehrlich based studies. He found that Fourier shape analysis could distinguish basal and englacial grains.

'Tractional' grains were less angular and textured than englacial particles. He indicated that the method could discriminate between different cold subenvironments whereas 'qualitative or semi-quantitative' S.E.M. textural analyses have often been inconclusive, (Dowdeswell, 1982, p. 1321). A roughness coefficient (P) was used :

$$P = \sqrt{0.5 \sum R_n^2}$$

where R_n is the amplitude of the nth harmonic. He also concluded that caution should be exercised when using Fourier analysis to compare data from samples of differing grain size, a point examined in Section 3.4.

Dowdeswell, et al (1985), in a more extensive study, used grain shape and conchoidal fracturing patterns to distinguish glacial and non glacial events. The intensity of conchoidal fracturing was assessed as a percentage of the total visible surface area, (a la Setlow and Karpovich, 1972). They concluded that the quantitative examination of quartz sand particle surface morphology could, in marine cores, be 'a useful indicator of glacial and non-glacial episodes '. However, a multiparameter approach to analysis of the environmental history of marine cores was preferable.

Mazzullo and Magenheimer (1987) went back to first principles to investigate the underlying assumption of grain-shape studies; that shapes of quartz grains from a given source 'reflect the genesis or lithology of the source and are distinct from the shapes of quartz grains from other sources', (Mazzullo and Magenheimer, 1987, p. 379). To test this assumption, weathered bedrock samples from a 700 mile transect from the mouth of the Brazos River to the Texas - New Mexico border were collected. The transect crossed three source terrains : The Llano Uplift of Central Texas, the Great Plains of North and West Texas and the Gulf Coastal Plain of South and East Texas. Subsequent grain shape analysis revealed that the underlying assumption was correct for quartz grains released from crystalline rocks, quartz grains derived from wind generated sedimentary rocks and quartz-cemented sedimentary rocks. Quartz grains had been subjected to 'varied mechanical and chemical processes (eg. crystallization, abrasion, quartz cementation) during the genesis of these sediment sources and these processes had imprinted the grains with 'unique and source indicative shapes', (Mazzullo and Magenheimer, 1987, p. 379). The assumption was false for quartz grains from water transported sedimentary rocks. These had been subjected to fluvial and marine abrasion which did not affect their shapes.

Ehrlich, et al (1980), summarizing a decade's work produced the following conclusions :

a) Quartz shape frequency distributions are polydimensional and polymodal. Six or more variables are necessary to account for more than 90% of shape variation.

b) Each source rock yields quartz particles which are represented by shape frequency distributions with 3 modes or more.

c) This polymodality tends to be reduced with increasing abrasion in the variables which describe the finer details of the particle shape, (Ehrlich, et al, 1980, p. 477).

Also investigated was the relationship between size and shape. Apparently the relationship was not linear but manifested by discrete shifts in shape frequency distributions at around 125 microns. This breakpoint was attributed to different rates of transport of grain sizes above and below 125 microns.

Throughout the 1980's, a series of papers with increasingly longer titles, were published investigating shapes and surface textures of quartz grains from the U.S. Atlantic continental shelf (Brown, et al, 1980; Reister, et al, 1982). Prusak and Mazzullo (1987), attempted to determine the sources and distribution of late Pleistocene and Holcene shelf sediments. They distinguished two distinct sources of sediment for the Mid-Atlantic shelf, the Atlantic Coastal Plain and the Appalachian highlands. Spherical, rounded quartz grains with surface textures created by the weathering of the quartz grains in organic rich soil represented Atlantic coastal Plain types, while the Appalachian Highlands contributed nonspherical, angular quartz grains with crystalline nodes, grain embayments and euhedral quartz overgrowths. On the basis of the percentages of Appalachian and coastal plain sand, five distinct sedimentary provinces were defined :

i) Hudson Province - High percentages of Appalachian sand deposited by the Hudson river system.

ii) Southern New Jersey Province - High percentages of locally derived coastal -plain sand deposited by fluvial and littoral processes.

iii) Delaware Province - High to moderate percentages of Appalachian sand deposited by the Delaware river system

iv) Southern Delaware Province

v) Hatteras Province.

Reister, et al (1982), investigated patterns of quartz sand shape variations on the Long Island littoral and shelf regimes. A pattern of shape variation distinguished a beach-littoral zone, an inner zone, and outer zone, (mid and outer shelf). Two types of grain shapes, abraded and irregular were used to delineate these zones. The irregularly shaped sand of glaciofluvial origin off Long Island became abraded in the beach environment. Samples containing high proportions of abraded sand occurred offshore to a depth of 5 metres. Between depths of 5 and 10 metres, proportions of irregular-abraded grains were highly variable. It was suggested that an offshore exposure of glacial sand acted as a secondary source. This supersition was investigated by Williams and Thomas (1989a), and Morgan (1990). Samples taken landwards of 50 metres displayed irregular sand proportions representing an unresolved mosaic of reworked glacial sands.

2.3.1 **OTHERS**

While it would appear that Fourier Transforms are the only shape descriptor in use, there are examples of innovative applications of alternative techniques. Two authors who have always approached sedimentological problems from unusual angles, Orford and Whalley (1987), following Kaye's (1978) work, proposed using the Fractal dimension as a quantitative description of highly irregular particles. Noting the deficiencies in the Fourier Transform approach when analysing irregular particles which generated re-entrant values, they stated that 'decomposition techniques work best with particles that are basically regular in a macrosense', (Orford and Whalley, 1987, p. 269). Following the pioneering work of Mandelbrot (1977), the linear relationship between the grain perimeter and measurements of a number of fixed units or step lengths was investigated. They concluded that the Fractal dimension could be successfully applied to sedimentary particles, particularly particles that showed irregular outline morphologies which were less periodic and show greater irregularity, (see Plate 4). Williams, et al (1987), using digitized grain shape data attempted to quantify 'grain roughness'. In a two stage process, x,y positions of no interest ie. those on smooth sections of the curve were removed. An angular check was applied to triples of co-ordinate pairs. When the resulting angle did not exceed four fifths of an arbitary required angle, such as 25°, then the point was retained.

Valuable contributions to the body of shape analysis literature has come from powder and fine particle analysis, particularly in the area of automatic classification using image processing techniques. Indeed many new innovations, particularly in the pattern recognition sphere ,have been explored, yet not taken up in the sedimentological arena. Several papers outlined image analysis systems for characterizing particle outlines. Telford, et al (1987), detailed one implementation. Using optical binary (black or white) images they automatically found the X and Y boundary co-ordinates of the grain. Fourier components and Fractal dimensions were calculated for particles but no results given. Hills (1988), devised a microcomputer based system for collecting shape data by extracting outlines of fossil specimens viewed in reflected light. Discussion of Hills's ideas can be found in Section 5.3. Other examples of image processing applications can be found in Fico (1980) and Boon, et al (1982). The reader is referred to *'Advanced Particulate Morphology'* for further examples, (Beddow and Meloy, 1977).

While the geological/sedimentological arena has been slow to take up the use of global shape descriptors, powder and particle technologists have implemented many different types. Normand and Peleg, (1986); Kaye and Wright (1977); Rosier, et al (1987) and Thomas, et al (in press) , all used the Fast Fourier Transform method to generate shape descriptors. Beddow and Vetter (1977), suggested the calculation of several shape descriptors from the coefficients, an example being the ratio of the maximum dimension drawn through the centroid divided by the dimension perpendicular to this line. Beddow, et al (1977), suggested the use of three descriptors based on averages of the sequence of coefficients of the Fourier series. *'Lumpiness'* was the average of the lower order harmonics, *'roughness'* from an average of the intermediate harmonics, and *'texture'* from the coefficient of the highest harmonics. Kaye (1981), gave a more extensive review of shape studies within particle research.

Clark (1987), produced an excellent summary/commentary on the popular methods of grain shape characterization, alternative methods and possible innovations. An interesting section was discussion of Full and Ehrlich's (1982), rejection of the use of the Fast Fourier Transform (FFT) on the basis that for a small number of coefficients, the FFT was only marginally faster. This is counter to experience elsewhere, (see above). Authors within the image processing arena have noted, 'without the popularization of the Fast Fourier transform algorithm by Cooley and Tukey, and others in 1965, transform processing of images would probably have remained in the domain of optics', (Hall, 1979, p. 1).

Fourier Descriptors have been used extensively in other shape studies, (Zahn and Roskier, 1972; Kuhl and Giardnina, 1982; Wallace and Wintz, 1980). A comprehensive study of the application of Fourier methods for the descriptions of wing shape in mosquitoes was carried out by Rohlf and Archie (1984). Outlines of wings from 127 species of North American mosquitoes were digitized and methods used included Fourier analysis of both radii and tangent angle change functions. Elliptic Fourier analysis, (ie. Fourier Descriptors) were also included. Matrices of Fourier results were discriminated using multivariate analysis. They concluded that individual Fourier coefficients could never be morphologically meaningful, therefore only use of suites of coefficients could delineate shape difference. This conclusion is confirmed by the results of Fourier Descriptors used in Discriminant analysis (Section 3.9.2). No one coefficient was able to separate grain populations. Analysis of the 'best' methods indicated that transforms dependent on finding a 'centre' were unsuitable for more intricate wing shapes and use of elliptic Fourier coefficients were preferred.

2.4 SUMMARY

Two decades of intensive research have installed the use of harmonic decomposition of a grain profile as a viable method of shape description. However, as indicated in the introduction, it has yet to become widely used in the sedimentological arena. This is in marked contrast to its uptake by particle morphologists in industry. This 'under use ' is indicated by the 'ad nauseum' description of the technique in almost all papers published between 1970 and the present day. While the Fourier technique has proved to be a useful tool, it only separates grains on shape and tells little about provenance and depositional history. Subsequent integration with S.E.M. analysis has added that essential ingredient but the question must be asked, 'why go to the trouble of implementing and pressing for the use of Fourier Analysis and then couple it with a semi-qualitative technique, such as S.E.M. analysis, which has come under increasing criticism'?. The answer may be that study of only one aspect of a grain's form, ie. shape is inadequate and a multi-multidimensional approach using texture is the only way to generate real conclusions. This statement is more fully discussed in Section 5.4.

CHAPTER 3

METHODOLOGY

3. METHODOLOGY

Six mathematical measures were implemented to quantify quartz grain form. Their selection was guided by the need to select pattern features which discriminated best between samples of quartz grains. Shape was one obvious feature but use of textural measures such as the co-occurrence matrix, edge detection and segmentation, autocorrelation and the 2-D Fourier transform are innovative approaches to quartz grain research. It has been indicated that cognitive features previously used to discriminate quartz grain samples such as MV's, blocks, and conchoidal fractures were difficult to 'recognise' within these mathematical treatments. This presented the problem of applying previous semi-quantitative databases to interpretation of results from the mathematical models. An additional problem was the complexity of the quartz grain surface which contained many features in varying sizes and orientations. However a combination of these methods covered many possible textural permutations, (see Section 5.7). While many of these methods have been previously applied to simple textures such as grids or blobs, little work has been done on complex texture where hierarchical variation is considerable. As referred to in Section 1.1 only gross textural form was measured. Actual feature recognition must be the concern of subsequent researchers.

3.1 IMAGE PROCESSING SYSTEM

The heart of an image processing system is a digital image processor. It consists of hardware performing four basic functions; image acquisition, storage, fast processing and display, (Gonzalez and Wintz, 1987). Most image processors can digitize an image in one frame time, (1/30th second) and are called 'frame grabbers'. Image processors are interfaced to a general computer such as an IBM PC. Interlinked are display devices such as monochrome or colour television monitors. The computer hardware used here included a 40 megabyte PC fitted with an 'Itex' image processing board. Using many of the prewritten algorithms computer programs were written to develop a powerful set of algorithms to specifically analyse quartz sand grains. All programs were written in 'C', a popular low level programming language.

3.2 PREPROCESSING - INITIAL PROCESSING OF S.E.M. IMAGERY

Quartz sand grains were initially cleaned and mounted for S.E.M. scanning using the techniques outlined by Krinsley and Doornkamp (1973). Sediments were sized using standard sieve techniques and individual grains were cleaned by boiling in dilute hydrochloric acid. Following washing in distilled water, they were boiled in concentrated Stannous Chloride before a final wash in distilled water. This procedure removed all organic extraneous material and stains. Subsequent light microscope examination removed non quartz and obvious polycrystalline members. Quartz grains were used due to their resistance to mechanical and chemical disintegration. 0.5 mm size grains were mounted on individual aluminium stubs and sputtercoated with a 30A^{o} layer of gold to conduct a build up of surplus electrons on the grain surface to earth. 'Charging up ' caused problems in later texture analysis where areas of grain appeared as bright uniform areas with no recognisable texture and is discussed in Section 5.2.

Three hundred grains per sample were used for this study. As the principle aim was mathematical quantification of sand grain form, use of existing databases relating quartz grain populations to specific surface texturse were important in interpreting the textural results. This relationship is developed more fully in Section 4.1 and Section 5.7.

The three grain population types were selected to fulfill certain criteria :

a) Grain samples had to display distinctive surface textures and shapes.

b) Grains had to show simple microtextures. This made correlation between the mathematical descriptors and qualitative assessments easier to assess, (see Section 5.7).

The three populations chosen were :

i) Desert grains.

ii) Fire Island beach grains.

iii) Crushed quartz grains.

A resume of their distinctive surface textures is given in Section 4.1.

Each grain was scanned at approximately x90 magnification. This standard was chosen because it produced a reasonably large image from which many major textures could be discerned, and a good representation of the quartz boundary. Indeed, Bull (Pers Comm), has implied that studies of quartz grain surfaces at higher magnifications produce cognitive problems of surface feature recognition. This is directly related to the hierarchical nature of texture, a theme explored in the Section 2.2. (A standard magnification was also important for calculating the Fourier Descriptors, (see Section 3.4)).

The electron image was constructed of a large number of grey levels, (up to 256). The image grey level distribution at this juncture approximated by a 'Gaussian' distribution. However, variations in the means and standard deviations of grain images from one scanning session to another necessitated the need for a form of histogram equalisation, (see Section 3.2.3).

3.2.1 IMAGE CAPTURE

Each individual image was 'frame grabbed' and stored in compressed format as a 512 x 512 digitised array, (see Section 1.2). Each image took approximately ¼ megbyte of available memory. An unprocessed image is shown in Plate 1. In this 'unrefined' state, the top of the image consisted of a 'banner' displaying magnification and scale details. The quartz grain in the centre of the image was surrounded by partial quartz grain forms set on a featureless background containing areas of sticky tape on the aluminium stub (bottom left). This background, while essentially redundant, provided problems in later analyses as background pixel values were similar to quartz grain interior values.

3.2.2 SEGMENTATION

' Segmentation is one of the most important elements in automated image analysis because it is at this step that objects or other entities of interest are extracted from an image for subsequent processing........' (Gonzalez and Wintz, 1987 p. 331).

Image segmentation assumes that objects consist of a region of homogeneous intensity which changes abruptly at the object's border. There are two major approaches to image segmentation, edge based and region based, both of which are applied here. Many segmentation algorithms assume that an image contains only two principal brightness values, light and dark. Hills's (1988) system to analyse microfossils used a thresholding technique. He was able to use this method because his objects and background could be distinguished by their respective grey level values. However, this is not the case for quartz grains, hence the need for a mixture of the two approaches. A comprehensive review of segmentation methods is given in Gonzalez and Wintz (1987).

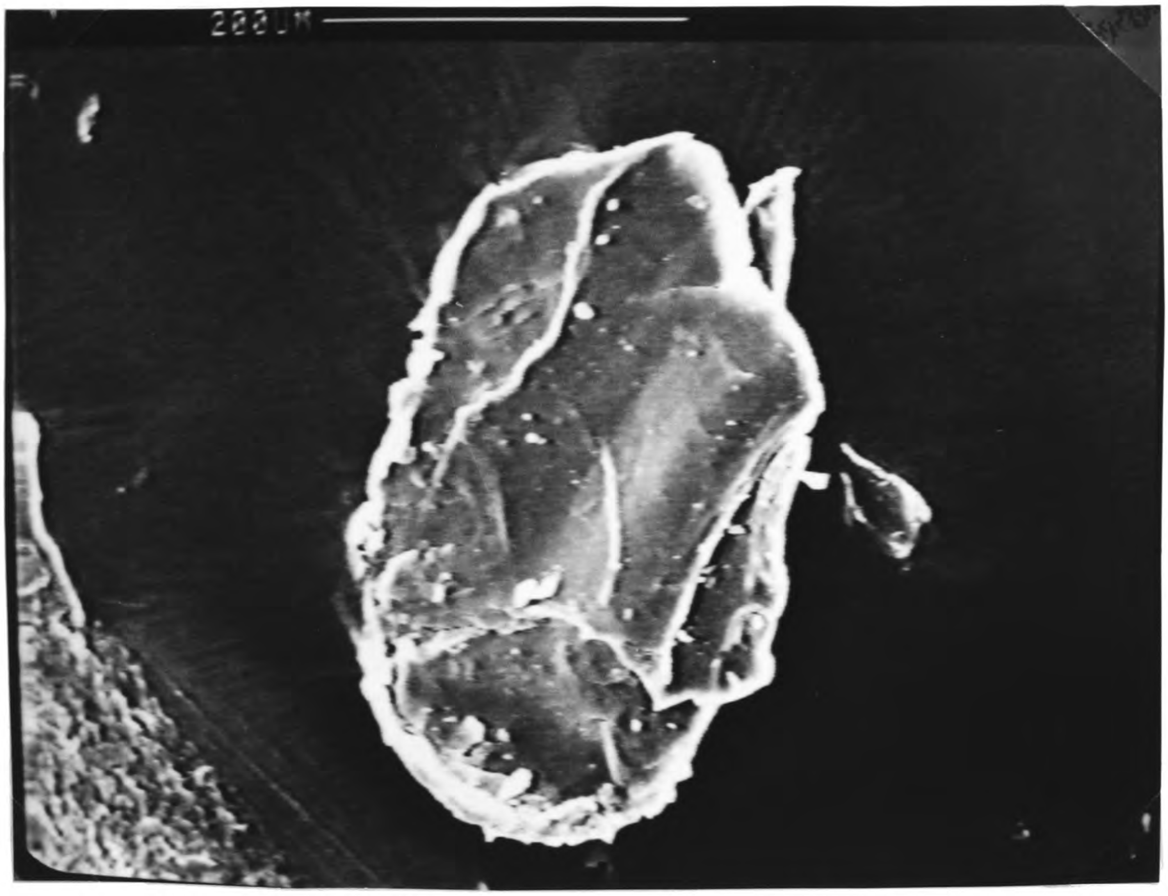


Plate 1 - Unsegmented S.E.M. image of a quartz sand grain - note the scale at the top and the cluttered background

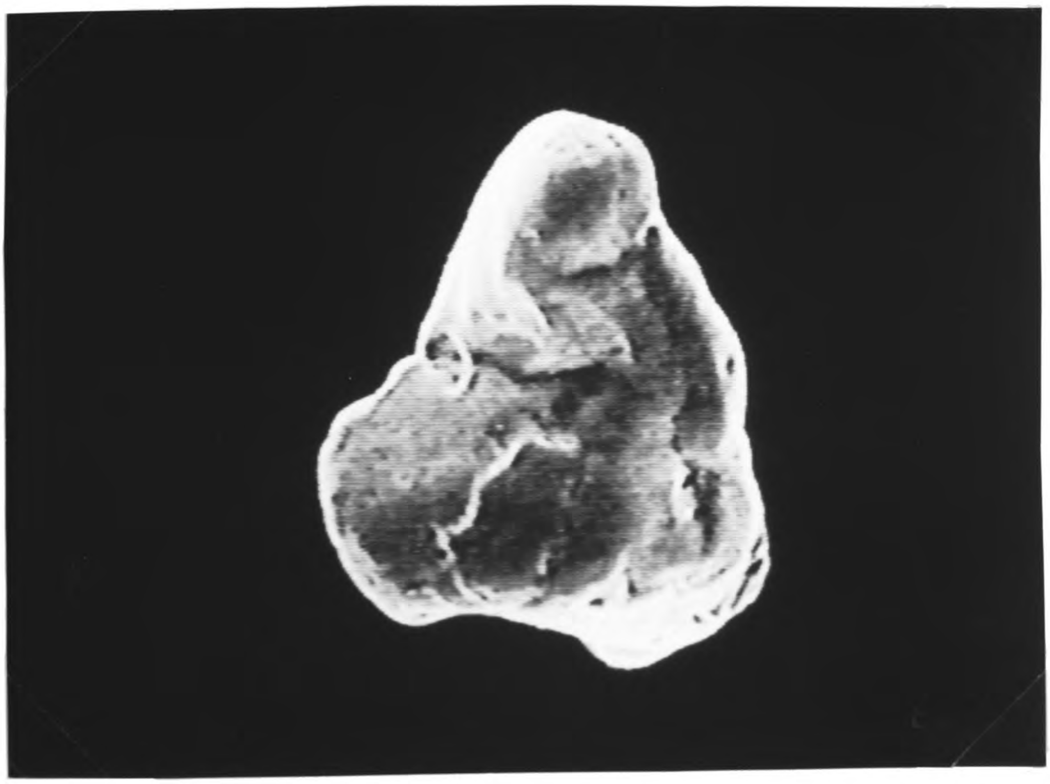


Plate 2 - Segmented quartz grain image. The background is set to pixel value zero.

Initially the banner at the top of the image was removed by changing the pixel value in the section to 0 (black). A Roberts gradient operator (see Section 3.5.2) passed over the whole image defined the grain boundary. It was then possible to 'threshold change' all pixels within the grain interior to a uniform pixel value. All exterior pixel values were changed to 0, leaving only the grain hull which then acted as a template. The template pixel values subtracted from the original image left only positive values, ie. the quartz grain. All other extraneous background and shadow effects around the grain boundary were removed by simple pixel manipulation.

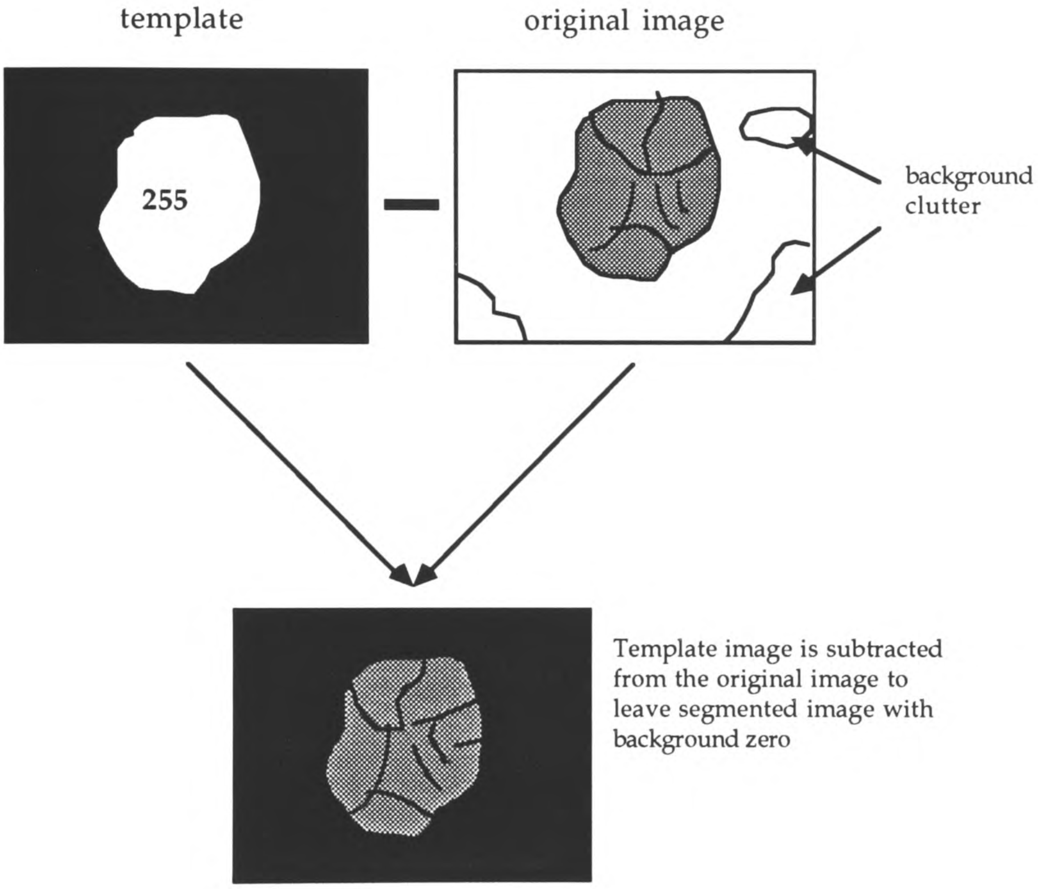


Figure 3 - Construction of the image template used in segmentation

Figure 3 shows the segmentation process. The template constructed from the original grain shape has a background value of zero and a grain value of 255. When the template values are subtracted from the original image values less than zero i.e the background are set to zero. Pixels with a positive value retain their original value leaving a segmented grain image (Plate 2).

3.2.3 HISTOGRAM EQUALIZATION

Changes in S.E.M. operating conditions altered the gray level distribution of the image, a common occurrence between scanning sessions. This had important considerations for comparative analysis and indicated the need for image standardisation before analysis. Connors and Harlow (1978) investigated the effect of image equalization on SGLDMs results computed from radiographs and considered how well histogram reduced images were an accurate representation of the original data image. They concluded that normalization, via histogram equalization or other methods, was an important preprocessing step, to remove variance in operating conditions, particularly contrast, and make the SGLDM results invariant to film exposure and development. A histogram of gray levels is one method of 'global' description of an image.

Histogram equalization collects together sets of pixel values from the original image into sets of roughly equal numbers (or probability). For instance, if 7 pixels had a value 1, 3 were 2's and there were 10 3's, we could 'equalize' the histogram by lumping the 1's and 2's together. Formally, the process is a mapping transform. Every pixel in the original image having a value r_k is transformed in intensity to the value s_k by the $T(r_k)$ transform $P_r(r_k) = n_k/n$ where Pr(k) is the probability of the kth grey level, n_k is the number of times this level appears in the image and n is the total number of pixels in the image, (Gonzalez and Wintz, 1987). Only values greater than 0 were included, ie. only the grain surface was included in the equalisation process. The object was to produce a transform that reduced the number of gray levels and produced a uniform distribution. In this instance a flat distribution was produced. An artificial example of the workings of the technique is shown in Table 1 below, (after Gonzalez and Wintz,1987).

r_k	n_k	$P_r(r_k) = n_k / n$
$r_0 = 0$	500	0.2
$r_1 = 1/9$	1020	0.408
$r_2 = 2/9$	60	0.024
$r_3 = 3/9$	100	0.04
$r_4 = 4/9$	300	0.12
$r_5 = 5/9$	12	0.0048
$r_6 = 6/9$	50	0.02
$r_7 = 7/9$	100	0.04
$r_8 = 8/9$	200	0.08
$r_9 = 1$	158	0.0632

Table 1 - Hypothetical gray level distribution of a 50 x 50 pixel image.

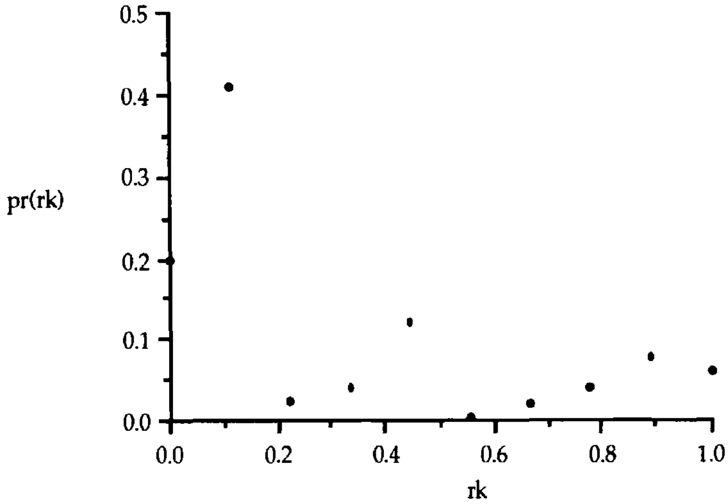


Figure 4 - Histogram of probability of the gray level against number of times of occurrence (r_k)

The transformation function gives :

$$
\begin{aligned}
S_0 = T(r_0) &= \sum Pr(r_j) \\
&= P_r(r_0) \\
&= n_k/n \\
&= \underline{0.2}
\end{aligned}
$$

and

$$
\begin{aligned}
S_1 = T(r_1) &= \sum Pr(r_j) \\
&= Pr(r_0) + Pr(r_1) \\
&= 0.2 + 0.408 \\
&= \underline{0.608}
\end{aligned}
$$

The new values are shown below , in Table 2:

S_k values	r_k values	New n_k values
$S_0 = 0.2$	$r_0 = 0$	$S_0 = r_2 = 500/2500 = \underline{0.2}$
$S_1 = 0.608$	$r_1 = 0.111$	$S_1 = r_5 = 1020/2500 = \underline{0.408}$
$S_2 = 0.632$	$r_2 = 0.222$	$S_2 + S_3 = r_6 = 160/2500 = \underline{0.064}$
$S_3 = 0.672$	$r_3 = 0.333$	
$S_4 = 0.792$	$r_4 = 0.444$	$S_4 + S_5 + S_6 = r_7 = 300 + 12 + 50$
$S_5 = 0.7968$	$r_5 = 0.555$	$= 362/250 = \underline{0.1448}$
$S_6 = 0.8168$	$r_6 = 0.666$	
$S_7 = 0.8568$	$r_7 = 0.777$	$S_7 + S_8 = r_8 = 200/2500 = \underline{0.08}$
$S_8 = 0.9368$	$r_8 = 0.888$	
$S_9 = 1.0$	$r_9 = 1.0$	$S_9 = r_9 = 158/2500 = \underline{0.0632}$

Table 2 - New S_k values mapped with r_0 values

From Table 2, it can be seen that S_0 values can be mapped onto discrete R_k values. S_0 (0.2) now maps onto r_2 (0.222) and S_2 (0.632), S_3 (0.672 map onto r_6 (0.666). There are now 100 + 60 = 160 pixels. Dividing by n gives a new value of 0.064. These values produce the new histogram using only six gray levels compared to ten for the original image.

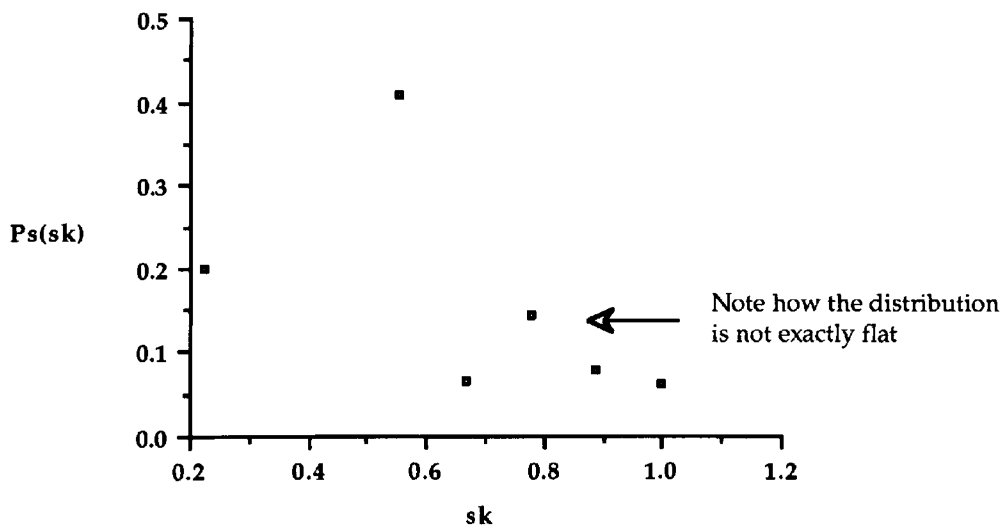


Figure 5 - New equalized histogram (After Gonzalez and Wintz, 1987)

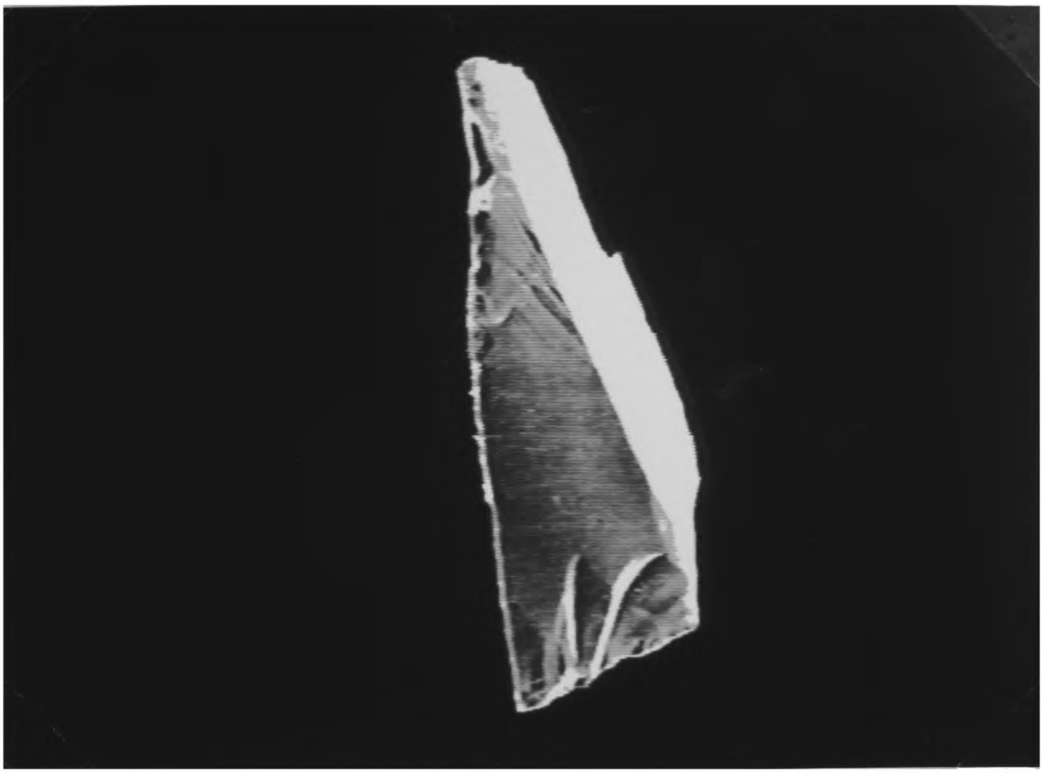


Plate 3a - Un-equalized crushed quartz grain image.

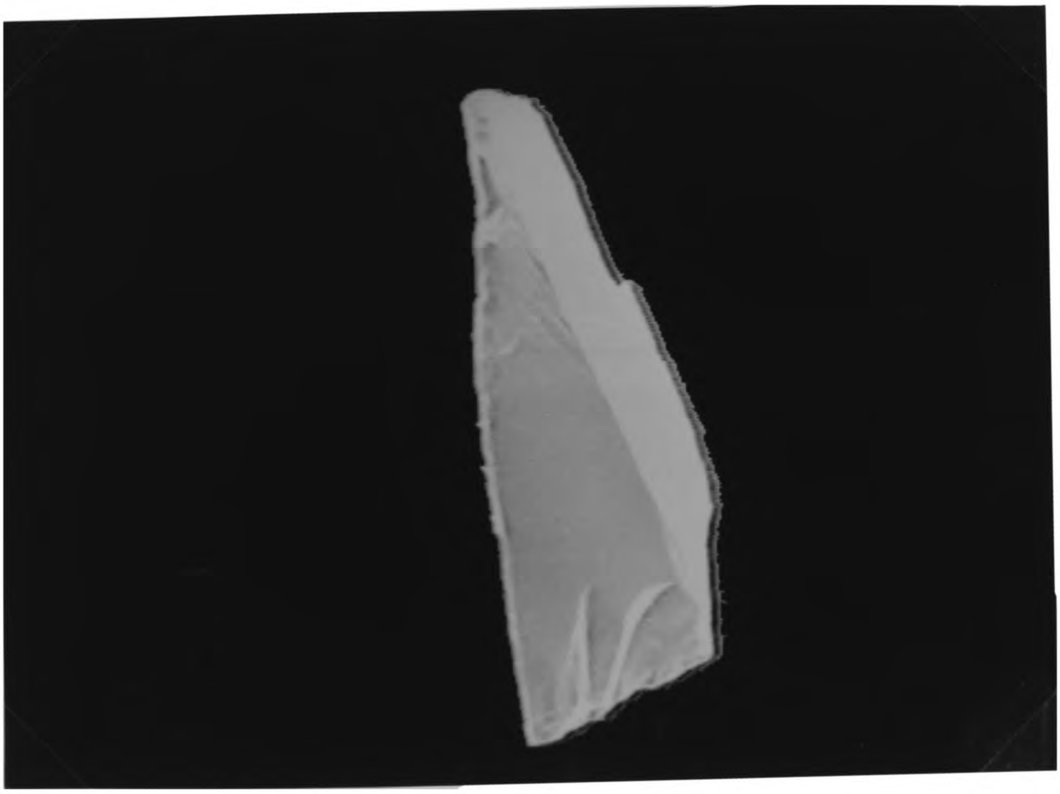


Plate 3b - Histogram equalized quartz grain image

As there were hardware restrictions on the number of gray levels that could be used in the co-occurrence matrix, the equalization reduced the gray levels from 256 to 60. This resulted in less memory storage allocation. Note how some gray levels are left unallocated. Plates 3a and 3b shows a grain before and after equalization.

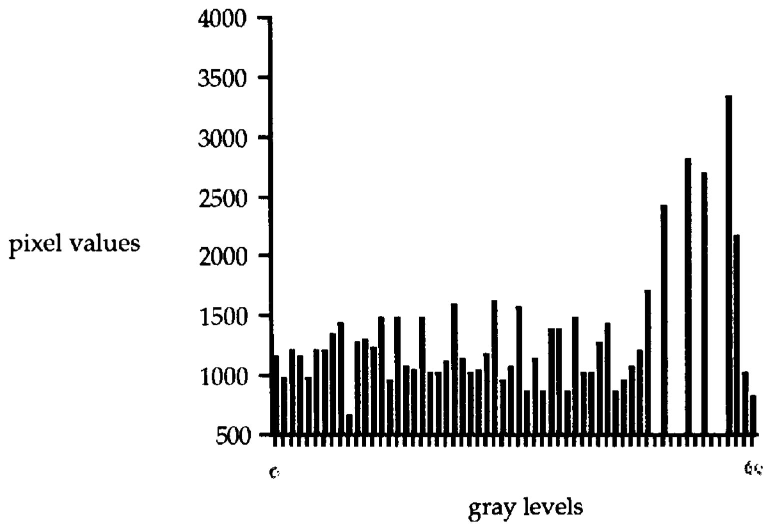


Figure 6 - Gray level histogram obtained from a normalized quartz sand grain image.

3.2.4 NOISE REMOVAL

Noise, the 'contamination or degradation' of an image, is usually introduced into an image by an electronic sensor such as an S.E.M. or video camera. 'Snow' noise is characterized by extreme pixel to pixel changes rather than small changes observed from natural scenes. It's removal was important because it could have led to spurious results particularly in edge detection and co-occurrence matrix calculations.

A rationale for diminishing spurious information is through image smoothing. Three methods are commonly used:

i) Neighbourhood averaging

ii) Median filtering

iii) Lowpass filtering.

Neighbourhood averaging is a spatial domain technique, using an N x N image, f(x,y). A smoothed image g(x,y) is generated whose gray level at every point (x,y), is obtained by averaging the gray level values of the pixels of f(x,y), contained in a predefined neighbourhood of (x,y) (see Gonzalez and Wintz, 1987).

Usually a 3 x 3 neighbourhood is used, (Gonzalez and Wintz, 1987). One drawback to the neighbourhooding method is its ability to blur edges and other sharp details. A way around this is to use the *median* filter in which the gray level of each pixel is replaced by the median of the gray levels in a neighbourhood of that pixel. This method tends to reduce spikelike components and preserves edge sharpness, (Gonzalez and Wintz, 1987). The median filter implemented here, used a 3x3 neighbourhood or 'mask'. The nine values in the neighbourhood were sorted in ascending order and the median value, (the 5th value) determined and assigned to the middle pixel.

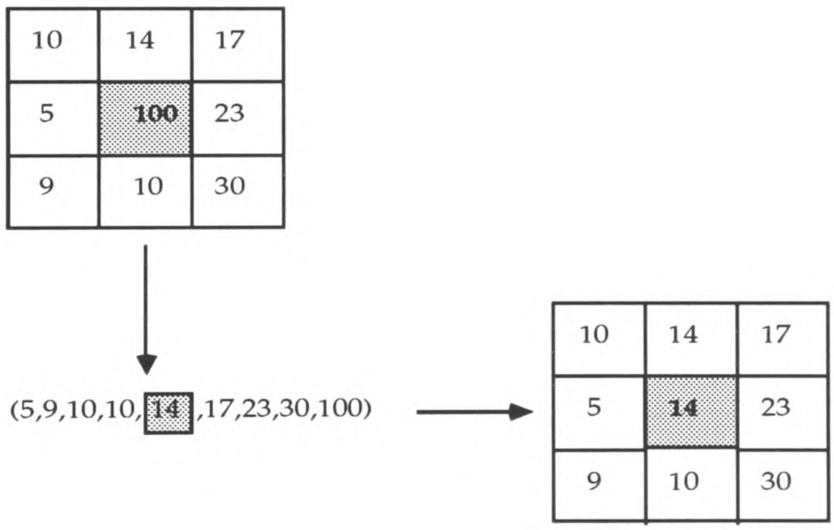


Figure 7 - Implementation of the median filter

3.3 SGLDM'S (CO-OCCURRENCE MATRICES)

3.3.1 CONSTRUCTION OF THE SGLDM

The SGLDM has been widely used as a measure of texture and is generated from the statistics of the spatial distribution of gray levels within the quartz grain image. In contrast to other textural measures which use only histograms, SGLDM 's consider not only the distributions of intensities but also the positions of pixels with similar intensity values. In this application the whole grain surface is considered to be a single 'region', with one SGLDM produced per grain. Future applications may use SGDLM's at smaller resolutions in an attempt to quantify small scale textural change. However, time constraints do not allow this here.

The SGLDM method is based on the estimation of the second order joint probability density function $P(i,j, \partial,\theta)$. Each entry in the matrix records the probability of going from gray level i to gray level j given an interspacing ∂ and direction θ. In many cases, the θ is ignored and elements are added together to create a *'symmetrical matrix'*. This is important where there is no apparent textural directionality or orientation within the object. As the placement and hence orientation of a sand grain on an S.E.M. stub was not controllable this was permissable. Figure 8 illustrates the matrix construction.

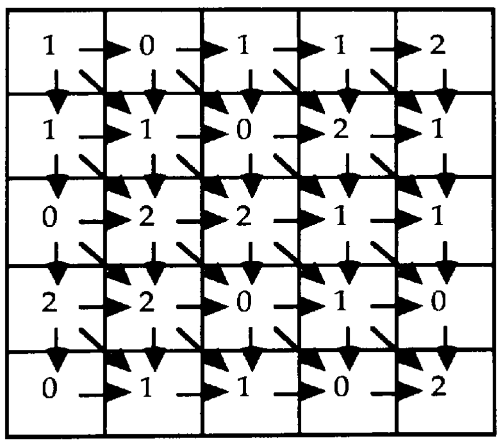


Figure 8 - Construction of the symmetric SGLDM.

The first stage in constructing a horizontal SGLDM requires calculation of the number of times that pixels with certain values occur next to one another in the original image as shown in Figure 8. For this work a symmetric matrix was generated. This construction presented several problems. The size of the potential matrix, 256 x 256, was too large for the computer processor which can only handle a maximum 64 x 64 matrix without complicated memory manipulation. The histogram equalization technique was used to reduce the image to 60 gray levels (see Section 3.2.3). Since the human visual system can distinguish less than 64 distinct gray levels this reduction in contrast was permissable (Hall, 1979).

Only those pixel values greater than 0 (ie. on the grain surface) were used. A window was passed over the image using the offset ∂. For each, ∂, a SGLDM was produced. Previous work has used a number of displacements but Wezka, et al (1976), reported that small values yielded the best results, dependant on the textural set, (see Section 2.2.2.b).

A combination of 7 offsets,(∂) were used:

1) 1 pixel
2) 5 pixel
3) 10 pixel
4) 20 pixel
5) 50 pixel
6) 75 pixel
7) 100 pixel

3.3.2 '*HARALICK*' TEXTURAL MEASURES

Once each symmetric matrix was formed, a set of feature functions were used to characterise the contents of each matrix, (Gonzalez and Wintz,1987). These values were used to train a recognition system to identify quartz grains, (see Section 3.9). While these features contain information about the textural characteristic of the image, specific textural characteristics seen on the quartz grain image are hard to identify within the matrix, (Haralick,1982). The reader is referred to the Results and Discussion sections when analysing this section.

Four features commonly used include contrast, entropy, homogenity, and correlation (Haralick, 1982). The researcher will find that these measures are described by a variety of names and notations, illustrated with the comparison between Haralick's (1973) paper and Gonzalez and Wintz's account (1987). The researcher is warned ! To avoid problems the following notation is used;

$p(i,j)$ - (i,j)th entry in a normalised matrix

Ng - Number of distinct gray levels in a quantized image.

Few papers have given any real values for the textural features (see Haralick, 1973, 1979, and

1986). For comparative study the SGLDM for each sand grain had to be normalised, dividing individual values by the matrix sum of occurrences, giving values between 0 and 1, (Zucker and Terzopoulos, 1980). From this the following measures were calculated :

a) HOMOGENEITY (or angular second moment)

Homogeneity is calculated using the following formula:

$$f_1 = \sum_i \sum_j P(i,j)^2$$

When a texture contains expansive uniformed regions with little change in pixel value, as displayed by the crushed quartz grain (Plate 3a), then the SGLDM contains a small number of very large values and the homogeneity value is large. When texture is more random i.e on smaller scales, the matrix will contain a large number of small entries and values will be low. Reference to the Results section shows the variation between grain types and also different offsets, (see Section 4.3.6).

b) CONTRAST

Contrast is given by :

$$f_2 = \sum_{K=0}^{n+1} \sum k^2 \sum P(i,j)$$

and is a measure of local change within pixel values on the grain surface. Obviously large contrast values indicate rapid variation in texture i.e pixel values at small offsets change rapidly .

c) ENTROPY

Entropy is calculated using the following formula :

$$f_3 = -\sum_i \sum_j P(i,j) \log P(i,j)$$

Entropy is correlation between a chaotic system and an associated statistical system, and is a measure of the amount of disorder in a system. In a sense it is a measure of how stable a system is. If an image contains flat homogeneous regions, it is described as stable with a low entropy value approaching zero, i.e. it is possible to predict the pixel values. However, with rapidly changing surfaces and textures it is not easy to predict the probabilities and entropy values increase towards a maximum chaotic state where every pixel value would be random with no pattern. Reference to Figure 31 a-d shows how these values alter with displacement and grain types.

d) CORRELATION

Given by the formula :

$$f_4 = \frac{\sum_{i \neq j} \sum_{i \neq j} ij\, p(i,j) - \mu x(i)\, \mu y(j)}{\sigma_x(i)\, \sigma_y(j)}$$

This is a measure of correlation and responds to highly ordered structures within textures particularly linear features. Although the values are taken from a symmetric SGLDM, the results show that linear trends can be determined for each sand grain type, (see Section 4.3.6). Haralick, et al (1973), used a similar method, using average values of four SGLDM's calculated using the angles of 0,90,135 and 45 degrees respectively.

All the 'Haralick' textural features calculated from the quartz grain images were then passed to the SPSSx™ package as discriminating variables. Average results for each sand grain type are shown in Figures 31 a - c.

3.4 FOURIER DESCRIPTORS

3.4.1 INTRODUCTION

The Literature Survey has charted the development of Fourier techniques in particle shape analysis. The implementation of Fourier Descriptors (FD) presents a method which could describe shapes from a variety of sediments , not just 'regularly' shaped quartz grains but irregular shapes such as loessic material, (see Plate 4). The method involves expanding a function of arc length around the boundary in a Fourier series, (Illing,1990).

Fourier analysis recognises that a continuous complex waveform can be broken down into a set of simple harmonic waves. The lowest frequency found to be a component of the composite wave is the fundamental frequency. The profile of a composite wave constructed from simple harmonic components depends both on the 'phase' and 'amplitudes' of the constituent waves, (Kaye, 1981). The actual number of coefficients required to regenerate the shape will depend on the nature of the curve. Rapidly curving boundaries with lots of high frequency components will require more coefficients than slowly changing shapes. Where the profile outline has a large number of protuberances this greatly increases the number of harmonics needed to describe the outline. In general, the lower frequency terms in the Fourier series of the waveform of a profile corresponds to information on form (external Morphology), intermediate frequency terms give information on structure, (Topography), and very high frequency information yields information on texture.

3.4.2 CALCULATION OF FOURIER COEFFICIENTS

A grain boundary may be defined by the co-ordinates of a sequence of boundary pixels. If these pixels are considered as defining a closed loop in the complex plane, a discrete Fourier transform of the resulting contour, in terms of a path length parameter can be obtained, (Wallace and Wintz, 1980) . The discrete Fourier transform of a contour representation is given by a series of coefficients, Fourier Descriptors.

X and Y positions can be determined relative to an arbitary origin and can start as a sequence of complex values from an arbitrary contour point. This characteristic makes this technique attractive when compared to previous methods where the centroid of each grain had to be calculated, (Clark , 1987).

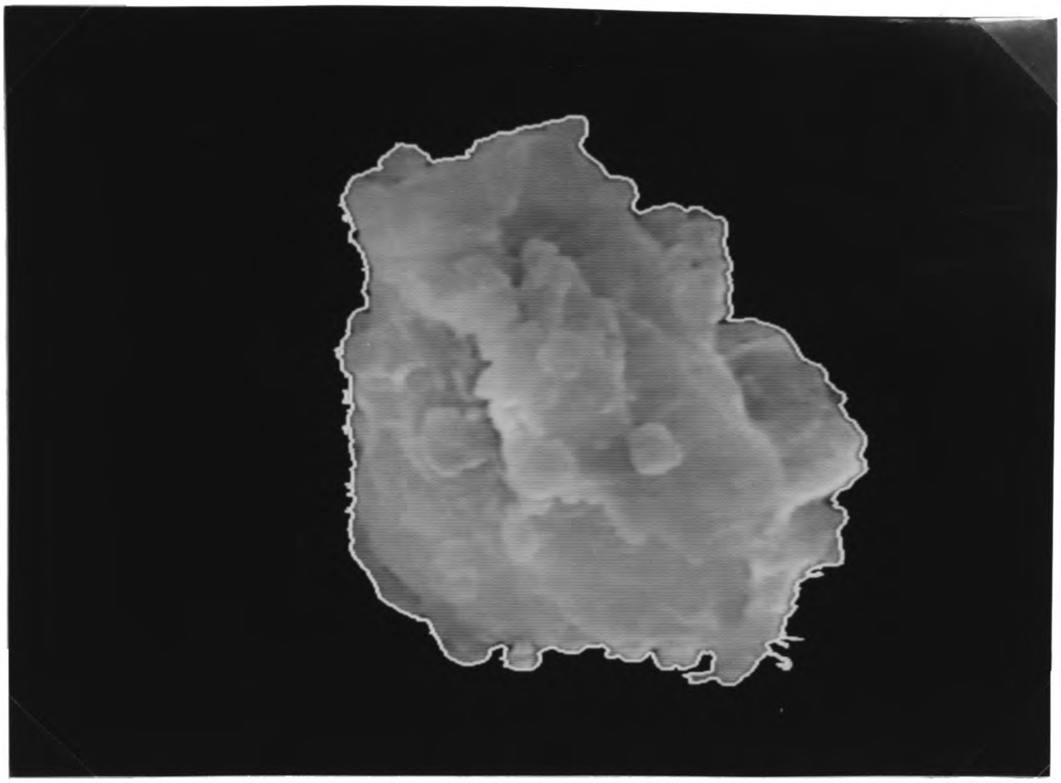


Plate 4 - Segmented image of a loess particle. The white boundary pixels are used in the calculation of Fourier Descriptors.

The segmentation of the grain image has been outlined in Section 3.2.2. As the background was set to zero (Figure 3), a scanning algorithm was used to detect the appearance of the first non zero pixel in any row, i.e on the grain boundary. Starting at that point all boundary X and Y co-ordinates were calculated and values used in the F.D.'s calculation.

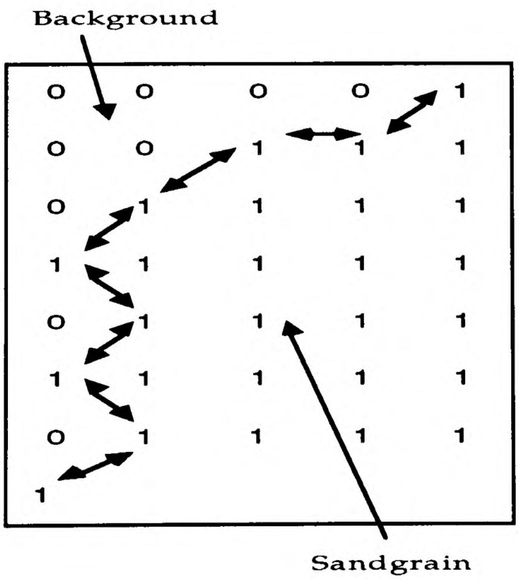


Figure 9 - Calculation of the quartz grain boundary x,y co-ordinates.

On the video monitor the boundary positions were converted to pixel values of 255 (white), to visually represent the contour and check its accuracy, (see Plate 4).

If this contour is now viewed as being in a complex plane, with the ordinate being the imaginary axis and the abscissa being the real axis (Figure 10) then the x,y coordinates of each point in the contour become complex numbers $x + jy$.

Plates 5a - c show the increasing accuracy of using more coefficients. The Fourier Descriptors were reinput into the FFT program to obtain X and Y co-ordinates. The figure is similar to one used by Orford and Whalley (1987), generated to show the limitations of the Fourier transform method when analysing complex shapes. Use of 256 coefficients more than adequately describes the figure. If the radial method (see Section 2.2.2) had been used on this image, re-entrant values would have presented substantial problems. Reference to Plate 4 and the Fourier Descriptor graph (Figure 21), shows the ability of the method to analyse other sediment types which displayed more complex shapes than quartz.

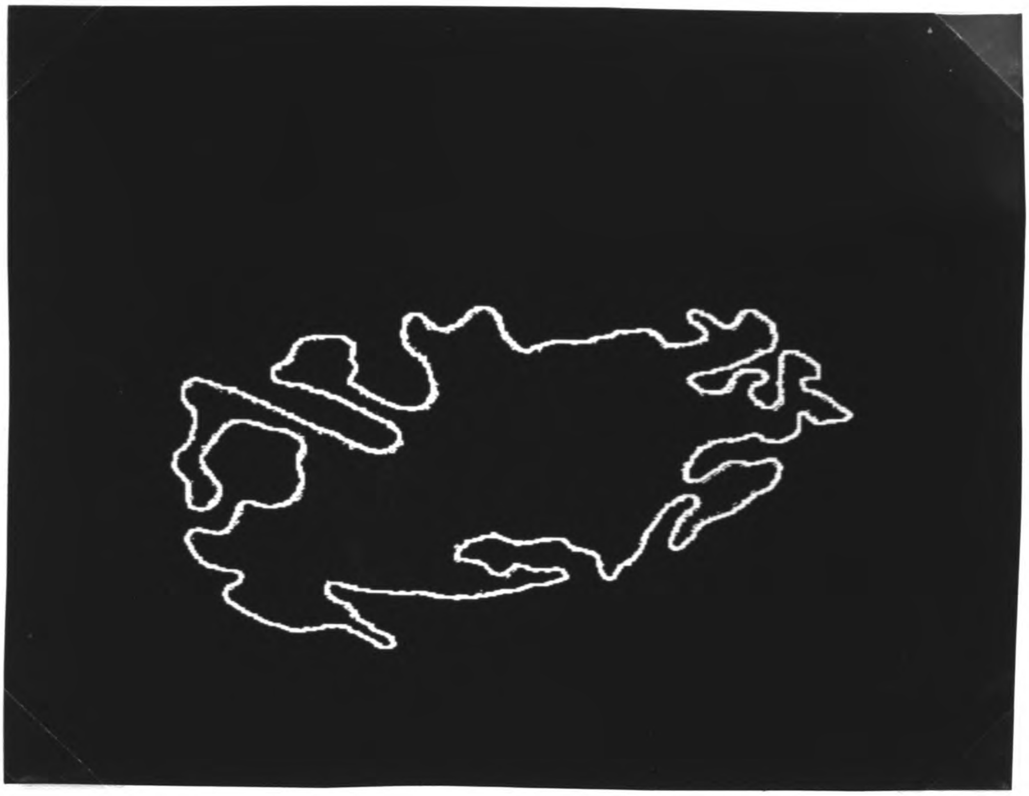


Plate 5a - Original image used to demonstrate the ability of Fourier Descriptors to analyse complex shapes. (From Orford and Whalley, 1987).

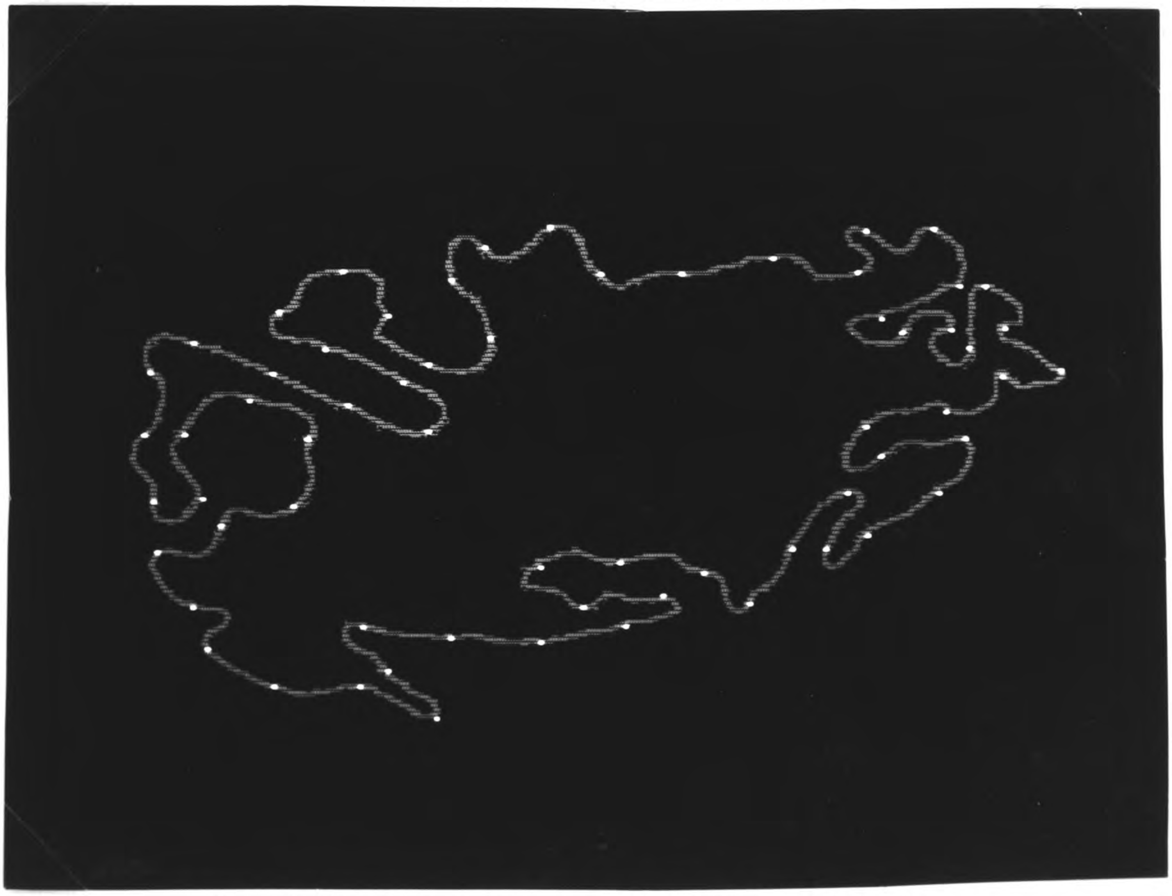


Plate 5b - Shape reconstruction using 32 Fourier descriptor coefficients.

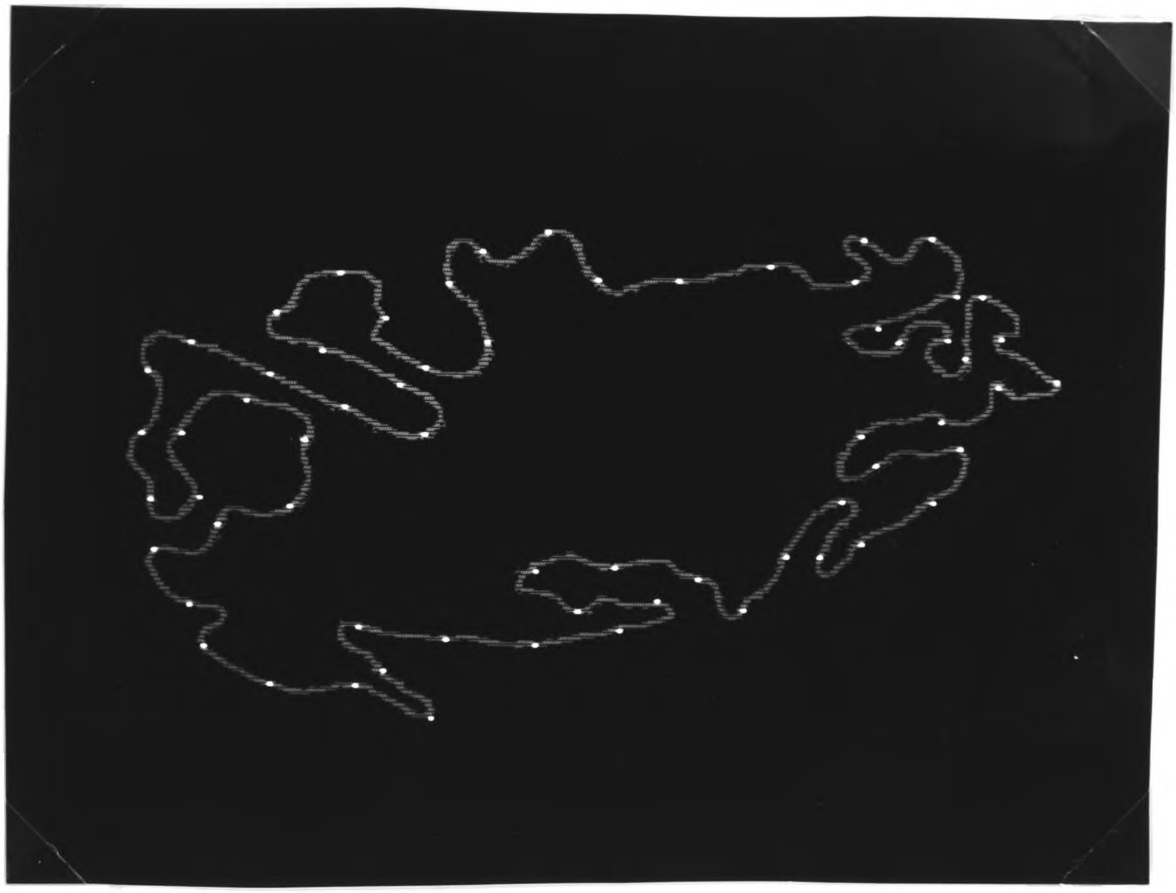


Plate 5c - Shape reconstruction using 64 coefficients.

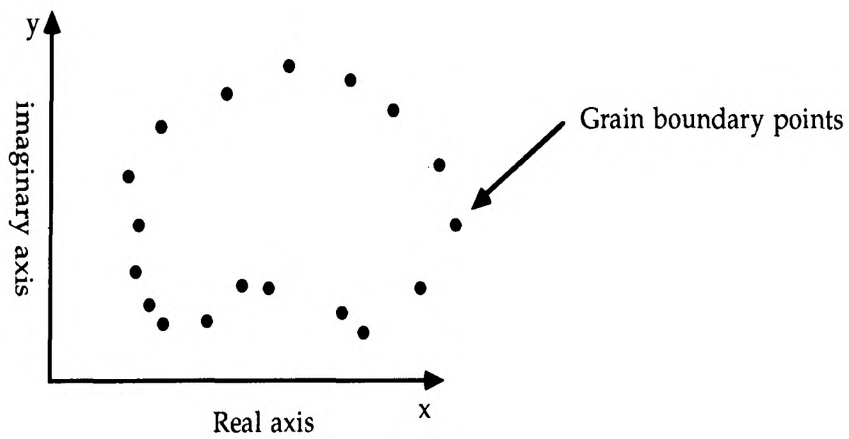


Figure 10 - Representation of a grain boundary in the complex plane, (After Gonzalez and Wintz, 1987).

The contour is then divided into 256 equal lengths and the positions recorded. This contour is smoothed and resampled by interpolation to give points equally spaced in the path length around the contour. The boundary is resampled at N equally spaced intervals of path length S, where N is a power of 2, to provide boundary points Zj. This is neccessary for the F.F.T implementation, which speeds calculation of the coefficients. In notation form, a Fourier Descriptor may be defined as :

$$Z_j = \sum_{k=0}^{n-1} c(k) \exp(2\pi i k S_j)$$

$$\text{where} \quad S_j = j / n \quad \text{and} \quad c(k) = 1/n \sum_{k=0}^{n-1} Z_j \exp(-2\pi i k S_j)$$

Wallace and Wintz (1980), outlined a normalization procedure which produced coefficients which were invariant to scale changes, translation, changes in orientation and boundary tracking start point and this has been followed here so that comparison could be made between different grain types. To normalize for position the coefficient c (0) was set to zero. Dividing each coefficient by c (1) produced scale normalization.

As the use of S.E.M. imagery provides greater resolutions than obtained by light microscopy, changes in resolution, (i.e. magnification) will determine how much of the quartz grain's surface texture contributes to the grain boundary. Figure 20 shows how the coefficients develop with increasing resolution. As boundary length is an important consideration, the optimum resolution to be employed will be user and use specific. However, for any comparative analysis, resolution must be fixed and all grain images be equal in size. The magnification used here was approximately x90. The form of the graph indicates that at low magnifications, ie. x22, the magnitude of the harmonics appears to be greater than corresponding harmonics at higher magnifications. This may be possibly due to a 'smoothing' of the grains outline at higher magnifications, so changing the degree of angularity. Illing (1990), in a study of the use of Fourier Descriptors to describe aircraft shape showed that the descriptors were predominantly noise removing. Since noise was mainly high frequency in nature use of low frequency coefficients would remove noise and act as a type of filter.

Grogan, et al (1990), studied the performance of the Fourier Descriptor method under conditions of varying image resolution, when analysing the shape of fixed winged aircraft. Their conclusions that the best matching performance of the Fourier Descriptors to a standard database occurred when imagery was sampled at approximately the same spatial resolution, would seem to be supported by Figure 20. Therefore, for comparative analysis, it is important to keep the spatial resolution of the quartz grain images as similar as possible. However, Grogan, et al (1990), did not mention the number of coefficients used in shape reconstruction.

The use of large numbers of coefficients was required to map very fine detail of the grain edges which were visible in high resolution S.E.M. imagery. This fine detail, reflecting the contribution of surface texture to the grain shape, included small pits, notches, conchoidal fracture and microblock development which combined to influence boundary shape. Use of a large number of boundary coefficients allowed detailed grain textures to be described. Although the grain boundary was subject to some pixel discreteness effects, these did not generate significant high frequency noise. Coefficient results in modulus form were used as 'Fourier Features' in SPSSx™ Discriminant analysis, (see Section 4.3.1).

3.5 EDGE DETECTION

3.5.1 THEORY

'Edge detection is a means of generating compact descriptors which preserve most of the structural information in an image.' (Canny, 1983, p. 6 - 7).

Edge detection analysis can fall under the banner of 'image segmentation', the process that subdivides an image into it's constituent parts or objects. As such, segmentation is an important element in automated image analysis because objects or other selected features can be used for description and recognition, (Gonzalez and Wintz, 1987).

Segmentation algorithms are based on two basic properties of gray level value; discontinuity and similarity. As mentioned in the Introduction, edges are an important cognitive trait in quartz grain microtextural analysis and their appearance, development and automatic recognition have been widely studied quantitatively in image processing and qualitatively in quartz microtextural analysis, (see Marr and Hildreth, 1980; Goudie and Bull, 1984). In this application, the interest lies with internal edges or discontinuities on the quartz grain surface.

Edge information conveys image information and scene content and is used extensively by the human visual system (HVS). Bull (pers Comm), has stressed that edges are one, if not the most important diagnostic feature within a quartz grain texture. In contrast to the image processing world, the S.E.M. world has not produced a quantitative description of what an 'edge' is or a quantitative framework in which to analyse it.

Gonzalez and Wintz, (1987, p. 334) defined an edge as a 'boundary between two regions with relatively distinct gray-level properties'. However, Haralick (1984), has defined several different types of edges. Step edges exist between regions of differing intensity, the edge existing between each pair of neighbouring pixels where one pixel is inside the brighter region and the other is outside the region. A roof edge describes a differential change between increasing and decreasing brightness values. Therefore, 'edge' refers to places in an image where there appears to be a jump in brightness value or a local extremum in brightness value derivative, (Haralick, 1984).

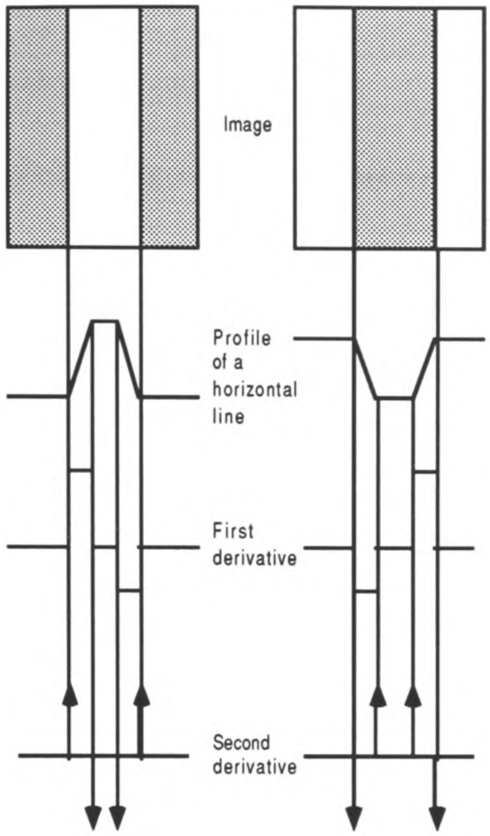


Figure 11 - Edge detection by derivative operators.
(a) light object on dark background, (b) dark object on light background,
(from Gonzalez and Wintz, 1987)

The idea underlying most edge detection techniques is the computation of a local derivative operator. Figure 11 shows an homogeneous image on a dark background. The gray level profile along a horizontal scan line is shown as a ramp due to blurring as a result of sampling. The first derivative of an edge model is 0 in all regions of constant gray level and assumes a constant value during a gray level transition. The second derivative is 0 in all locations except at the start and finish of gray level transition. The magnitude of the first derivative is used to detect the presence of an edge, while the sign of the second derivative determines whether an edge pixel lies on a dark or light side of an edge. From this, the first derivative, at any one point in an image, can be obtained by using the magnitude of the gradient at that point, while the second derivative can be calculated by the 'Laplacian', (Gonzalez and Wintz, 1987).

In the study of quartz grain edges, a simpler method, the Robert's gradient method was used, (see Section 3.5.2).

3.5.2 THE ROBERT'S GRADIENT OPERATOR

The gradient of an image f(x,y) at location (x,y) may be defined as a two dimensional vector :

$$G[f(x,y)] = \begin{bmatrix} Gx \\ \\ Gy \end{bmatrix} = \begin{bmatrix} \dfrac{\delta f}{\delta x} \\ \dfrac{\delta f}{\delta y} \end{bmatrix}$$

The vector G points in the direction of maximum rate of change of f at location (x,y). In edge detection the magnitude of this vector, (the gradient) is important and is given by :

$$G[f(x,y)] = [G^2x + G^2y]^{1/2}$$

In practice, the gradient is approximated by absolute values :

$$G[f(x,y)] = |G_x| + |G_y|.$$

For digital images, the derivatives are approximated by differences. One such approximation is the Robert's gradient given by the relationship :

$$G[f(x,y)] = \{ [f(x,y) - f(x+1, y+1)]^2 + [f(x+1, y) - f(x, y+1)]^2 \}^{1/2}$$

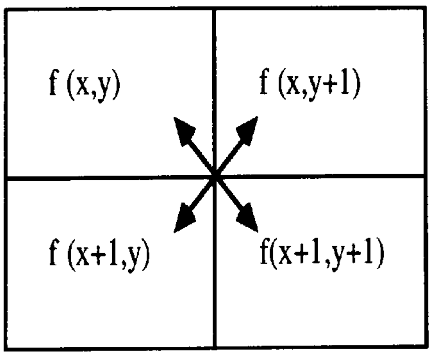


Figure 12 - Computation of the two-dimensional, discrete Robert's gradient

The gradient value is proportional to the difference in gray level between adjacent pixels, i.e. the gradient assumes large values for prominent edges in an image, small values in regions that are smooth and zero in regions of constant gray level. All gradients were calculated at one pixel distance.

Gradient values were placed at position (x,y) and a new image, a *gradient image* produced. As these new values did not show large variations, a threshold value was used for output to produce a reasonable image. Figure 13 shows a diagramatical example of an edge and its resulting gradients. An edge made up of single pixels produces a double edge so that edges on the gradient image appear much thicker than on the original image. In addition, diagonal edges become 'double edges'. An erosion filter was applied to the image to reduce the problem of double edges illustrated in figure 13.

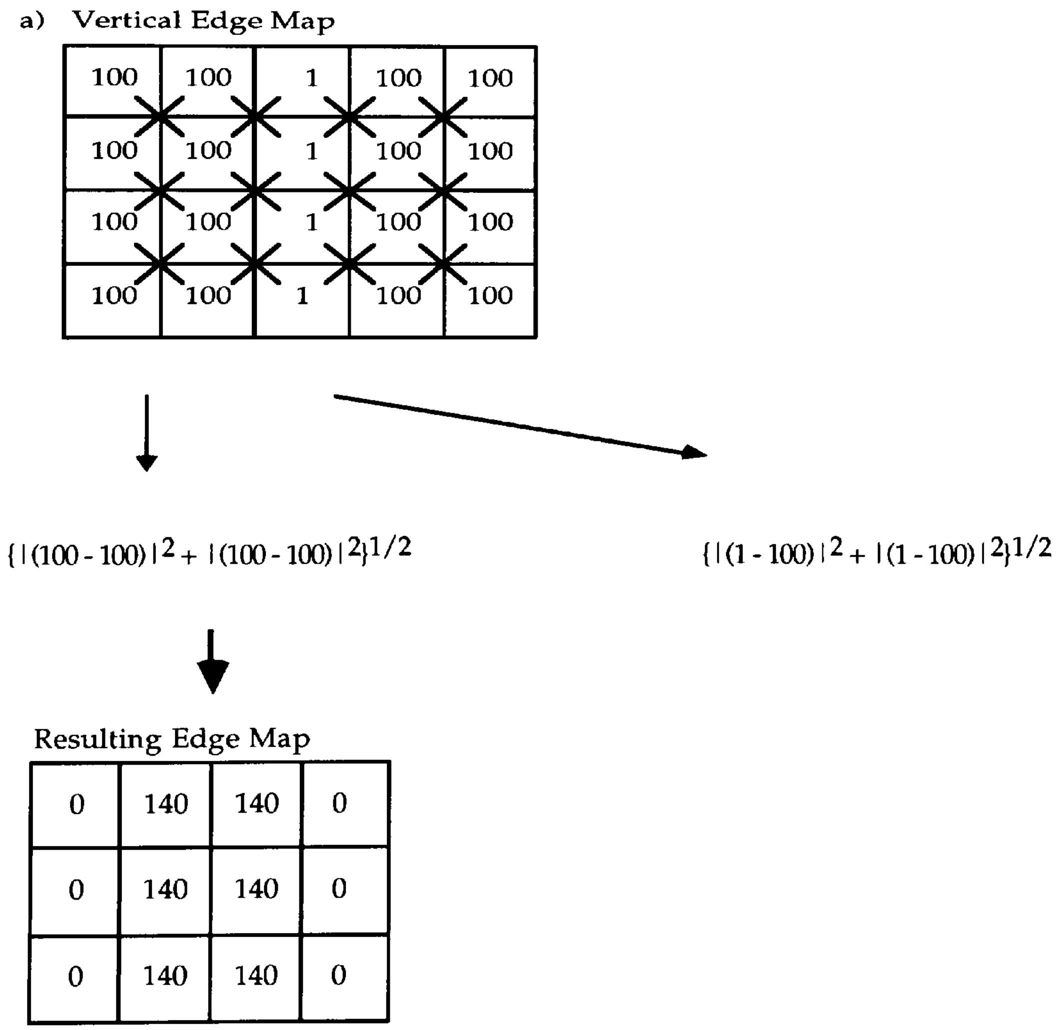


Figure 13 - Generation of edge map

b) Diagonal Edge Map

100	100	100	1	100
100	100	1	100	100
100	1	100	100	100
1	100	100	100	100

$\longrightarrow$

0	99	0	99	0
99	0	99	0	0
0	99	0	0	0
0	0	0	0	0

Plates 6a, b and c show the effeciency of the Roberts operator, operating on a simple figure. Note how the edges are thickened after filtering.

For each sand grain, a gradient map was produced and gradient values stored as a frequency histogram, (Figure 30 a-d). As there were boundary problems between the grain's edge and the background, gradient calculations which contained zero, ie. the background values and homogeneous areas, were not used. As the quartz grains were approximately the same size no attempt was made to normalise values. Gradient values in frequency histogram form are presented in Section 4.3.5. The histogram represents the number of occurrences of a particular gradient value plotted against gradient value (see Figure 30).

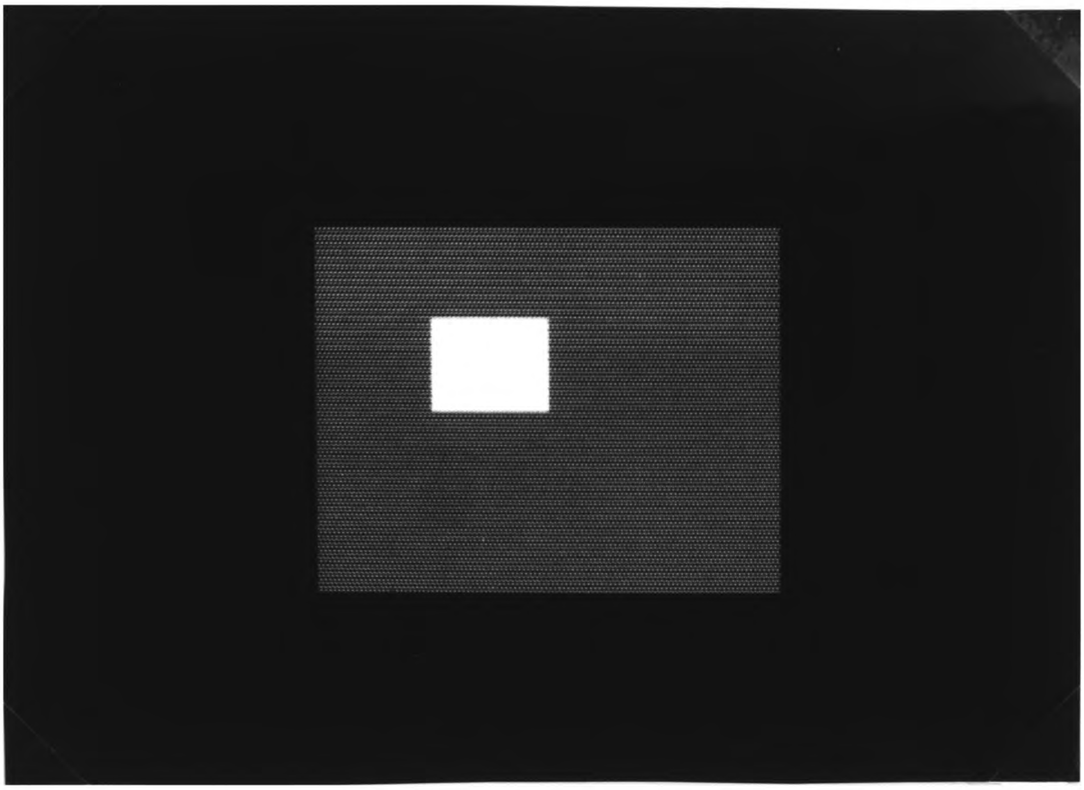


Plate 6a - Original image used to demonstrate edge detection.

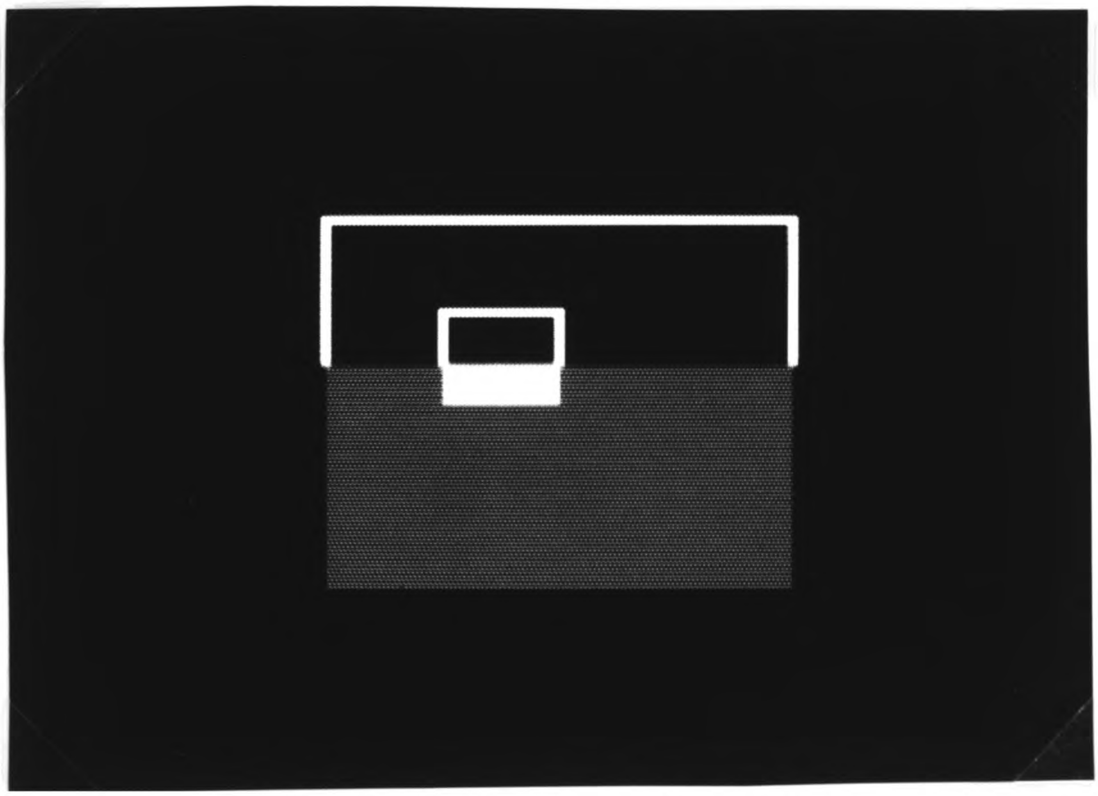


Plate 6b - Edge detection , note thicknesses of edges.

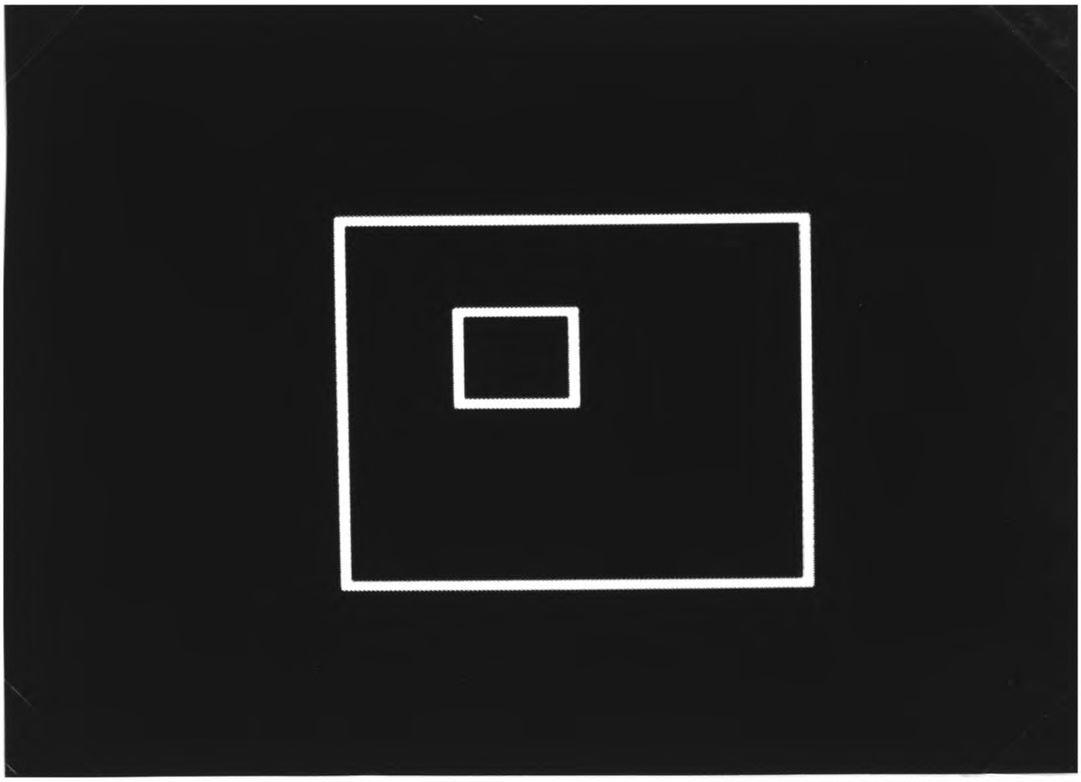


Plate 6c - Completed edge detection.

3.6 2-D FOURIER TRANSFORM

Previous methods outlined such as the SGLDM operate in the spatial domain. However an important range of image transforms work in the frequency domain and examines the composition of an image in terms of periodic functions. One method commonly used in texture analysis is the 2-D Fourier Transform.

Frequency refers to the rate of repetition of a periodic event. In image processing terms, it is the rate at which the brightness (gray levels) of an image change with distance. High spatial frequencies relate to rapidly changing detail, low frequencies correspond to slowly changing grey levels. For example, a sharp edge would consist of high spatial frequencies and a large shaded area would consist of low frequencies.

One approach to the analysis of these periodic forms is to decompose them into a series of periodic functions of varying frequencies in a similar way to the boundary decomposition (see Section 3.5). The Fourier Transform uses sine waves as the basis of decomposition, defined by :

$$F(u) = \int_{-\infty}^{\infty} f(x) \exp[-j2\pi ux]\, dx$$

The Fourier transform of a real function is complex :

$$F(u) = R(u) + jI(u)$$

where R(u) and I(u) are the real and imaginary components of F(u).

Usually this is written in exponential form :

$$F(u) = \left| F(u) \right| e^{j\phi(u)}$$

$$\text{where} \quad \left| F(u) \right| = \left[R^2(u) + I^2(u) \right]^{1/2} \quad \text{and} \quad \phi(u) = \mathrm{Tan}^{-1} \left[\frac{I(u)}{R(u)} \right]$$

The magnitude function $|F(u)|$ is called the *Fourier spectrum* of f(x) and $\phi(u)$ is the *phase angle.* The square of the spectrum

$$P(u) = \left| F(u) \right|^2 = R^2(u) + I^2(u)$$

is the *'power spectrum '* of f(x).

With image gray levels, the data is discrete. The Discrete Fourier Transform (DFT) is given by the following pair of equations :

$$F(u) = 1/N \sum_{K=0}^{n-1} f(x) \exp [-j2\pi \, ux/n]$$

and

$$f(x) = \sum_{K=0}^{n-1} F(u) \exp [j2\pi \, ux/n]$$

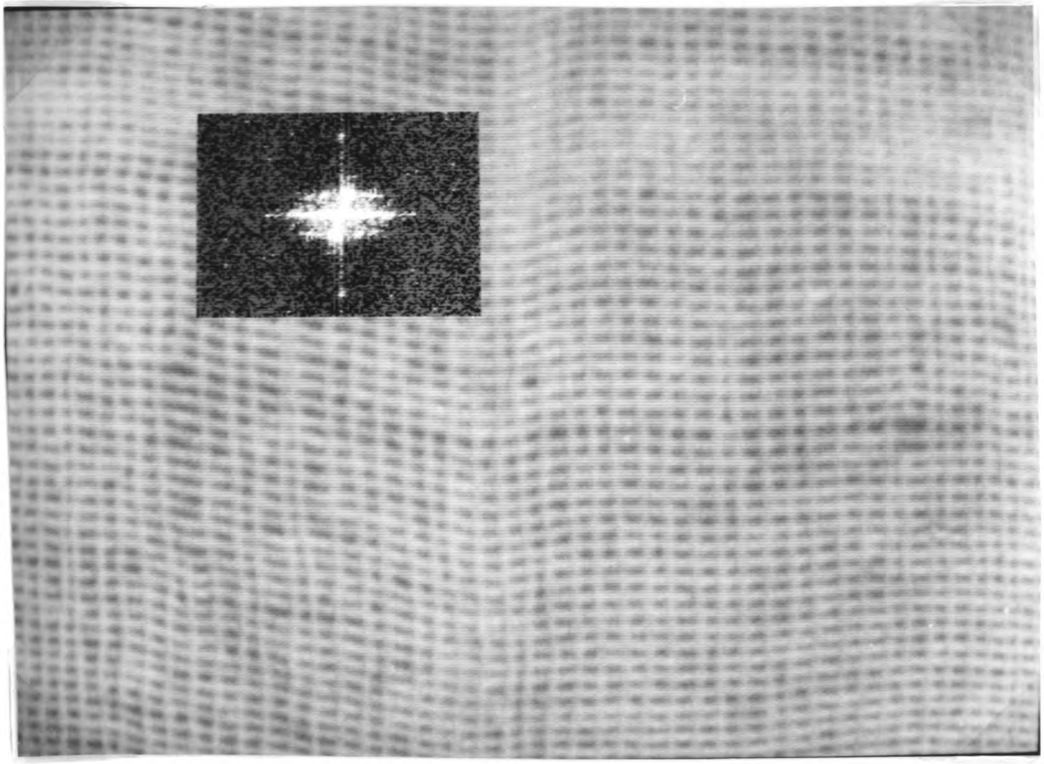


Plate 7 - 2-D Fourier transform of a 'cloth' texture. The spectrum is shown in the top left corner.

In practice, images are sampled in square arrays and for a M x N gray level image, the two Dimensional Fourier transform pair are given by the following :

$$F(u,v) = 1/N \sum_{K=0}^{n-1} \sum_{K=0}^{n-1} f(x,y) \exp [-j2\pi \, (ux + vy)/N]$$

and

$$F(x,y) = 1/N \sum_{K=0}^{n-1} \sum_{K=0}^{n-1} F(u,v) \exp [j2\pi \, (ux + vy)/N]$$

This transform is separable so can be computed by first taking the discrete Fourier transform of the rows and then taking the discrete Fourier transform of the columns of the result, (James, 1987).

The spectrum was displayed with the zero frequency component at the centre of the display in the *optical* form. Each value of the spectrum was multiplied by $(-1)^{i+y}$ where x and y were the row and column indices. In many cases, the zero component was very large and tended to obscure the rest of the data, so log values were plotted. From Plate 7 note how the horizontal structure of the cloth is displayed by the spectrum.

A major problem was how to extract variables from the Fourier spectrum that could be used for discrimination. One method was to use the *cut-off-frequency* loci outlined by Gonzalez and Wintz (1987). Two variations of this method could have been used. A set of standard loci could have been constructed by computing circles that enclosed various amounts of the total signal power, P_t. Alternatively, the method employed here used standard circle radii centred at the origin of the optical form and calculated the percentage of the total power within each standard band (Gonzalez and Wintz, 1987, p.166). In this implementation eight radii bands were used, with each band representing 12.5% of the total spectral range, thus :

Band	
1	0.0 - 12.5%
2	12.5 - 25%
3	25 - 37.5%
4	37.5 - 50 %
5	50 - 62.5%
6	62.5 - 75%
7	75 - 87.5%
8	87.5 - 100%

The band widths were selected arbitarily. The values were graphed (Figure 25 a-d) and used as discriminating variables in the pattern recognition paradigms.

The radial distribution of values in $|F|^2$ is sensitive to coarseness in the image. A coarse texture will have high values of $|F|^2$ concentrated near the origin while for fine texture the values of $|F|^2$ are more spread out.

3.7 TEXTURAL UNITS

The implementation of Wang and He's (1990) statistical approach for textural analysis was attractive on several fronts. It was the first new approach for several years in the textural analysis literature and secondly, it was a relatively easy algorithm to code and results could be contrasted to older, more established spatial methods such as SGLDM's. However, it was computationally expensive to implement, (see Section 4.3.4). It is a local operator describing texture in small subregions of the image.

3.7.1 APPLICATION

The method operates on a 3 x 3 pixel neighbourhood. Wang and He, (1990) proposed use of a Texture unit, 'the smallest complete unit which best characterizes the local texture aspect in all the eight directions from a given central pixel', (Wang and He,1990, p.61). Figure 14 shows a 3 x 3 pixel neighbourhood transformed into a texture unit number. A neighbourhood of 3 x 3 pixels is denoted by a set containing nine elements $V = \{V_0, V_1, \ldots\ldots V_8\}$, where V_0 represents the intensity value of the central pixel and V_i is the intensity value of the neighbouring pixel i. The texture unit is a set containing eight elements $T_u = \{ E_1, E_2, \ldots\ldots E_8\}$ where E_i is calculated by :

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \\ 2 & \text{if } V_i > V_0 \end{cases} \quad \text{for } i = 1, 2, \ldots\ldots$$

The element E_i occupies the same position as pixel i, (Wang and He, 1990). Each element of T_u has one of 3 possible values , the combination of all the eight elements results in $3^8 = 6561$ possible texture units. The texture unit number (Ntu) was found using the formula :

$$N_{tu} = \Sigma\, 3^{i-1} E_i$$

From Figure 14 this would give :

$$N_{tu} = (3^{1-1}.\ 2) + (3^{2-1}.\ 0) + (3^{3-1}.\ 2) + (3^{4-1}.\ 0) + (3^{5-1}.\ 0) + (3^{6-1}.\ 1) + (3^{7-1}.\ 2) + (3^{8-1}.2) = 6095$$

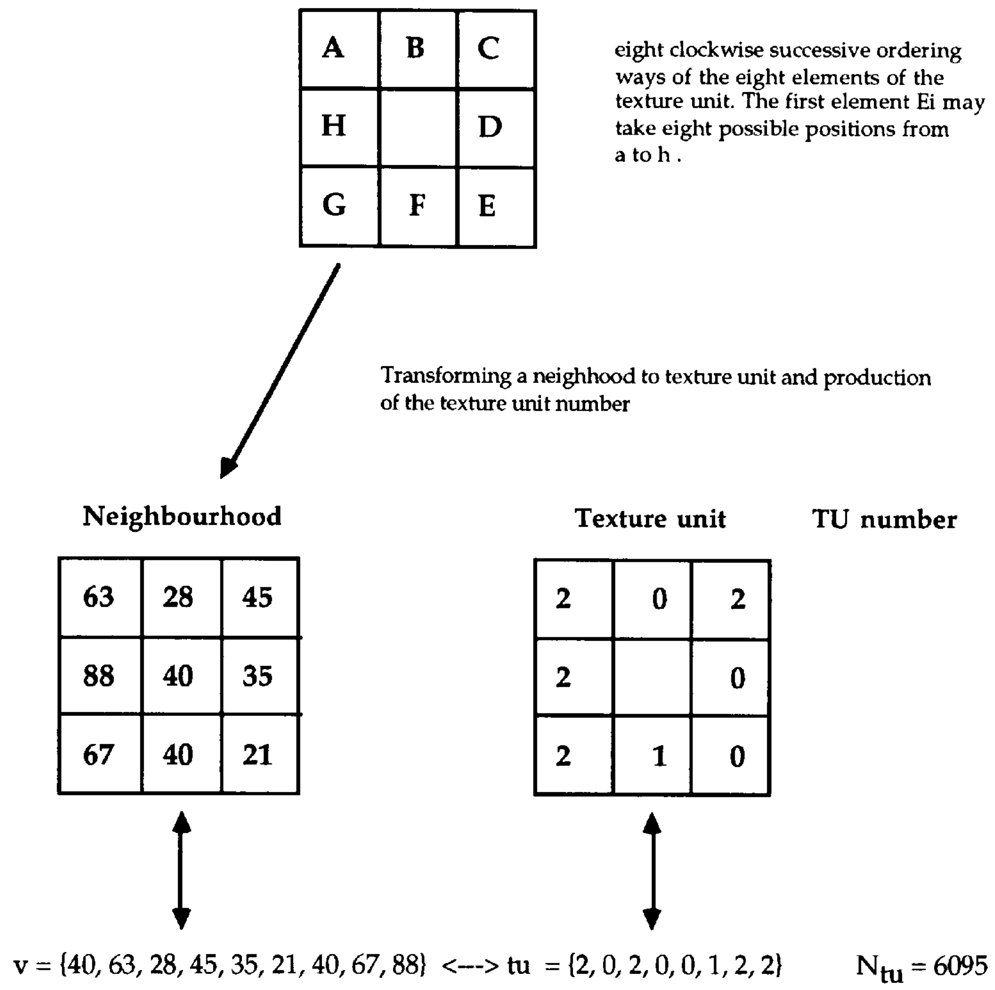


Figure 14 - Production of the Textural unit, N_{tu}

In implementation, each ordering possibility was calculated, with Tu numbers generated for each pixel ordering (a - h). The occurrence frequency function of all the texture units produced a 'Textural spectrum', 1 textural spectrum for each pixel ordering. Wang and He (1990,p.62), have stated that 'in the texture spectrum, an increase in percentage of texture components in an image will result in a tendency to form a particular distribution of peaks. Therefore different textures should produce characteristic textural spectra. The Textural spectrum illustrates the textural information in a 'primitive' form and several measures can be calculated from the spectra in a similar method to Haralick co-occurrence measures.

a) Black - White Symmetry (BWS) given by :

$$BWS = 1 - \left[\frac{\sum_{i=0}^{3279} \left| S(i) - S(3281 + i) \right|}{\sum_{i=0}^{6560} S(i)} \right] \times 100$$

S(i) = occurrence frequency of the textural unit

BWS values are normalized from 0 to 100 and measure the symmetry between the left half (0 - 3279) and the right half (3281 - 6560) of the texture spectrum. The authors stated that 'a high BWS value can be understood by noting that if we invert the intensity values of the original image, the texture spectrum of the new image will remain approximately the same', (Wang and He,1990 p. 63) In effect, if the two halves of the spectrum are totally symmetrical then a high percentage should result.

b) Geometric symmetry (GS) is defined by :

$$GS = \left[1 - \frac{1}{4} \sum_{j=1}^{4} \frac{\sum_{i=0}^{6560} \left| S_j(i) - S_{j+4}(i) \right|}{2 \times \sum_{i=0}^{6560} S_j(i)} \right] \times 100$$

GS values were normalized from 0 to 100 and measure the symmetry between the spectra under the ordering ways, (a,e) (b,f) (c,g) and (d,h) for a given image. A high GS value indicates that a image rotation of 180 degree will not change the textural spectrum and are therefore a measure of the 'shape regularity of the image'.

In a similar implementation to Weszka, et al (1976), Wang and He (1990), applied their method to 'Brodatz' textures and natural scenes extracted from an airborne Synthetic Aperture Radar (SAR). Nine sub-images were used that described areas occupied by 3 different rock units. Using BWS and GS values, all three rock units were delineated, (see Figure 15). An interesting point is that the diagram does not have a horizontal axis scale !

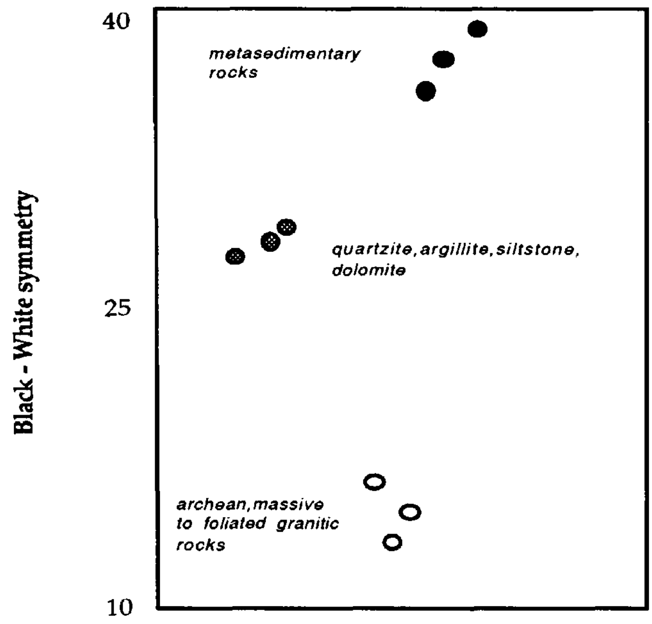


Figure 15 - Separation of terrain types using BWS values, (from Wang and He, 1990)

Results for the three quartz grains populations are shown in graph form as average BWS and GS values, (Figure 28 a & b). Raw spectral data using all eight BWS ordering directions were used both in discriminant analysis and in the neural net as a pattern recognition feature.

3.8 AUTOCORRELATION

Autocorrelation, in an image analysis context, is a measure of the degree of self similarity between an image and itself, shifted to successive offset positions. Every pixel is compared successively to every other pixel. All positions of similarity and dissimilarity will be detected. Each observation, ie. pixel, is separated from the preceeding pixel by a distance referred to as a 'lag distance', r, which may be taken in any direction. Davis (1986), has used the analogy of two link chains laid side by side. If one chain is moved relative to the other then all of the links are offset by r.

The autocorrelation function of the quartz grain image at lag r can be defined in a number of ways depending on the normalization procedure. The autocorrelation of the gray scale levels, I, normalized by the mean I, is utilized here, ie. a gray scale array ('picture') which has been divided by its mean value giving :

$$C(r) = \langle I(\underline{x})\, I(\underline{x} + r) \rangle / \langle I \rangle^2$$

where the mean value of I x I is taken over all pairs of pixels separated by a distance r, and the mean value of I is taken from the whole of the picture area. From this equation, it can be seen that this is very computationally expensive. Each pixel must be multiplied by every other pixel, then offset and recalculated. Therefore, this method had to be implemented on a mainframe computer, the DEC Genvax. This involved time costly transfer of data from the PC's to the mainframe. This transfer effectively defeated a main objective of this thesis in that the system should be PC based.

The covariance results were displayed as 'intensity diagrams' where the covariance values at a particular 'lag' were displayed as a grey scale map. In addition, the values were displayed in their 'lag' position. Referring to Figure 23, the darkest areas indicate the greatest correlation, light areas display least correlation. The scale was altered to range from 0 to - 60 and 0 to + 60 and + 60 on the y axis. Again referring to Figure 23, 'lag' distances of five pixels correlated well, while larger lags do not correlate. In addition to the computation difficulties, a major drawback to the technique was an inability to derive measures from it, as was done with the SGLDM's, (see Section 4.3.2). Also looking at a pilot diagram (Figure 23), little consistency in form could be seen. A diagram of a more regular texture, such as cloth (Plate 7) produced obvious vertical and horizontal structures. However, it appeared that sand grains could not be differentiated by this method, a conclusion more fully examined in Section 4.3.2.

3.9 PATTERN CLASSIFICATION

3.9.1 INTRODUCTION

'To obtain meaningful and accurate image classifications there is a need for the environmental scientist to take the computer operators seat and interact with the image data by supervising the classification sequence ', (Schmidt, 1975, p. 202).

The ability to quantitatively and automatically classify a quartz sand grain into a certain population based on shape and surface texture is an important objective to this study.

Classification theory is dependent on statistical theory, particularly through the use of probability. The probability of an event happening is referred to as P(A), the probability of A. Conditional probability is the probability of an event happening based on another event and is written $P(A \mid B)$ or 'the probability of A given B'. Conditional probability can be thought of as 'summarising our knowledge of something after incorporating what we know about it', (James, 1987, page 21). The use of conditional probabilities to put a quartz grain into a group forms the basis of classification theory and is known as 'Bayes rule'. From the shape and texture measurements, X from a quartz grain which may come from any one of m groups: G_1, G_2, ... , G_m. Bayes' rule says assign to group i where :

$$P(G_i \mid X) > P(G_j \mid X) \qquad \text{where } j \text{ not} = i$$

i.e. assign to the group with the largest 'conditional probability', (James, 1987). The difficulty with the technique is finding the conditional probabilities, which have to be estimated from data gathered from each quartz grain group. This problem has given rise to several applications of the Bayes rule. The normal model for estimating the conditional probability of obtaining a given measurement within a group follows a known distribution. The most common form of distribution to assume for $P(G_i \mid X)$ is the normal distribution. The normal distribution produces groups that tend to form elliptical clusters with points tending to congregate around the mean. Therefore, the classification rule divides the sample space into regions that belong to each group based on a 'decision line' where $P(G_1 \mid X)$ is greater than $P(G_2 \mid X)$.

James's (1987) summary of the major elements in classification includes :

i) The best classification rule is Bayes Rule

ii) If the groups display normal distribution and have the same shape, ie. identical covariance matrices then the Bayes Rules takes the form of linear discriminant functions.

iii) Most importantly for the work on quartz grains, a linear classification will work well on groups that are widely separated or eliptically symmetrical.

Each set of textural data was analysed individually and in combination using the SPSSx™ statistical package . The data sets were :

a) 256 Fourier Descriptor coefficients in modulus form

b) 2-D Fourier Transform radial variables calculated from the spectrum

c) Textural Unit measurements - BWS and G.S

d) SGLDM measures - contrast, entropy, homogeneity and correlation

e) Edge Histogram data - from the Roberts edge detector method

Each data set was initially analysed individually within discriminant analysis. A summary table of the important variables, an all group scatter plot, and a correct classification table were produced. Data sets were then amalgamated to produce new variable models and classifications, (see Section 4.3.7). Each model was analysed by the 'bootstrap' method to assess the correct classification, (see Section 3.9.2).

3.9.2 DISCRIMINANT ANALYSIS

Discriminant analysis attempts to classify cases into one or more mutually exclusive groups on the basis of various characteristics, to establish which characteristics are important for distinguishing among the groups and to evaluate the accuracy of the classifications.

The basis of the techniques requires that linear combinations of variables are formed which best separate the cases. Certain basic assumptions need to be made about the data. Each sample must be from a multivariate normal population and the population covariance matrices must all be equal. For this to be valid training data must be both representative of all data for that class and display a normal distribution. Tests for normality were used before classification. The former criteria are discussed in section 5.8.

The linear discriminant equation is :

$$D = B_0 + B_1X_1 + B_2X_2 + \dots + B_pX_p$$

X's are values of the independent variables and the B's are coefficients estimated from the data. If the linear discriminant function is to succeed the groups must differ in their D values.

Therefore, the B's coefficients are chosen so that the values of the discriminant function differ as much as possible between the groups thus making the ratio :

$$\frac{\text{Between - groups sum of squares}}{\text{Within - groups sum of squares}}$$

at a maximum. An example is given demonstrating how the discriminant score is calculated.

Based on unstandardized discriminant function coefficients, the discriminant score is obtained by multiplying the unstandarized coefficients by the values of the variables, summing these products and adding the constant. Using the discriminant score a rule is obtained for classifying cases into groups, based on Bayes rule. Using Bayes classification it is then possible to calculate how many of the cases have been correctly assigned based on their Discriminant functions.

In the SPSSx^{TM} output, where a case (a quartz grain) has been misclassified it is indicated by an asterisk. This means that a misclassified quartz grain can be identified and selected for qualitative analysis. From these results, a classification table is assembled giving the correct and incorrect classifications, both in percentage and real values. An all-group scatter plot is also obtained showing the groups and their spatial relationships,based on distance between their means, (see Figure 22).

While this appears straight forward, a note of caution must be added. A model usually fits the sample from which it is derived better than it will fit another sample from the same population and therefore the percentage of cases correctly assigned by the discriminant function is an inflated estimate of the true performance in the population. There are several ways to obtain a more accurate classification. The one used here is the 'bootstrap' method where one case is omitted in turn, recalculating the function based on the remaining cases and then classifying the case left out. In addition new test data results from the three grain populations were added to the model as a fourth group and then classification was attempted. The success of this experiment is given in Section 4.3.7.

To reduce the number of variables used for discrimination, a stepwise selection routine was used, to produce the optimal model for the data using only a few 'best' variables. This was potentially useful as a data reduction method, particularly for the Fourier coefficients where the use of 256 coefficients was large and unwieldy. Also using 'stepwise' it was possible to identify the best discriminating variables. The first variable included had the largest value for the selection criterion. After its entry the criterion value was re-evaluated for all variables not in the model and the variable with the largest acceptable criterion value was entered next. The variable selection criteria used here was the Mahalanobis distance (D_{ab}^2) which is a generalized measure of the distance between groups. The distance between groups A and B is defined as

$$D_{ab}^2 = (n - g) \sum_{i=1}^{k} \sum_{j=1}^{k} W_{ij} * (\bar{X}_{ia} - \bar{X}_{ib})(\bar{X}_{ja} - \bar{X}_{jb})$$

where k is the number of variables in the model, x_{ia} is the mean for the ith variable in group A and W_{ij}^* is an element from the inverse of the within-groups covariance matrix, n is the total number of cases, g is the number of groups.

A summary table (Table 3) listed the significant variables model and quantified the percentage of cases correctly classified.

The assumptions for two groups are similar for three groups but instead of one discriminant function, two discriminant functions are calculated. The first function had the largest ratio of between groups to within group sums of squares while the second, uncorrelated to the first, had the next largest ratio. Discriminant results are shown in Section 4.3.

3.9.3 NEURAL NETS AS QUARTZ GRAIN PATTERN CLASSIFIERS

The neural net used in this thesis was a software implementation using a pre-written package. The rationale for using a neural network approach has been given in Section 1.6.1. Neural networks are comprised of a large number of simple processing elements called units, each interacting with others via excitory and inhibitory connections, (Khanna, 1990).They are able to 'learn' by incorporating past experience into interconnection patterns. Whereas the statistical models, when confronted by a classification problem, proceeds to serially compute the most likely classification, the neural net performs the computation in *parallel* and uses the results of it's computation to adjust it's interconnection patterns. Rumelhart, et al (1986), produced major aspects important for PDP modelling :

1) Set of processing units
2) State of activation
3) Output function for each unit
4) Pattern of connectivity

5) Propagation rule for propagating patterns of activities

6) Activation rule for combining inputs affecting a unit with it's present state to produce an output

7) Environment within which the learning system operates.

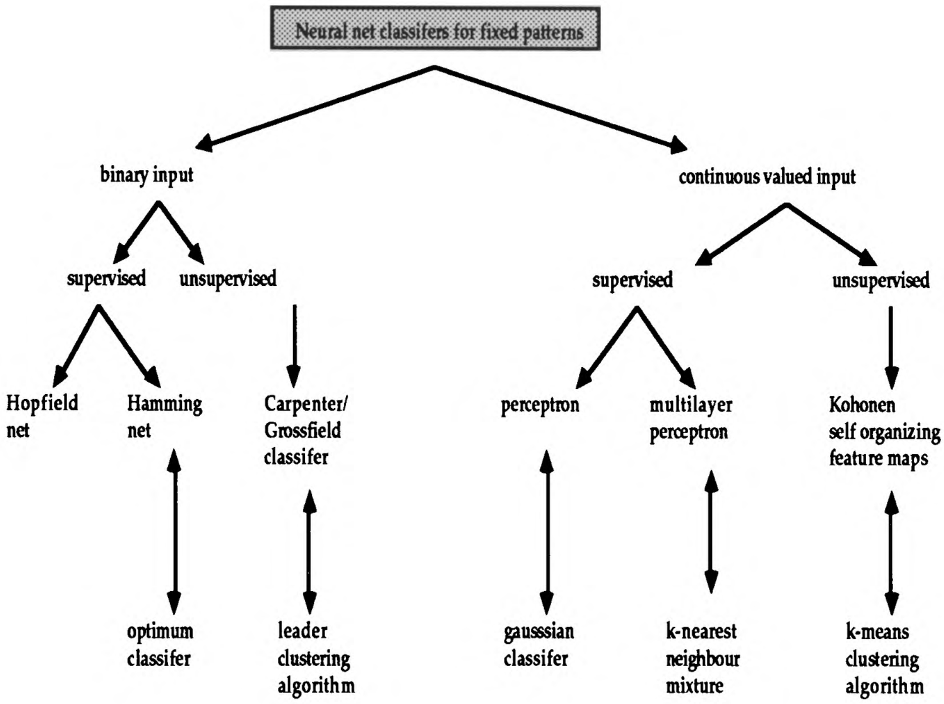


Figure 16 - Neural net classifiers for fixed patterns (from Khanna, 1990).

There are several paradigms or learning strategies that can be used to build a neural net. One of the most commonly used is the Delta rule, (or Widrow-Hoft method or Least Mean Square method). The Delta rule is learning strategy applied to the case where pairs of patterns, an input pattern and a target output pattern, are to be associated, where the contents of specific patterns do not matter as much as the pattern of correlations among the patterns, (Khanna, 1990). When a set of pairs of input and output patterns are presented, learning (ie. weight modification) occurs only when the output generated by the network in response to the input does not match the output provided in the pair.

The delta rule minimises the squares of the differences between the actual and the desired output values summed over the output units and all pairs of input/output vectors. Therefore, the delta rules minimises the error function with each complete cycle of pattern presentations.

The processing units represent objects such as features. In this case, textural and shape descriptors are used in the distributed PDP model. Inputs into the PDP model are given weightings which are associated with the interconnection. Modification of the interconnections implies modification of the associated weights and occurs whenever the neural net learns something in response to new inputs or changes in the features, (Khanna, 1990). This has important implications for sand grain microtextural research where presentation of a stimulus pattern, ie. textural descriptors, generates another pattern that it has associated with this pattern. Interestingly, presentation of a portion of a pattern should cause the network to generate complete versions of the pattern. For sand grain microtextural analysis, the neural net is used in training mode, where both the input and output group/category is known. Unknown test patterns are then used in the 'trained' neural net for classification.

The use of a neural net approach to automatic quartz grain classification is a totally novel approach.

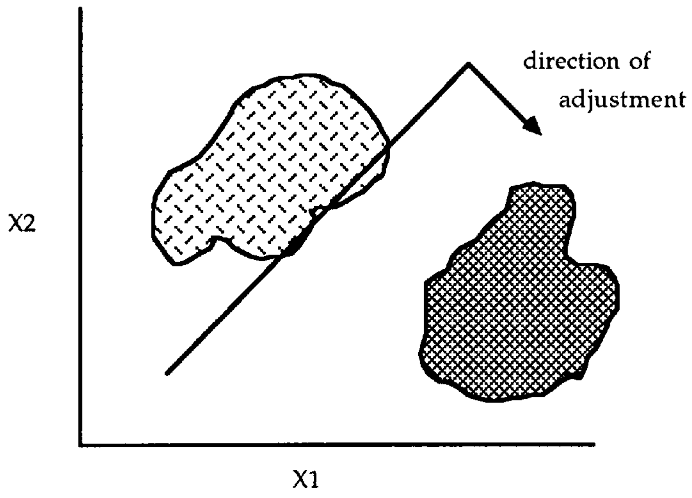


Figure 17 - Adjustment of weights to achieve separation

In the neural net implemented here, a generalized form of the delta rule using back propagation was used. The application of the back propagation rule involved two phases. During the first phase, the input was presented and propagated forward through the network to compute the output value for each unit. This output was then compared with the target resulting in a eight term for each output unit. The second phase involved a backward pass through the network, during which the five term is computed for each unit in the network. The aim is to adjust the strengths of the connections to reduce the difference measures or least mean squares, (LMS). The back propagation was a gradient descent procedure with the system following the contour of the error surface, moving downhill in the direction of steepest descent.

Two problems with the neural net were :

a) determining the number of iterations needed to train the net .

b) determining the neural net structure i.e how many hidden layers to use.

Khanna (1990), has indicated that a neural net needs no more than two hidden layers to solve problems, with the accuracy of the net controlled by the number of neurons per layer and not number of layers. With this in mind, construction of a neural net was very much a 'suck it and see' approach. In addition, the size of the training set may be crucial and was determined by an empirical approach.

'Textural Unit' values were used as input pattern measures in the neural net, (see Section 3.7). They were chosen because the input pattern was fairly simple, i.e. only eight BWS measures, and they had performed well in Discriminant analysis, (see Section 4.3.4). The software used normalised values between 0 and 1. For each pattern, the input units are turned on to see what effect they have on the output units.

Each sweep, or epoch through the training set, resulted in a set of weights which produced the correct pattern interpretation, i.e. Desert, Crushed quartz or Fire Island grains. To quantify how close the approximation was to a perfect solution, an error measure, the value of (t-a) squared was used. When this value was summed over all patterns, a Total Sum of Squares (TSS) was produced. The TSS value was sampled at every 50 epochs. As the neural net becomes better trained the TSS value should fall, (see Figure 36).

The classification performance of a trained neural net is determined by use of a test file containing textural unit data from different grains from the three populations. Results, in percentage form, are presented as *'correct classifications'* of grains which the net assigned to correct groups. The configuration of the neural net was altered to see the effect on performance. An eight node and twelve node network was used and results compared, (Figure 37).

3.10 SUMMARY

The methods have not previously been used to analyse quartz grain surface texture or shape. The Fourier Descriptor approach is a departure from the Fourier transform method and is attractive due to it's ability to model shapes from a wider variety of sediments ranging from very irregular loess grains to rounded desert types. The surface textural methods have all been shown to be adaptable to quartz grain surfaces. However, autocorrelation proved too computationallly complicated to implement to any degree. The simplest method to use and the method with a cognitive essence was the edge gradient approach. This allowed for a large degree of data reduction but still produced recognisable 'maps' of each grain. It's links with the human visual system are discussed in Section 5.6.

This section has presented only a small proportion of the statistical textural algorithms available and has not dealt with the more complex structural implementations, (see Section 6.1).

CHAPTER 4

RESULTS

4. RESULTS

Results are presented in four sections :

a) Qualitative description of selected grain types

b) Image processing results

c) Mathematical models results

d) Pattern recognition results.

Mass raw data presentation is avoided where possible. Examples of certain results, such as Fourier Descriptors and 2-D Fourier transforms are given, but raw co-occurrence matrices or edge histograms are avoided. In all cases, group 1 samples are Desert grains (des), group 2 are Fire Island grains (fire) and group 3 are Crushed quartz (pqt) examples.

4.1 QUALITATIVE QUARTZ GRAIN DESCRIPTION

Bull's (1976), comment on the importance of qualitative description (Page 8) does have relevence for these particular applications, as subjective discrimination of textural types aids interpretation of the quantitative models particularly when grains were quantitatively misclassified, (see section 4.3).

4.1.1 DESERT GRAINS

Five types of textural features have been described as characteristic of aeolian quartz grains. The most obvious feature is grain rounding which varies from perfectly spherical to angular (Krinsley and Trusty, 1985). Upturned plates, the subject of a detailed study by Krinsley and Wellendorf (1980), appear as parallel ridges ranging in length from 0.5 - 10 μ and result from breakage along cleavage planes in the quartz lattice. The size aspect of the grain is important as grains of this size (300 - 400 μ) generally travel as saltating or creeping bedload during which they are subject to successive high speed collisions. At collision, some of the kinetic energy of each particle is converted to elastic energy in the grain. As grains in air travel many times faster than in a similar particle in water, abrasion is severe and much more pronounced, creating the upturned plates. These are subsequently modified by solution and precipitation (Margolis and Krinsley, 1974).

Fracture plates created by crack propagation, low topographic relief, and meandering ridges created by conchoidal fracturing, are all common features found an aeolian grains. The grain surface will be covered by asperity peaks, small scale surface disruptions created by spinning grains colliding with each other. A typical desert grain is shown in Plate 8a, displaying a high degree of rounding, low surface topography and a finely pitted surface.

4.1.2 FIRE ISLAND BEACH GRAINS

Quartz grains microtextures from the Long Island barrier system have been subject to several studies, (Krinsley and Donahue, 1968; Williams and Thomas, 1989a). Of particular note is the work of Morgan (1990), reviewed in Section 2.1. The samples used for his work originated from Long Island beach sites which derived their sediment from various Pleistocene glacial outwash sources. Figure 18 shows the location.

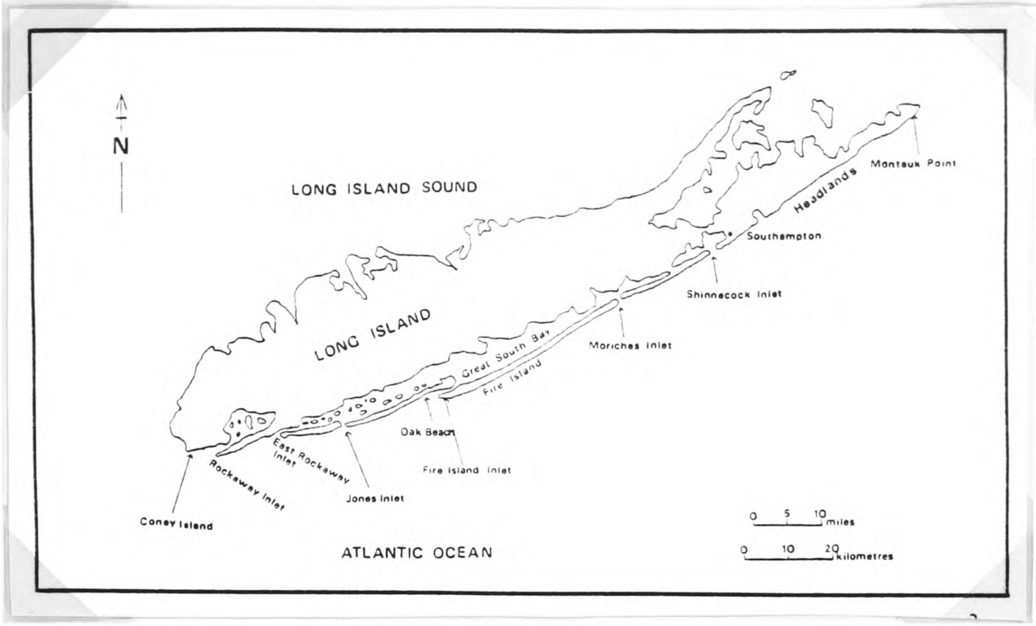


Figure 18 - Location map of Long Island, New York, USA.

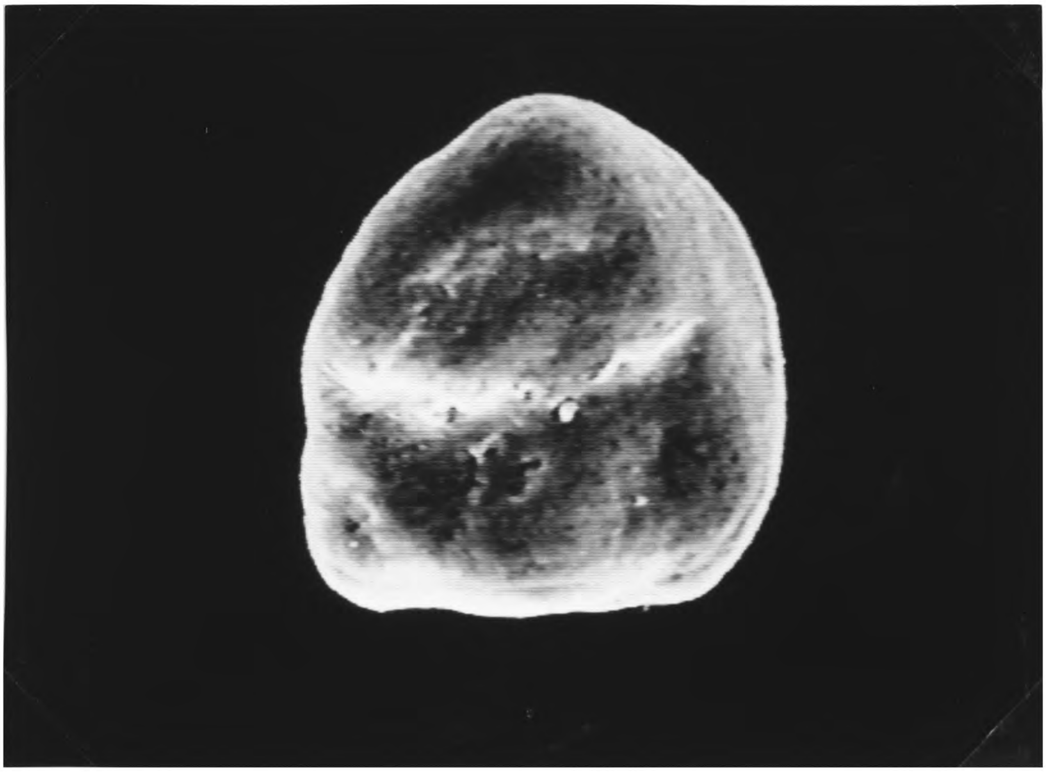


Plate 8a - Desert sand grain

Plate 8b - Fire Island Beach grain

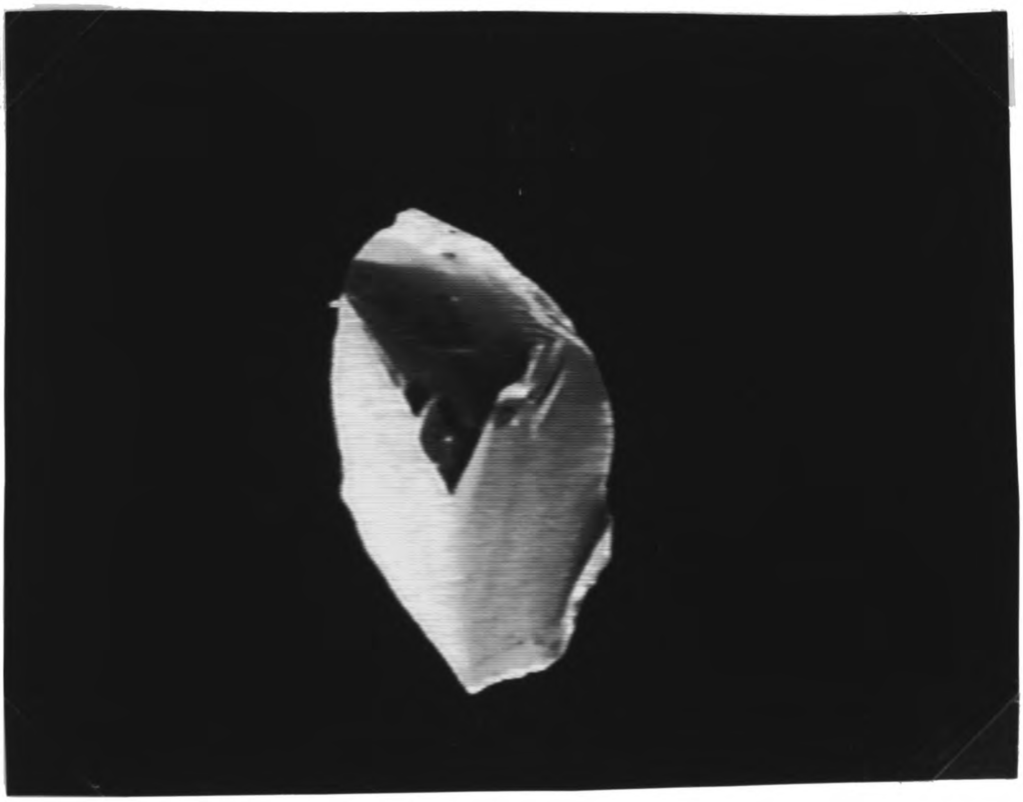


Plate 8c - Crushed quartz grain

The microtextures displayed reflected both the previous glacial sedimentary regimes and modification by nearshore processes. 'Blocky' microtextures, striations, angular outline and high topographic relief in conjunction with diagnostic subaqueous features, such as mechanical V's have all been cited as diagnostic of glacio-marine microtexture (Krinsley and Doornkamp, 1977; Williams, et al, 1985; Morgan, 1990). A representative grain is shown in Plate 8b. The grains displayed differing texture components at varying scales and therefore provided a good test of the algorithms ability to decipher complex textures.

4.1.3 CRUSHED QUARTZ GRAIN

To test the effectiveness of the textural algorithms it was necessary to include a sample which displayed minimal or unique microtextural development when compared to the beach and aeolian samples. Crushed quartz grains, produced by mechanical disintergration of large quartz crystal from a pegamatic source have been commonly used in comparative studies, notably Culver, et al (1983), for statistical analysis of microtextures.

The microtextures developed on the grains were simplistic, consisting of large conchoidal fracture regions of flat homogeneity, minimal surface disruption and very angular outlines. In a sense, these grains acted as a control for comparison with the other grains. The major textural component was large homogeneous regions displaying little variation in gray levels, (Plate 8c).

4.2 IMAGE PROCESSING RESULTS

One immediate result of using 'captured' quartz grain images was the inability to change magnification and viewing angles, and so lose the ability to study textural combinations at differing magnifications. However this problem was not viewed as a disadvantage but as a positive step because :

i) Standardization was introduced re : viewing magnification

ii) Only one textural morphology was displayed, and as in i) standardization was achieved.

Both these partially fulfill the criteria set out in the Introduction, to reduce variability within the discipline's methodology and introduce standardisation.

Plate 4 shows the implementation of the boundary tracking algorithm. Note that the boundary was complete and did not have occluded sections. Illing's (1990), work on the use of Fourier Descriptors showed that for small levels of occlusion they do work , but are reliant on the whole shape being present. If part of the shape is missing then all of the descriptors will be affected, (Illing ,1990). Therefore, the use of an efficient algorithm to locate the boundary accurately was necessary. Discretization of the boundary due to the pixel shape, ie. square is apparent at fine detail however it has nominal effect on the coefficients. Plates 5a - c showed a shape similar to one used by Whalley and Orford (1983), in their work to show how Fourier Transforms failed to accurately describe intricate shapes with re-entrant values. The use of Fourier Descriptors removes this problem and accurately describes the shape.

A problematic aspect of S.E.M. operation was 'charging up' of portions of the grain surface where insufficiently coated with gold. This led to bright areas where no texture could be seen, a particularly common occurrence near grain edges (Plate 3a). Clark (Pers. Comm.), has indicated that these areas may have to be eliminated from the algorithms. However, the extent of these 'bright areas' was small compared to the overall pixel area of the grains (approximately 40,000 pixel^2). As such, they were ignored.

As each S.E.M. image (including background) contained 512 x 512 pixels (262,144 pixels), this required a large amount of memory allocation. The 'proposal for future work' section indicates areas where redundancy in the images could be eliminated by data compression techniques such as Huffman coding, (Kidner and Smith, 1991). Histogram equalization did not appear to alter the overall texture pattern significantly confirming the findings of Connors and Harlow (1980), (see Section 3.2.3). As all quartz images were equalized using the same method the texture model results were directly comparable. In addition, grain sizes were roughly similar eliminating a source of potential error.

4.3 MATHEMATICAL MODEL RESULTS

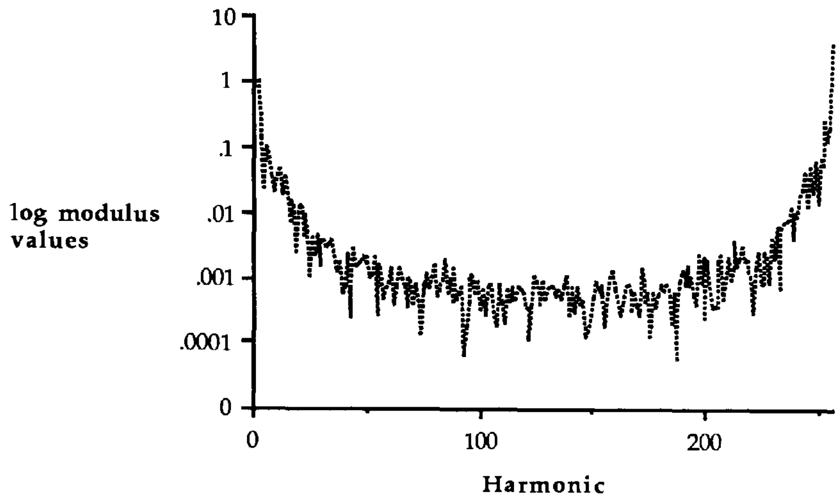
4.3.1 FOURIER DESCRIPTORS

The Literature Survey section highlighted previous studies using Fourier Transforms (see Ehrlich, et al, 1977), which used several methods to evaluate the nature of the shape frequency distribution, (Section 2.3). A common method, shape frequency histograms, plotted harmonic amplitude as a function of frequency of occurrence, and when used in conjunction with Q-Mode factor analysis subjectively separated shape families, (Ehrlich, et al, 1977).

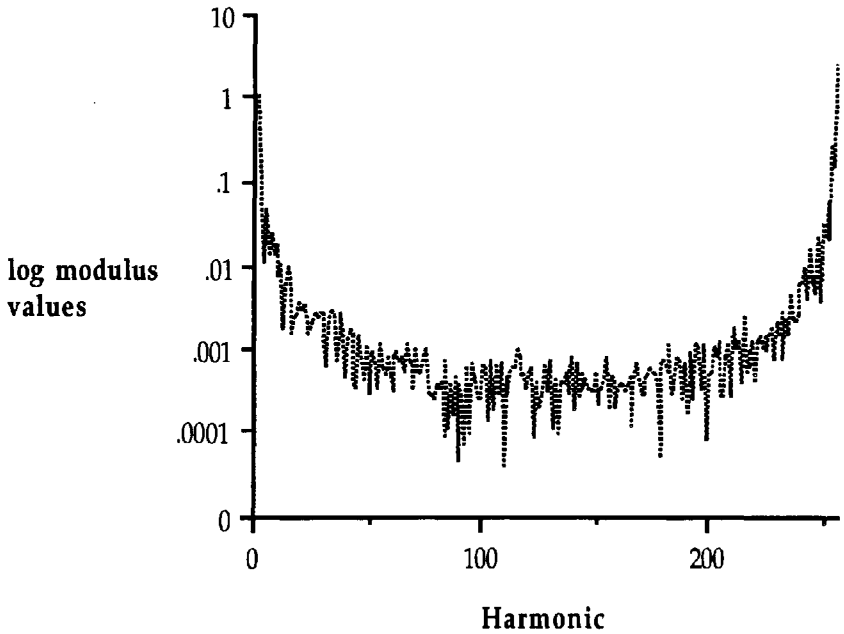
Due to the previous success of Fourier Transforms in analysing quartz grain populations, the Fourier Descriptor implementation would appear to have the greatest potential of all the methods used here, to perform between group separations and hence pattern recognition of sand grains. The Literature Survey and Methodology sections highlighted one aspect of previous Fourier transform implementations, use of only the first twenty or so coefficients to describe gross shape. However, reference to the Summary table of discriminating variables produced by discriminant analysis using Fourier Descriptor coefficients, indicated that 14 coefficients were used but the interesting point is the makeup of these variables, (Figure 22). All three coefficient types described by Dowdeswell (1982), (form,topography,and texture) were used in the statistical model. The implications are discussed in Section 5.5.

The presentation of results and analysis is slightly different to that of Ehrlich and Co.. This work has obviously not used the extensive amount of grains employed in previous shape studies. Therefore, the intention is not to study the variation in grain shape within sedimentary environments but to appraise whether Fourier Descriptors have potential as an effective shape descriptor. Therefore performance analysis is not restrained by the large variability in quartz grain suites indicated by previous work. Average modulus values were plotted against harmonic number and used as pattern features in *'between sample'* discrimination. The important coefficients for each sample were selected from the Discriminant model generated with SPSSx™.

Figure 19, (a to c) shows average log modulus values for each sample plotted against harmonic number. Note that the graphs for all three grain types appear visually similar but do have different harmonic responses. However reference to the discriminant analysis results (Figure 22) indicates separation is possible.

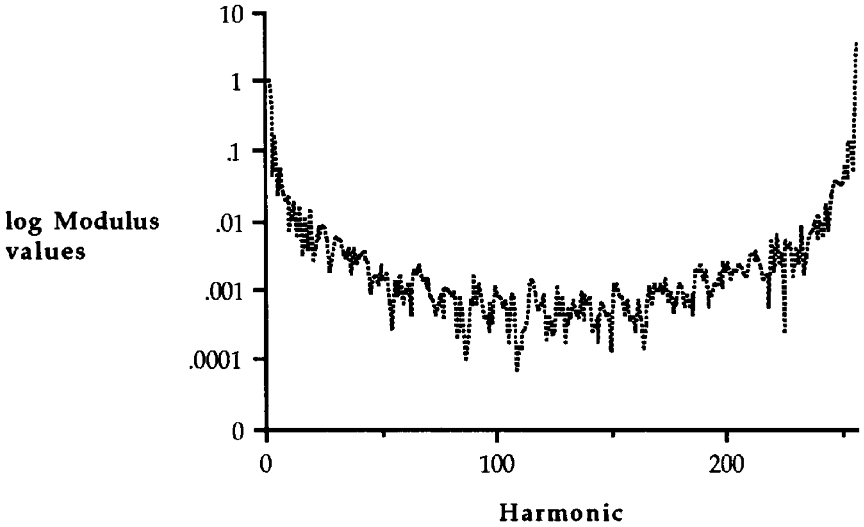


a) Desert quartz grain



b) Fire Island quartz grain

Figure 19 a & b. Average Fourier Descriptor values (in Log modulus form)



c) Crushed quartz grain

Figure 19 c - Average Fourier descriptor values (in log modulus form)

Section 3.4 has indicated the necessity for standardization in grain size and magnification. Figure 20 shows the Fourier Descriptor results for one sand grain at two different magnifications. Obviously different magnifications produce different grain shape coefficients regardless of the normalization procedures outlined in Section 3.4.2. This is the result of increasing magnification producing more complex boundary shape through the addition of small scale surface detail. Loess grain results (Figure 21), shows the feasibility of using this method for complex shaped particles.

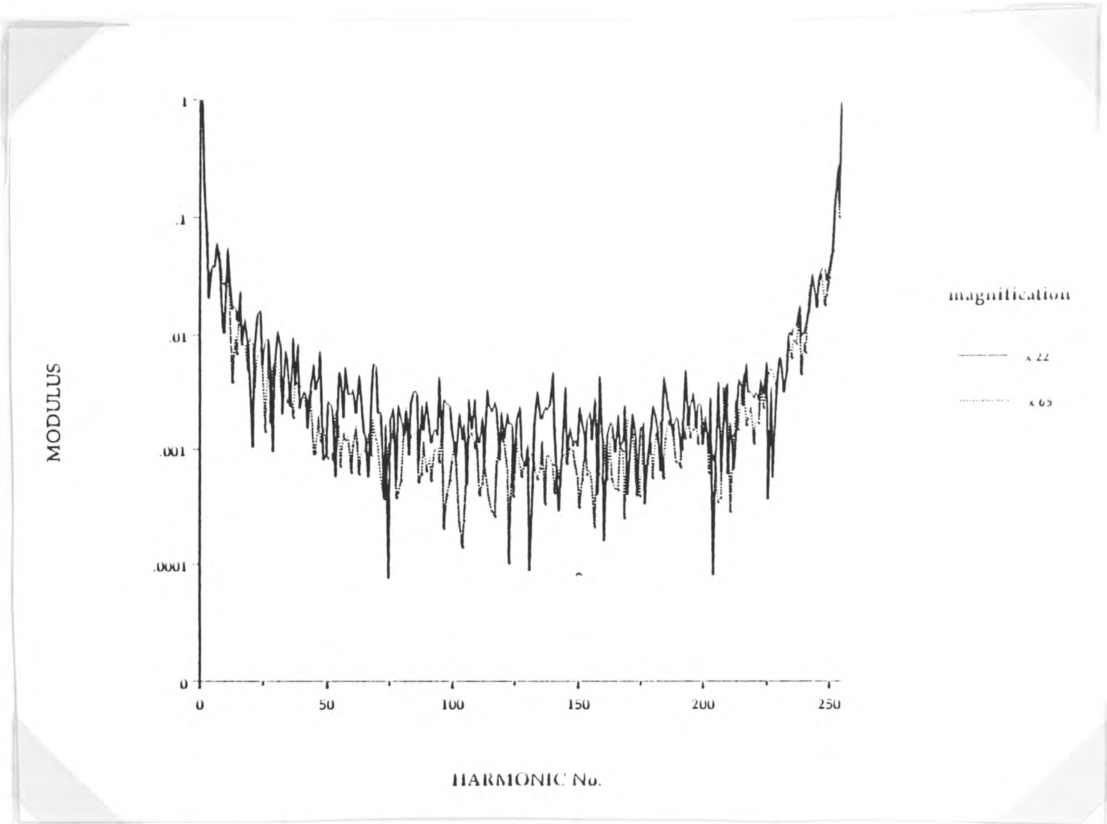


Figure 20 Effect of changing magnification on coefficient results

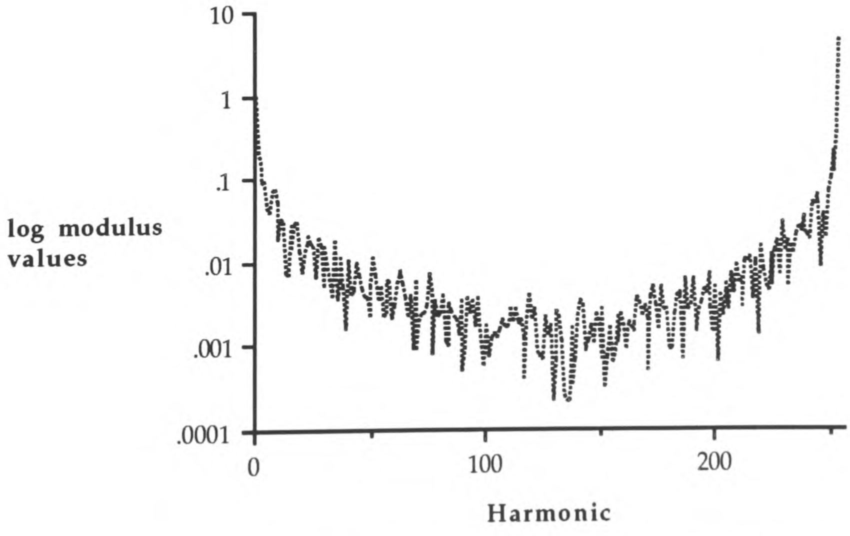


Figure 21 - Fourier Descriptors for a loess grain

As discussed in Section 3.9.2, Discriminant Analysis attempts to classify cases into one or more mutually exclusive groups using the linear combinations of variables which best separate the cases. The classification table indicates the percentage success rate achieved. These results were generated using model data and the *note of caution* regarding the validity of the success rate when applied to the *real world*, must be considered in analysis. The bootstrap score, found by the bootstrap method indicates a lower success rate and provides a more realistic value, (Section 3.9.2).

Table 3 shows the classification table while Figure 21 shows the all group scatterplot.

FOURIER DESCRIPTOR CLASSIFICATION RESULTS

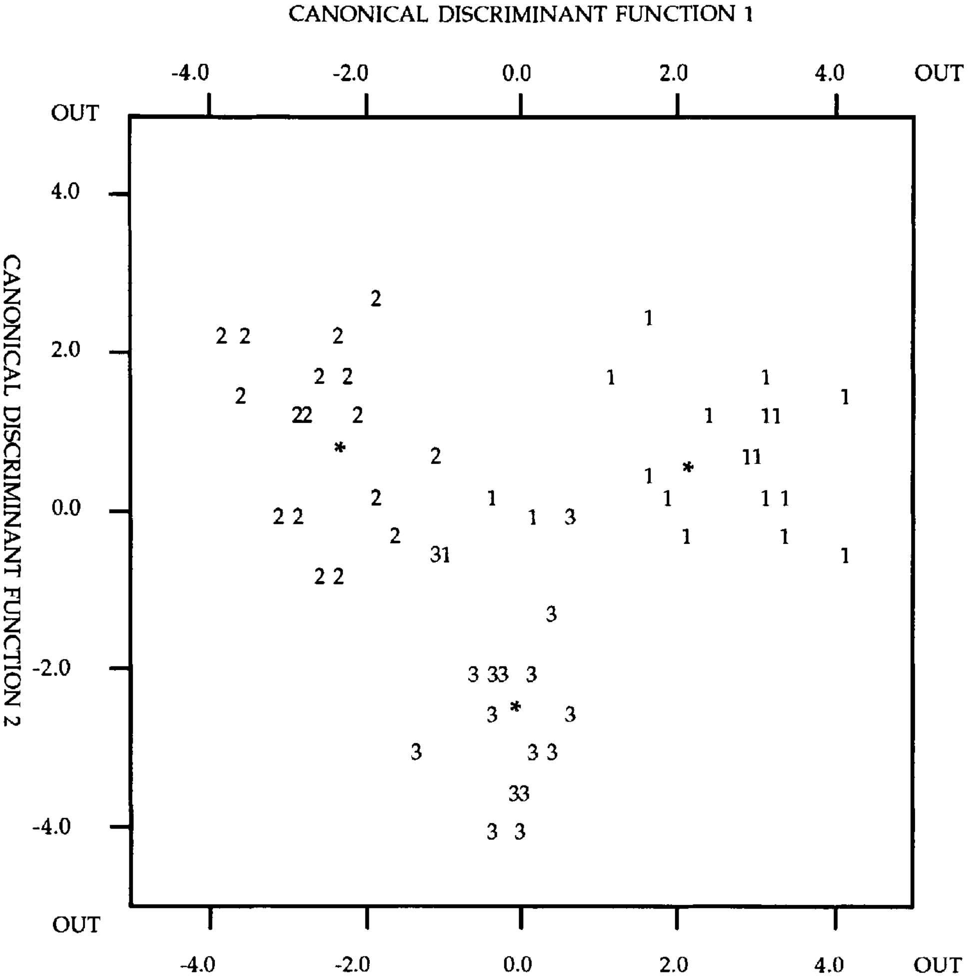
ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	90.0%	10.0%	0.0%
GROUP 2	300	0.0%	100.0%	0.0%
GROUP 3	300	5.9%	0.0%	94.1%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED :: 94.64%

BOOTSTRAP CLASSIFICATION : 90%

Table 3 - Fourier Descriptor classification table

The scatterplot is a visual output indicating the 'spread' of the population types based on their means.



FOURIER DESCRIPTOR SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	V164		1	.87916	.0329	0.11238	.3142	1	3
2	V2		2	.77438	.0094	0.67664	.0596	2	3
3	V72		3	.71153	.0071	0.96156	.0388	1	2
4	V4		4	.63849	.0033	1.27792	.0407	2	3
5	V126		5	.61176	.0053	1.42447	.0386	1	2
6	V208		6	.52559	.0012	1.90402	.0204	1	2
7	V56		7	.41777	.0001	2.81175	.0075	2	3
8	V197		8	.39154	.0001	3.30490	.0055	2	3
9	V45		9	.35292	.0001	3.63461	.0033	1	2
	V135			.32615	.0001	4.21287	.0023	1	2
10	V76		10	.27786	.0000	4.71879	.0036	2	3
11	V253		11	.24976	.0000	5.54048	.0021	2	3
12		V4	12	.25893	.0000	5.48683	.0009	1	3
13	V240		11	.22769	.0000	5.84236	.0011	1	3
14	V140		12	.21260	.0000	6.42443	.0013	2	3
15			13						

Figure 22 - Fourier Descriptor scatterplot and summary table

The interesting point to note from Figure 22, is the inclusion of a wide selection of coefficients in the model. This indicates that all types of coefficients, (form, topography and surface texture) have been included. This contrasts to previous work where only the first twenty coefficients have been used, (see Section 5.5).

4.3.2 AUTOCORRELATION

A sample autocorrelation diagram for a crushed quartz grain is shown in Figure 23. While similar diagrams were produced for all quartz grains, their form varied markedly and no recognisable pattern could be seen. However, they did produce information concerning the correlation of pixels. The best correlations were obtained at small spacings, (5 - 10 pixels) with correlation dropping off at larger distances. These results dovetail with the co-occurrence results where discrimination was best at small separations of ∂ , (see Section 4.3.6)

The autocorrelation algorithm caused a number of computational problems which the PC based system found difficult to overcome, particularly the calculation time for results. Data transfer to the GENVAX was time consuming and computationally expensive.

While it would appear that the autocorrelation algorithm was redundant as a textural measure, the autocorrelation diagram of a 'cloth texture', (Plate 7, Figure 24), shows that regularly structured textures can be adequately described. Importantly, vertical and horizontal components are maintained in the autocorrelation output. This is more than the other textural measures achieved. In conclusion, computational difficulties have hampered the development of this method, a state reflected in the lack of implementations, (see Section 2.2.2a).

No attempt was made to use the autocorrelation results in discriminant analysis.

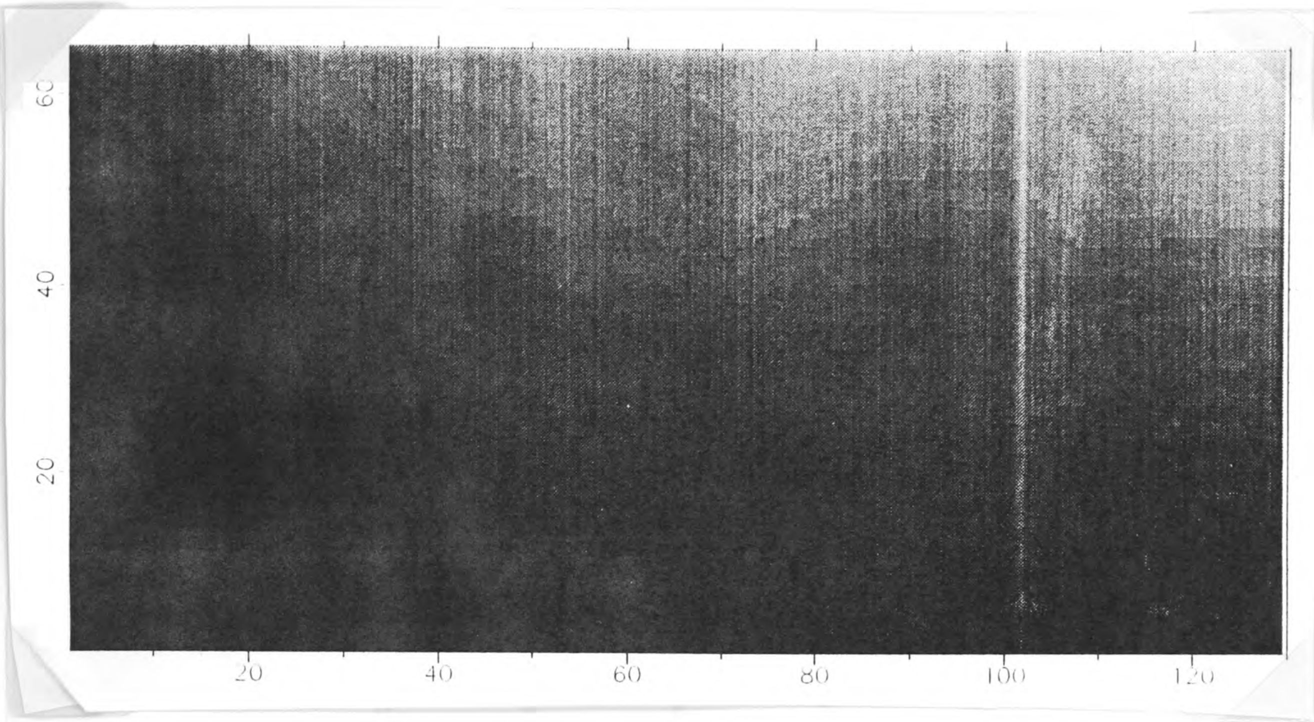


Figure 23 - An example of an Autocorrelation diagram for a crushed quartz grain .

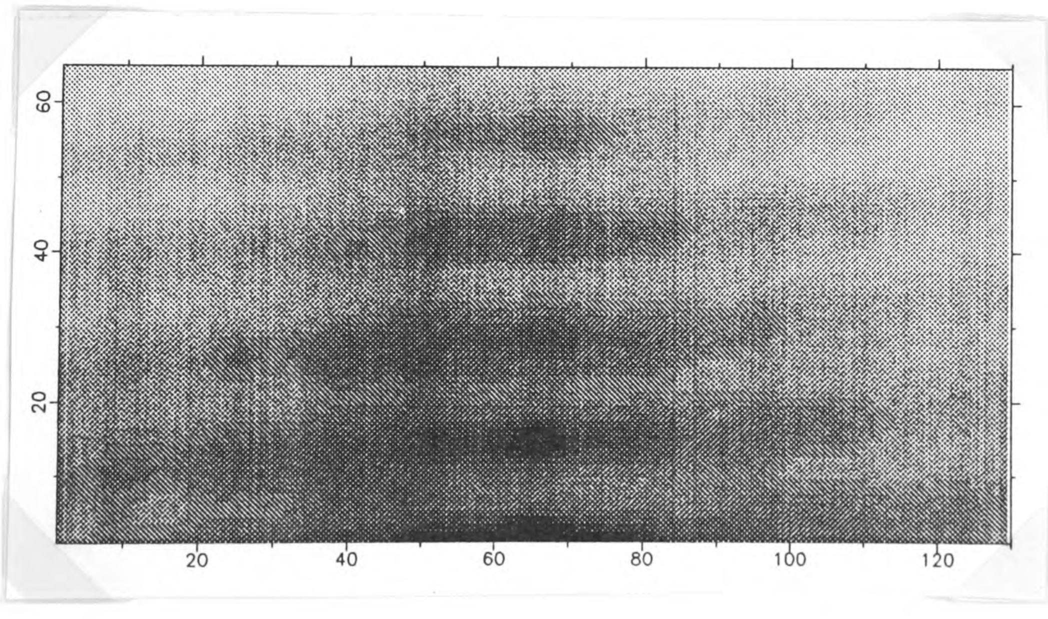


Figure 24 - Autocorrelation diagram for cloth.

4.3.3 2-D FOURIER TRANSFORMS

Section 3.6 outlined the use of fixed radii to calculate the power within the spectrum. The following graphs show average results for the quartz grain populations and also a cumulative percentage.

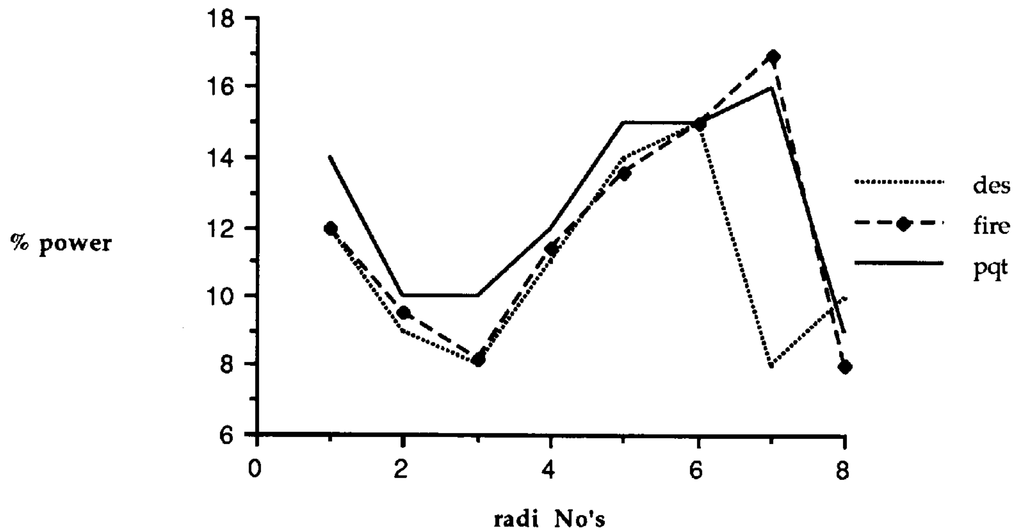


Figure 25 - Average 2-D Fourier plots for the three quartz grain populations

Figure 25 shows the average radial plots for the quartz grain populations obtained from the power spectrum. The radii numbers on the horizontal axis represent the bands (see Section 3.6). The average power spectra is similar in desert and Fire Island quartz grains however there is marked difference between them and the crushed quartz grains. The only region where the desert and Fire island grains differ, is in the higher frequencies bands. The implications for texture analysis are discussed in Section 5.7.

The cumulative frequency graph (Figure 26), confirms that both Fire Island and desert grain types are similar in their power spectra. However, it is interesting to note, that the percentage values for each band are similar. No one band contains a large amount of power. Again this is discussed in Section 5.7.

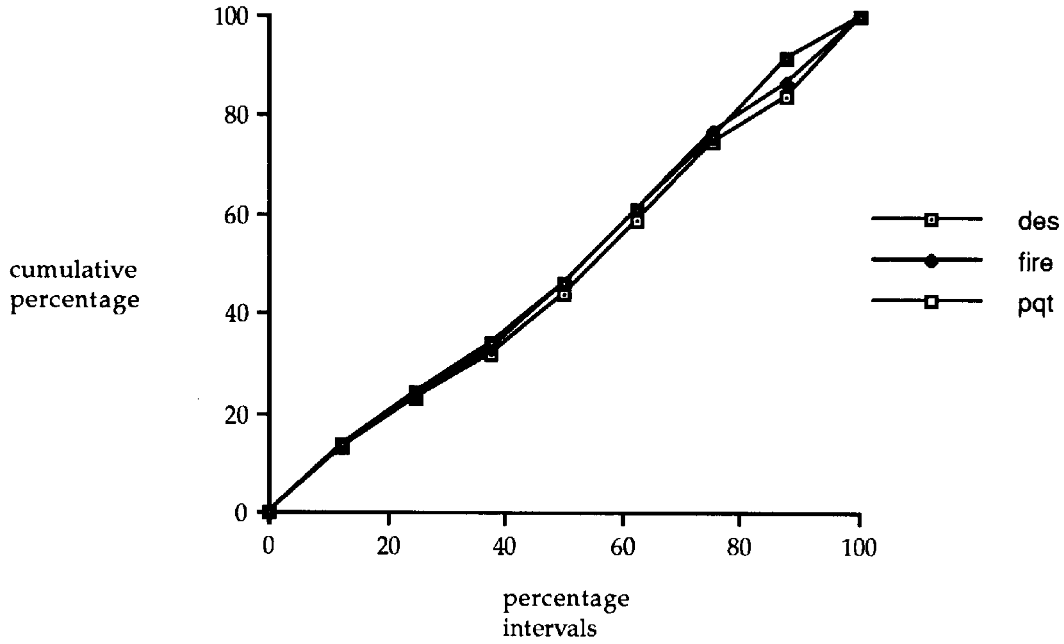


Figure 26 - Cumulative frequency chart for the three grain types.

Figure 27 shows the all group scatter plot, and summary table, Table 4 shows the classification table. The scatter plot shows little separation between the three groups, with the group centroids appearing closely linked. This is reflected in the classification table which produced an overall classification of 72.22% and is in contrast to other textural measures which produced significantly better results. The most discriminating were the desert grains with 85%. Only ring 2 was omitted from the stepwise routine. These results contradict the empirical evidence presented by the graphs which indicate little difference between the values. The most discriminating variable was band seven, where the desert and quartz grains divert most from each other.

In computation terms this routine was more expensive to run than other textural algorithms due to calculation of the Fourier Transform of both rows and columns.

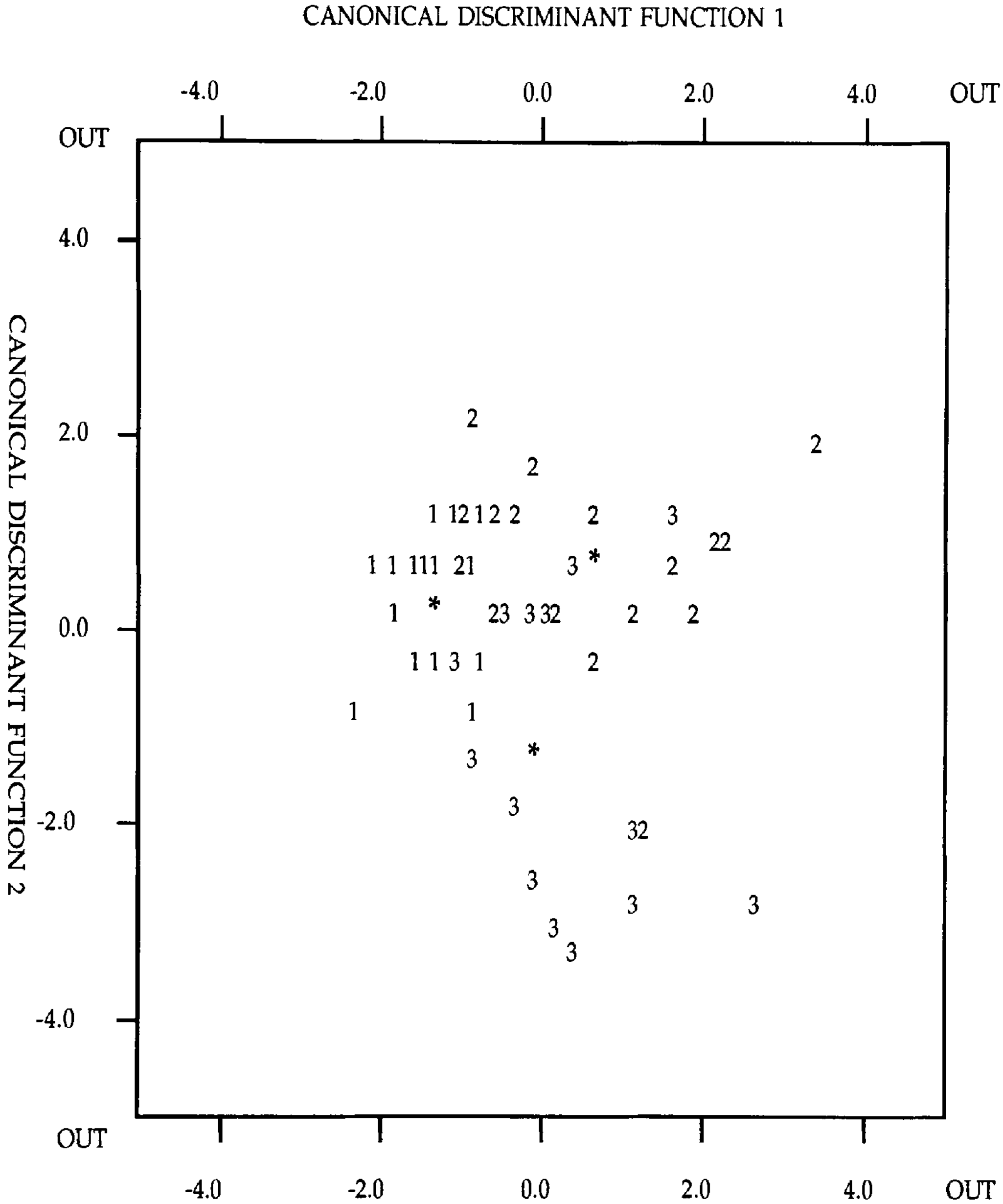
2-D FOURIER TRANSFORM CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	85.0%	10.0%	5.0%
GROUP 2	300	22.2%	66.7%	11.1%
GROUP 3	300	18.8%	18.8%	62.5%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : **72.22%**

BOOTSTRAP CLASSIFICATION : 66 %

Table 4 - 2-D Fourier transform classification table



2-D FOURIER TRANSFORM SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	R7		1	.93427	.1766	0.04931	.4974	1	2
2	R3		2	.82079	.0409	0.43960	.1717	2	3
3	R6		3	.63757	.0010	0.93104	.0482	1	2
4	R1		4	.49444	.0000	2.17005	.0046	2	3
5	R4		5	.44175	.0000	2.63144	.0026	1	3
6	R5		6	.37211	.0000	3.18006	.0024	2	3

Figure 27 - 2-D Fourier transform scatterplot and summary table

4.3.4 TEXTURAL UNITS

The Methodology section has outlined the calculation of the Black - White Symmetry (BWS) measure and Geometric Symmetry (GS). Average BWS results are given in Figure 28a, and average GS results in Figure 28b. The presentation of raw spectra data is avoided. The spectrum number on the horizontal axis refers to the ordering system used in calculating the spectra, (see Figure 14).

All three grain types have similar BWS signatures differing only in magnitude. They all trough at spectrum ordering 5 and peak at ordering 7. The Fire Island grains had similar values for ordering way four and eight indicating some type of linear structure in the textural units. While easy to program, computationally this algorithm was expensive due to the need to calculate a textural spectrum for all possible 8 orderings and then calculate BWS and GS values. As with other algorithms the results were difficult to match to specific quartz grain textures.

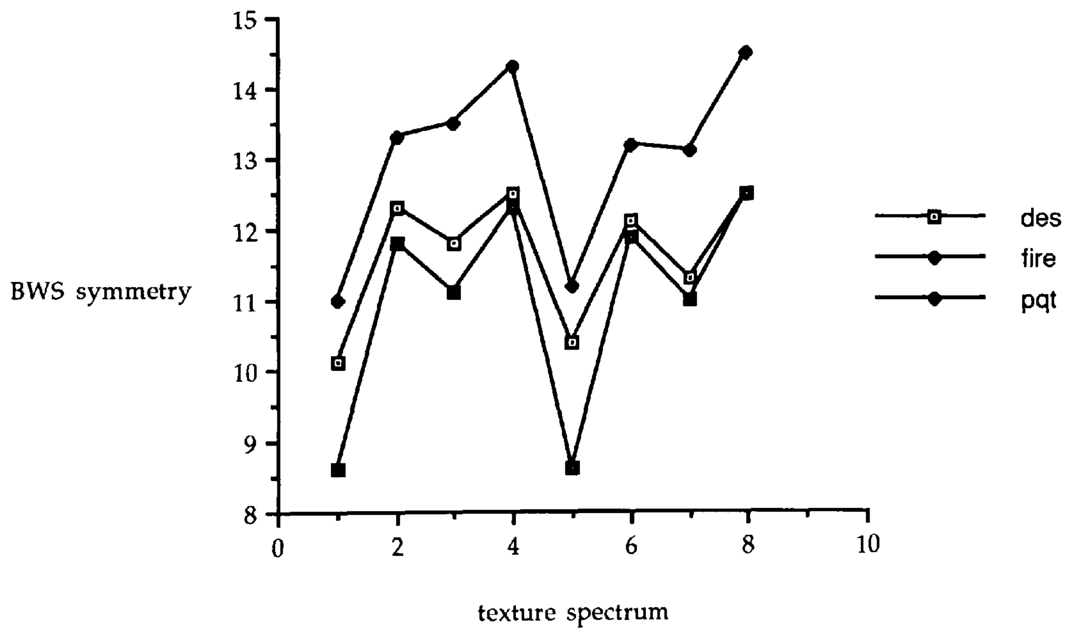


Figure 28a - Average BWS results for the three populations

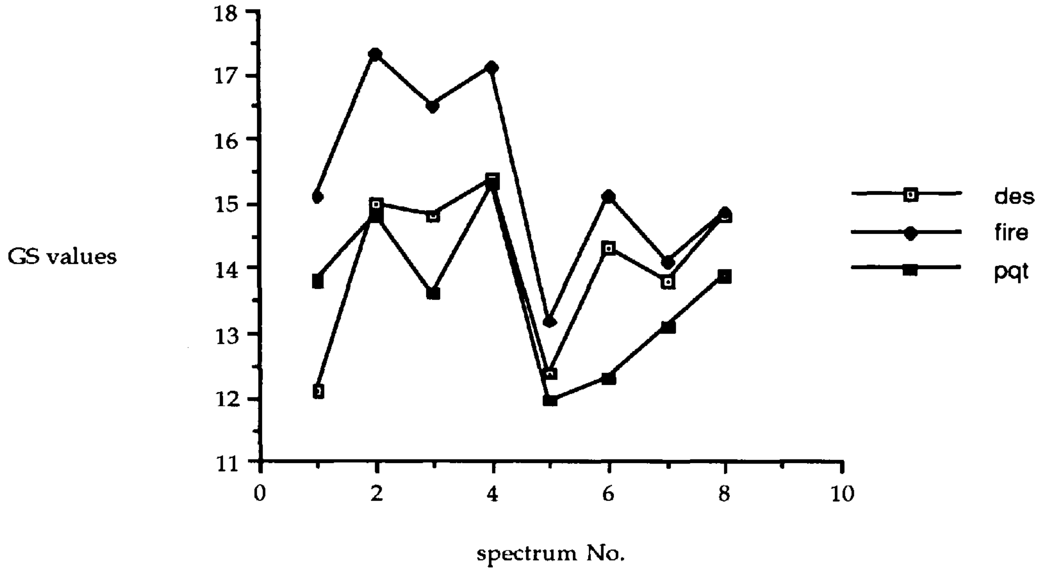


Figure 28b - G.S. results for the three populations.

As discussed in Section 3.7, GS values measure the symmetry between the spectra under the ordering ways a & e, b & f, c & g and d & h. Wang and He (1990), indicated that a high GS value occurrs when there is a regular shape to a texture, i.e rotating the image by 180 degrees will produce a similar shape texture. From this it may be concluded that the Fire Island grains displayed the more regular textural shape, while crushed quartz were more irregular in texture.

Figure 29 shows the all group scatter plot, summary table and Table 3, the classification table. As with the Fourier Descriptor plots, the scatter plot indicates a reasonable separation with an 89% success rate. Crushed quartz was a problematic group to classify with 23% of grains assigned to Fire Island samples. Note that the GS values were the primary discriminating variable.

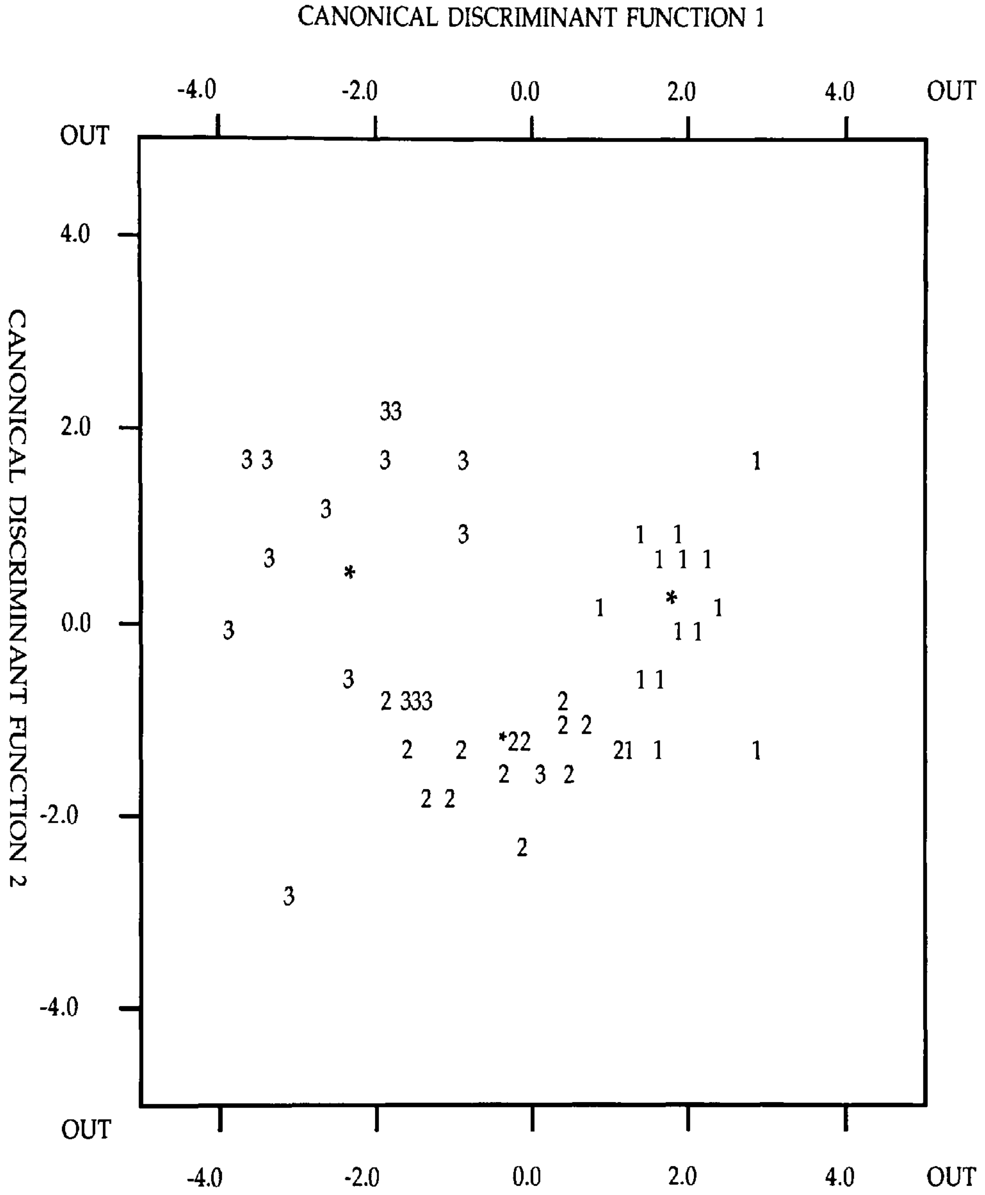
TEXTURAL UNIT CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	95.0%	5.0%	0.0%
GROUP 2	300	0.0%	94.4%	5.6%
GROUP 3	300	0.0%	23.5%	76.5%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : **89.09%**

BOOTSTRAP CLASSIFICATION : 79 %

Table 5 - Textural unit classification table



TEXTURAL UNIT SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	GS		1	.40837	.0000	1.52971	.0006	2	3
2	BS6		2	.31201	.0000	2.91417	.0000	1	2
3	BSN		3	.24578	.0000	4.15353	.0000	2	3
4	BS2		4	.20972	.0000	4.67907	.0000	1	2
5	BS7		5	.15504	.0000	5.77438	.0000	2	3
6	BS5		6	.14785	.0000	5.83147	.0000	2	3

Figure 29 - Textural unit scatterplot and summary table

4.3.5 EDGE GRADIENTS

Both the Literature Survey and Methodology sections have highlighted the cognitive importance of edges in describing texture. Rosenfield and Troy (1970), suggested use of amount of edge per unit area as an efficient measure. As stated in the Methodology section, grains were of a similar size eliminating the need for calculating edge gradients per unit area. Edge frequency histogram data is shown in Figure 30a, with number of occurences of a particular gradient value plotted against gradient value. B,c and d are the individual examples.

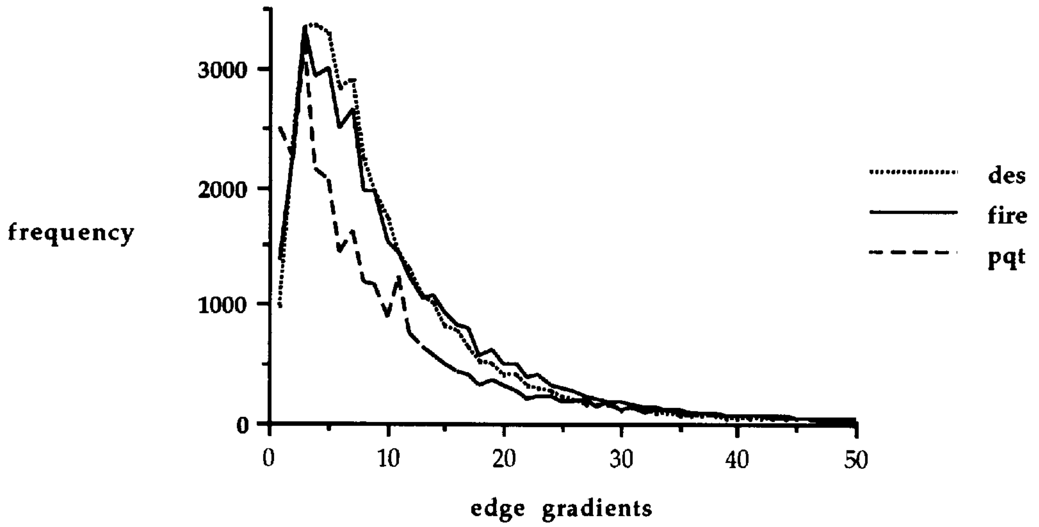


Figure 30a

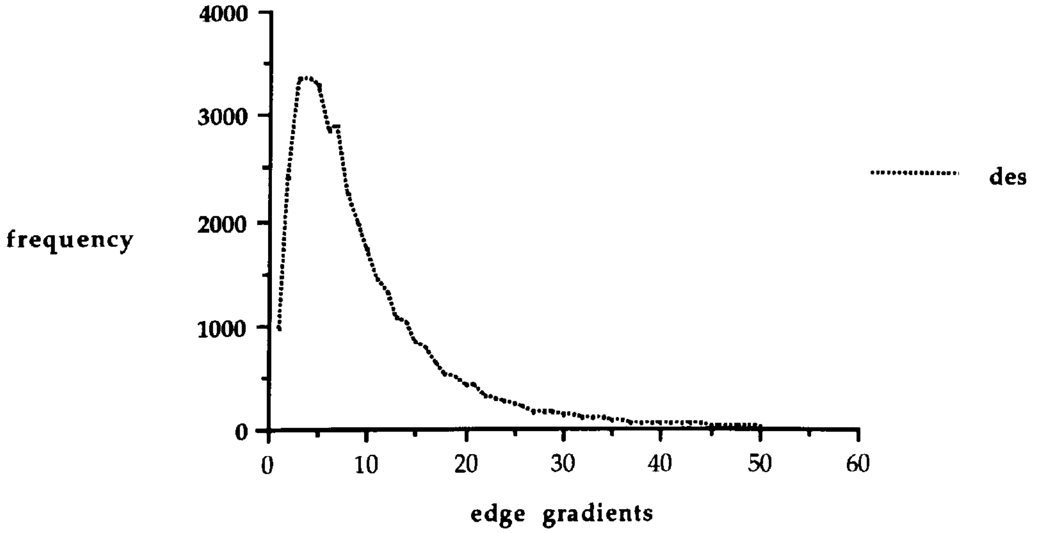


Figure 30b

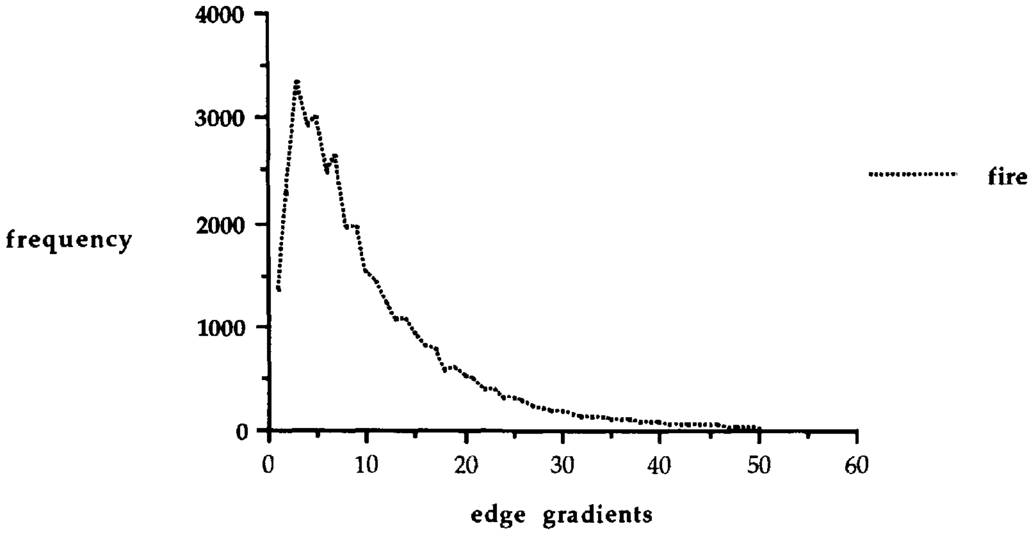


Figure 30c

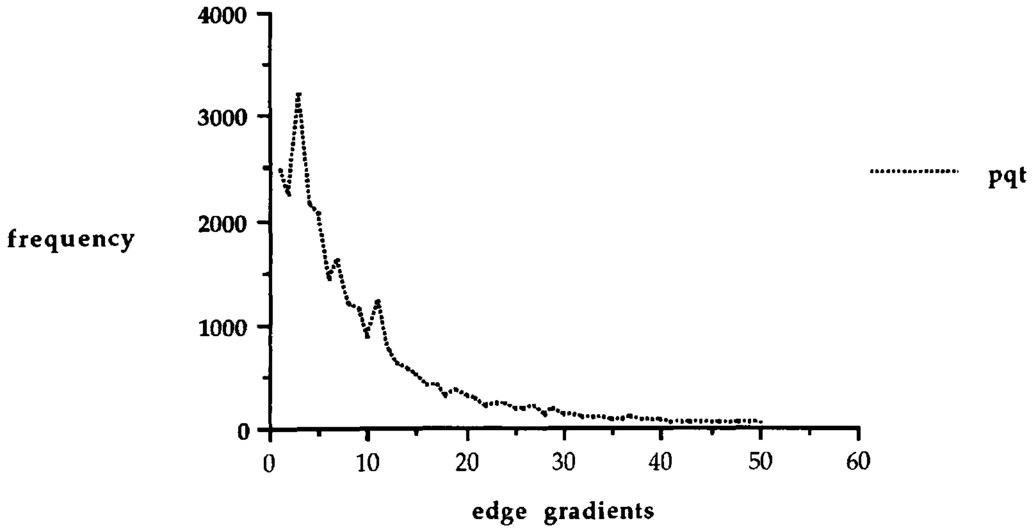


Figure 30 d

Figures 30a - d - Edge frequency histograms.

The presentation of edge data in this form is a departure from more established methods, (see Rosenfeld and Troy, 1970 and Rosenfeld and Thurston, 1971). However, as Section 5.7 will show, the use of edge gradients holds many attractions.

The graph indicates that fewer edges were to be found on crushed quartz grains , a conclusion supported by the qualitative asssessment given in Section 4.1 and reference to Plate 8c. Fire Island and desert grains had similar edge signatures. However, the Fire Island results indicated more large gradients associated with their surfaces. This is possibly due to the intense surface breakage patterns associated with glacio-marine grains, (see Williams and Thomas, 1989a , and Plate 8b). See Section 5.7 for more discussion on these interpretations.

The use of histogram data precluded its inclusion as a pattern recognition feature in Discriminant analysis.

4.3.6 SGLDM'S

The calculation of the SGLDM proved computationally expensive and time consuming, even allowing for the reduction in gray levels, (see Section 3.2.3). Section 5.7 highlights both strengths and weaknesses of this approach. Figure 28, a- d shows average plots for homogeneity, contrast, entropy and correlation, (see Section 3.3.2).

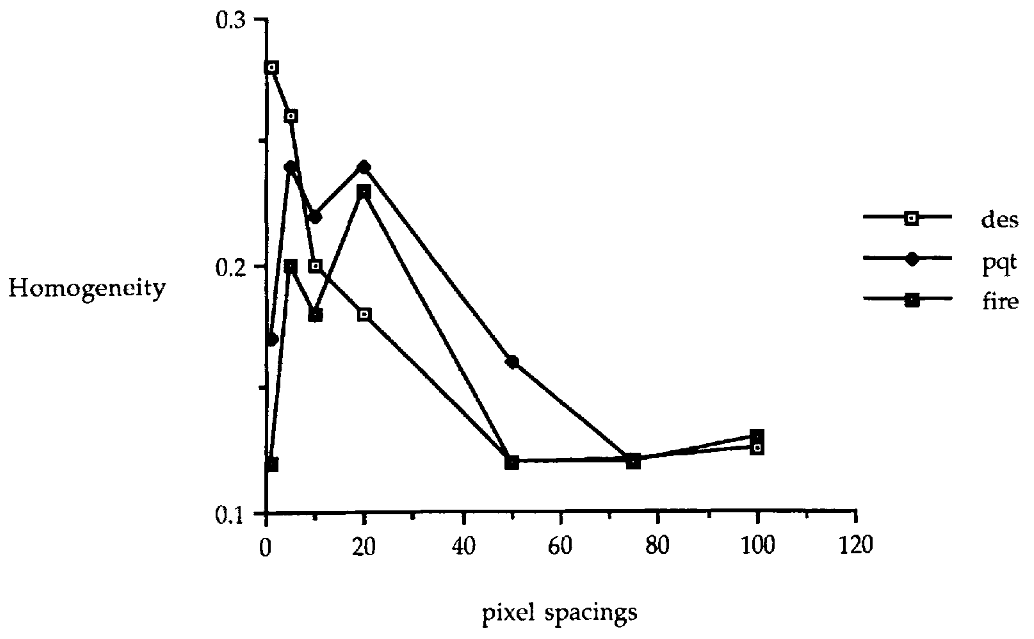


Figure 31a - Homogeneity plot obtained from the SGLDM data

These results indicate several differences between grain types. At small spacings the desert grains revealed a more homogeneous texture. However, at larger spacings this trend was reversed. Crushed quartz and Fire Island grains displayed similar results but the former had larger values at the largest separations. This is possibly an indication of the presence of large homogeneous areas on the grain surface, (Plate 8c).

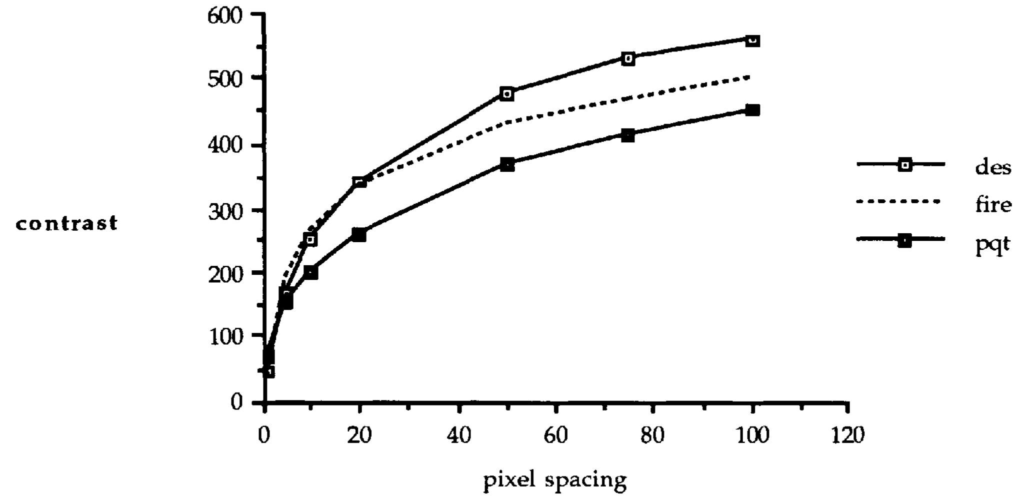


Figure 31b - Contrast plot obtained from the SGLDM data

Contrast plots were similar for all three grain types. Desert grains had the largest contrast at the wider spacings. This links in with the homogeneity results where desert grain textures were not as homogeneous at the larger spacings. Crushed quartz had less contrast at the wider spacings due to the presence of large homogeneous areas.

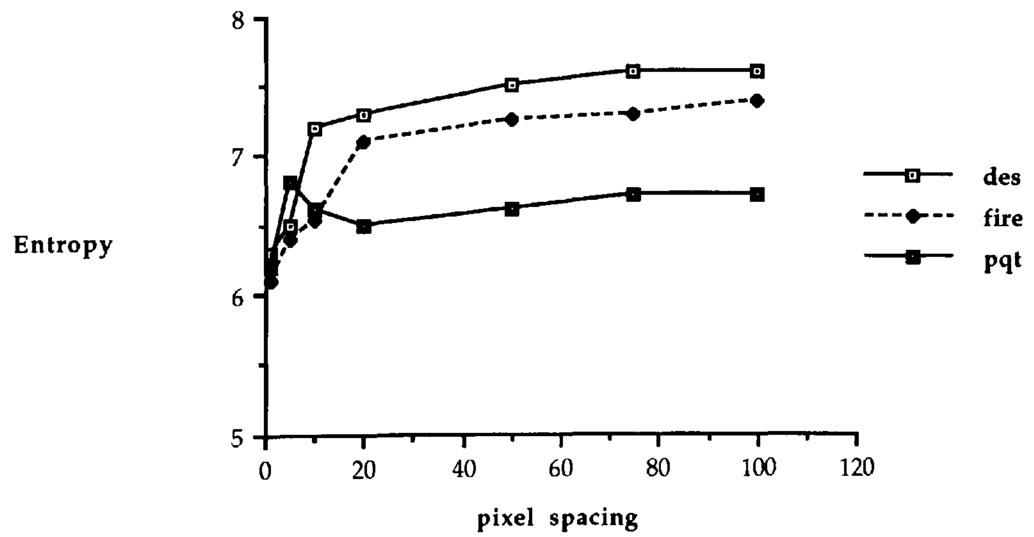


Figure 31c - Entropy plot obtained from the SGLDM data

Entropy values indicated that desert grains had a more random arrangement of pixels and therefore a more irregular texture. As in the previous results crushed quartz grains had a lower entropy value indicating a more regular predictable texture, (see Section 5.7).

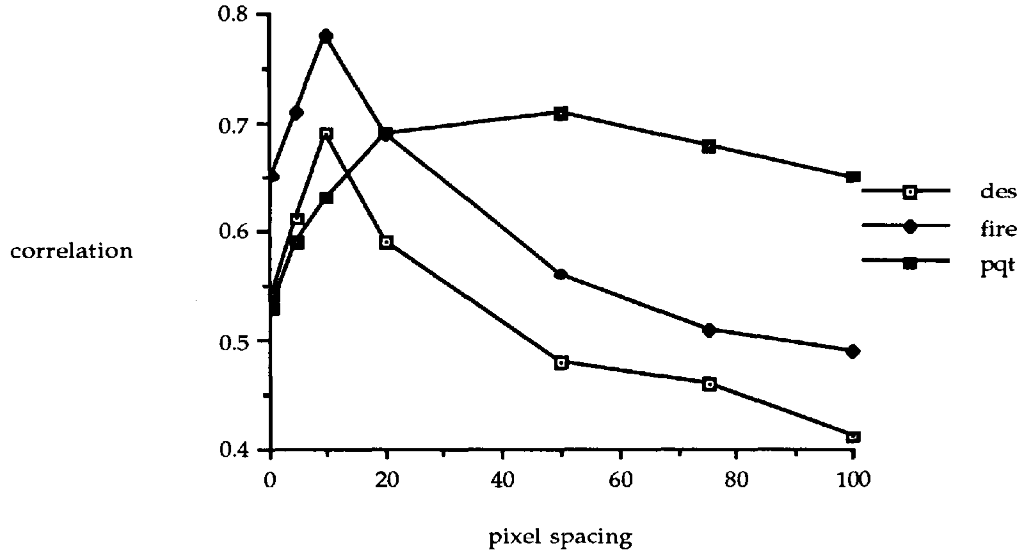


Figure 31d - Correlation plot obtained from the SGLDM data

Largest correlation values were found in Fire Island types at small spacings. This may be due to greater structure in the surface texture. Crushed quartz grains revealed greater correlation at the larger spacings. Again this is indicative of the large flat areas found on these grains.

Figure 32 shows the all group scatter plot, summary table and Table 4, the classification table. Results indicate a reduced success using this method when compared to Fourier Descriptors, (see Table 3).

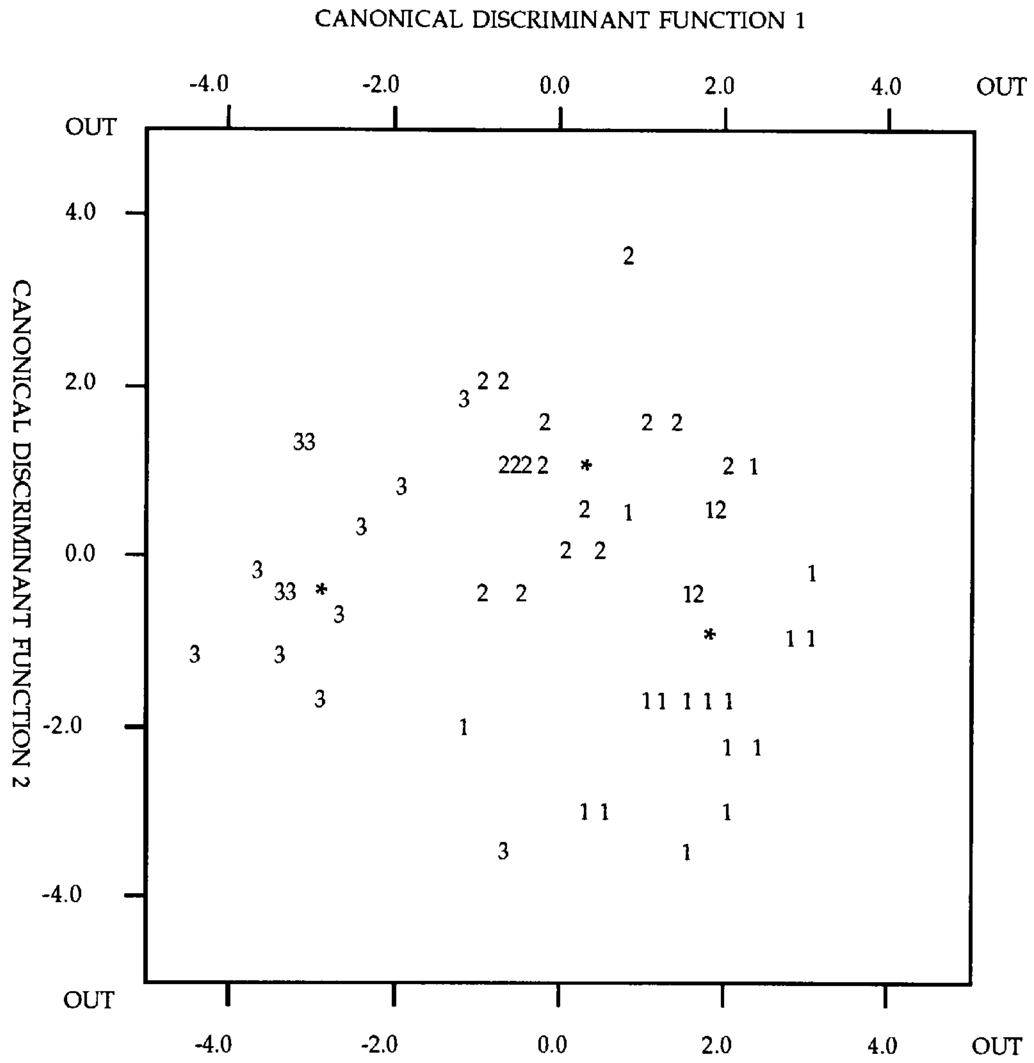
CO-OCCURRENCE CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	85.0%	10.0%	5.0%
GROUP 2	300	10.5%	89.5%	0.0%
GROUP 3	300	5.9%	5.9%	88.2%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : 87.50%

BOOTSTRAP CLASSIFICATION : 81%

Table 6 - Co-occurrence classification table



CO-OCCURRENCE SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	ENT75		1	.72957	.0002	0.17607	.1959	1	2
2	COR75		2	.55692	.0000	0.77516	.0313	1	2
3	HOMO75		3	.52056	.0000	1.07075	.0261	1	2
4	CON75		4	.40326	.0000	1.43964	.0176	1	2
5	CON10		5	.34729	.0000	1.79810	.0132	1	2
6	HOMO5		6	.24068	.0000	2.43027	.0052	1	2
7	HOMO1		7	.17036	.0000	3.96358	.0003	1	2
8	ENT1		8	.16077	.0000	4.51610	.0003	1	2
9	HOMO100		9	.14877	.0000	4.93646	.0003	1	2
	COR10			.14136	.0000	5.12959	.0005	1	2
10	CON5		10	.13236	.0000	5.30450	.0007	1	2
11	CON20		11	.11796	.0000	5.63131	.0009	1	2
12	HOMO50		12	.10809	.0000	5.82952	.0014	1	2
13		COR10	13	.11130	.0000	5.71625	.0008	1	2
14	CON100		12	.10612	.0000	5.94966	.0012	1	2
15			13						

Figure 32 - Co-occurrence scatterplot and summary table

Figure 32 indicates that a variety of measures at different spacings were used to discriminate between populations. This supports the conclusions of Weszka, et al (1976), that a variety of spacings is optimal for discrimination.

4.3.7 COMBINED DISCRIMINANT RESULTS

One of the original goals of this work was to study the combined benefits of using two or more mathematically derived textural models . Few workers have done this, although researchers have indicated that this combination of features is preferential, (see Section 2.2.2). Discriminant results in the form of all group scatterplots, summary and classification tables are given for the following model combinations :

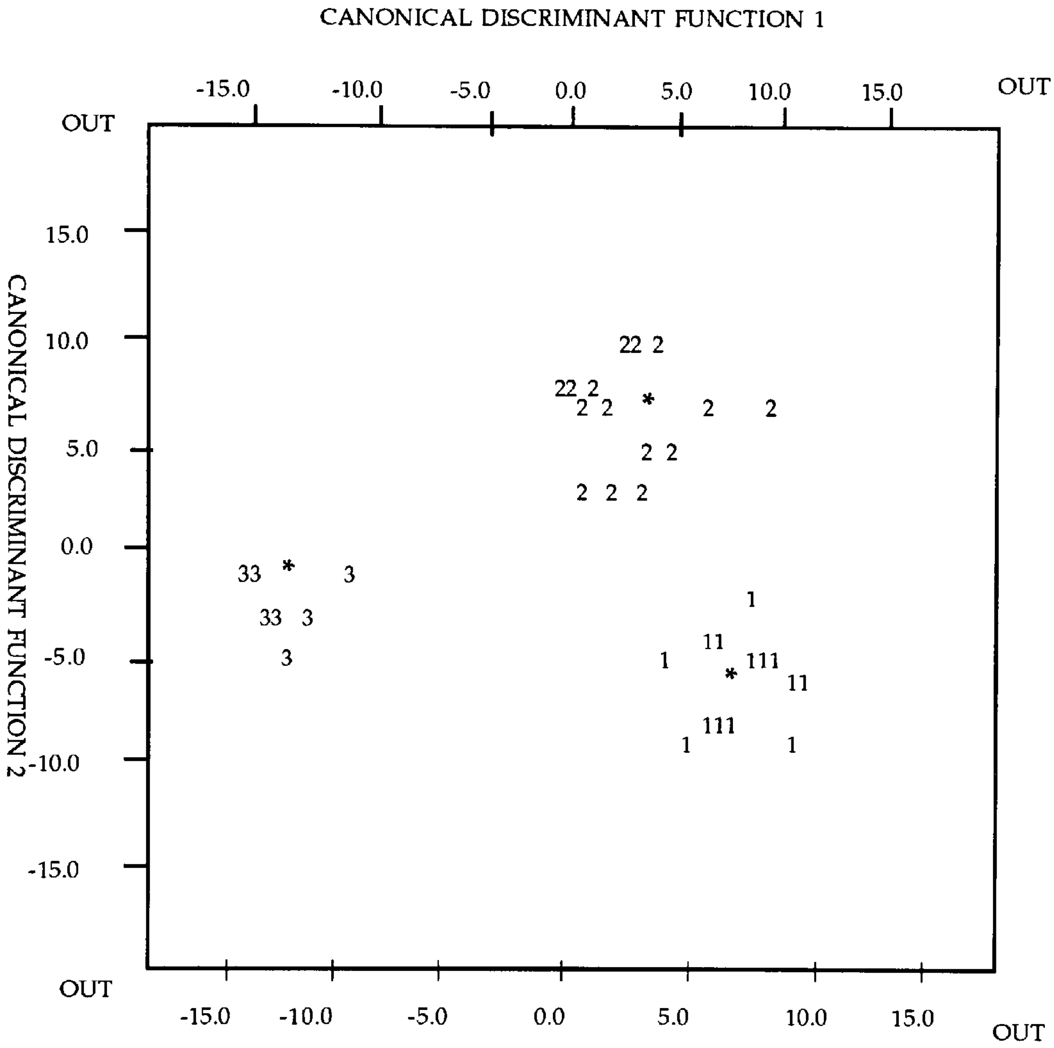
a) SGLDM results with Fourier Descriptors
b) SGLDM results with Fourier Descriptors, 2-D Fourier Transforms
c) SGLDM results with Fourier Descriptors, 2-D Fourier Transforms and Textural units.

FOURIER DESCRIPTOR & CO-OCCURRENCE CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	100.0%	0.0%	0.0%
GROUP 2	300	0.0%	100.0%	0.0%
GROUP 3	300	0.0%	0.0%	100.0%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : 100.00%
BOOTSTRAP CLASSIFICATION : 94%

Table 7 - Fourier Descriptor & Co-occurrence classification table



FOURIER DESCRIPTOR CO-OCCURRENCE SUMMARY TABLE

STEP	ACTION ENTERED	REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	V164		1	.83957	.0097	0.21834	.1674	2	3
2	ENT75		2	.59905	.0000	0.60385	.0648	1	2
3	COR75		3	.48116	.0000	1.18034	.0176	1	2
4	HOMO5		4	.33574	.0000	1.54494	.0126	1	2
5	CON10		5	.30006	.0000	2.28375	.0034	1	2
6	HOMO1		6	.19138	.0000	4.03620	.0001	1	2
7	HOMO100		7	.17051	.0000	4.91005	.0000	1	2
8	COR10		8	.15769	.0000	5.41841	.0000	1	2
9	V72		9	.14218	.0000	5.84262	.0001	1	2
	V109			.13058	.0000	6.82168	.0000	1	2
10	V215		10	.11984	.0000	7.41139	.0000	1	2
11	V143		11	.11251	.0000	8.04595	.0000	1	2
12	V175		12	.10000	.0000	8.65348	.0000	1	2
13	V231		13	.09212	.0000	9.80141	.0000	1	2
14	V200		14	.08516	.0000	10.79824	.0000	1	2
15			15						

Figure 33 - Fourier Descriptor & Co-occurrence scatter plot and summary table

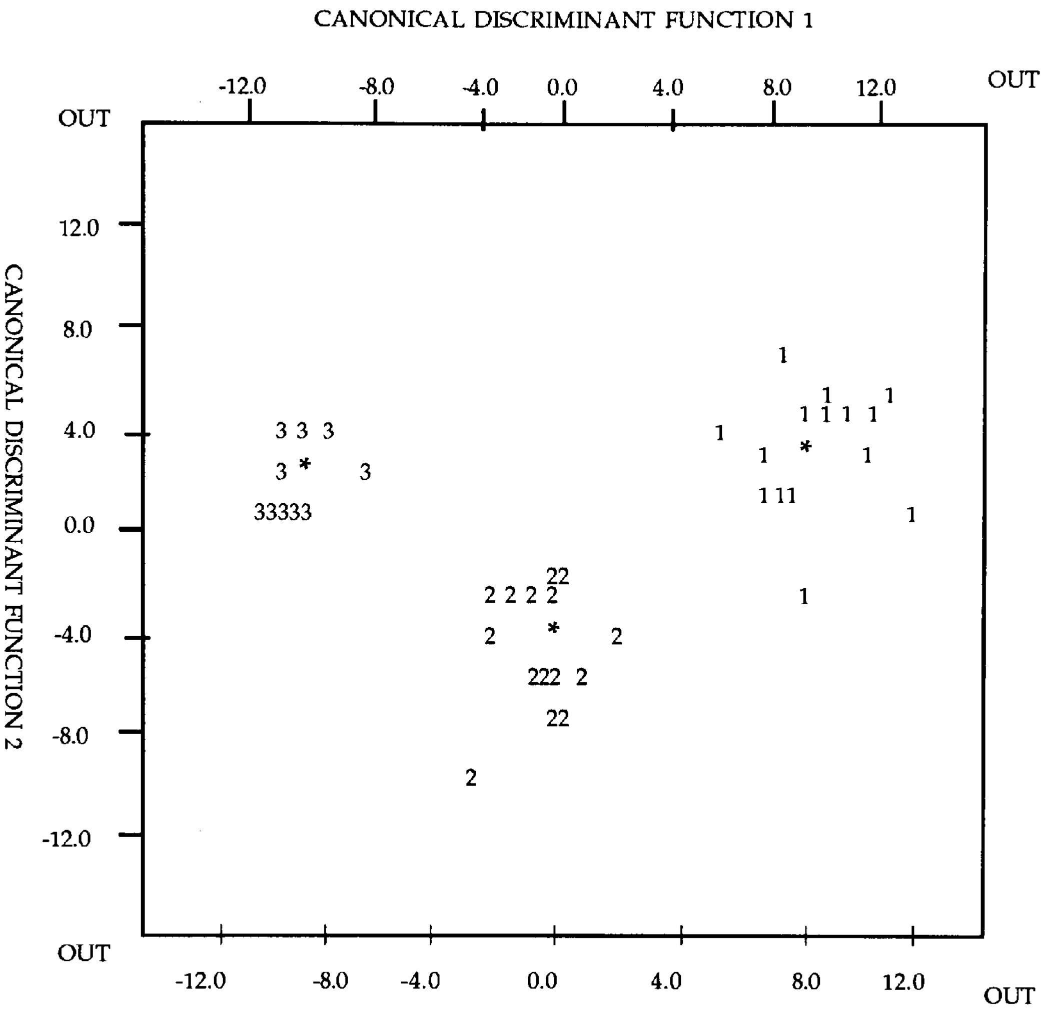
FOURIER, CO-OCCURENCE, 2-D FOURIER TRANSFORM
CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	100.0%	0.0%	0.0%
GROUP 2	300	0.0%	100.0%	0.0%
GROUP 3	300	0.0%	0.0%	100.0%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : 100.00%

BOOTSTRAP CLASSIFICATION : 94%

Table 8 - Fourier descriptor, Co-occurrence and 2-D Fourier Transform classification table



FOURIER CO-OCCURRENCE 2-D FT SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	V164		1	.84738	.0147	0.21170	.1811	2	3
2	ENT75		2	.61063	.0001	0.56756	.0811	1	2
3	COR75		3	.50051	.0000	1.10308	.0262	1	2
4	R5		4	.41782	.0000	2.18505	.0038	2	3
5	V234		5	.38467	.0000	2.65824	.0028	2	3
6	V135		6	.32084	.0000	3.22313	.0010	1	2
7	V22		7	.28473	.0000	3.64330	.0009	1	2
8	R6		8	.25083	.0000	4.21304	.0007	1	2
9	V182		9	.22063	.0000	4.89202	.0004	1	2
10	V178		10	.20085	.0000	5.21961	.0006	1	2
11	R8		11	.18473	.0000	5.95126	.0009	2	3
12	V42		12	.16769	.0000	6.62368	.0008	2	3
13		R5	11	.17564	.0000	6.14614	.0003	1	2
14	V163		12	.16346	.0000	6.83399	.0003	1	2
15	R1		13	.14903	.0000	7.58715	.0002	1	2

Figure 34 - Fourier Descriptor, Co-occurrence & 2-D Fourier Transform scatter plot and summary table

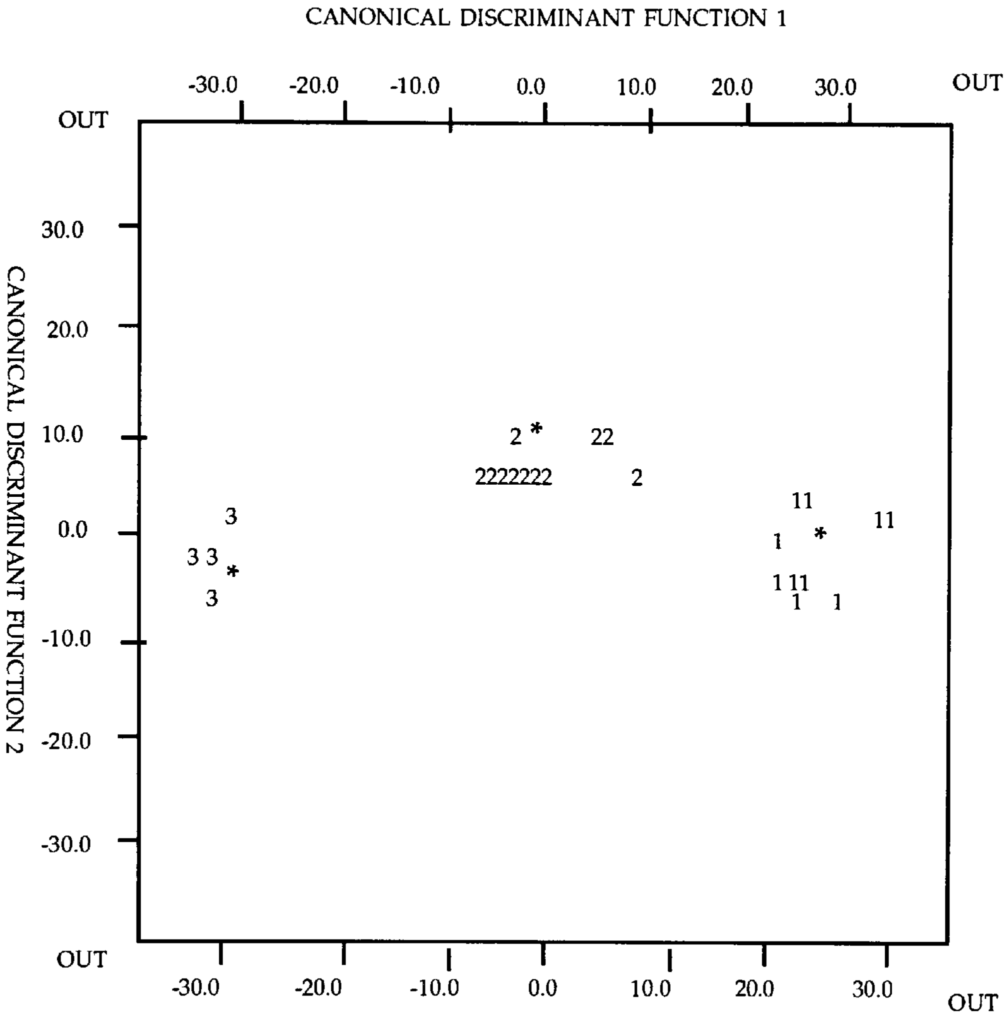
SGLDM, FOURIER DESCRIPTOR, TEXTURAL UNITS
& 2-D FOURIER TRANSFORM CLASSIFICATION RESULTS

ACTUAL GROUP	No.	PREDICTED GROUP MEMBERSHIP 1	2	3
GROUP 1	300	100.0%	0.0%	0.0%
GROUP 2	300	0.0%	100.0%	0.0%
GROUP 3	300	0.0%	0.0%	100.0%

PERCENT OF GROUPED CASES CORRECTLY CLASSIFIED : 100.0%

BOOTSTRAP CLASSIFICATION : 94%

Table 9 - SGLDM, Fourier Descriptor, Textural units & 2-D Fourier Transform classification table



SGLDM, FOURIER DESCRIPTOR, TEXTURAL UNITS
& 2-D FOURIER TRANSFORM SUMMARY TABLE

STEP	ACTION ENTERED	REMOVED	VARS IN	WILKS' LAMBDA	SIG.	MINIMUM D SQUARED	SIG.	BETWEEN GROUPS	
1	GS		1	.43700	.0000	1.65139	.0004	2	3
2	R4		2	.34950	.0000	2.43599	.0001	1	2
3	HOMO20		3	.28744	.0000	3.49061	.0000	1	2
4	BS5		4	.22666	.0000	4.36866	.0000	1	2
5	V245		5	.20038	.0000	5.39470	.0000	2	3
6	V45		6	.17396	.0000	6.28450	.0000	1	2
7	COR20		7	.15875	.0000	6.85360	.0000	2	3
8	V119		8	.13966	.0000	7.43442	.0000	1	2
9	V215		9	.12360	.0000	8.49364	.0000	2	3
10	V128		10	.10867	.0000	9.70220	.0000	1	2
11	V95		11	.09323	.0000	10.93354	.0000	1	2
12		V45	10	.09564	.0000	10.80067	.0000	1	2
13	V125		11	.08703	.0000	11.99900	.0000	2	3
14	V139		12	.07946	.0000	13.10649	.0000	2	3
15		V119	11	.08127	.0000	12.68193	.0000	2	3

Figure 35 - SGLDM, Fourier Descriptor, Textural units & 2-D Fourier Transform scatter plot and summary table

The summary tables for the combined models indicated that a mixture of features were used. The best separation was achieved when four texture measures were used, (Figure 35). Interestingly shape variables (prefixed by a 'v') were prominant. The results indicate that feature combinations were more successful than single feature discrimination alone.

4.3.8 NEURAL NETWORKS

Figure 37 shows the correct classification results for eight node and twelve node neural nets. The results are for all the grains and represent how well the network performed when allocating grains to a particular population, (desert, fire, crushed quartz) using Textural Unit data (see Section 4.3.4). The threshold for selection determined that an output value of 0.6 or above was acceptable. The Total sum of squares (TSS) graph shown below indicates the 'learning' ability of the network , (Section 3.9.3). The form of the graph in relation to previous workers results is examined in Section 5.8. To examine the relationship between training and network performance, several levels of network training were employed using 500, 1000 and 1500 epochs. Reference to Figure 37 indicates increased performance with higher levels of training.

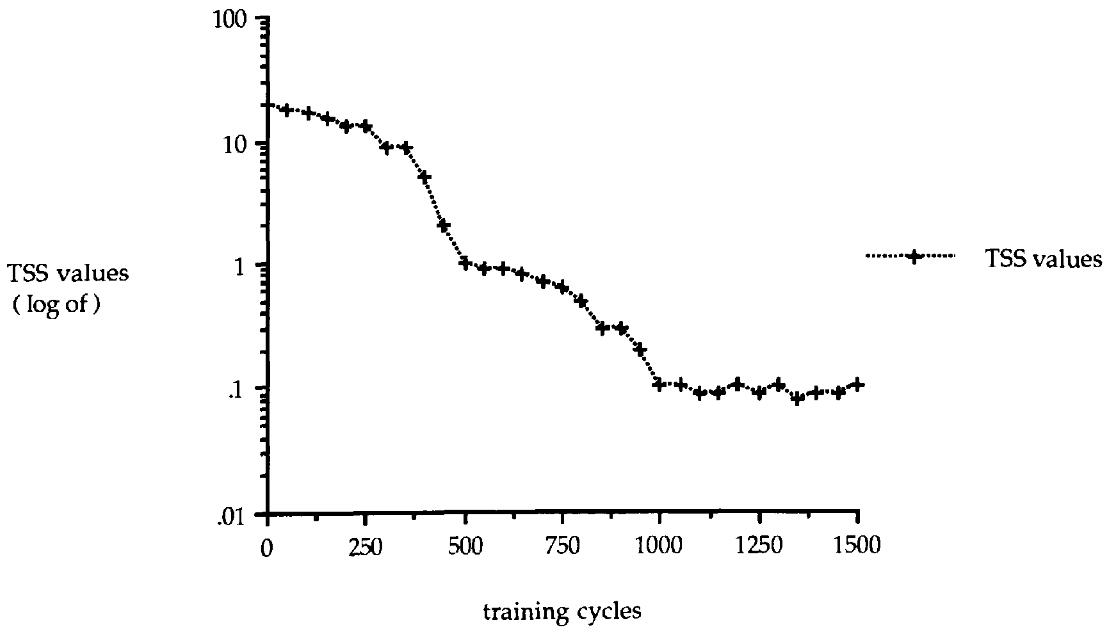


Figure 36 - TSS values calculated at fifty epoch intervals, (the log values are used to extenuate the differences).

8 NODE

epochs	*500*	*1000*	*1500*
Des	58	63	79
Fire	51	59	72
PQT	47	56	69

12 NODE

	500	*1000*	*1500*
Des	61	66	82
Fire	59	60	74
PQT	49	56	71

Figure 37 - Neural network results as percentages correctly classified, (8 and 12 node nets)

4.4 RESULTS SUMMARY

The presentation of results in a form suitable for analysis posed a number of problems. All the algorithms produced a vast amount of observations on each grain type and the following is an indication of these numbers per grain :

Fourier Descriptors	Two hundred and fifty six coefficients
Textural Units	Eight textural spectra
SGLDM	Four measures calculated from seven dispacements (28 values)
2-D F.T.	Eight radial measures
Edge gradients	Dependent on size of grain @ 40000 edge gradients.

Leaving aside the edge results, each grain was observed 300 times. Multiplied by the entire grain samples used, 900, this project produced some 270,300 observations. This vast amount of information and its relationship to quartz grain study is discussed in chapter five. The form of the presentation of results was therefore chosen to reduce presenting large amounts of data to the reader. This was achieved through use of averages and compilations to make the results more attractive and understandable.

The qualitative description of grain types indicated apparent differences between textures. Crushed quartz grains displayed large homogenous regions, with few edges or surface features such as microblocks or conchoidal fractures. Fire Island grains displayed greater textural development with conchoidal fracturing , microblocks and MV's a common occurrence. Desert grains had lower surface topography, a fine broken surface covered by chemical modification.

The Fourier Descriptors were able to accurately analyse quartz grain shape. Results indicated quantitative shape differences between grain types. This was supported by Discriminant Analysis results which successfully separated the populations.

Of the statistical methods, autocorrelation proved too time consuming to apply. In addition pilot results were confusing, with individual sand grains producing unique autocorrelation results. The 2-D Fourier transform method produced similar signatures for all three grain types. Divergence was found only in the desert samples. The overall classification confirmed that the method was unable to separate these textures.

Texture units, again produced similar results for the three types. Crushed quartz grains displayed lower BWS values therefore, the spectrum was not as symmetrical as in the other types. Desert grains had the highest values and it can be concluded that they had the more symmetrical spectrum i.e. no one texture unit dominated the spectrum. SGLDM results indicated differences existed between the three types. All four measures produced some indication of the textures characteristics found on each grain type . However the subjective linking together of texture types and SGLDM results was difficult, (see Section 5.7). In contrast to other other methods the Edge gradient method provided textural results which had cognitive significance. The method was successful as a discriminating feature. Combining textural measures produced much better classification results than individual measures only. This confirms previous workers results, (see Section 2.2.2).

CHAPTER 5

DISCUSSION

5. DISCUSSION

This discussion focuses on a number of aspects. Initial consideration is given to the application of image processing hardware and software and its use within the microtextural field. Attention is paid to the ideas of grain form and its relationship to the textural algorithms . The algorithms are appraised both individually and in combination, concentrating on their suitability for this approach and interpretation of results. Statistical and pattern recognition approaches are considered in terms of ease of implementation, usefulness and applicability and finally thoughts are turned to the position of this new type of textural analysis within the sedimentological arena focusing on it's strengths and weaknesses. Future work concentrates on improvements that could be made in application and technical approaches.

5.1 THE APPROACH

This project's aim has been creation of an innovative, quantitative environment in which to evaluate all aspects of particle form particularly texture and shape, (see Introduction).

This environment was constructed through use of computer software and hardware implementing existing image processing algorithms. The computational difficulties that Hills (1988) alluded to on page 145, have been partially solved. Earlier workers, such as Orford and Whalley (1983), and Clark (1981), have pointed to development of this type of analysis as an essential area for research. As the quotations on Page 2 indicate, there is little doubt that image processing techniques will contribute to the microtextural study of quartz grain surfaces in the future, (see Literature Survey section). However, as discussed later, in what areas will they serve the wider needs of sedimentologists ?

5.2 THE COMPUTER SYSTEM

The software and hardware utilized in this project have been P.C. based. This is the most likely resource available to the sedimentologist, due to low cost and flexibility. The heart of the system, the image processing system, must have certain features to make it suitable for this work. It must be possible to interface the prewritten algorithms for pixel manipulation with a program language such as C or C++. This creates a more flexible environment in which to implement shape descriptor and textural algorithms. Many image processing systems are *'menu driven'* and cannot process irregular images such as quartz grains which may require individual segmentation procedures before analysis can begin. As technology develops more powerful machines such as workstations will be used for this type of work.

The system described here, a PC host with an 'ITEX' image processing board, is flexible, but for sand grain analysis a big hindrance was not having a direct connection to the Scanning Electron Microscope, (S.E.M) enabling rapid grain processing. While the storage of grain images on video tape is very useful, particularly for interchange with spatially separated researchers, the porting of images from the S.E.M. via video tape to the image processing system is time consuming. However, the inability to link the S.E.M. with the image processing software was only a political hiccup and not a technical problem. Union of the two systems would create a system comparable to other automated systems such as 'Arthur II' but the amount of information that could be obtained from such an S.E.M. based system has proved to be many magnitudes greater, (see Results summary section). Telford, et al's (1987), quote on page 2 is rather prophetic. Digital representation of a quartz grain image has allowed the investigation of more complex aspects of grain form.

5.3 IMAGE PROCESSING AND QUARTZ GRAIN IMAGERY

The development of image processing techniques has been driven by a need to extract information from a wide variety of images in many different conditions. With the advent of rapid data acquisition satellite systems, initial pattern recognition techniques have become essential before subsequent analysis can continue. Therefore, the techniques used here, such as SGLDM's, 2-D Fourier analysis, Fourier Descriptors have all been previously applied to a variety of images particularly aerial and satellite images. Their subsequent application to quartz grain surfaces is one further example of their flexibility. Their success, indicated by Discriminant Analysis and Neural Network results, (see Section 4. 3 onwards) suggests that they can play an important role in the quantitative analysis and classification of quartz grain form.

On an image processing front, problems that were encountered were technical ones created by S.E.M. operating conditions. As discussed in Section 4.2, the most potentially damaging problem for later analysis was the effect of 'charging up', where the surface of the grain was 'washed' out. An example of a crushed quartz grain which experienced considerable charging up has already been shown in Plate 3a. It is therefore advisable to ignore such grains. A small amount of charging up was considered permissable but was carefully monitored. The problem of noise contamination was reduced through use of image filters and histogram equalization techniques, (see Section 3.2.2 and 3.2.3).

The equalization procedure is a necessary pre-processing step in any comparative analysis. While the histogram equalization procedure was used here, additional methods such as direct specification are widely used, and descriptions of alternative techniques can be found in Gonzalez and Wintz, (1987). Future researchers may consider the effects of different equalization and filtering methods on the textural algorithms.

Segmentation, using a template of the quartz grain to segment the back ground from the quartz grain image, was rather crude but effective. It may have been possible to use a sophisticated linking algorithm as outlined by Hills (1988), or Gonzalez and Wintz (1987), in which pixel values in the grain interior could be isolated from the background. However the combination of edge detection, thresholding and production of a template generated a very good grain boundary which was essential for the calculation of Fourier Descriptors (see Section 3.4.1). Occasional adhering particles on the grain surface produced spurious boundary portions but these results were still included and represent experimental error.

The actual size of the grain image was obviously an important consideration. The effect of magnification on the Fourier Descriptors has already been shown, both here and by other workers. In any comparative study the initial viewing magnification must be kept within acceptable bounds. While no attempt was made to quantify the effect of changing image magnification, magnification is an important consideration for the textural analysis. The image processing and pattern recognition world has paid much attention to the information that texture can tell about an image. This study has also considered the nature of texture and its configurations (see Literature Survey section). In contrast, S.E.M. workers appear to have only superficially considered the implications of general textural research on their own subject (see section 5.6).

One area for consideration is how the system developed here compares to previous systems and image processing work. The system which has produced many published results is the 'Arthur II' system, basically a videodigitizer using a T.V. camera to view loose grains mounted in glycerine. The edge finding algorithm 'sees' the grain boundary as pixel units of low light intensity compared to the surrounding medium, (Mazzullo and Kennedy, 1984). Twenty, to one thousand edge points were generated per grain depending on *'grain size and magnification'*. These points compare to the thousands of boundary points generated by the system described here. In addition, much greater surface detail can be seen using an S.E.M. image. Telford, et al's (1987), system used a binary picture of a grain from which the particle's outline could be calculated. Again, while both systems are good, the increase in information that can be obtained from S.E.M. imagery regarding all aspects of grain form is considerable. In addition, the ability to convert a grain grey level image into digital form increases the power of the system, making the application of textural algorithms a reality. This ability to manipulate digital images is the biggest strength of the approach.

While the implementation of each textural algorithm to each individual grain is time consuming, it compares favourably to the method of other researchers, particularly Mazzullo, and workers, who found it necessary to provide additional qualitative S.E.M. analysis to their quartz shape results possibly to reduce the number of grains needed to produce meaningful results. The findings of Rohlf and Archie's (1984), conclusion on mosquitos using shape, (see Literature Survey section) has some bearing, in that individual Fourier coefficients could never be 'morphologically meaningful'. This is discussed further in section 5.5.

One reason why particle recognition systems have failed to flourish (see section 2.3) is a lack of technical skills amongst potential workers. However this is now changing as computer systems become commonplace in all academic arenas. Software and hardware is becoming more *'user friendly'* and accessable. So what technical skills would a potential researcher need to develop in order to implement an automated quartz grain recognition system ? The ability to learn a computer programme is necessary and an ability to implement algorithms. The algorithms used here were chosen for their ease of implementation. More complex approaches to textural analysis such as structural methods could have been used. However this may have proved inhibiting for new researchers.

The use of P.C.'s increased the amount of data that can be processed and stored. For each grain analysed, a total of 346 variables were calculated, not including intermediate calculations. For all samples this equals 311,400 observations. Floppy disc storage means that a valuable database can be assembled. The construction of a grain morphology database has several attractions. A major problem with this work has been lack of any previous results with which to attempt comparative analysis. Production of a database would then make grain classification an easier task. Unknown samples could be analysed and classified using a neural network or conventional methods.

5.4 QUARTZ GRAIN FORM

A principal aim was to produce quantitative measurements of all aspects of quartz grain form. Using Whalley's (1972), formula as a basis for investigation, it has become apparent that the development of mathematical descriptions of shape and texture outlined here may produce an alternative function, such as :

form = f (boundary shape and surface texture)

Roundness, angularity and sphericity as concepts become redundant within this framework. Nearly all aspects of quartz grain can be described by use of Fourier analysis in one form or another. However, Barrett's (1980), ideas on the interrelationship of texture, shape and grain morphology now needs re-examination. Barrett (1980), considered shape to include every aspect of external morphology including overall shape roundness and surface texture, and form was used for gross or overall particle shape, independent of roundness and surface texture. Whalley's (1972, p. 962), conjecture that 'surface texture cannot be recognised in the projected outline of a particle' would now seem to have been superceded by new technology including the S.E.M. and other methods of image analysis. In addition, Barratt's (1980), statement has also been superceded by the work presented here. The use of Fourier Descriptors in tandem with textural algorithms in which coefficients describe overall shape, roughness and surface texture, would seem to have produced a method of quantifying the contribution of surface texture to overall shape. The Literature Survey has outlined the progress that powder technologists have made in quantifying shape and understanding its meaning. It might be argued that these researchers have been the real driving force behind this subject's development.

While Barrett (1980), considered a hierarchical placement of form, roundness and texture, few papers have attempted to describe the interrelationship between them in terms of sedimentary process. Mazzullo and Magenheimer's (1987), investigation into original grain shapes indicated that shape was a result of quartz genesis, and grains from one lithological type differ in shape from other populations. Quartz surface texture is the manifestation of the depositional processes imprinted on the surface. As grains are reworked by fluvial, glacial and aeolian action, new textures are imprinted to create a complex palimpsest surface. However, the extent to which these processes alter the basic inherited grain shape is debatable. Aeolian action is an efficient mechanism for shape alteration, but Mazzullo and Magenheimer (1987), reported that the shape of quartz grains from water transported sedimentary rocks subjected to fluvial and marine abrasion were not affected. The shapes of these grains are therefore *'relicts'* of the sources of water transported rocks and do not reflect the genesis or lithology of their present sources.

Is surface texture a sensitive indicator of a quartz grain's depositional history ? The answer to this must lie with the many workers who have investigated quartz grains from many depositional settings. The findings of workers such as Krinsley, Bull and Morgan indicated that surface textural study is indeed a valuable tool to understanding sediments and their dynamics. The recent combination of surface textural study and shape analysis form highlighted in Section 2.3, has been driven by the need to provide additional information to supplement shape studies, with the sensitivity of textural development providing the missing link. However microtextural workers do not seem to have required the addition of shape studies into their work to achieve results and conclusions. Perhaps the advent of image analysis equipment will persuade both sets of workers to investigate alternative areas to incorporate into their work.

5.5 QUARTZ GRAIN SHAPE

'A more honest justification of the use of outlines is that computational difficulties inhibit the extraction of anything else from most images', (Hills, 1988 , p. 487).

A discussion of quartz grain shape could consider several aspects. The first is the actual implementation of the shape descriptor and its use. Secondly the question 'what does shape actually mean in sedimentological terms?' could provide an involved discussion. Consideration of the first point raises several issues about the implementation of Fourier Descriptors and their effectiveness for the types of shape displayed by quartz and other grains. The advantages in using Fourier Descriptors in preference to Fourier transforms, as championed by Ehrlich and others, are many. The transform approach and its drawbacks particularly the problem of re-entrant values and the need to accurately locate the grain centroid have been outlined in the Methodology and Literature Survey sections. Indeed these problems have been cited as one reason why the technique has failed to find a wider audience.

The application of Fourier Descriptors has proved easy to implement within an image processing framework, and importantly, easy to understand. This confirms Clark's (1987 p.266) statement that 'the $r(\theta)$ approach , by virtue of its dependence on some centroid and its extreme sensitivity to the location of that centroid is rather less well suited to data acquired from an imaging system'. Clark (1987) also considered the effects of digitization on the coefficient results. It was not possible to assess these effects in this research. One drawback with the implementation of Fourier Descriptors is the need to have the whole grain boundary present. Even if part of the shape is missing then all of the Descriptors will be affected. Grain images with occluded boundaries were removed from analysis.

Once contour boundary points are located it is relatively easy to find the coefficients as demonstrated in the Methodology section. This is confirmed by Wallace and Wintz's statement that 'The performance of this algorithm............ is a highly effective feature for shape description.' (Wallace and Wintz, 1980, p.124). The question why this technique has not been readily introduced into quartz grain shape studies is possibly answered by Clark's (1987), observation that the introduction of complex numbers in the calculations put potential workers off the method. Wallace and Wintz (1980, p.124), further suggested that 'In addition the unique interpolation properties of Fourier Descriptors enable a much higher level of estimation performance than competing methods '. In addition, the technique allowed the shape of almost all sediment particles to be analysed. This has been an added bonus for this work. While only quartz grains were considered the versatility of Fourier descriptors to analyse particle shapes from a wide size range has been significant. This was demonstrated by analysis of the loess grain, the irregular shape of which would have taxed the Fourier Transform method, (Plate 4). Not only is the description of complex shapes now possible, but also much smaller grains from silt size and smaller can be analysed! While this research has indicated the potential of the technique, future work on a large scale quartz grain data set is needed to evaluate its true potential for shape analysis.

The use of a wide range of harmonics in 'between sample' discrimination, (see Figure 22) is a departure from the analysis presented by Ehrlich and workers in which only the first twenty harmonics were used, (see Section 2.3). The use of S.E.M. imagery, with greater magnifications produced a more detailed edge boundary and this is reflected in the mixture of harmonics being necessary for discrimination. The implication of this is that standardization cannot be introduced into classification i.e. all harmonics must be included in initial classification. Only then can variable reduction take place, (see Table 3).

What does the ability to quantitatively describe shape really tell us about a grain and its depositional history? The work of Ehrlich and others has been shown in Section 2.3 to be a powerful tool in understanding the sediment provinces of large scale depositional systems. Their pioneering work has also removed much of the subjectivity associated with previous grain shape studies. This project was not intended to generate new insights into depositional systems merely to develop a more robust method of shape analysis which could analyse a wider selection of grain types, and to test its effectiveness in separating differing grain shapes. To this end this section of the project has succeeded, as statistical results have indicated. Hills (1988), remarks, (page 146) indicate a lack of consideration of the numerous methods of image analysis used for other image databases, outlined in Section 4.3. A vast amount of information has been obtained from these databases, which may be applicable to quartz grain microtextural analysis.

5.6 TEXTURE

The inclusion of general *'textural study '* in the analysis of quartz grain microtextures, provides a slightly different rationale to that taken by previous workers. As the Introduction and Literature Survey section indicated, few papers contained thoughts on the nature of texture *per se*. The argument for this type of approach is that the underlying nature of texture must be understood before methods of quantitative analysis can begin. The problems associated with applying Setlow and Karpovich's (1972), methods of textural anlysis have been highlighted in Section 2.2.1. The weakness of the human visual system in estimating proportions had been determined in previous textural studies, so it is no surprise that Setlow and Karpovich's work fell on stony ground.

Pickett's (1970), work on texture has been discussed in Section 2.2.1. The idea that texture recognition can be either deliberate or impressionistic, presents some interesting ideas concerning microtextural study. From personal communications, many experienced workers such as Krinsley and Bull appear to have developed instinctive feelings about sand grain textures and are able to separate grains based on this ability. Pickett (1970), equates this ability with everyday reading. The experienced workers have learned a type of vocabulary and grammar based on the natural laws that govern the shape and texture of the sand grains. However this *'feeling '* is difficult to translate into usable algorithms for an automated system or use insubsequent interpretation. The major problem in development of an automatic system that can discriminate texture and shape is neatly stated by Benke, et al (1988, p. 158), 'Machine discrimination of textures is an area of considerable interest, requiring measurement of specific features rather than knowledge of the underlying structure and synthesis of the texture'. This would indicate that relating previous qualitative results to algorithm results is difficult and self defeating. The textural algorithms were able to discriminate textures as well as a human perceiver and in the case of edges was clearly superior. The hierarchical variation in quartz grain texture associated with differing magnifications has not been assessed here. Again, this may be an area for future work. A technique which may be useful for this type of analysis might possibly be the textural masks developed by Laws (1980).

5.7 TEXTURAL ALGORITHMS

'It would be of value if measures on digital images of textures could be found that correlated with human performance in discriminating these textures.' (Benke, et al , 1988. p. 158).

'Pattern generation processes in nature are certainly very complex and usually impossible to simulate exactly. However it may be useful to single out some important features of these processes. If a model can incorporate such features , the patterns it describes may be similar to real texture in significant ways.' (Ahuja and Rosenfeld, 1981, p. 225).

This work has employed algorithms which proved successful in other area of textural research notably terrain analysis, (see Literature Survey section). It was not the intention here to develop new methods but to use pre-existing algorithms. However, the application of these algorithms to quartz grain images is new and makes a significant contribution towards automatic quantification of sediment surface textures. Choice of algorithms was based on previous research on algorithm performance, referred to in Section 2.2.2.

An interesting aspect is the choice of statistical based algorithms textural analysis. The structural approach is a more involved subject with more complex mathematical applications. Actual feature identification i.e. M.V.'s, conchoidal fractures has not been possible within this statistical environment. Feature identification is obviously the next stage in development of a fully automated system.

Of the five textural algorithms used, only the detection of edges and the use of edge gradients fulfilled Benke, et al's (1988), previous quote (p. 145). The use of edges as a discriminanting textural variable was attractive on two fronts. Previous workers considered edges as an important cognitive feature and Section 2.1 has discussed work where the study of edges has played an important role. Edges are also important for forming the primal sketch referred to in Section 2.2.4. However one drawback to their study in microtextural research work has been lack of a standard definition of an 'edge'. Many edge type features have been qualitatively described ranging from meandering ridges to scratches to conchoidal fracture. All these features contain some type of discontinuity or edge. The use of a gradient operator, such as the Roberts, provides a global description of all edges displayed on a grains surface without need to subjectively define what an edge is or its visual appearance. This is a major advantage of an automated system compared to a human perceiver based approach. Reference to Section 4.3.5 shows that edge histograms can be used to discriminate between different grain types. The attraction is that new researchers in the microtextural field can apply edge detectors and produce more accurate results than previous and achieves one of the goals of the project, the introduction of standardization into the methodology. The potential use of edge detectors in this field is vast. Edges may be used as a method of defining homogeneous regions on a sand grain surface and therefore used as a structural measure of texture. In addition the analysis of edges is invariant to rotation of the quartz grain image and makes it attractive as a texture measure.

This research has not produced an extensive investigation of edge detectors or their suitability for this type of work. Edge detector performance is dependent on the type of image to be analysed. It is left to future research to investigate further. However, what is not in doubt is the suitability of edge algorithms for this type of work. One area where future work may go is use of edge detectors to define regions or 'texture elements' from which extraction of significant features such as conchoidal fractures or microblock breakage areas can be attempted.

Of the other algorithms used, the most difficult to implement was the autocorrelation method. The problems with computation time etc. referred to in Section 3.8 prohibited it from being considered as a useful method of textural discrimination. This was unfortunate, because the results obtained from the cloth texture (Plate 7) appeared promising. The diagrams produced for the sand grains were highly unpredictable. Whether enough grains were studied is debatable but the results did indicate that quartz grain pixel values correlated over small separations. This backed up the results obtained from the SGLDM's (see below). In addition, there appeared to be no repetative correlation i.e. no repeating pattern on a quartz grain surface. This confirms the results obtained from the Entropy measure which indicated that pixel values tended towards randomness and did not correlate.

As outlined in the Literature Survey section, the SGLDM method and its offspring have proved a robust and practical method of texture analysis for a number of images. Its application to quartz grain images is another example of the method's flexibility. Results shown in Section 4.3.6 confirmed that the best discrimination was obtained using small displacements, a result that supports the findings of Weszka, et al (1976). All algorithms results, indicated that quartz grain textures were dominated by small scale texture particularly the desert grains. Discriminant analysis successfully separated the populations and the conclusion must be that this method has considerable potential for this type of problem. While it proved easy to implement, a major drawback was interpretation of the results obtained from the Haralick measures. Lack of real values published in previous work meant that comparative analysis with other databases was sketchy. In addition the use of this method for this type of texture for the first time meant that no comparison could be made using results from previous workers.

Texture Units proved a difficult technique to understand. The measures that were produced from each spectrum were not immediately assessable. The technique described the local texture aspect of a given pixel, i.e. the relative gray level relationship between a central pixel and its eight neighbours. Wang and He's rationae for using this approach was that the statistics on occurrence frequency of all the texture units over the whole image should reveal texture information of the analysed image, (Wang and He, 1990). Therefore the shape of the texture spectrum should be indicative of a certain texture. Certainly looking at the results in Section 4.3.4, this has proved correct. What is interesting to note is the shape of the graphs where all three grain types peak and trough at the same points. Are the textures that similar ? The answer provided from Discriminant Analysis, and the neural nets is no. However, this textural measure shares one problem with other statistical methods. It is impossible to tell anything qualitative about the texture of quartz grains from the results and results bear no reference to previous semi or qualitative studies.

2-D Fourier Analysis proved disappointing as a discriminating measure. The results supported other workers conclusions on the method, (see Weszka, et al, 1976). As a measure implementation was time consuming to implement mainly due to calculating coefficients for columns and rows. The power spectrum results were similar for all three grain types and this was reflected in the Discriminant results, (see Figure 27). No frequency dominated, with power evenly spread throughout the spectrum. This indicates that all quartz grains exhibited a *fine texture* , *i.*e small scale features and confirms results obtained from autocorrelation and SGLDM's that small scale textures dominate. A coarse texture would have displayed high values of $|F|^2$ concentrated near the origin, (Weszka, et al, 1976). As with the autocorrelation results, when analysing regular textures with strong repetitive texture such as cloth the technique worked well, but for quartz grains with complex textural patterns no immediate structure could be seen, (see Plate 7).

5.8 QUARTZ GRAIN CLASSIFICATION

'...not all pattern recognition problems are classification problems. At the very least it may be desirable to be able to reject a pattern if it is unlike any of the patterns the system was designed to recognise. It is important for the classifier to supply a confidence measure with each decision and perhaps alternative choices and their confidences.' (Duda, 1970, p.5).

What is the objective in classifing quartz grains using measures of form ? The classification process can occcupy two positions within particle form analysis. It can be used as a precursor tool, where unknown grains are analysed in an attempt to find distinctive populations within a sediment sample. Shape analysts, such as Mazzullo and workers, have used shape in a similar way, using it to find distinct populations then applying texture analysis to ground truth their results, (see Literature Survey section). In the second classification, it could be used to validate existing results. Bull's quote on page 8 indicates qualitative analysis is essential for any positive analysis. Classification then becomes a method of supporting theories and assumptions, as found in Morgan's (1990), work. So where do the classification methods fit into this scenario ? The use of automated shape and texture analysis has demonstrated an ability to separate distinctive grain populations. This is confirmed by the discriminant analysis and neural net results. Therefore these measures could be used both as a precursor or cursor in any investigation of sediment form. Classification would either point a researcher to the major form trends within a sediment sample, or confirm/deny results obtained by previous semi-quantitative analysis.

How meaningful were the classification results? The answer to the question revolves around two issues. Firstly any classification accuracy is negatively related to the number of classes. With one class the accuracy is 100% and with an infinite number of classes the accuracy is near zero, (Curran, 1986). Therefore, using only three classes for discrimination is unrealistic for training purposes. Where the technique would be useful, is analysing quartz grains from an unknown sedimentary sample, recognising distinct subpopulations within the data. The results produced here should be considered in relation to the limitations of the thesis.

Reference to Figures 33, 34 and 35 visually demonstrated the effectiveness of combining textural measures. The benefits of using additional information have been cited by many workers and is confirmed here by increased classification success. The relevance of these findings for other workers is clear. For maximum classification results, shape and texture measures should be used in tandem and not in isolation!

Neural networks proved an attractive method of classification because of the revival in their use and their supposed modelling of simple cognitve processes. They performed as well as Discriminant Analysis and provided ideas on future implementations. A great advantage they have over conventional classifiers is a non dependence on assumptions about the underlying statistical distributions. The need to establish 'normality' is therefore removed. This conclusion is in agreement with previous comparative research, on neural nets and conventional classifiers, (see Huang and Lippmann, 1987). The problems of training and construction of the network, discussed in Section 3.9.3, could easily be overcome by more empirical research. Their ability to recognise quartz grains from incomplete data was another positive feature. Incomplete data is always a problem in any quantitative study and this approach may be one solution to that. An area of some concern is the '*Black box* ' qualities, referred to in Section 1.6.1. Further research in their ability to recognise quartz grains is needed but as a method of classification they were fascinating!

Has this project moved the discipline forward as requested by Krinsley and Marshall (1987), in Section 2.1 ? The answer must be a qualified yes. With the exception of edge analysis the algorithm results have not revealed anything about the textures beyond describing them in statistical terms. However this is sufficient for a machine based classification system. The application of terms such as 'fine' or 'coarse' do not reveal detailed verbal discription about the textures. But what this approach has done is to provide the numerical parameters referred to by Barrett (1980), in Section 2.1. These measures have also provided a wealth of data, generating a mathematical reference for each sand grain type. In addition, new quartz grain texture configurations can now be analysed, such as chemically affected surfaces. As Section 2.1. has shown, analysis of these textures have been previously avoided because they have been impossible to describe using existing nomenclature, or quantify using established human methods of analysis, such as a checklist approach.

While this project provided methods for producing a general description of texture, it failed to define major textural elements such as conchoidal breakages, microblocks, etc. which make up a quartz grain surface texture. Implementation of structural models of texture may be the answer and is recommended in future work , (see Section 6.1).

Have the results indicated a relationship between surface texture and shape? This is a difficult question to answer. One indication is provided from the Discriminant Analysis results which separated grains both on texture and shape. When shape and texture measures were used in combination, both sets of variables were used in analysis, indicating some interdependence. Whether grain shape and surface textures are really interdependent is open to question. Referring to Barrett's (1980), assumption that form, roundnesss and surface texture are independent properties of shape, (see page 4), the Fourier Descriptor classification results, (see Figure 22), indicated that high frequency terms (small surface details) were major discriminating variables. Possibly the use of S.E.M. imagery, showing very detailed features of a grain's peripheral boundary, has indicated the effect of surface texture on grain shape.

CHAPTER 6

CONCLUSIONS

6. CONCLUSIONS

Quantitative description of shape and surface texture has been achieved. A new method of shape description using Fourier Descriptors has proved successful. Advantages over previous shape descriptors included both an ability to analyse complex particle shapes and ease of application. These features allow analysis of a wider size range of sediment particles. Results have indicated that the method can separate quartz grain populations based on shape. A combination of variables were used for discrimination ranging from low frequency terms, which described gross shape, to high frequency terms describing the contribution of surface texture to grain shape.

The use of PC based hardware and software for this type of analysis has proved successful. Low costs, flexibility, and availability, produce an attractive system. Extensive prewritten software means that researchers can implement a shape and surface texture analysis system without much difficulty. This may make the subject more accessable to an increasing number of workers. This will produce a wider variety of work with different approaches and ideas.

The use of Scanning Electron Microscope (S.E.M.) images, as opposed to light microscope images used by previous workers, has generated a significant increase in information about quartz grain form. While it was possible to apply a number of textural algorithms to quartz grain surfaces, their performance and suitability varied. A re-occurring problem was relating qualitative texture description to algorithms results. One algorithm that was particularly attractive was edge texture. In comparison to previous qualitative descriptions of edges on quartz grain surfaces, it was a vast improvement. Standardisation and accuracy of definition was achieved. This implementation allowed some degree of correlation between algorithm and human performance. No previous researcher has defined edges on a grain surface in the type of detail or reproducability achieved by this algorithm. The application of more complex edge detection routines would obviously improve on this.

Of the statistical algorithms, SGLDM's were successful in discriminating grain types. Again the problem of interpretation remained. The Textural units approach (see Section 3.7.1), was untried as a textural measure. Its discrimination success rate was on a par with other algorithms. Autocorrelation proved too cumbersome to implement and was discarded. 2-D Fourier Transforms performed at a level comparable to previous work, (see Section 2.2.2c) and its value as a textural measure for this type of image must be questioned. The use of structural methods of texture analysis was not included here. However, from the problems of relating algorithm results to real textures, a structural approach may produce more useful results.

Classification of the three grain types was good. However discriminant results must be judged in the context of the thesis. While other workers have found Discriminant Analysis useful as a method for separating different quartz grain populations, the results here are *model results* only. In practice, success rates would be lower. Neural nets were an innovative approach to classification and results indicated that they could become a very useful tool, not just in the area of microtextural reseach, but in other areas of sedimentology.

The combined classification results (see Section 4.3.7), also indicated that use of more than one textural measure was superior. Both shape and texture measures were used as discriminating variables. This quantitatively confirms the approach taken by Mazzullo and workers, who integrated surface texture and shape analysis as a more powerful method of analysis. It was not possible to quantify the relationship between texture and shape. However S.E.M. imagery provided a more detailed description of the grain boundary and included the contribution of surface texture to grain shape. This is reflected in the wide range of Fourier Descriptor coefficients used in discrimination, (see Section 4.3.).

This project has gone some way to moving S.E.M. analysis from a semi-quantitative sphere to a quantitative domain and in the process provided standardization in methodology.

6.1 FUTURE WORK

Areas which may improve the system include technical innovation, application of different algorithms and use of structural methods for describing texture.

The implementation of parallel processing methods may be beneficial for several reasons. It may be possible to apply the shape and texture algorithms simultaneously to the quartz grain image and not serially, as with this system. This would significantly speed up analysis. In addition, classification could be performed in close to real time using the neural network approach within this parallel environment. The use of an efficient data compression technique, such as Huffman coding, would aid in the storage of grain images and data, (see Kidner and Smith,1991). This would allow the development of an extensive data base.

Alternative textural algorithms that could be applied include variations in SGLDM's outlined in Section 2.2.2b. The use of Filter masks outlined by Laws (1980), or random walk procedures (Wechsler and Kidode, 1979), are good examples. The reader is recommended to Van Gool, et al (1983), for more ideas. Other shape descriptors that could be used include Walsh and Haar transforms.

Structural methods for analysing texture have developed significantly. The need for such methods is a direct result of the inability to correlate statistical texture analysis results and original textures. This problem has been discussed in Section 5.7. The author strongly recommends that subsequent workers in this field investigate these methods in preference to the statistical approaches used here.

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