

**AN INTELLIGENT CLASSIFICATION SYSTEM FOR
AGGREGATE BASED ON IMAGE PROCESSING
AND NEURAL NETWORK**

by

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**Thesis submitted in fulfillment of the
requirements for the degree of
Doctor of Philosophy**

March 2009

ACKNOWLEDGEMENTS

First and foremost, All Praises be to Allah the Almighty, for delivering me the patience, the strength and the guidance in completing this thesis successfully.

I would like to express my heartfelt gratitude to my supervisor, Assoc. Prof. Dr. Nor Ashidi Mat Isa for his supports and motivations. His guidance and incisive advice have inspired me to generate fruitful approaches in achieving the objective in this research. Without his efforts, I would not able to bring this research to a completion.

My sincerest gratitude is extended to both of my co-supervisors, Dr. Kamal Zuhairi Zamli and Prof. Khairun Azizi Azizli for their tremendous assistance in the data collection and organization, time, ideas and thesis editing.

My warmest acknowledgements to my beloved father, mother and sisters for their endless love and encourage me all along without hesitation. Special thanks to my brothers, Dr. Fuad, Shahir, Raid, Jameel and Dr. Emad. I treasure dearly their concern and moral support.

I would like to express my greatest appreciation to my project friends, Mr. Ariffuddin Joret, Mr. Zamani Md Sani and Ms. Sri Raj Rajeswari, and not to forget my lab friends, Dr. Syed Sahal, Ms. Wang Shir Li, Mr. Nor Rizuan Mat Noor, Mr. Fakroul Ridzuan, Mr. Mohd Fauzi and Mr. Wan Fahmi for their kindness, cooperation and lively discussions. I am also thankful to my nice housemates, Dr. Anwar Al-Mofleh, Dr. Anas Quteishat, Mr. Mu'tasem Al-Khasawneah and all my relatives and hometown friends in Jordan for their unlimited support and encouragement.

Finally, I would like to thank all staff at the School of Electrical and Electronic Engineering, University of Science Malaysia for their support. I would also like to thank the Institute of Postgraduate Studies (IPS) for their financial support by awarding me the USM Graduate-Assistance scholarship.

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LIST OF ABBREVIATIONS

2D	Two Dimensions
3D	Three Dimensions
AFE	Automatic Feature Extraction
AIMS	Aggregate Imaging System
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
ASTM	American Society for Testing and Materials
AutoAgg	Automatic Intelligent Aggregate Shape Classification System
BFG	Broyden-Fletcher-Goldfarb-Shanno quasi-newton
BR	Bayesian Regularization
CCD	Charge Coupled Device
CGB	Conjugate Gradient with Powell-Beale restarts
CGBC	Conditional Gaussian model based Bayesian Classifier
CGF	Conjugate Gradient with Fletcher-Reeves updates
CGP	Conjugate Gradient with Polak-Ribiere updates
c-MLP	Cascaded Multilayered Perceptron
CMOS	Complementary Metal Oxide Semiconductor
CPA	Computer Particle Analyzer
CPU	Central Processing Unit
CS	Circle Segments
DA	Discriminant Analysis
DIP	Digital Image Processing
DSP	Digital Signal Processor
ECG	Electrocardiogram
EI	Elongation Indices

FEM	Finite Element Method
FF	Forgetting Factor
FI	Flakiness Indices
FOV	Field of View
GA	Genetic Algorithm
GD	Gradient Descent
GDM	Gradient Descent with Momentum
GDX	Gradient Descent with Momentum and Adaptive Learning Rate
GUI	Graphical User Interface
H ² MLP	Hierarchical Hybrid Multilayered Perceptron
HIQSA	High Quality Shaped Aggregate
HMLP	Hybrid Multilayered Perceptron
ICA	Independent Component Analysis
ITI	Incremental Decision Tree Induction
KDD	Knowledge Discovery in Databases
KPCA	Kernel Principal Component Analysis
LASS	Laser-based Aggregate Scanning System
LM	Levenberg Marquardt
LMDT	Linear Machine Decision Tree
LMS	Least Mean Square
LVQ	Learning Vector Quantization
MKM	Moving K-Mean
MLP	Multi-Layered Perceptron
MRA	Multiple Ratio Shape Analysis
MRLS	Modified Recursive Least Square
MRPE	Modified Recursive Prediction Error
MSBRG	Modified Seed Based Region Growing

MSE	Mean Square Error
OC1	Oblique Classifier
OSS	One Step Secant
PCA	Principal Component Analysis
RBF	Radial Basis Function
RLS	Recursive Least Square
RNN	Recurrent Neural Network
RoR VSI	Rock on Rock Vertical Shaft Impact
RP	Resilient back Propagation
RPE	Recursive Prediction Error
SBRG	Seed Based Region Growing
SCG	Scaled Conjugate Gradient
SFS	Sequential Forward Selection
SVM	Support Vector Machine
UIAIA	University of Illinois Aggregate Image Analyzer
VIS	Video Imaging System
w/c	Water to Cement ratio

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SISTEM PENGKELASAN PINTAR AGGREGAT BERDASARKAN PEMROSESAN IMEJ DAN RANGKAIAN NEURAL

ABSTRAK

Bentuk dan tekstur permukaan agregat mempengaruhi kekuatan dan struktur konkrit. Secara tradisi, mesin pengayakan mekanikal dan pengukuran manual digunakan bagi menentukan kedua-dua saiz dan bentuk agregat. Cara yang digunakan adalah manual, mengambil masa yang lama, terlalu subjektif dan memerlukan banyak tenaga. Oleh itu, dalam penyelidikan ini, satu sistem pengelasan pintar yang terdiri daripada proses Algoritma Pengekstrakan Ciri Automatik (AFE) dan sistem pintar rangkaian neural bagi pengelasan agregat dibina. Algoritma AFE yang dicadangkan mampu bagi mengekstrak momen Hu, Zernike dan Affine dari objek yang telah disegmentasi. Tiga teknik bagi pemilihan ciri iaitu analisis diskriminan (DA), analisis komponen utama (PCA) dan ruas-bulatan (CS) digunakan bagi mengenal pasti kegunaan dan kepentingan ciri-ciri tersebut dalam pengelasan agregat. Di dalam penyelidikan ini, satu algoritma baru iaitu Kuasa-dua Terkecil Jadi Semula Terubahsuai (MRLS) diperkenalkan pada rangkaian Perseptron Berbilang Lapisan Hibrid (HMLP). Keupayaan algoritma MRLS telah diuji menggunakan beberapa data piawai. Selain itu, dua senibina baru rangkaian neural dicadangkan bagi memperbaiki kebolehupayaan rangkaian MLP dan HMLP iaitu Kaskad-MLP (c-MLP) dan rangkaian HMLP Berhirarki (H^2 MLP). Akhir sekali, satu sistem automatik pintar bagi pengelasan yang dinamakan AutoAgg dibina. Sistem ini mengandungi algoritma AFE yang telah diubahsuai bagi mengekstrak ciri secara automatik dan rangkaian H^2 MLP yang telah dilatih dengan algoritma MRLS sebagai pengelasan pintar. Sistem ini berkebolehan bagi mengambil gambar, mengekstrak ciri momen optimum dan mengkelaskan agregat kurang dari satu saat. Sistem ini juga dapat mengklasifikasikan agregat kepada enam bentuk dengan ketepatan 99% daripada 4242 imej yang telah diuji.

AN INTELLIGENT CLASSIFICATION SYSTEM FOR AGGREGATE BASED ON IMAGE PROCESSING AND NEURAL NETWORK

ABSTRACT

Aggregate's shape and surface texture immensely influence the strength and structure of the resulting concrete. Traditionally, mechanical sieving and manual gauging are used to determine both the size and shape of the aggregates. These methods, which are often performed manually, tend to be slow, highly subjective and laborious. Therefore, in this research, an intelligent classification system consisting of the Automatic Features Extraction (AFE) algorithm and the intelligent Neural Network classification for aggregate recognition is designed and developed. The proposed AFE algorithm is capable of automatically extracting the Hu, Zernike and Affine moments from the segmented object. Then, three feature selection techniques namely the Discriminant Analysis (DA), Principal Component Analysis (PCA) and Circle Segments (CS) are employed to identify the useful and important features of aggregate for its classification. In this study, a new learning algorithm called Modified Recursive Least Squares (MRLS) is introduced for the Hybrid Multilayered Perceptron (HMLP) network. The effectiveness of the MRLS algorithm is demonstrated using several benchmark data sets. Additionally, two new Artificial Neural Network architectures are proposed to improve the performance of the MLP and HMLP network in handling aggregate classification problem. The first architecture is called Cascaded MLP (c-MLP) and the second architecture is called Hierarchical HMLP (H^2 MLP) network, respectively. Finally, an automatic intelligent aggregate classification system called AutoAgg is developed. The system contains the modified AFE algorithm as automatic features extraction and the H^2 MLP network trained with MRLS algorithm as intelligent classification. The system is capable of automatically capturing the image, extracting the features and classifying the aggregate in less than one second. Here, the system classifies the aggregates into six shapes with an accuracy of 99% based upon 4242 tested aggregate images.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Pattern recognition is the scientific discipline whose goal is centered on the classification of objects into a number of categories or classes. Depending on the applications, these objects can be images or signal waveforms or any type of measurements that need to be classified. These objects of interest are generally referred to as patterns (Theodoridis & Koutroumbas, 1999).

Machine or computer vision is an important area of pattern recognition. Computer vision refers to the automatic extraction of information regarding a scene or three dimensional objects as captured in two-dimensional images by some photographic process (Yow, 1998). It is a highly active research area with many applications such as automation (e.g. on the assembly line), inspection (e.g. of integrated circuit chips to detect defects in them), security (e.g. face and fingerprint recognition), medical diagnosis (e.g. detection of abnormal cells that may indicate cancer), remote sensing (e.g. automated recognition of possible hostile terrain to generate maps) and aids for the visually impaired (e.g. mechanical guide dogs). A more detailed list of computer vision applications can be found in Lowe (2008).

Computer vision techniques are used for agricultural and material applications, such as detection of weeds in a field, recognition of plastics in the factory, sorting of fruits on a conveyer belt in the fruit processing industry, etc. The cognitive functions that such a system must support include the capability to distinguish among objects,

their positions in space, motion, sizes, shapes and surface texture (Stillings *et al.*, 1995). The underlying approach for all of these techniques is the same. First, digital images are acquired from environment around the sensor using a digital camera. Then image-processing techniques are applied to extract useful features that are necessary for further analysis of these images. After that, several analytical discriminant techniques, such as statistical, bayesian or neural networks will be used to classify the images according to the specific problem at hand.

Digital Image Processing (DIP) is an ever expanding and dynamic area with applications reaching out into our everyday life such as medicine, space, exploration, surveillance, authentication, automated industry inspection and many more areas (Gonzalez & Woods, 2002). Applications such as these, involve different processes like image enhancement, segmentation and features extraction. Image enhancement is used to improve the image quality such as de-noising, sharpening or smoothing the image. Segmentation is used to decompose an image into several parts of an object based on certain criteria. Feature extraction is applied to extract the features needed for the recognition purpose. Various features such as colour, texture, shape and sketch features can be extracted from the image.

Shape description is an active research area (Li & Ma, 1994; Mehre *et al.*, 1997). There are three ways to describe shape feature, namely boundary-based, region-based or a mixture of two. The shape descriptors are usually required to be invariant for translation, scaling and rotation. Fourier descriptors and moment invariants have proven to be successful in the two approaches, respectively.

Image moments have been used in image processing applications through years, since their first introduction by Hu (1962). Moment is an important shape descriptor in computer vision and has been used widely in pattern recognition applications (Munoz-Rodriguez *et al.*, 2005; Realpe & Velazquez, 2006; Rizon *et al.*, 2006). Moment can be applied as a method to describe characteristics of certain object such as surface area, position, orientation and many other parameters (Awcock & Thomas, 1995). There are numerous types of moments, such as invariant moment, Legendre, Zernike, pseudo-Zernike, rotation and complex moment that have been used in object or pattern recognition applications (Teh & Chin, 1988).

Feature selection can be viewed as the process of searching important attributes or features from a large dataset, in order to preserve class separation as much as possible in the lowest possible dimensional spaces. The main purpose of feature selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy. Feature selection include methods such as sequential backward selection (Pudil *et al.*, 1994), sequential forward selection (Pudil *et al.*, 1999), sequential floating search method (Reeves & Zhe, 1999), discriminant analysis (Johnson & Wichern, 2002), principal component analysis (Chao & Chong, 2002) and circle segments (Wang, 2007).

Artificial neural networks (ANNs) are widely used to solve pattern recognition and classification problems, owing to its ability to work like human brain. Among the various types of ANN models, the Multilayer Perceptron (MLP) is one of the commonly applied model (Mat-Isa *et al.*, 2008). It is considered as a model free approach in building a learning system for data analysis, prediction as well as classification tasks.

The MLP is generally easy to use and good in approximating any input output map (Barletta & Grisario, 2006).

1.2 Importance of Aggregate Shape in Concrete Making

Quarries provide earth materials such as sand, clay, gravel and crushed rocks that will be processed further into raw material inputs for buildings and construction, agriculture and industrial processes. The demand for these materials is derived by the demand for the goods and services that these materials provide, with each user industry defining specifications fit for their final products (Rajeswari *et al.*, 2004). The rapid growth from construction sector automatically accelerates and gives rise for higher demand for aggregates which is the major constituent of construction particularly for concrete.

At least three-quarters of the volume of concrete is occupied by aggregates and hence it is not surprising to know that its quality is of considerable importance (Neville, 1995). Report from Rajeswari (2004), showed that the nature and the degree of stratification of rock deposit, the type of crushing plant used and the size reduction ratio are amongst the key factors that greatly influence the shape of aggregate particles and the quality of fresh and hardened concrete. The ability to produce high strength concrete with good bonding characteristics and at the same time maintaining the workability of fresh concrete and adequate strength for the hardened concrete is an excellent contribution to the science of concrete technology which is known racing for higher strength. Similarly, report from Hudson (1995 & 1996) clearly showed that improvement in the shape of aggregates had been proven to be a major factor in the reduction of the water to cement ratio needed to produce a concrete mixture. This high

quality aggregate also has the ability to decrease the cost of production and placement of concrete and hence increase the characteristics of the concrete such as strength and its overall quality.

Rajeswari *et al.* (2003) also stated that the improvement in the shape of crushed rocks used as aggregates is amongst the most important characteristics of high quality aggregates particularly for use in the concrete or construction industry. Aggregates with beefed up characteristics such as more cubical and equidimensional in shape with better surface texture and ideal grading are considerably gaining much more attention particularly from the concrete industry as these aggregates greatly assist in increasing the strength and enhancing the quality of concrete. This work also scientifically showed the optimum orientation and packing of high quality shape aggregate particles (i.e. cubical and angular) in a concrete mix compared to the poorly shaped particles (i.e. irregular, elongated, flaky and flaky&elongated). Hence, aggregates with improvement in particle shape and texture act as a catalyst for the development of good mechanical bonding and interlocking between the surfaces of aggregate particles in a concrete mix.

Overall, stronger aggregates with improvement in particle shape and textural characteristics tend to produce stronger concrete as the weak planes and structures are being reduced. Substitution of equidimensional particles derived as crushed product produces higher density and higher strength concrete than those which are flat or elongated because they have less surface area per unit volume and therefore pack tighter when consolidated. Aggregates which are flat or elongated decrease the workability by poor packing, reducing the bulk mass and consequently decreasing the compressive strength of concrete with much more requirements of sand, cement and water. Thus, it

is of utmost importance to change the traditional quarrying scenario towards optimization of the crusher performance to produce high quality aggregates so that this will be in tandem with the current development and changes in the concrete industry. Furthermore, it is necessary to develop a more quantitative and systematic measurement system for aggregate classification.

1.3 Problem Statement

Over the years, standard techniques and test procedures complying with British Standards, American Society for Testing and Materials (ASTM) and New Zealand Standards have been widely used to analyze and evaluate the shape, size grading and surface texture of aggregates (Rajeswari, 2004). Generally, the grading profile of aggregates is identified by sieving with standard sieves and sieve shakers. The flakiness and elongation gauges are the aids used to determine the flakiness and elongation indices (FI's and EI's) of coarse aggregates while the shape of fine aggregates is determined through the voids content percentage (uncompacted and compacted) and flow cone method. However, the analysis for coarse aggregate particles has limitations since it involves manual gauging of individual aggregate particles. It is also difficult for engineers to analyze the concrete for improvement in real time due to lack of accuracy and systematic database storage for the mass aggregate production.

Previous studies have shown that, good aggregates tend to produce stronger concrete compared to the bad aggregates. The absence of real time output monitoring could lead to waste of resource and energy if bad shaped aggregates are found later in the production process. As this argument illustrates, there is a need to automatically monitor the aggregate inputs from the crusher machine.

A number of imaging system has been developed for aggregate analysis (Parkin *et al.*, 1995; Wang, 1998, Joret *et al.*, 2005a). Although useful, the existing works tend to focus on image processing and little emphasis on automatic classification. Furthermore, earlier classification also relies on two levels; good and poor shapes. A counter argument suggest that more levels of classification are required in order to improve the classification and hence give better indication of the quality of aggregates for concrete production approach (i.e. classify the aggregate into six shapes).

Also, most of the existing systems measure the aggregate by analyzing its features as length, width, perimeter and size. However, these features are unattractive for object with different positions, orientations and scales, so further interpretation is required to extract more useful information from the aggregate. For instance, geometrical moments are useful information for describing object shapes, owing to its invariant with position, orientation and scale change.

Today, there is almost no technical endeavor that is not impacted by digital image processing. But, there is no general agreement among authors regarding where image processing stops and other related areas, such as image analysis and computer vision, start (Trifas, 2005). Each application has different procedures of digital image processing techniques which are suitable for the specific problem. In this case, interesting work is needed to identify and select the appropriate algorithms that can be applied to automatically segment and extract the significant features from the captured aggregate image.

In most of the feature extraction cases, larger than necessary number of feature candidates are generated. However, the irrelevant or uncorrelated features could actually cause a reduction in the performance of the system (Melo *et al.*, 2003). In order to solve this problem, feature selection techniques need to be carried out to summarize the data and assist in identifying the appropriate features for more focused analysis.

Analytic tools such as ANNs, are very powerful in solving complicated and non-linear problems. But, there is no universal agreement about the best classification methods to recommend for all occasions, whose performance is affected by the data types and the application conditions (Ming, 2000). As classifiers perform best with different types of data, the real challenge for many comparison studies is not to determine the best method in general. Instead the researchers should find out which method works best for some specific data sets (Hand, 1986). Thus, the performance comparison between various classifiers is considered necessary to know which classifier is the best, fast and most useful for developing the automatic aggregate classification model.

The Multilayered Perceptron (MLP) networks are highly nonlinear; therefore modeling a linear system using a nonlinear MLP network was not sufficiently appropriate. Mashor (2000b) suggested that modeling a linear system with a linear model will be a better solution. Therefore, the MLP network with additional linear input connections was proposed. The new network is called the Hybrid Multilayered Perceptron (HMLP). The HMLP allows the network inputs to be connected directly to the output nodes with some weighted synaptic; it produces linear connections in parallel with the nonlinear original MLP model. On the other hand, Azimi-Sadjadi *et al.* (1990)

introduced the Recursive Least Squares (RLS) algorithm with constant forgetting factor as the training algorithm for the MLP network. Here, the challenge is how to modify the RLS algorithm such that the additional weights of the HMLP network can be estimated (details about this problem will be discussed in Chapter 4).

Neural networks can be used to solve a wide variety of problems, but there are many major difficulties to overcome. Amongst the difficulties encountered are slow convergence rate, complexity of structure and poor performance for some of the learning algorithms. Lim (1996) reported that multiple classifiers are able to improve the performance of individual classifier. Hence, motivation is needed to represent the neural network architecture in a format suitable for use with the specific problem.

1.4 Research Objectives

The main aim of this research is to develop an intelligent classification system for aggregate based on image processing and neural network. The system would be able to classify the aggregate into six shapes; angular, cubical, irregular, elongated, flaky and flaky&elongated. The system would be automatic, accurate, consistent, fast and user-friendly. In order to fulfill the aforementioned goals, this study is intended to investigate the best salient features for aggregate recognition, propose automatic features extraction, employ the best neural network for classification and develop the intelligent aggregate classification system. The specific research objectives include:

- To investigate an automatic feature extraction technique to extract aggregate characteristics (features). The technique would contain the best enhancement algorithm, the best clustering algorithm and the best segmentation and edge

detection algorithm for aggregate images. The technique would have the ability to automatically extract the geometrical moments from the segmented object. Hu, Zernike and Affine moments would be extracted from both aggregate area and boundary. These moments provide shape-dependent features with high discriminatory ability, which are invariant to object rotation, translation and size scaling in the image.

- To determine the useful and important features for aggregate recognition using feature selection techniques. The discriminant analysis (DA), principal component analysis (PCA) and circle segments (CS) would be employed. Comparison of the results obtained from the three techniques would be completed and the best technique for the problem at hand would be determined.
- To introduce a new learning algorithm, that would be used to train the Hybrid Multilayered Perceptron (HMLP) network. The new learning algorithm is a modified version for the Recursive Least Squares (RLS) algorithm. The proposed algorithm not only has the ability to classify the aggregate shape but also the ability to classify any pattern classification data.
- To improve the performance of the MLP and HMLP network by proposing two new artificial neural network (ANN) architectures. The first architecture is called Cascaded MLP network and the second architecture is called Hierarchical HMLP network, respectively. The two architectures would be tested and compared with many learning algorithms. Then, the best learning algorithm with the best neural network would be used for automatic aggregate shape classification.

- To build an automatic intelligent aggregate classification system that contains automatic features extraction and intelligent classification. The system will assist user for easier and better aggregate classification process. The system would be also compared to the existing system used in aggregate classification.

1.5 Thesis Outline

This thesis consists of six chapters organized as follows:

Chapter 1 presents an introduction of pattern recognition, machine vision, digital image processing (DIP), shape features, moment invariants, feature selection and artificial neural networks (ANNs). The importance of aggregate in concrete making is discussed, followed by the problem statement, the objectives and the outline of the thesis.

In Chapter 2, a comprehensive literature review on aggregate, DIP and ANNs is provided. The architecture of the MLP and HMLP networks is explained, and their applications to various fields are reviewed. In addition, a brief description of the available imaging systems used for measuring aggregate shape characteristics is presented at the end of this chapter.

In Chapter 3, the methodology of image processing techniques used in aggregate recognition is described. The modified Automatic Features Extraction (AFE) algorithm which is proposed for segmentation and features extraction is discussed. The modified AFE algorithm is applied to automatically extract Hu, Zernike and Affine moment invariants from both aggregate's area and boundary. Besides that, the discriminant analysis, principal component analysis and circle segments methods are employed to

choose the best features that represent the aggregate images, thus minimizing features redundancy.

In Chapter 4, a new learning algorithm called Modified Recursive Least Squares (MRLS) is introduced for the Hybrid Multilayered Perceptron (HMLP) network as intelligent pattern classifier. The effectiveness of the proposed algorithm is evaluated using a number of benchmark data sets. The benchmark data sets investigated include the Wisconsin Breast Cancer, Glass, Ionosphere, Iris, Pima Indian and Wine benchmark problems. The results for the HMLP network trained with the MRLS algorithm are compared with many machine learning classifiers published in the literature.

In Chapter 5, two ANN architectures called Cascaded Multilayered Perceptron (c-MLP) network and Hierarchical Hybrid Multilayered Perceptron (H^2 MLP) network are proposed for aggregate classification. The two ANN architectures, their training algorithm and the performance comparison with other ANNs are presented. The appropriate neural network for aggregate classification is identified during the comparison study. At the end of this chapter, an automatic intelligent aggregate shape classification system called AutoAgg is developed. The description, components, facilities, novelties and applications of the AutoAgg and its comparison with the existing systems are provided.

In Chapter 6, conclusions and contributions of this research are highlighted. Some areas for future work are also suggested at the end of this thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Data classification can be regarded as the process of discriminating the measurements taken from the extracted features of an input pattern, and assigning the input pattern into one of the possible target classes according to some decision rule (Chen, 2005). The fundamental aspects of this research which is on aggregate, image processing and neural networks will be reviewed in a number of sections. The first section begins with the description of the aggregate shape and its characteristics. Then it proceeds to the role of aggregate in concrete making and the manual classification of the aggregate shape. The second section of this chapter deals with digital image processing fundamentals, such as image sampling and quantization, and certain image processing techniques, such as image enhancement, image segmentation, features extraction and features selection. In the third section, an overview of theory of neural networks which includes the architecture design, operational concept and learning process of a network is reviewed. Finally, a literature study on the implementation of image processing and neural networks for aggregate classification systems is reviewed at the end of this chapter.

2.2 Aggregates

Aggregates, whether crushed or naturally reduced in size are classified into several group of rock types with common characteristics. The classification of BS 812: Part 1: 1975 is most convenient since the aggregates are classified based on their

petrological nature ranging from ‘**artificial group**’ up to ‘**schist group**’ (Neville, 1981).

Table 2.1 shows the general petrological classification of aggregates.

Table 2.1 Petrological classification of aggregates (British Standards Institution BS 812: Part 1: 1975)

1. Artificial group	4. Gabbro group	7. Hornfels group	10. Quartzite group
<ul style="list-style-type: none"> • Crushed brick • Slags • Calcined bauxite • Synthetic aggregates 	<ul style="list-style-type: none"> • Basic diorite • Basic gneiss • Gabbro • Hornblende-rock • Norite • Peridotite • Picrite • Serpentine 	<ul style="list-style-type: none"> • Contact-altered rocks of all kinds except marble 	<ul style="list-style-type: none"> • Ganister • Quartzitic sandstone • Recrystallized Quartzite
2. Basalt group	5. Granite group	8. Limestone group	11. Schist group
<ul style="list-style-type: none"> • Andesite • Basalt • Basic porphyrite • Diabase • Dolerites of all kinds including theralite and teschenite • Epidiorite • Lamprophyre • Quartz-dolerite • Spilit 	<ul style="list-style-type: none"> • Gneiss • Granite • Granodiorite • Granulite • Pegmatite • Quartz-diorite • Syenite • Quartz-diorite • Syenite 	<ul style="list-style-type: none"> • Dolomite • Limestone • Marble 	<ul style="list-style-type: none"> • Phyllite • Schist • Slate • All severely sheared rocks
3. Flint group	6. Gritstone group	9. Porphyry group	
<ul style="list-style-type: none"> • Chert • Flint 	<ul style="list-style-type: none"> • Including fragmental volcanic rocks • Arkose • Greywacke • Grit • Sandstone • Tuff 	<ul style="list-style-type: none"> • Aplite • Dacite • Felsite • Granophyre • Keratophyre • Microgranite • Porphyry • Quartz-porphyrite • Rhyolite • Trachyte 	

Apart from the general eleven groups of rock types, aggregates are further classified into six class of shapes known as rounded particles, angular, irregular, flaky, elongated and flaky&elongated in BS 812: Part 1: 1975. Figure 2.1 shows the standard aggregate shape classification.

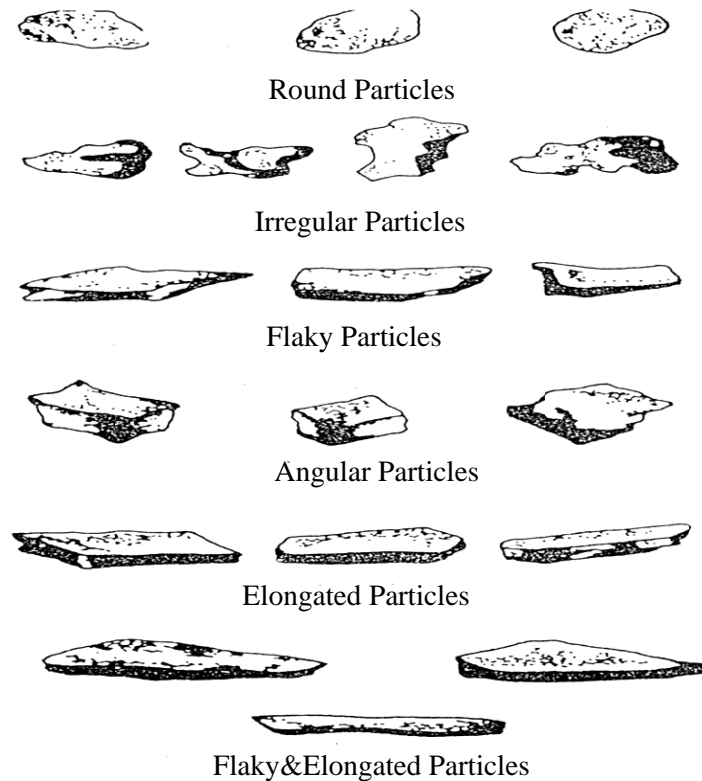


Figure 2.1 aggregate shape classifications (BS 812: Part 1: 1975)

Aggregates play a vital role in the construction industry as it occupies more than 70% of the concrete’s volume. Here, concrete is a composite material comprising of cement, water, fine and coarse aggregates and at times, chemical admixtures and/or additives, designed with the objective of determining the most economical and practical combinations of materials to produce a product that will satisfy the performance requirements for which it is to be used (Anon, 2001a). As the major ingredient for concrete mix, aggregate properties such as particle shape, size grading and textural qualities are being given special considerations and importance for construction

application. Generally, particle shape depends on various factors such as the rock type, breakage energy, crusher type and the degree of stratification of rock deposit (Kojovic, 1995; Donza *et al.*, 2002). The effect of particle shape is significant in the quarrying industry since it affects the quality of construction aggregates. The increasing need and requirement for high strength and quality concrete also drives the quarrying industry to produce high quality aggregates with improvement in its characteristics. Accordingly, excerpts from Hamer (1990 & 1991) shows that aggregate production are changing towards production of aggregates with improved qualities such as more cubical and equidimensional in shape, better graded size and textural characteristics.

As aggregates occupy bulk of the volume of concrete, aggregate properties such as size grading, shape and surface texture have significant influence on the properties of concrete in both fresh and hardened state and also the bulk density of the matrix (Jamkar & Rao, 2004; Anon, 2001a). Reports and data from Kaplan (1959) also showed that the compressive strength, flexural strength and elastic properties of concrete are among the important concrete properties influenced by aggregate characteristics. In terms of particle orientation, the largest particles would pack down first and smaller particles would fill the voids between the larger particles. This process is repeated until the voids are so small that can only be filled by the water or cement paste. The success of this process is governed primarily by the particle gradation. The shape of the particles has a great effect on this process, in which elongated or flaky particles does not allow the particles to achieve their optimum packing configuration. This results in larger voids in between the particles. Optimum packing of aggregates ensures that the maximum strength is being achieved by the concrete (Anon, 2001a; Neville, 1995).

Aggregate characteristics such as shape and textural features also influence the concrete's workability. If compared to cubical shape aggregates, aggregates which are rough textured, angular and elongated in shape requires higher amount of cement to produce a workable concrete. This is due to much higher amount of cement required to fill up the voids which failed to be occupied by these rough textured, angular and elongated particles (Hudson, 1997).

Significantly, Figures 2.2 (a) and (b) show the physical nature of the poorly shaped normal aggregates and high quality shaped aggregates (HIQSA), respectively. The normal aggregates are the products from the conventional type compression crusher while the high quality shaped aggregates (HIQSA) were produced by crushing the aggregates with the Metso Barmac Rock on Rock Vertical Shaft Impact (RoR VSI) Crusher which is available in School of Material and Mineral Resources Engineering, Universiti Sains Malaysia (USM).



(a)



(b)

Figure 2.2 Aggregate shapes; (a) Bad shape (irregular, flaky, elongated and flaky&elongated) and (b) Good shape (angular and cubical)

2.2.1 Aggregates Role in Concrete

Concrete is a three-phase heterogeneous material with cement paste, aggregate and interface between cement paste and aggregate (Rao & Prasad, 2002). Aggregates are used as fillers in concrete; therefore they should be of suitable high quality, which will promote lower costs per unit of production (Anon, 2001b). Reports and research findings from Rajeswari *et al.* (2003 & 2004) and Azizli *et al.* (2004) clearly explained that stronger aggregates with improvement in particle shape and textural characteristics tend to produce stronger concrete as the weak planes, fissures and structures within the aggregate particles were being reduced during impact crushing. The concrete strength test work conducted on concrete cubes consisting of high quality shaped aggregates (HIQSA) produced excellent results and valuable information.

Substitution of high quality shaped aggregates (HIQSA) as the coarse aggregates in a concrete mix resulted in higher strength and quality concrete than those which are flat or elongated existing in normal aggregates. The high quality shaped aggregates which are more cubical and equidimensional in shape have less surface area per unit volume, therefore get packed tighter when consolidated. However, aggregates which are flat or elongated decrease the workability of concrete by poor packing, reducing the bulk mass and consequently decreasing the compressive strength of concrete with much more requirements of sand, cement and water. The significant effect of aggregate properties, both physical and mechanical towards the strength, quality and optimum packing configuration in concrete has also been scientifically proven and discussed by Rajeswari (2004). It is evident that, the shape of coarse and fine aggregate particles greatly influences the properties of both the fresh and hardened concrete. The poorly shaped particles of normal aggregates (Figure 2.2(a)) tend to get orientated and packed

in a poor manner in a concrete mix, resulting in lots of voids and honeycomb structure when the concrete hardened.

Accordingly, poorly shaped aggregates require more cement paste to produce workable concrete mixtures, thus increasing the production cost. Hudson (1995 & 1996) reported that the improvement in the aggregate shape could greatly contribute towards the reduction in the water to cement ratio (w/c) needed to produce a concrete mixture. High quality aggregates enable the reduction of water demand associated with good workability for fresh concrete. Therefore, high quality aggregates has the ability to decrease the cost of production and placement of concrete and hence increase the strength and overall quality of concrete. Thus, the presence of elongated and flaky particles in excess of 10% to 15% of the weight of coarse aggregate is generally considered undesirable. The Malaysian Standard, M.S. 30 test methods (JKR 20600-0010, 1991) of the Specification for Structural Concrete for example specifies the elongation index of coarse aggregate particles for concrete as not to exceed 30%, while the flakiness index for concrete and road construction restricted not to exceed 35% and 25%, respectively.

2.2.2 Characterization and Classification of Aggregate Shape

Concrete aggregates are divided into two categories. Coarse aggregates are greater than 5mm (stone) and fine aggregates are lesser than 5mm to dust. Numerous test methods have been developed to measure or quantify the shape properties of both coarse and fine aggregates especially for construction purposes. Generally, graded aggregates will be produced in size range that doubles their nominal bottom size particle. The finest size coarse aggregates is graded from 5 mm to 10 mm top size, followed by

10 mm to 20 mm, and next from 20 mm to top size of 40 mm and so forth (Neville, 1995; Ramli, 1991).

2.2.2.1 Coarse Aggregate Shape

Few standard methods are employed for coarse aggregate shape measurement such as Flakiness Index and Elongation Index (FI and EI) as well as Euler's Polyhedron Formula. The following sections will discuss these methods in details.

2.2.2.1.1 Flakiness Index and Elongation Index

In the British Standard BS 812: Section 105.1 and 105.2 (1989), the flakiness and elongation of an aggregate sample are measured indirectly in terms of flakiness or elongation indices, which are, respectively defined as percentage of mass of particles classified as flaky or elongated. The particles are classified as flaky or elongated according to the rather arbitrary assumptions that a particle is flaky if its thickness is less than 0.6 times the sieve size and the particle is elongated if its length is greater than 1.8 times than the sieve size (Lees, 1964). Figure 2.3 shows the British Standard thickness gauge used for measuring flakiness index.

The expression for flakiness index is given in Equation (2.1).

$$\text{Flakiness Index, } FI = \frac{M_3}{M_2} \times 100 \quad (2.1)$$

where,

M_2 = the sum of the masses of fractions that have a mass greater than 5% of the total mass.

M_3 = the mass of all the flaky particles.

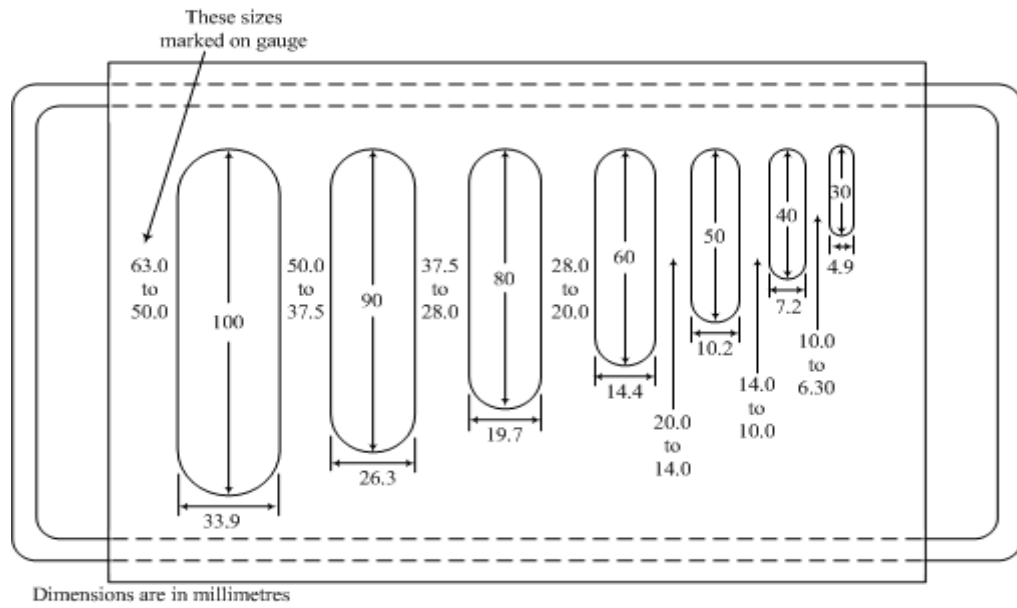


Figure 2.3 British standard thickness gauge (BS 812: Section 105.1: 1989)

The elongation index is calculated as the percentage by mass of aggregate particles that are regarded as elongated. If any size fraction of the aggregate sample has a mass smaller than 5% of the total mass of aggregate sample, the particular size fraction is not included in the test and the total mass of aggregate sample is adjusted accordingly. Figure 2.4 shows the British Standard elongation gauge.

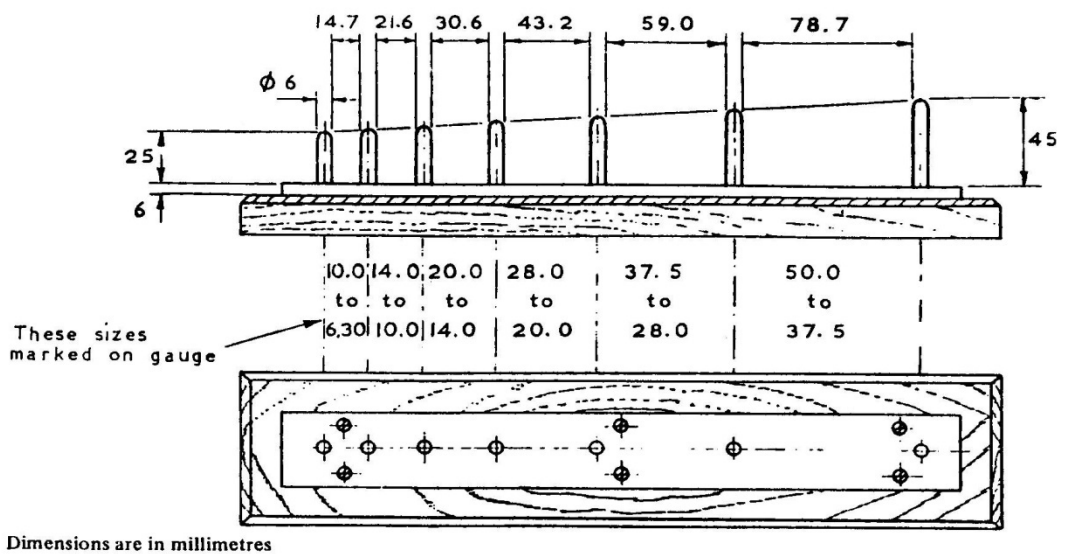


Figure 2.4 British standard elongation index gauge (BS 812: Section 105.2: 1989)

The expression for elongation index is given in Equation (2.2).

$$\text{Elongation Index, } EI = \frac{M_4}{M_2} \times 100 \quad (2.2)$$

where,

M_2 = the sum of the masses of fractions that have a mass greater than 5% of the total mass.

M_4 = the mass of all the elongated particles.

Using the expressions 2.1 and 2.2, the quality of product shape can be identified based on the mass or proportion of flaky and elongated particles in which, low values of FI and EI are an indication of good or better particle shape.

2.2.2.1.2 Euler's Polyhedron Formula

A quantitative way of evaluating and defining the shape properties of coarse aggregates could be achieved with the usage of Euler's Polyhedron Formula which requires overall assessment of the faces, edges and corners of the particles. The Euler's formula describes the relation between the number of faces (f), edges (e) and corners (c) of a regular convex polyhedron in which the number of corners plus the number of faces is equal to the number of edges plus 2. Equation (2.3) shows the expression of the relation between the faces (f), edge (e) and corner (c) of this mathematical formulation.

$$c + f - e - 2 = 0 \quad (2.3)$$

where,

f = number of faces,

e = number of edges and

c = number of corners

The Euler's Polyhedron formula, $c + f - e - 2 = 0$ has been adopted and used by Hartge *et al.* (1999) to investigate the morphological properties of soil aggregates. Table 2.2 shows the classification of polyhedron with respect to the number of faces, edges, corners and edge per face ratio as suggested by Hartge *et al.* (1999).

Table 2.2 Classification of polyhedron by Hartge *et al.* (1999)

	Faces	Edges	Corners	Digital Term	Edge Per Face
Tetraeder	4	6	4	2	1.5
Pentaeder	5	8	5	2	1.6
Hexaeder					
• trigonal	6	10	6	2	1.66
• cubic	6	12	8	2	2.0
Hexaeder (mean)	6	11	7	2	1.83
Mean (total)	5	8.3	5.3	2	1.64

The flakiness and elongation indices (FI's and EI's) of aggregates are widely used to identify the product shape, in which low values of FI and EI are an indication of good or better particle shape. Although valuable information on product characteristics could be obtained, there are no clear definition and description given on the degree of flakiness, elongation or cubicity of samples. Through a very detailed study, Rajeswari (2004) found that particle shape and the morphological properties of aggregates can be quantified precisely by using the Euler's Polyhedron formula. In this case, the Euler's Polyhedron Formula has been adopted to identify and quantify the geometrical parameters of the crushed and uncrushed aggregates. The variations produced through visual observation in the counted numbers of faces, edges, corners and edge per face (e/f) ratio for crushed or uncrushed aggregates can be used to determine the class of aggregate shape. The geometrical information of the exterior feature of aggregates together with the numerical and statistical data gained from the shape analysis using the Euler's Polyhedron formula were finally used to classify aggregates into six class of

shapes namely as cubical or equidimensional, angular, irregular, flaky, elongated and flaky&elongated.

2.2.2.2 Fine Aggregate Shape

The fine aggregates require a more refined technique compared to coarse aggregates with the voids content analysis and the flow cone method remains as the most prominent techniques of analyzing fine aggregate properties.

2.2.2.2.1 Uncompacted and Compacted Void Content

The American Society for Testing and Materials (ASTM) has developed a test method called Standard Test Method for Uncompacted Void Content of Fine Aggregate (as influenced by Particle Shape, Surface Texture and Grading) or better known as ASTM Test Method C 1252 (Jackson & Brown, 1997).

The uncompacted and compacted voids content test work are the standard test work conducted to determine the angularity, sphericity and surface texture of fine aggregates tested in the same grading. Voids are the differences between the total volume and the volume occupied only by the aggregate particles. The amount of space or voids is a function of the aggregate gradation, shape and textural characteristics and also the amount of compaction of the material.

Three procedures are included for the measurement of voids content. Two procedures use graded fine aggregate (standard grading or as-received grading), and the other uses several individual size fractions for voids content determinations. For the