QUALITY ANALYSIS OF THE AGGREGATE IMAGING SYSTEM (AIMS) MEASUREMENTS

A Thesis

by

MANJULA BATHINA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2005

Major Subject: Civil Engineering

QUALITY ANALYSIS OF THE AGGREGATE IMAGING SYSTEM (AIMS) MEASUREMENTS

A Thesis

by

MANJULA BATHINA

Submitted to Texas A&M University
in partial fulfillment of the requirements
for the degree of

MASTER OF SCIENCE

Approved as to style and content by:

Eyad Masad (Chair of Committee)	Cliff Spiegelman (Member)
Amy Epps Martin (Member)	David V Rosowsky (Head of Department)

May 2005

Major Subject: Civil Engineering

ABSTRACT

Quality Analysis of the Aggregate Imaging System (AIMS) Measurements. (May 2005)

Manjula Bathina, B.Tech, Jawaharlal Nehru Technological University, INDIA

Chair of Advisory Committee: Dr. Eyad Masad

Coarse and fine aggregates form the skeleton of any type of pavement and influence the performance of the pavement structure. Characterization of the physical characteristics (shape, angularity, and texture) of coarse and fine aggregates is the first step towards the development of valid specifications for these characteristics. Current test methods used in practice have several limitations in quantifying the shape and texture properties. An imaging based test method "Aggregate Imaging System (AIMS)" has been recently developed and shown to be capable of directly measuring the characteristics of coarse and fine aggregates.

In this thesis, the quality of AIMS measurements is evaluated through the analysis of repeatability, reproducibility, and sensitivity. The analysis results are also compared to the results from other available test methods. AIMS provides the distribution of shape characteristics in an aggregate sample. Statistical analysis is conducted in order to determine the distribution function that best describes the distribution of shape characteristics. The parameters of the distribution function can be related to the performance of pavement layers. A new method based on the "Categorical Units" is developed to test differences between aggregate samples in terms of shape characteristics. It is demonstrated that this method is capable of quantifying the differences between aggregates and can be used to capture the influence of change in aggregate source or production techniques on aggregate characteristics.

DEDICATION

This thesis is dedicated to god and the persons I love most, my father “Sridhar Bathina”and mother “Aruna Bathina,” with all my love and gratefulness. This thesis is also dedicated to my brother Shashidhar and sisters Malathi and Sana.

ACKNOWLEDGEMENTS

I would like to express my special thanks to Dr. Eyad Masad for his support and encouragement in pursuing my graduate studies and for giving me the opportunity to be part of this research project. I would like to express my sincere appreciation and thanks to Dr. Cliff Spigelman for his guidance in completing this thesis.

I also thank the National Cooperative Highway Research Program (NCHRP) for providing the necessary funds to complete this work. Special thanks to Taleb Alrousan for his help during this project. I also thank Ms Aparna Kanugo, Mr. Syam, and Mr. Jeremy for their help in conducting the tests. Thanks to my friends Sehoon Jang, Prabha Ranjani, Anuroopa Kancherla and my officemates for their support. Last, but not least, I thank my best friend Saritha Poosa for always being there when I needed her.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

FIGURE Page

CHAPTER I

INTRODUCTION

The physical characteristics (shape, angularity, and texture) of coarse and fine aggregates are related to the engineering properties of pavement materials such as shear resistance, fatigue response, workability, and durability, and consequently they play a vital role in the performance of pavements. Characterization of the physical characteristics of aggregates is crucial in improving the performance of various types of pavements. Current test methods in use by Superpave^{TM}, a product of Strategic Highway Research Program (SHRP), are limited in their ability to directly and objectively quantify aggregate physical characteristics. However, there are many test methods that have been developed recently at various research institutions with the objective of measuring these characteristics. Evaluation of such test methods for their applicability helps in determining their advantages over current test methods and incorporating such test methods into aggregate specifications.

One of the test methods that has been shown to be successful in accurately measuring aggregate characteristics is the Aggregate Imaging System (AIMS). AIMS is an imaging

---

This thesis follows the style and format of *Journal of Materials in Civil Engineering*.

based test method capable of measuring the physical characteristics of coarse and fine aggregates. This sophisticated test method was designed to be versatile enough to measure the distribution of shape, angularity, and texture of various sizes of aggregates. This thesis includes a comprehensive evaluation of the quality of the AIMS measurements. The quality is evaluated through measuring the repeatability, reproducibility and sensitivity of the AIMS measurements. Repeatability is defined as the variation within the measurements conducted by the same operator, reproducibility is defined as the variation among multiple operators, and sensitivity is captured by the distribution of aggregate physical properties within the measured sample.

The results are compared to other methods for measuring aggregate shape characteristics. In addition, a new method is proposed to test the statistical differences among aggregate samples that are measured using AIMS. The evaluation presented in this thesis is important in the future implementation of AIMS in routine analysis of aggregate physical characteristics.

OBJECTIVES OF THE STUDY

The primary objective of this thesis is to evaluate the quality of the "Aggregate Imaging System (AIMS)" measurements. This objective is achieved through the following tasks:

- Conducting statistical measurements of AIMS such as repeatability, reproducibility and sensitivity.

- Comparing the statistical parameters such as repeatability, reproducibility and sensitivity of AIMS with other test methods.
- Determining the probability distribution function that best describes the shape characteristics in an aggregate sample.
- Developing a statistical method for testing the differences among aggregates in terms of the physical characteristics measured by AIMS.

THESIS ORGANIZATION

This thesis is organized into six chapters as follows:

- Chapter I introduces the motives of this study and the test method "Aggregate Imaging system (AIMS)" evaluated in this thesis, followed by the objectives and outline of the thesis.
- Chapter II consists of a literature review describing the aggregate characteristics related to pavement performance, and various test methods used for measuring the aggregate characteristics. The literature review focused on the AIMS describing its hardware and software components and the working principles of the test method.
- Chapter III deals with the evaluation of statistical properties of AIMS such as repeatability, reproducibility, and sensitivity. These properties are assessed on a wide range of coarse and fine aggregate samples following the ASTM standards for evaluating repeatability and reproducibility of the test method.

- Chapter IV describes the comparison of statistical properties of AIMS with other test methods that are currently in practice by the pavement industry for measurement of aggregate shape properties.
- Chapter V describes the distribution functions that were evaluated for describing the aggregate shape distributions measured by AIMS. The parameters of these functions were assessed to find differences among aggregate samples. Also, a new method based on the "categorical units" is proposed in this thesis to detect statistically significant differences among aggregate samples measured by AIMS.
- Chapter VI includes the conclusions and recommendations of this thesis.

CHAPTER II

LITERATURE REVIEW

INTRODUCTION

This literature review focuses on the significance of aggregate characteristics in influencing the performance of pavements. A brief review of the various test methods available for measuring shape characteristics with emphasis on the Aggregate Imaging System (AIMS) is presented.

AGGREGATE PROPERTIES AFFECTING PAVEMENT PERFORMANCE

The performance of any pavement depends primarily on the materials it constitutes. Aggregates form the skeleton of any pavement and are crucial for its performance. The performance of hot mix asphalt (HMA) mixtures in terms of mix stiffness and fatigue cracking was described by Monismith (1970). Aggregate characteristics such as size, shape, and surface texture were considered crucial factors in determining the HMA performance. Use of rough textured aggregates with dense gradation was recommended to improve mix stiffness and increase fatigue life of thick pavements. For thin pavements smooth textured aggregates were recommended since they produce less stiff mixtures and increase the fatigue life of thin pavements (Monismith 1970).

The influence of aggregate properties on PCC pavements was described by Meininger (1998). The properties of the concrete mix is affected by the fine aggregate content and its shape. Very high texture reduces the concrete mixture workability and handling. The percentage of flat and elongated particles also affects the concrete mix as a higher percentage of flat and elongated particles might result in voids and incomplete consolidation of the mix and hence cause spalling. Also the performance of PCC mix in terms of transverse cracking, faulting of joints and cracks, punch outs, and spalling at joints and cracks are related to coarse aggregate particle shape and angularity (Meininger 1998). The bond strength between cement paste and aggregates is remarkably affected by the coarse aggregate shape, angularity, and surface texture (Mindness and Young 1981). Kosmatka et al. (2002) stated that the bond strength in concrete increases as the coarse aggregates changes from smooth and rounded to rough and angular. Weak bonding in the concrete pavement promotes distresses such as longitudinal and transverse cracking, joint cracks, spalling, and punch outs (Fowler et al. 1996; Meininger 1998; Folliard 1999). Higher bond strength is desired in concrete mix because it increases the flexural strength and hence is preferred when high compressive strength is needed. The relationship between aggregate shape properties and the resilient modulus, and the shear strength properties of unbound aggregates used in base layers was studied by Barksdale and Itani (1994), and significant positive correlation was observed between them. It was indicated by Saeed et al. (2001) that the aggregate particle angularity and surface texture mostly affect the shear strength and stiffness of unbound layer performance. Shear strength is the most important property and influences the unbound pavement layer performance.

TEST METHODS FOR MEASURING AGGREGATE CHARACTERISTICS

The current Superpave^{TM} system specifies three tests to determine the shape properties of coarse and fine aggregates. The coarse aggregate angularity is determined by "ASTM D5821Standard Test Method for determining the percentage of particles in coarse aggregate" (ASTM D5821-95). The fine aggregate angularity is determined by the voids in an uncompacted fine aggregate sample "AASHTO T304 Uncompacted void content method A" (AASHTO Standard T304). The percentage of flat and elongated particles in coarse aggregate is determined by "ASTM D4791 Standard test for flat particles, elongated particles, or flat and elongated particles in coarse aggregates" (ASTM D4791). These test methods for coarse aggregate angularity have several limitations in measuring aggregate shape properties. The flat and elongated test measures the percentage of particles above a specified dimension ratio, rather than distribution of relative sizes (Fletcher et al. 2003). Though surface texture is considered an important characteristic for pavement performance Superpave tests do not emphasize surface texture measurement (Fletcher et al. 2002). Superpave tests could not discern in some cases between poor and high quality fine aggregates (Huber et al. 1998; Chowdhury et al. 2001). These limitations indicate that there is a pressing need to develop test methods that are capable of measuring aggregates characteristics comprehensively and relate their results to pavement performance (Fletcher et al. 2003).

Presently there are several test methods that rely on imaging technology to capture the shape properties of aggregates and relate them to mix performance. A review of these test methods can be found in reference (Masad 2001). These test methods were developed at various research organizations, and some of these use various imaging techniques. The test methods studied are classified into direct or indirect methods based on the analysis concept they employ in measuring aggregates. Indirect test methods classify aggregate shape characteristics by bulk measurements of the aggregate sample whereas direct methods rely on measurements made directly on the surface of particles (Alrousan 2004). The test methods studied in this thesis are shown in Table 2.1 (Alrousan 2004).

Table 2.1. Test Methods For Measuring Aggregate Shape (Alrousan 2004)

Test Method	**Direct (D) or indirect (I) method**
Uncompacted Void Content of Fine Aggregates AASHTO T304	I
Uncompacted Void Content of Coarse Aggregates AASHTO TP56	I
Compacted Aggregate Resistance (CAR)	I
Percentage of Fractured Particles in Coarse Aggregate ASTM D5821	D
Flat and Elongated Coarse Aggregates ASTM D4791	D
Multiple Ratio Shape Analysis	D
VDG-40 Video grader	D
Buffalo Wire Works PSSDA	D
Camsizer	D
Wipshape	D
University of Illinois Aggregate Image Analyzer (UIAIA)	D
Laser-Based Aggregate Analysis System	D

Alrousan (2004) evaluated the test methods in Table 2.1 and concluded that AIMS is the most comprehensive system capable of measuring the shape characteristics of both coarse and fine aggregates. The evaluation was based on the repeatability of the measurements, accuracy, applicability to the various types of aggregates, readiness for implementation, and ease of use.

THE AGGREGATE IMAGING SYSTEM (AIMS)

AIMS was developed by Dr. Eyad Masad. It utilizes image processing and analysis techniques in determining the shape characteristics of aggregates. AIMS is capable of capturing the aggregate characteristics in terms of shape, angularity, and surface texture for aggregates from 37.5 mm to 150 mm (Masad 2004). The performance of pavements can be better predicted when all the aggregate physical characteristics such as angularity and surface texture are measured accurately with such a sophisticated test equipment and hence pavement quality and life is better designed (Masad 2003). The physical description of AIMS is done with the help of Fig 2.1.

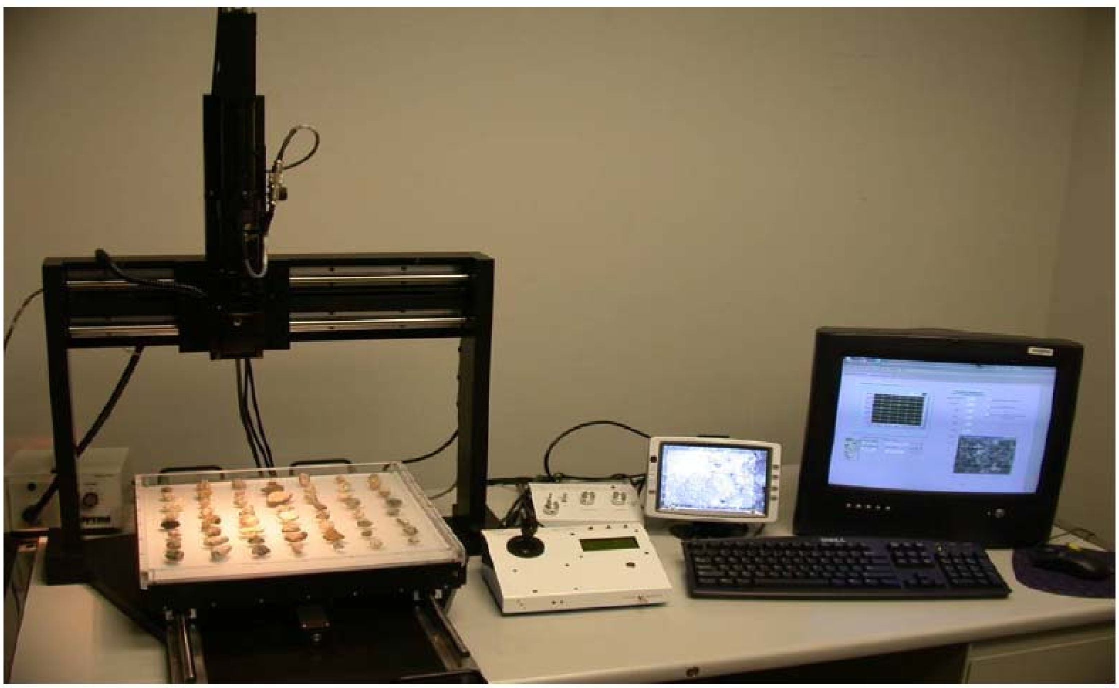

Fig.2. 1. Aggregate Imaging System (AIMS) (Alrousan 2004)

The test equipment consists of a computer automated unit that comprises of aggregate measurement tray with marked grid points at specified distances along x and y axes. The test sample is placed on specified grid points for coarse aggregates (56 particles) and the fine aggregate sample is spread uniformly on the entire tray for measurement. The camera unit consists of an optem zoom 160 video microscope, equipped with bottom and top lightning to capture images in black and white format as well as gray format. The camera moves along specified grid locations in x, y, and z directions. The travel distance in the x and y directions is 37.5 cm and 10 cm in the z direction. The x, y and z axes movement is controlled by a closed loop direct current (DC) servo and highly repeatable focus is achieved by GTS-1500. The entire test equipment is computer automated and controlled by LabView^{TM} (version 6.1) and IMAQ Vision (version 2.5) software for image acquisition and motion control of the test equipment. The first step in measurement is the calibration of the instrument for the type of analysis to be performed. The user has a real-time image window for selecting the type of analysis and size of aggregates to be analyzed. The measurements for the fine and coarse aggregates are conducted using two separate modules as discussed in the following sections (Alrousan 2004).

Fine Aggregate Module

For fine aggregates, the angularity and texture properties have been found to have reasonable correlation (Masad et al. 2001). Therefore, AIMS measures only the angularity of fine aggregates on black and while images. The fine aggregate analysis starts by spreading aggregates on the tray. The back lightning is used to capture the images of all the particles as the camera moves at specified locations in the x and y axes. The images are captured in black and white format. The camera with a 0.5X objective lens with a 1X dove tail tube and 2/3 inch camera format at a working distance of 181 mm is used to provide a field of view of 26.4 mm by 35.2 mm. The images are captured so that the resolutions listed in Table 2.2 are met for all the images. Images are captured with a pixel size less than 1 percent of average aggregate diameter. The aggregate images that are not within the specified size are removed. The images acquired are displayed in a real-time image window during the entire measurement process in black and white format (Alrousan 2004).

Table 2.2. Resolutions and Field of View Used in Fine Analysis for Fine Sieve Sizes 0.5X lens

(1) Particle Size (mm)	**(2) Average Particle diameter (mm)**	**(3) Magnification**	**Field of View (mm)**	**Resolution= 640/70.4 or 480/52.8 (pixel/mm)**	**Average Particle diameter in pixels (2)*(5)**	**Size Range Upper-Lower (Pixels) (1)*(5)**
4.725-2.36	3.56	2.00X	13.2X17.6	36.36	129.45	172-86
2.36-1.18	1.77	4.125X	6.4X8.5	75.29	133.26	178-88
1.18-0.6	0.89	8.25X	3.2X4.3	148.84	132.46	176-89
0.6-0.3	0.45	16X	1.65X2.2	290.91	130.9	175-73
0.3-0.15	0.225	16X	1.65X2.2	290.91	65.45	72-44
Gradation		2.75X	9.6X12.8	50.0		

Coarse Aggregate Module

The coarse aggregates are analyzed for shape, angularity, and texture in two separate scans. The test procedure consists of capturing images of all aggregates in a test sample (56 particles) placed on specified grid locations, with the movement of the camera in the x-axis first and then along the y-axis. Each image is captured for the individual particle at each location separately in black and white format for angularity and a gray format for texture analysis. The camera lens used in capturing images has 0.25X objective with a 1X dove tail tube and a 2/3 inch camera format at a working distance of 370 mm. It provides a maximum field of view of 52.8 mm X 70.4 mm. For angularity analysis the black and white images are captured with the help of backlighting and the images acquired are displayed in a real-time image window during the entire measurement process. The particles are placed at a center to center distance of 50 mm in the x direction and 40mm in the y direction and the captured images are analyzed for angularity analysis to meet the resolution criteria mentioned in Table 2.3.

Table 2.3. Resolutions and Field of View Used in Coarse Analysis for Coarse Sieve Sizes 0.25X lens

(1) Particle Size (mm)	(2) Average Particle diameter (mm)	(3) Magnification	Field of View (mm)	Resolution=640 /70.4 or 480/52.8 (pixel/ mm)	Average Particle diameter in pixels (2)*(5)	Size Range Upper-Lower (Pixels) (1)*(5)
9.5-4.725	7.1125	1	52.8 X 70.4	9.12	64.87	86-43
12.7-9.5	11.1	1	52.8 X 70.4	9.12	101.23	116-87
19.0-12.7	15.85	1	52.8 X 70.4	9.12	144.55	173-117
25.4-19.0	22.2	1	52.8 X 70.4	9.12	202.46	231-174
> 25.4	25.4	1	52.8 X 70.4	9.12	231.65	>232

Top lighting is used in capturing images for texture analysis. In the texture scan, the microscope is first focused on the reference point (axis is set to zero) with the help of back lightning, then an aggregate particle is placed on the calibrated point, and the depth of the aggregate particle is measured as the camera focuses on the top surface of the aggregate particles. The depths of all the particles are used for analysis of shape. The resolution criteria listed in Table 2.4 are met for texture analysis.

Table 2.4. Resolutions and Field of View Used in Texture Analysis for Coarse Sieve Sizes 0.25X lens

Particle Size (mm) Pass-Retain	Average Particle diameter (mm)	Particle Min. Expected Area(mm)	%25of particle Min Expected Area(mm^2)	Suggested Magnification	Fieldof view	Covered Area(mm^2)	Resolution= 640/70.4or 480/52.8(pixels/mm)
9.5 – 4.725	7.1125	22.32	5.58	16X	3.3X4.4	14.52	145.45
12.7 – 9.5	11.1	90.25	22.56	12X	4.4X5.9	25.96	108.00
19.0 – 12.7	15.85	161.29	40.32	9X	5.9X7.8	43.68	82.10
25.4 – 19.0	22.2	361	90.25	6X	8.8X11.7	102.96	54.70
> 25.4	25.4	645.16	161.29	5X	10.6X14.1	149.46	45.40

AIMS Analysis Software

The analysis software was developed as a stand alone application for AIMS. The software analyzes the aggregate shape properties in terms of five parameters (radius angularity, gradient angularity, form index, sphericity, and texture) for coarse aggregates and stores them in a Microsoft Excel file in separate sheets. The results are presented in terms of all measurements of the aggregate sample and a summary of some statistical parameters such as mean, standard deviation, and graphical presentation of the distribution of measured aggregate property in an aggregate sample are given. More details on the analysis software are presented by Alrousan (2004).

APPLICATION OF AIMS IN PAVEMENT ENGINEERING

AIMS has been identified as a sophisticated test method to classify the shape, angularity and texture properties of coarse and fine aggregates. As such, Masad et al. (2005) have presented several applications for AIMS in pavement engineering. The first application is for the quality control and quality assurance of aggregates during their production. Also, the measured characteristics can be related to the performance of various pavement layers. Skid resistance of pavements is influenced by aggregate shape properties. AIMS can be used to measure the change in shape properties after being subjected to polishing and relate the reduction in texture and angularity to skid resistance. Crushing techniques vary in their operations and consequently have great influence on aggregate shape properties. It has been suggested that AIMS can be used to assess the shape properties of aggregates produced by different crushing techniques and assist in the development of desirable aggregate characteristics. Various crushing methods can be evaluated as aggregates can be measured after crushing by various procedures and the crushing methods that produce aggregates with desired shape properties can thus be identified. (Alrousan 2004).

ANALYSIS PRINCIPLES

AIMS evaluates the shape and texture characteristics of coarse and fine aggregates by analysis of images of the aggregate particles captured during measurement (black and white format, and gray format). The black and white images are analyzed for form and angularity, and gray images are analyzed for texture respectively. The principles involved in analyzing all the parameters are comprehensively discussed by Alrousan (2004).

Radius Method (Angularity)

The analysis of angularity by the radius method was developed by Masad et al. (2001) using black and white images. In the radius method the angularity index is measured as the difference between the particle radius in a certain direction to that of an equivalent ellipse.

$$\textit{Angularity Index}\ \text{(Radius Method)} = \sum_{\theta=0}^{355} \frac{|R_\theta - R_{EE\theta}|}{R_{EE\theta}} \tag{2.1}$$

where R_θ is the radius of the particle at an angle of θ ; and $R_{EE\theta}$ is the radius of the equivalent ellipse at an angle of θ (Masad et al. 2001).

Gradient Method (Angularity)

The gradient method is based on the principle that at sharp corners of the image the direction of the gradient vector changes rapidly whereas it changes slowly along the outline of rounded particles. The angularity is calculated based on the values of angle of orientation of the edge points (θ) and the magnitude of difference of these values $(\Delta\theta)$. The sum of angularity values for all the boundary points are accumulated around the edge to get the angularity index. The angularity index is calculated by the sum of angularity values for all the boundary points accumulated around the edge of the aggregate particle. The angularity is mathematically represented as.

$$\textit{Angularity Index} \text{ (Gradient Method)} = \sum_{i=1}^{N-3} \left| \theta_i - \theta_{i+3} \right| \tag{2.2}$$

where N is the total number of points on the edge of the particle with the subscript i denoting the i^{th} point on the edge of the particle. (Masad 2003)

Sphericity (Form Analysis)

Using sphericity the form is quantified in three dimensions. The three dimensions of the particle the longest dimension (dL), the intermediate dimension (dI), and the shortest dimension (ds) are used in the following equations for sphericity and shape factor.

$$\text{Sphericity} = \sqrt[3]{\frac{d_s . d_I}{d_L^2}} \tag{2.3}$$

$$\text{Shape factor} = \frac{d_s}{\sqrt{d_L . d_I}} \tag{2.4}$$

The two major and minor axes are analyzed from the black and white images (eigen vector analysis) while the depth of the particle is measured by auto focusing of the microscope (Fletcher et al 2003).

Form Index (Form Analysis)

Form analysis using the form index was proposed by Masad et al. (2001), and is used to quantify the form in two dimensions. The form index uses incremental change in the particle radius and is expressed by the following equation:

$$\text{Form Index} = \sum_{\theta=0}^{\theta=360-\Delta\theta} \frac{\left|R_{\theta+\Delta\theta} - R_{\theta}\right|}{R_{\theta}} \tag{2.5}$$

where R_θ is the radius of the particle at an angle of θ; and $\Delta\theta$ is the incremental difference in the angle.

Texture Analysis

Wavelet analysis is employed by AIMS for analyzing texture. The wavelet analysis uses short high-frequency basis functions and long low-frequency basis functions to isolate fine and coarse variations in texture. The wavelet analysis can be explained with the help of Fig 2.2. The coefficients LH, HL, and HH hold the directional texture information. The LH coefficients picks up the high frequency content in the vertical direction, the HL coefficients picks up the high frequency content in the horizontal direction, and the HH coefficients picks up the high frequency content in the diagonal direction. The texture contents in all directions are given equal weight and the texture index is computed as the simple sum of squares of the detail coefficients at that particular resolution. The texture index is given by the equation.

$$Texture\ Index_n(\text{Wavelet Method}) = \frac{1}{3N}\sum_{i=1}^{3}\sum_{j=1}^{N}\left(D_{i,j}\left(x,y\right)\right)^2 \tag{2.6}$$

Where n is the decomposition level; N is the total number of coefficients in a detailed image of texture; i takes values 1, 2, or 3 for the three detailed images of texture; j is the wavelet coefficient index; and (x, y) is the location of the coefficients in the transformed domain (Masad 2004).

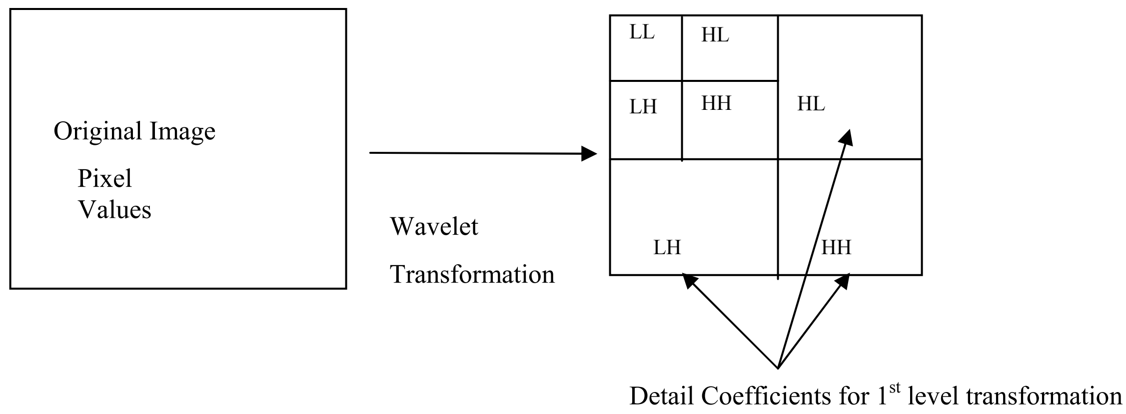

Fig.2. 2. Two-level wavelet transformation

CHAPTER III

STATISTICAL EVALUATION OF AIMS MEASUREMENTS

INTRODUCTION

AIMS measures the shape, angularity, and texture of coarse and fine aggregates. Comprehensive statistical analysis of AIMS measurements in terms of repeatability, reproducibility, and sensitivity have not been conducted before. Repeatability refers to the level of variation of measuring the characteristics of aggregates by the same operator. Reproducibility refers to the variation in measurements conducted by different operators. Sensitivity analysis quantifies the ability of AIMS to capture the differences in distribution of shape characteristics between different aggregates. The measurements were conducted on aggregates that cover a very wide spectrum of geological origin and shape characteristics. Three operators participated in conducting the measurements.

REPEATABILITY OF AIMS

In evaluation of repeatability only single test equipment was used. Three operators were trained on using the test equipment with the same set of instructional guidelines. Random aggregate samples were obtained from all sources. A sample size of 1 kilogram of coarse aggregates and 0.5 kilogram of fine aggregates was used in this study. All the tests for repeatability and reproducibility of AIMS were conducted at the Texas Transportation Institute (TTI). Repeatability of a test method is the variation observed in multiple measures by the same operator on the same material. Repeatability is a desired feature of a test method. Any test method should have high repeatability (low variation). Two different approaches were followed in evaluating AIMS repeatability. In the first one (Repeatability Study- I), the operator was asked to return the measured aggregates back to the sample bag, and obtain a new set of particles for the following measurements. In the second repeatability analysis (Repeatability- II), all measurements were conducted on the same exact particles.

Repeatability Study- I

The materials included 13 types of coarse aggregates and 5 types of fine aggregates. (shown in Table 3.1). The coarse aggregate size of 12.5-9.5 mm and fine aggregate size of 2.36-1.18 mm were used in the evaluation of repeatability study- I. For each test run the operator randomly picked 56 particles from the sample bag of an aggregate, and after the test run the operator placed the 56 particles back in the sample bag. The operator randomly picked another 56 particles for the following test. The above procedure was followed by all the operators for all the materials. This analysis helps in assessing the repeatability of AIMS for the same aggregate source but not necessarily the same particles.

Table 3.1. Aggregates Sources and Sizes for Repeatability Study- I and Reproducibility

Label	Source	Aggregate Description	Aggregate Sizes	
			12.5-9.5 mm	2.36-1.18 mm
1	Montgomery, AL	Uncrushed River Gravel	X	X
2	Montgomery, AL	Crushed River Gravel	X	X
3	Childersburg, AL	Limestone	X	
4	Auburn, AL	Dolomite	X	
5	Birmingham, AL	Slag	X	X
6	Brownwood, TX	Limestone	X	X
7	Fairfield, OH	Crushed Glacial Gravel	X	
8	Fairfield, OH	Uncrushed Glacial Gravel	X	
9	Forsyth, GA	Granite	X	
10	Ruby, GA	Granite	X	X
11	Knippa, TX	Traprock	X	
12	San Antonio, TX	Limestone	X	
13	Augusta, GA	Granite	X	

Repeatability Study- II

In this analysis of repeatability, only a single operator performed the measurements. For the first test run the operator randomly picked 56 particles from a sample of aggregates and for the following test run the same particles were randomly mixed within themselves. Thus the same particles were measured in each test with the only variable being their locations on the aggregate tray. This procedure helped in assessing the repeatability of AIMS without the effect of natural variation among particles from the same source.

REPRODUCIBILITY

The variation observed in multiple measurements made by the test equipment by different operators on the same material is referred to as reproducibility. The reproducibility of AIMS was evaluated using three operators. The same aggregates described in Table 3.1 were used in the evaluation of reproducibility. Random aggregate samples were used as in Repeatability study.

Statistical Analysis of Repeatability and Reproducibility

Each parameter measured by AIMS was evaluated independently for its repeatability and reproducibility. Standard deviation and coefficient of variation were used as measures for expressing the repeatability and reproducibility of AIMS. The analysis of repeatability and reproducibility were conducted under the guidelines of the ASTM E 177, C 802, C 670. (ASTM E 177 Standard Practice for Use of terms Precision and Bias in ASTM Test Methods, ASTM C802 Standard Practice for Conducting an Inter laboratory Test Program to Determine the Precision of Test Methods for Construction Materials, ASTM C 670 Standard Practice for Preparing Precision and Bias Statements for Test Methods for Construction Materials). The repeatability and reproducibility were evaluated for "m" materials by "p" operators and each operator made "n" measurements on each material. The arrangement of all the data by all the operators is shown in
Table 3.2

Table 3.2. Arrangement of Variation in Measurements Within Operators

Material	Operator	Data (measurements) (x_{ij})			Average (x_i)	Within Operator Variance(S_i^2)
1	1	1	2	3	x_1	S_1^2
	2	1	2	3	x_2	S_2^2
	3	1	2	3	x_3	S_3^2
2	1	1	2	3	x_1	S_1^2
	2	1	2	3	x_2	S_2^2
	3	1	2	3	x_3	S_3^2

The average measurement for each operator and each material (x_i) is calculated as follows:

$$x_i = \sum \frac{x_{ij}}{n} \tag{3.1}$$

Then, the variation observed for each operator and each material is

$$S_i^2 = \frac{\left(\sum x_{ij}^2 - n{x_i}^2\right)}{(n-1)} \tag{3.2}$$

The repeatability variation is pooled for the three operators for each material

$$S_{m(pooled)}^2 = \sum \frac{S_i^2}{p} \tag{3.3}$$

Reproducibility is evaluated by first calculating the average measurement for the three operators for each material as follows

$$\bar{x}_m = \sum \frac{x_i}{p} \tag{3.4}$$

Reproducibility is calculated for each material as follows

$$S_L^2 = S_{L_M^2} + S_{m(pooled)}^2 \tag{3.5}$$

Where

$$s_{\bar{x}_m^2} = \left[\sum x_i^2 - p(\bar{x}_m)^2\right] / (p-1) \tag{3.6}$$

$$s_{L_m^2} = s_{\bar{x}_m^2} - \left[s_{m(pooled)}^2 / n\right] \tag{3.7}$$

The results should meet two conditions in order to pool the repeatability and reproducibility variations for all “m” materials. The first test is called the homogeneity of variance in which, the variations observed in different operators for the same material should not vary significantly and we can examine the effect of a high or low variation of an operator compared to others with a plot of individual variances versus operators. The average variation with respect to the individual variation in each operator is considered high variance if the ratio of largest variance/sum of variances < 0.8 (ASTM C802). The variation is considered low if the ratio of highest variance/lowest variance < 87.5 (ASTM C802). The second test is referred to as the lack of interactions between materials and operators. Different operators perform measurements on different materials (and we can observe hierarchical ranking of all materials with respect to their measurements). However, when measurements differ significantly between operators, there tends to be an interaction among the materials and operators (the hierarchical ranking may differ from operator to operator). In order to find if these interactions were statistically significant or not we used an ANOVA test (analysis of variance) and the p-value is observed with a significance level of 95 percent. In the ANOVA test if the P-value > 0.05, we can conclude that with 95 percent confidence interactions between materials and operators are insignificant. The plot of material versus average measure for all materials (all operators) was observed for all the operators to check if any of the operators were varying in measurements significantly from the others. It was observed that the operators did not vary from each other significantly. Also this plot helps in identifying if all the operators rank the materials in same order. In some cases we found significant interactions between operators and materials.

Pooled Repeatability and Reproducibility of the Test Method

Standard deviations and coefficients of variations were pooled over all materials according to the guidelines of the ASTM C802 standards. In most cases the variations (standard deviations and coefficient of variations) were observed to be constant over all materials and hence the standard deviations were pooled over all materials and average coefficient of variation was calculated for all the materials.

REPEATABILITY AND REPRODUCIBILITY RESULTS

The results of repeatability and reproducibility of AIMS is shown in Table 3.3. The repeatability is expressed separately for multiple operators (three) and a single operator in both repeatability study- I and repeatability study- II. Standard deviation (SD) and coefficient of variation (CV) were used in all cases to express the repeatability and reproducibility of AIMS.

Table 3.3. Repeatability and Reproducibility Results for AIMS

	Property Measured	Repeatability –I Study		Repeatability -I Study		Repeatability -II Study		Reproducibility	
		3 Operators		1 Operator		1 Operator		3 Operators	
		SD	CV	SD	CV	SD	CV	SD	CV
Coarse Aggregates	Texture	36.037	0.139	29.869	0.102	1.576	0.049	37.395	0.163
	Radius Angularity	0.309	0.031	0.247	0.027	0.032	0.027	0.470	0.048
	Gradient Angularity	321.968	0.084	187.236	0.078	74.063	0.061	357.771	0.106
	Form-2D	0.229	0.031	0.176	0.029	0.017	0.015	0.303	0.041
	Sphericity	0.014	0.020	0.009	0.014	0.001	0.007	0.018	0.026
Fine Aggregates	Radius Angularity	0.319	0.029	0.245	0.028	0.093	0.036	0.387	0.041
	Gradient Angularity	190.779	0.046	178.113	0.040	52.515	0.037	0.331	0.032
	Form	0.306	0.032	0.289	0.030	0.268	0.046	314.718	0.071

The test method has good repeatability with the highest coefficient of variation (C.V.) equal to 13.9 percent. The test method is highly reproducible with the highest C.V equal to 16.3 percent for random aggregate samples. In case of using the same aggregate particles, the test method is highly repeatable with maximum C.V of 4.9 percent. For coarse aggregates, all the parameters measured resulted in less repeatability for the Repeatability study- I (three operators) compared with Repeatability study- II. In the case of fine aggregates, the repeatability is observed to be slightly higher in measuring radius angularity and form- 2D.

The difference between the two types of repeatability studies is attributed to the fact that three operators participated in the repeatability study- I. More importantly, the repeatability study- I analysis included using different particles from the same sample in each test. Therefore, part of the variation in repeatability study- I is due to the natural variation among particles from the same sample. In order to explore this point, the repeatability C.V. is also calculated for the same operator who conducted the repeatability study- II. The results of repeatability for the same operator in both repeatability study-I (one operator) and repeatability study- II is shown in Table 3.3. It is observed that the C.V. is less when the same particles are measured. Therefore, the difference in repeatability can be attributed to the natural variation of particles from the same aggregate. AIMS measures each particle individually and hence the test method is capable of capturing slight variations in different aggregates from the same sample.

SENSITIVITY OF AIMS

The sensitivity of any test method is identified as the variation in test results due to distribution of aggregate properties within a given aggregate sample. Sensitivity of any test method is desired to determine the ability of the test equipment to observe the distribution of aggregate characteristics within a given aggregate sample. Sensitivity of

AIMS was assessed on aggregate samples that are mixtures of two different aggregates with properties different on two extremes of the measurement scale. From the previous test results using various test methods it was observed that aggregate 1 exhibited low values for the aggregate shape, angularity and texture characteristics and aggregate 10 exhibited high values for these characteristics (Table 3.4).

Table 3.4. Description of Aggregates Used in Sensitivity Analysis.

Aggregate Label	Source	Description
1	Shorter Montgomery, AL Martin Marietta	River Gravel, Uncrushed
10	Ruby Quarry, GA Martin Marietta	Crushed Granite

Aggregates 1 and 10 were combined in two different proportions for the sensitivity evaluation and four aggregate samples 1, 2, 3 and 4 (100 percent of aggregate 1, 50 percent of aggregate 1 and 50 percent of aggregate 10, 30 percent of aggregate 1 and 70 percent of aggregate 10, 100 percent of aggregate 10 respectively) were used in evaluation of sensitivity. The mean values of the aggregate measurement were used for evaluation of sensitivity, and each parameter measured by the test method was evaluated independently for sensitivity. The test method is identified as sensitive if it is monotonic in its measurements when aggregates samples are compared to each other. It is expected that if the test method is sensitive enough to capture the aggregate distribution it shows a monotonic pattern of change in its measurements in the order of sample 1, sample 2, sample 3, and sample 4 respectively (represented by percentage of aggregate 10 on x-axis in the Figs. 3.1-3.6 as 0 percent of aggregate 10 in sample1, 50 percent of aggregate 10 in sample 2, 70 percent of aggregate 10 in sample 3,100 percent of aggregate 10 in sample 4). Also after the test method is evaluated for its monotonic pattern, the sensitivity is defined in terms of R^2 value for the straight line fit between the samples 1, 2, 3 and 4 in a monotonic pattern. The sensitivity results of AIMS are shown in Table 3.5.

Table 3.5. Sensitivity Results of AIMS

Test Method	Measured Parameter	Monotonic Pattern	R^2
AIMS	Form 2D	Yes	0.9434
	Radius Angularity	Yes	0.8632
	Gradient Angularity	Yes	0.9136
	Texture	Yes	0.9957
	Sphericity	Yes	0.8431
	3:1-5:1	Yes	0.8801

It is observed that AIMS follows a monotonic pattern in all the measurement parameters. Also the R^2 value can be used to assess the specific sensitivity of the test parameters. The following Figs 3.1-3.6 depict the sensitivity of AIMS for each parameter measured.

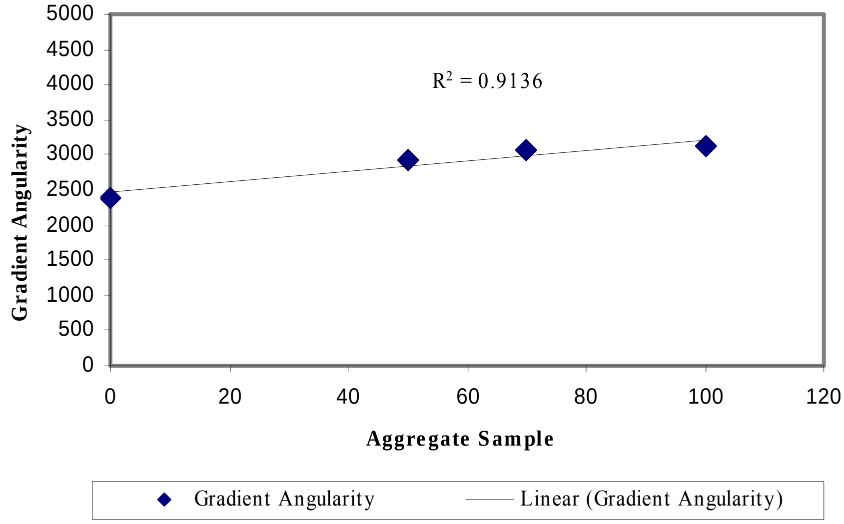

Fig.3.1. Sensitivity of AIMS for gradient angularity.

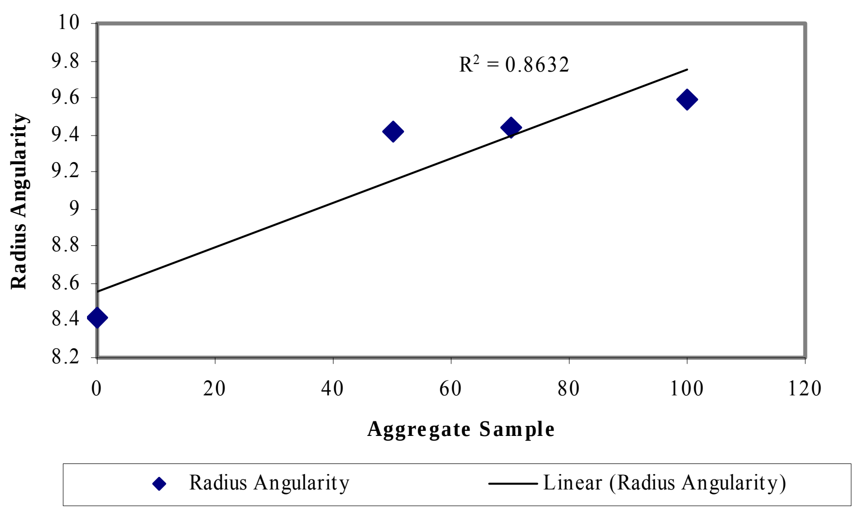

Fig.3.2. Sensitivity of AIMS for radius angularity

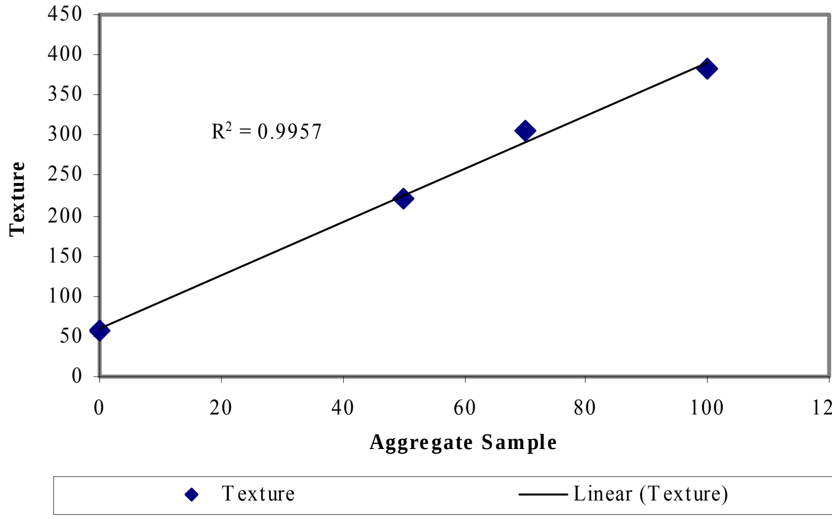

Fig.3.3. Sensitivity of AIMS for texture.

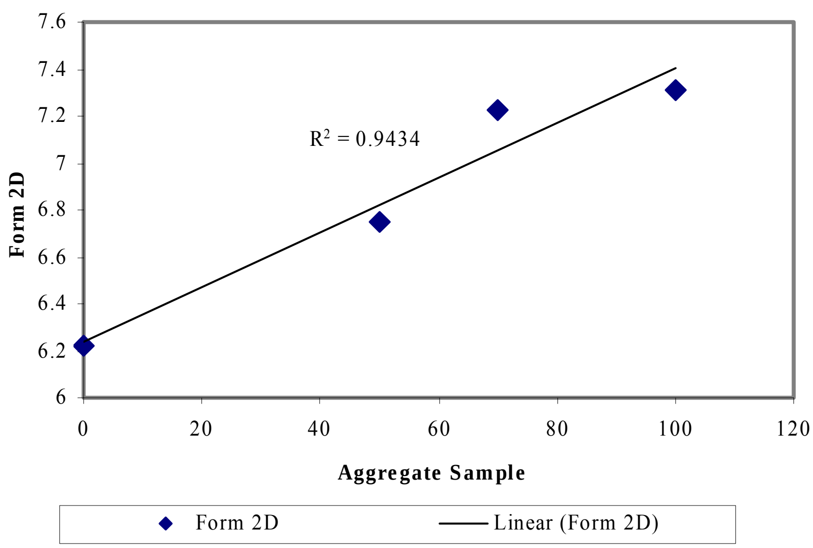

Fig.3.4. Sensitivity of AIMS for form 2D

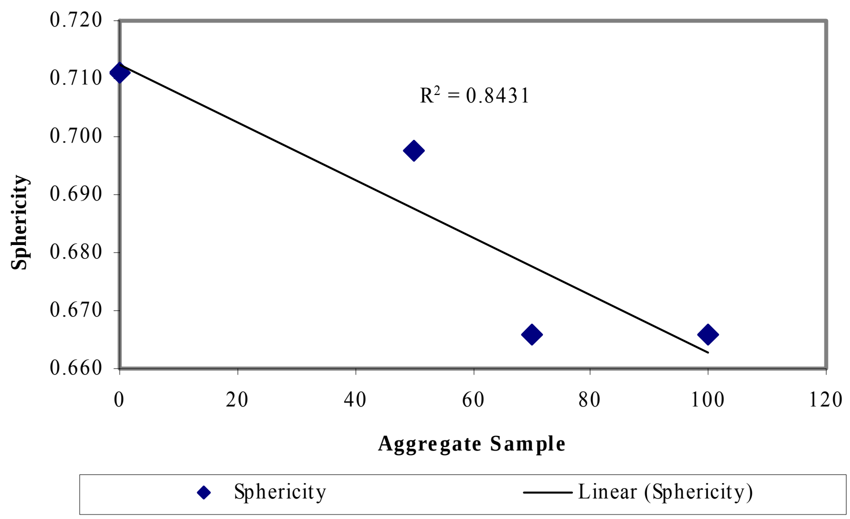

Fig.3.5. Sensitivity of AIMS for sphericity

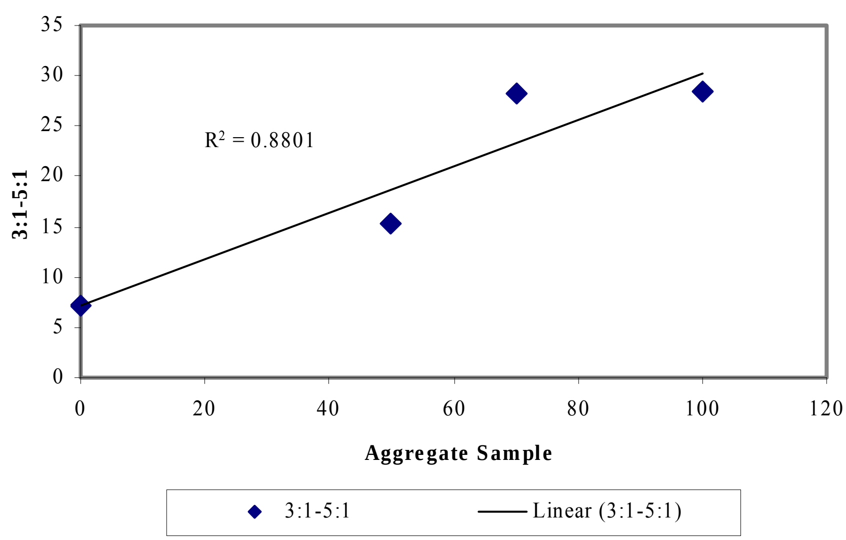

Fig.3. 6. Sensitivity of AIMS for 3:1-5:1

SUMMARY

In this chapter AIMS was evaluated for its repeatability, reproducibility, and sensitivity. The test equipment was found to be highly repeatable with low variation on the order of about 10.9 percent (C.V percent) when random samples were measured. However for the same operator the repeatability was observed to be 4.9 percent when same sample was measured. Thus this variation observed in repeatability study- I can be attributed to natural variation in aggregates in random samples. The reproducibility variation was observed to be 16.3 percent (C.V percent), this variation is also expected to decrease significantly if the same samples are measured by different operators. The test method is also found to be sensitive to the distributions of shape properties between different aggregate samples. The sensitivity for all the parameters measured by the test method was relatively high. Overall, the test method exhibited relatively good repeatability, reproducibility, and sensitivity.

CHAPTER IV

COMPARISON OF STATISTICAL PROPERTIES OF AIMS WITH OTHER TEST METHODS

INTRODUCTION

The repeatability and reproducibility of Aggregate Imaging System (AIMS) was established with multiple operators in the previous chapter. Presently there are many test methods in practice which measure aggregate shape and texture properties. Some of these methods have been in practice for decades and reflect aggregate shape properties using an average index while some are recently developed imaging based systems that capture the aggregate shape distribution for the entire sample. It was of interest to compare the statistical properties of these test methods with AIMS and develop a sub classification within the test methods based on their statistical properties such as repeatability, reproducibility, and sensitivity. The test methods compared with AIMS are shown below for their statistical properties measured in Table 4.1.

Table 4.1. Test Methods Compared with AIMS for Statistical Properties

Test method	Repeatability	Reproducibility	Sensitivity
Uncompacted Void Content of Fine Aggregates AASHTO T304	X	X	
Uncompacted Void Content of Coarse Aggregates AASHTO TP56	X	X	
Percentage of Fractured Particles in Coarse Aggregate ASTM D5821	X	X	
Flat and Elongated Coarse Aggregates ASTM D4791	X	X	
Multiple Ratio Shape Analysis	X	X	X
VDG-40 Video grader	X	X	X
Camsizer	X	X	
WipShape	X	X	X
University of Illinois Aggregate Image Analyzer (UIAIA)	X	X	X
Buffalo Wire Works PDSSA	X	X	X
CAR	X	X	

The tests for repeatability, reproducibility and sensitivity for all the tests methods shown in Table 4.1 were conducted at several locations. Table 4.2 shows the location where each test method was conducted. Three operators were involved in conducting the tests, repeating each of the tests three times on each sample. The operators for conducting all the tests were the same at each of the test locations. The operators were uniformly trained for using all the test methods with same set of instructional guidelines. The operators were trained for data collection aiming at accuracy rather than “good numbers” or “favorable results”. The aggregate samples used for conducting the tests were sieved washed and split into smaller samples according to ASTM and AASHTO procedures and distributed to several places for conducting the tests. The aggregate samples were the same set of 13 coarse and 5 fine aggregate types. (Shown in Table 3.1)

Table 4.2. Locations Where the Tests were Conducted

Test method	**Location at which the tests are conducted**
Uncompacted Void Content of Fine Aggregates AASHTO T304	TTI
Uncompacted Void Content of Coarse Aggregates AASHTO TP56	TTI
Percentage of Fractured Particles in Coarse Aggregate ASTM D5821	TTI
Flat and Elongated Coarse Aggregates ASTM D4791	TTI
Multiple Ratio Shape Analysis	TTI
VDG-40 Video grader	TTI
Camsizer	TTI
CAR	TTI
WipShape	University of Missouri-Rolla
University of Illinois Aggregate Image Analyzer (UIAIA)	University of Illinois
Buffalo Wire Works PDSSA	University of Tennessee-Knoxville

REPEATABILITY AND REPRODUCIBILITY RESULTS

The test results were evaluated for repeatability and reproducibility as described in chapter III under the guidelines of the following standards ASTM E177, C802, C670. The repeatability and reproducibility of each of the test methods was evaluated for each parameter measured by the test equipment. Since each of the test methods measures the aggregate characteristics using different parameters and different scales, it was decided to define the characteristics of an aggregate in terms of the parameters texture, angularity, form, and form/dimensional and express the repeatability and reproducibility of all the test methods for the above parameters. The repeatability and reproducibility of all the test methods are expressed in terms of standard deviation and coefficient of variation, shown in Table 4.3 for coarse aggregates and in Table 4.4 for fine aggregates.

REPEATABILITY AND REPRODUCIBILITY COMPARISON OF ALL TEST METHODS

It was observed in all the tests methods that the standard deviation and coefficient of variation is used to express repeatability and reproducibility. In order to establish the comparison of test methods based on repeatability and reproducibility several factors needed due consideration. All the test methods have their own parameters and scales. Also the parameters of different test equipment vary in their range, for example the maximum and minimum range for the parameters of camsizer differ by 20 percent, however AIMS has a wider range. Some of the test equipment measures an average index, while the imaging based systems measure the shape distributions of the entire sample, however the average index is used for evaluating the repeatability and reproducibility. The advantage of imaging based systems is not revealed since average index is used for all the test methods. All tests on aggregates were performed by trained operators and it is expected that the repeatability and reproducibility will be different for all the operators using various test equipment in different laboratories. All the tests were conducted using single test equipment and the effect of various devices of the same test method cannot be observed. Hence all the test methods were classified into three categories based on their repeatability and reproducibility coefficient of variation as low, medium and high variable. Low (A) CV<=10 percent, Medium (B) 10 percent < CV<=20 percent, High (C) CV>20 percent .This will help in comparison of test methods for their repeatability and reproducibility. The comparison of all test methods for their repeatability and reproducibility is shown in Table 4.5 for coarse aggregates and in Table 4.6 for fine aggregates.

Table 4.3. Repeatability and Reproducibility of Test Methods Measuring Coarse Aggregate Shape **Properties**

Shape Property	**Test Method**	**Parameter Abbreviation Used in This Study**	**Measure Parameter as Reported by Test Method**	**Standard Deviation (SD)**		**Coefficient of Variation (CV)**	
				Repeatability	**Reproducibility**	**Repeatability**	**Reproducibility**
Angularity	Uncompacted Void Content of Coarse Aggregates	UCVCC	% Uncompacted Void content	0.010	0.013	0.009	0.018
	% Fractured Faces	PFF	0 Fractured Faces	0.075	0.260	0.227	0.766
			1 Fractured Face	0.059	0.156	0.165	0.502
			≥2 Fractured Faces	0.050	0.361	0.123	1.150
	Camsizer	CAMCONV	Conv3	0.00034	0.00032	0.00032	0.00031
	WipShape	WSMACR	Min Avg. Curve Radius	0.001	0.004	0.010	0.037
	University of Illinois Aggregate Image Analyzer UIAIA	UIAI	Angularity Index	9.555	15.384	0.018	0.031
	Aggregate Imaging System AIMS	AIMS GRAD	Gradient Angularity	321.968	357.771	0.084	0.106
		AIMS RAD	Radius Angularity	0.309	0.470	0.031	0.048

Table 4.3. (Continued)

Angularity	Buffalo Wire Works PSSDA-Large	PSSDA-Large ROUND	Average Roundness	0.046	0.080	0.027	0.049
			3:1 - 5:1	4.753	6.917	0.309	0.398
Texture	University of Illinois Aggregate Image Analyzer UIAIA	UISTI	Mean Surface Texture Index	0.065	0.093	0.028	0.0556
	Aggregate Imaging System AIMS	AIMSTXTR	Texture Index	36.037	37.395	0.139	0.163
	Camsizer	CAMCONV	Conv3	0.00034	0.00032	0.00032	0.00031
	Un compacted Void Content of Coarse Aggregates UCVC	UCVCC	% Uncompacted Void content	0.010	0.013	0.009	0.018
	WipShape	WSMACR	Min Avg. Curve Radius	0.001	0.004	0.010	0.037
		UIAI	Angularity Index	9.555	15.384	0.018	0.031
Form/ Parameter	Camsizer	CAMSPHT	SPHT3	0.004	0.004	0.003	0.003
		CAMSYMM	Symm3	0.001	0.001	0.002	0.001
	Aggregate Imaging System AIMS	AIMSFORM	Form 2-D	0.229	0.303	0.031	0.041
		AIMSPH	Sphericity	0.014	0.018	0.020	0.026
	Buffalo Wire Works PSSDA-Large	PSSDA-Large ROUND	Average Roundness	0.046	0.080	0.027	0.049

Table 4.3. (Continued)

Form/ Dimensional Ratio	Flat and Elongated Ratio	FER	% of Flat and Elongated Particles	1.000	4.570	0.064	0.317
	Multiple Ratio Analysis MRA	MRA	<Wt. 2:1	0.015	0.025	0.033	0.053
			Wt 2:1- 3:1	0.016	0.025	0.039	0.060
			Wt 3:1-4:1	0.010	0.012	0.374	0.478
			Wt 4:1-5:1	0.005	0.007	0.132	0.312
	VDG-40 Video grader	VDG-40 SLEND	Slenderness Ratio	0.021	0.023	0.013	0.014
		VDG-40 FLAT	Flatness Factor	0.023	0.042	0.016	0.027
	Camsizer	CAML/B	l/b3	0.016	0.016	0.008	0.008
	Wip Shape	WSFER	<2:1	3.502	8.323	0.052	0.114
			<3:1	2.396	4.506	0.159	0.275
			<4:1	1.334	2.196	0.302	0.405
	University of Illinois Aggregate Image Analyzer UIAIA	UIFER	< 3:1	2.370	3.650	0.024	0.036
			3:1 - 5:1	2.136	3.180	0.204	0.268
Form/ Dimensional Ratio	Aggregate Imaging System AIMS	AIMSFER	<3 :1	5.061	7.383	0.063	0.091
			3:1 - 5:1	4.753	6.917	0.309	0.398

Table 4.4. Repeatability and Reproducibility of Test Methods Measuring Fine Aggregate Shape Properties

Shape Property	Test Method	Parameter Abbreviation Used in This Study	Measure Parameter as Reported by Test Method	Standard Deviation (S)		Coefficient of Variation (CV)	
				Repeatability	Reproducibility	Repeatability	Reproducibility
Angularity	Uncompacted Void Content of Fine Aggregates	UCVCF	% Uncompacted Void Content	0.002	0.0053	0.004	0.010
	Camsizer	CAMCONV	Conv3	0.0002	0.0002	0.0002	0.0002
	Aggregate Imaging System AIMS	AIMSGRAD	Gradient Angularity	190.779	314.718	0.046	0.071
		AIMSRAD	Radius Angularity	0.319	0.331	0.029	0.032
	Buffalo Wire Works PSSDA-Small	PSSDA-Small ROUND	Average Roundness	0.111	0.101	0.113	0.111
	Compacted Aggregate Resistance CAR	CAR	Aggregate Resistance	3241.977	4237.560	0.072	0.073
Form	Camsizer	CAMSPHT	SPHT3	0.0017	0.0018	0.0019	0.002
		CAMSYMM	Symm3	0.00032	0.00065	0.00035	0.0007
		CAML/B	l/b3	0.0015	0.0052	0.0011	0.003
	Aggregate Imaging System AIMS	AIMSFORM	Form 2-D	0.305	0.387	0.032	0.041
	Buffalo Wire Works PSSDA-Small	PSSDA-Small ROUND	Average Roundness	0.111	0.101	0.113	0.111

Table 4.5. Classification of Coarse Aggregate Test Methods Based on Repeatability and Reproducibility

Shape Property	Test Method	Parameter Abbreviation Used in This Study	Measure Parameter as Reported by Test Method	Classification Based on Coefficient of Variation (CV)	
				Repeatability	Reproducibility
Angularity	Uncompacted Void Content of Coarse Aggregate	UCVCC	% Uncompacted Void Content	A	A
	% Fractured Faces	PFF	0 Fractured Faces	C	C
			1 Fractured Face	B	C
			≥2 Fractured Faces	B	C
	Camsizer	CANCONV	Conv3	A	A
	WipShape	WSMACR	Min Avg. Curve Radius	A	A
	University of Illinois Aggregate Imaging System UIAIA	UIAI	Angularity Index	A	A
	Aggregate Imaging System AIMS	AIMSGRAD	Gradient Angularity	A	A
		AIMSRAD	Radius Angularity	A	A
	Buffalo Wire Works PSSDA-Large	PSSDA-Large ROUND	Average Roundness	A	A
Texture	University of Illinois Aggregate Imaging System UIAIA	UISTI	Mean Surface Texture Index	A	A
	Aggregate Imaging System AIMS	AIMSTXTR	Texture Index	B	B
	Camsizer	CAMCONV	Conv3	A	A
	Un compacted Void Content of Coarse Aggregate	UCVCC	% Uncompacted Void content	A	A

Table 4.5. Continued

Texture	Wip Shape	WSMACR	Min Avg. Curve Radius	A	A
	University of Illinois Aggregate Imaging System UIAIA	UIAI	Angularity Index	A	A
Form/ Parameter	Camsizer	CAMSPHT	SPHT3	A	A
		CAMSYMM	Symm3	A	A
	Aggregate Imaging System AIMS	AIMSFORM	Form 2-D	A	A
		AIMSSPH	Sphericity	A	A
	Buffalo Wire Works PSSDA-Large	PSSDA-Small ROUND	Average Roundness	A	A
	Multiple Ratio Analysis MRA	MRA	<Wt 2:1	A	A
			Wt 2:1- 3:1	A	A
			Wt 3:1-4:1	C	C
			Wt 4:1-5:1	B	C
	VDG-40 Video grader	VDG-40 SLEND	Slenderness Ratio	A	A
		VDG-40 FLAT	Flatness Factor	A	A
	Camsizer	CAML/B	l/b3	A	A
	WipShape	WSFER	<2:1	A	B
			<3:1	B	C
			<4:1	C	C
	University of Illinois Aggregate Imaging System UIAIA	UIFER	< 3:1	A	A
			3:1 - 5:1	C	C
	Aggregate Imaging System AIMS	AIMSFER	<3 :1	A	A
			3 :1 - 5:1	C	C

Low (A) CV<=10%, Medium (B) 10% < CV<=20%, High (C) CV>20%

Table 4.6. Classification of Fine Aggregate Test Methods Based on Repeatability and Reproducibility

Shape Property	Test Method	Parameter Abbreviation Used in This Study	Measured Parameter as Reported by Test Method	Classification Based on Coefficient of Variation (CV)	
				Repeatability	Reproducibility
Angularity	Uncompacted void content of Fine Aggregates	UCVCF	% Uncompacted Void Content	A	A
	Camsizer	CAMCONV	Conv3	A	A
	Aggregate Imaging System AIMS	AIMSGRAD	Gradient Angularity	A	A
		AIMSRAD	Radius Angularity	A	A
	Buffalo Wire Works PSSDA-Small	PSSDA-Small ROUND	Average Roundness	B	B
	Compacted Aggregate Resistance CAR	CAR	Aggregate Resistance	A	A
Form	Camsizer	CAMSPHT	SPHT3	A	A
		CAMSYMM	Symm3	A	A
		CAML/B	l/b3	A	A
	Aggregate Imaging System AIMS	AIMSFORM	Form 2-D	A	A
	Buffalo Wire Works PSSDA-Small	PSSDA-Small ROUND	Average Roundness	B	B

Low (A) CV<=10%, Medium (B) 10 %< CV<=20%, High (C) CV>20%

SENSITIVITY COMPARISON OF ALL THE TEST METHODS

The sensitivity of any test method is its ability to capture differences in aggregate shape distribution within a sample. The sensitivity of AIMS was evaluated in the previous chapter. The sensitivity of other imaging based test methods shown in Table 4.1 has been evaluated for comparison with the sensitivity of AIMS following the same procedures involved in the evaluation of sensitivity of AIMS (described in chapter III). Also for the evaluation of sensitivity of these tests methods the same aggregate samples were used as described in Table 3.1.

RESULTS AND CONCLUSIONS

The results observed on various test methods are summarized for each of the parameter measured by all the test methods in Table 4.7. A test method is identified as sensitive to aggregate distribution within a sample if it follows a monotonic pattern in the test results for sample 1, sample 2, sample 3 and sample 4 (represented by percent of aggregate 10 on x-axis in the Figs. 4.1-4.15 as 0 percent of aggregate 10 in sample1, 50 percent of aggregate 10 in sample 2, 70 percent of aggregate 10 in sample 3,100 percent of aggregate 10 in sample 4). It is observed in case of imaging systems AIMS, Video grader, and UIAIA followed a monotonic pattern in all the measurement parameters with each of the test methods. However MRI and PSSDA did not follow a monotonic pattern in their measurements and Wipshape also did not follow a monotonic pattern in some of the parameters measured by it. The R^2 value can be used to assess the specific sensitivity of each of the parameter measured by all test methods.

Table 4.7. Sensitivity of Test Methods

Test Method	Measured Parameter	Monotonic Pattern	R^2
AIMS	Form 2D	Yes	0.9434
	Radius Angularity	Yes	0.8632
	Gradient Angularity	Yes	0.9136
	Texture	Yes	0.9957
	Sphericity	Yes	0.8431
	3:1-5:1	Yes	0.8801
Video Grader	Slenderness Ratio	Yes	0.8989
	Flatness Factor	Yes	0.9705
MRI	<Wt. 2:1	No	0.0764
	Wt 2:1- 3:1	No	0.0018
	Wt 3:1-4:1	No	0.1076
	Wt 4:1-5:1	No	0.1580
PSSDA	Total Roundness	No	0.4414
UIAIA	Mean Angularity	Yes	0.9991
	Mean Surface Texture	Yes	0.9984
	< 3 : 1	Yes	0.9488
	3:1 - 5:1	Yes	0.9189
WipShape	Min Avg Curve Radius	No	0.7919
	2:01	Yes	0.9923
	3:01	No	0.4984
	4:01	Yes	0.6049

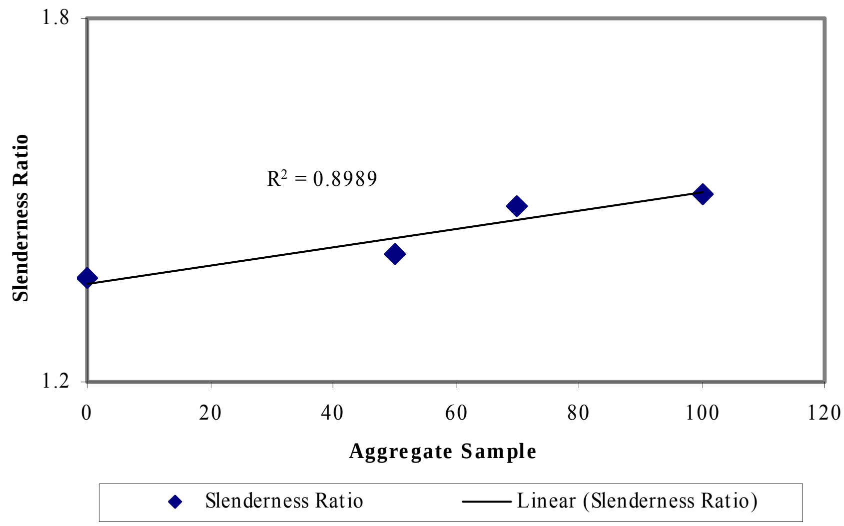

Fig.4.1. Sensitivity of Video grader for slenderness ratio

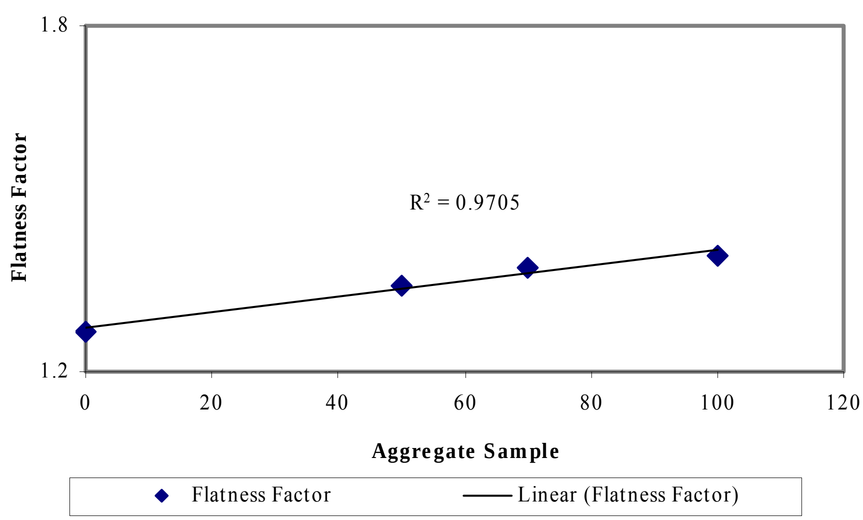

Fig.4.2. Sensitivity of Video grader for flatness factor

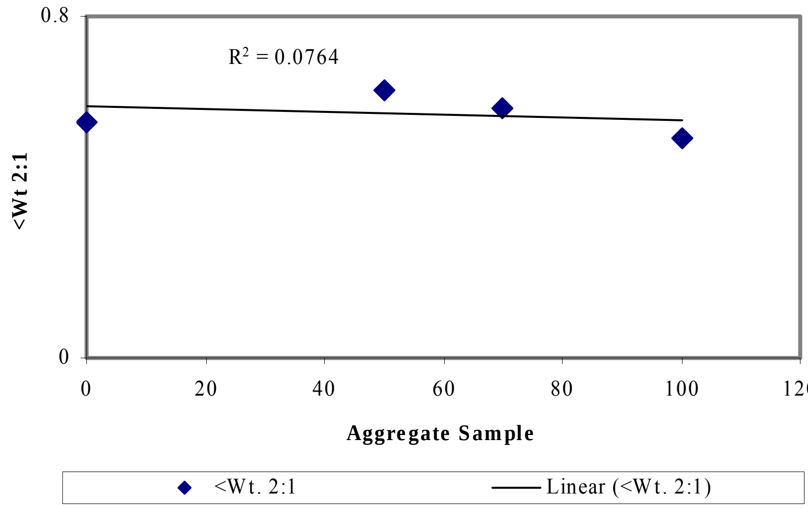

Fig.4.3. Sensitivity of MRI for < Wt 2:1

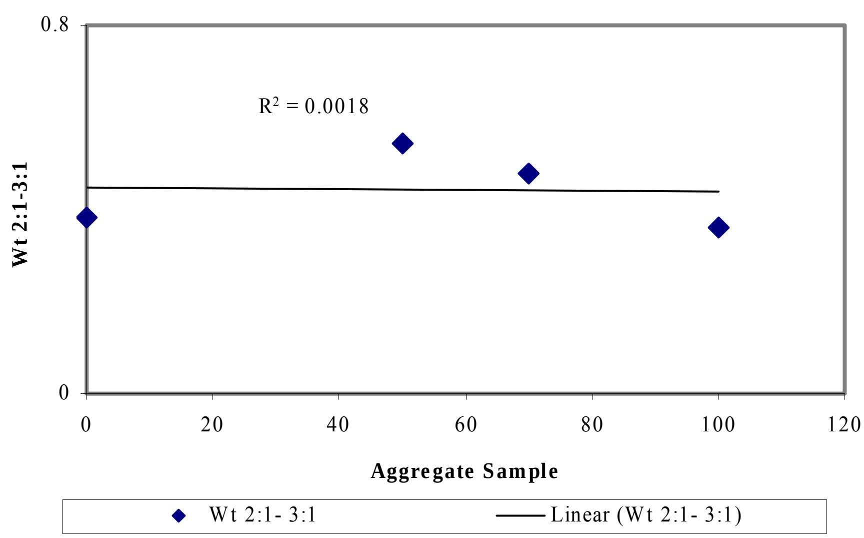

Fig.4.4. Sensitivity of MRI for Wt 2:1-3:1

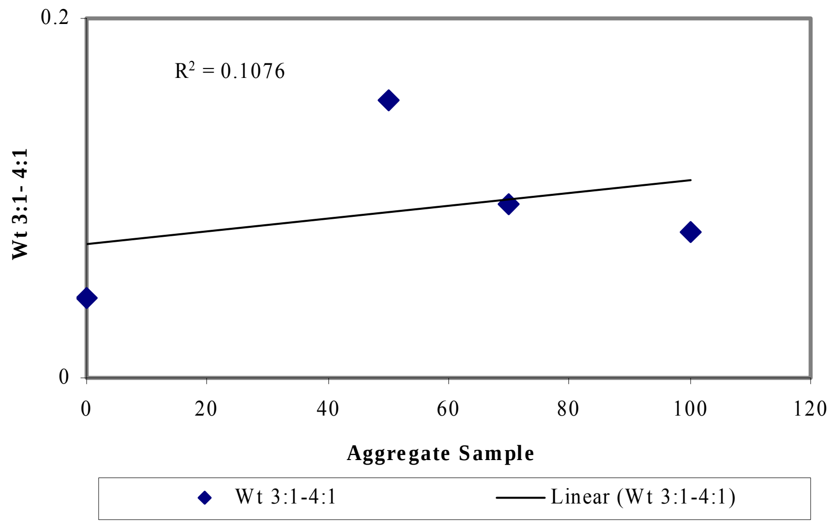

Fig.4.5. Sensitivity of MRI for Wt 3:1-4:1

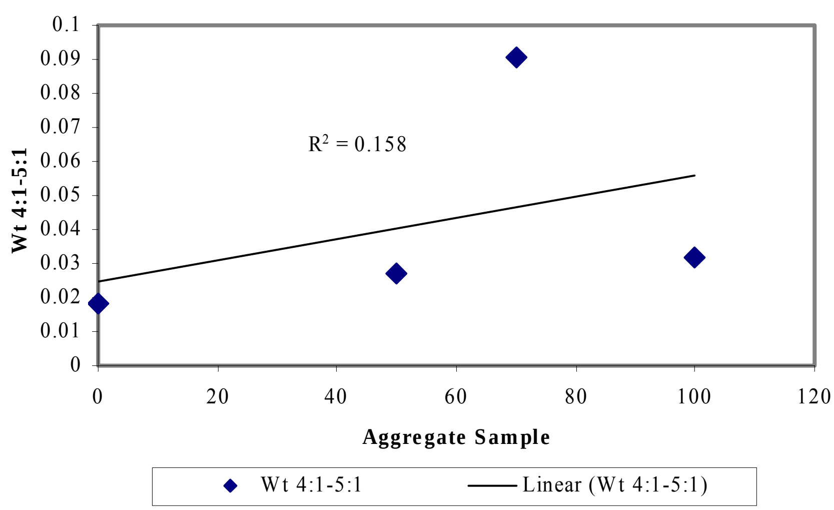

Fig.4.6. Sensitivity of MRI for Wt 4:1- 5:1

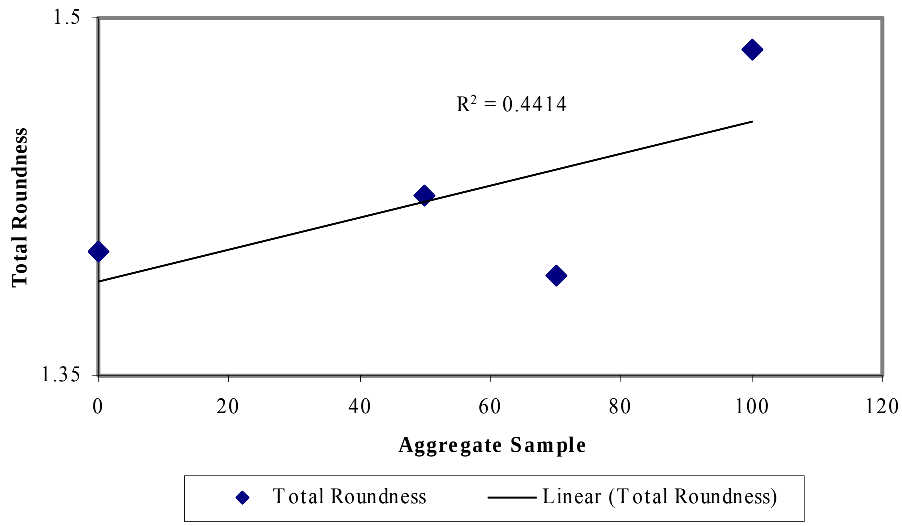

Fig.4.7. Sensitivity of PSSDA for total roundness

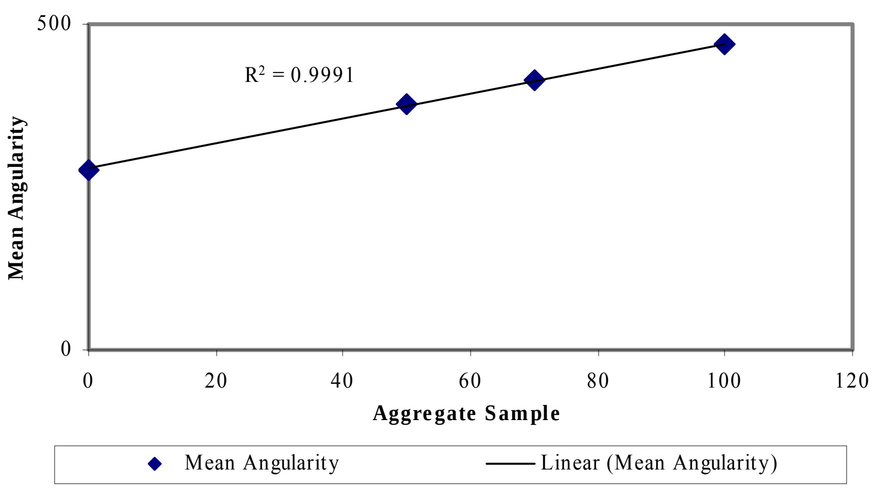

Fig.4.8. Sensitivity of UIAIA for mean angularity

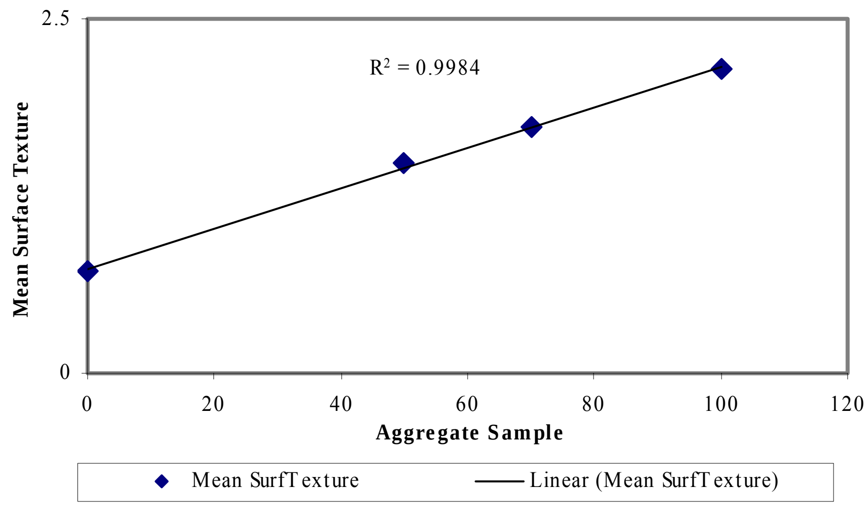

Fig.4.9. Sensitivity of UIAIA for surface texture

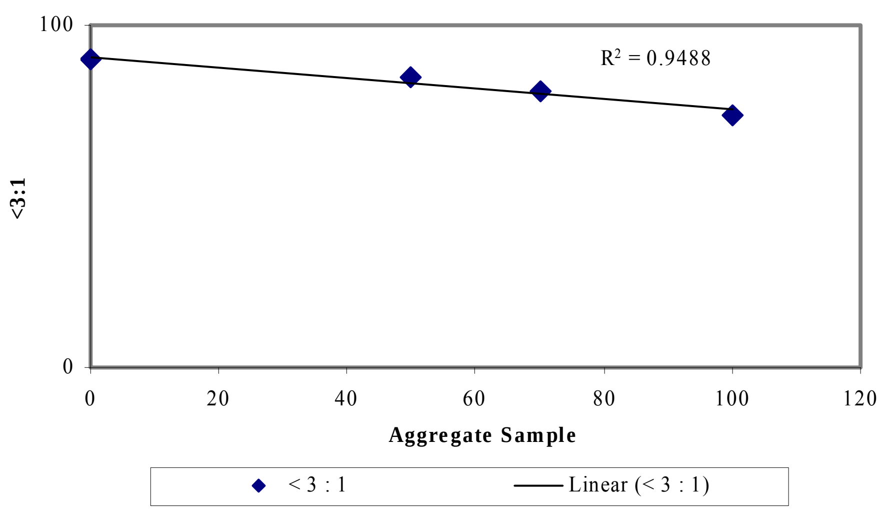

Fig.4.10. Sensitivity of UIAIA for <3:1

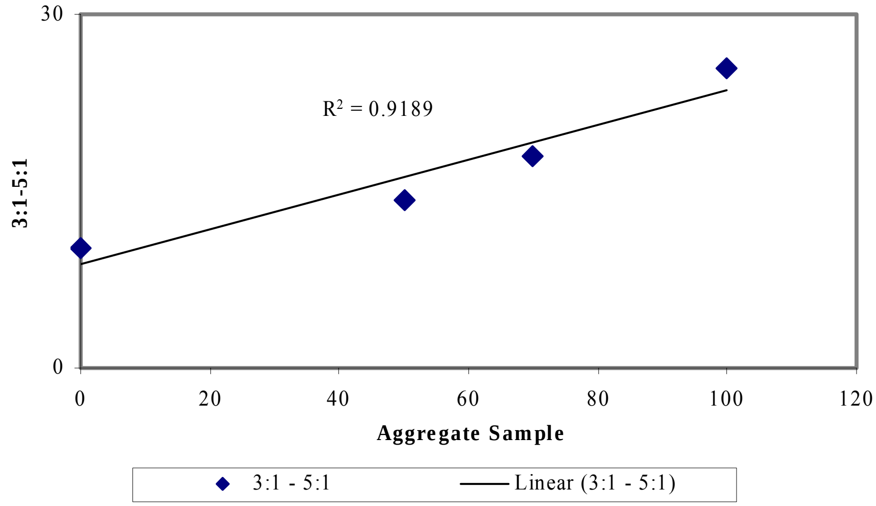

Fig.4.11. Sensitivity of UIAIA for 3:1-5:1

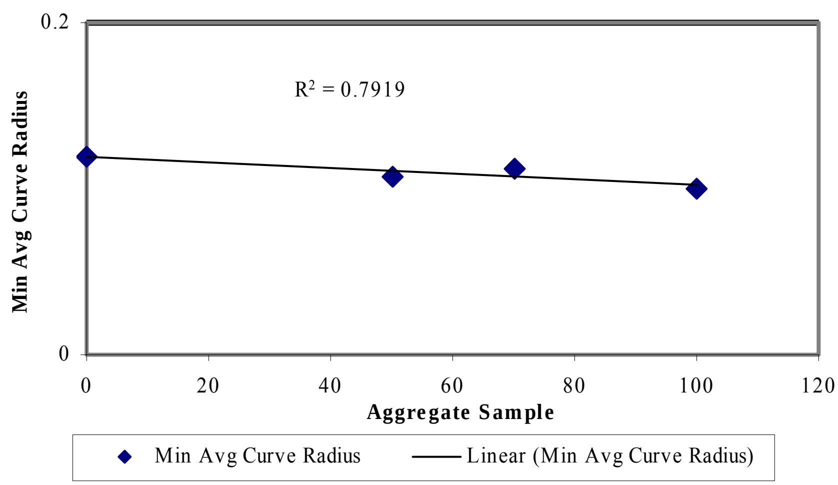

Fig.4.12. Sensitivity of WipShape for Min Avg Curve Radius

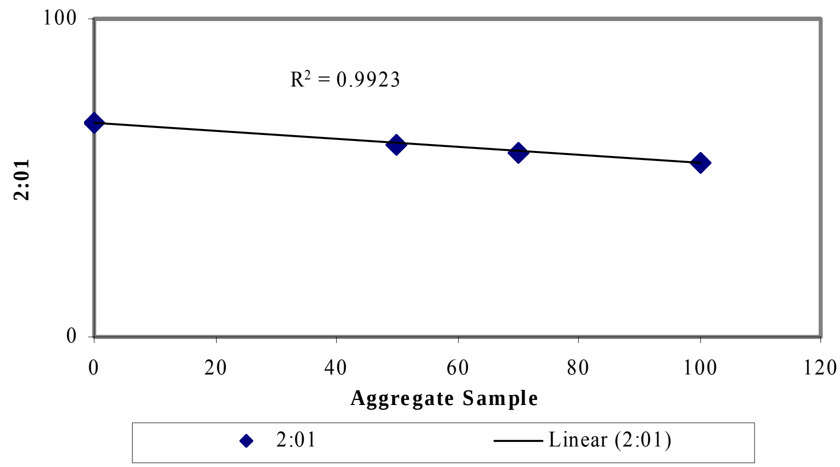

Fig.4.13. Sensitivity of WipShape for 2:01

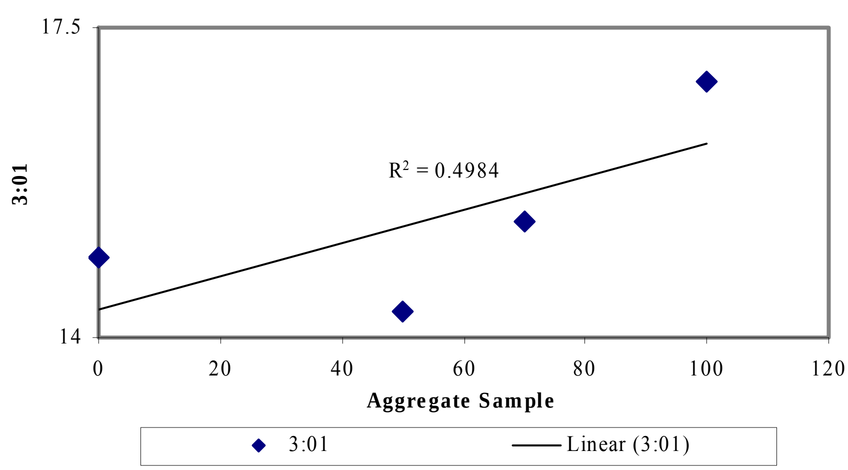

Fig.4.14. Sensitivity of WipShape for 3:01

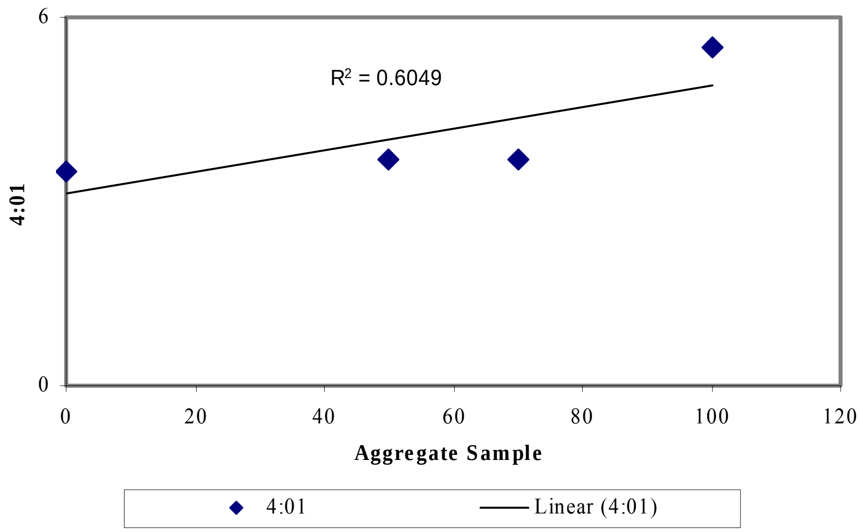

Fig.4.15. Sensitivity of WipShape for 4:01

SUMMARY

This chapter includes the comparison of statistical properties of AIMS (repeatability, reproducibility, and sensitivity) with other tests methods. The test methods were divided into three classes as having low, medium and high repeatability and reproducibility based on the coefficient of variation. It was observed that all the imaging based test methods were highly repeatable and reproducible (low coefficient of variation). AIMS, when compared with other test methods, was found to be highly repeatable and reproducible in measurement of both coarse and fine aggregates. It was also observed that many of the test methods had low repeatability and reproducibility (high coefficient of variation) in measurement of the property form/dimensional ratio (flat and elongated particles). The sensitivity of all these test methods was also evaluated and it was observed that AIMS, video grader, and UIAIA were sensitive to changes in aggregate distributions in all the parameters measured by them.

CHAPTER V

STATISTICAL METHODS FOR DESCRIBING THE DISTRIBUTION OF SHAPE CHARACTERISTICS AND TESTING DIFFERENCES AMONG AGGREGATES

INTRODUCTION

AIMS provides measurements on all particles in an aggregate sample. The results are presented by cumulative distribution functions. This chapter discusses the determination of functions that can describe the distribution of shape characteristics. The parameters of these functions can be related to the performance of pavement layers, and consequently the whole distribution of shape characteristics is accounted for in understanding pavement performance. This is followed by the development of a statistical method that can be used to determine the variation among aggregate samples based on the distribution of shape characteristics rather than average values only. Such a statistical method can be used to test the changes in aggregates due to changes in aggregate source or production methods.

EQUATION –I

Kim et al. (2004) used Eq. 5.1 to describe the aggregate shape and gradation cumulative distribution curves. The parameters of the equation g_a, g_n, and g_m were related to the resilient properties of unbound aggregate systems. The Figs. 5.1-5.3 show the effect of each of the parameters on the cumulative distribution curves.

$$Y = \frac{100}{\ln\left(\exp(1) + \left(\frac{ga}{x}\right)^{g_n}\right)^{gm}} \tag{5.1}$$

where

Y= percent passing a particular class, x

x = particle measured value (shape, angularity, texture)

g_a= fitting parameter corresponding to initial break in the distribution curve.

g_n= fitting parameter corresponding to maximum slope of the distribution curve.

g_m= fitting parameter corresponding to the curvature of the distribution curve.

This distribution function was applied to the cumulative distributions of AIMS test results on shape and texture distributions. For modeling this distribution function 13 coarse aggregate samples that vary in a wide variety of shape properties were selected shown in Table 3.1. The measured distributions for various aggregates were fitted to Equation- I and the parameters were found for each aggregate and each property measured. The parameters are shown for each property in Tables 5.1 - 5.5.

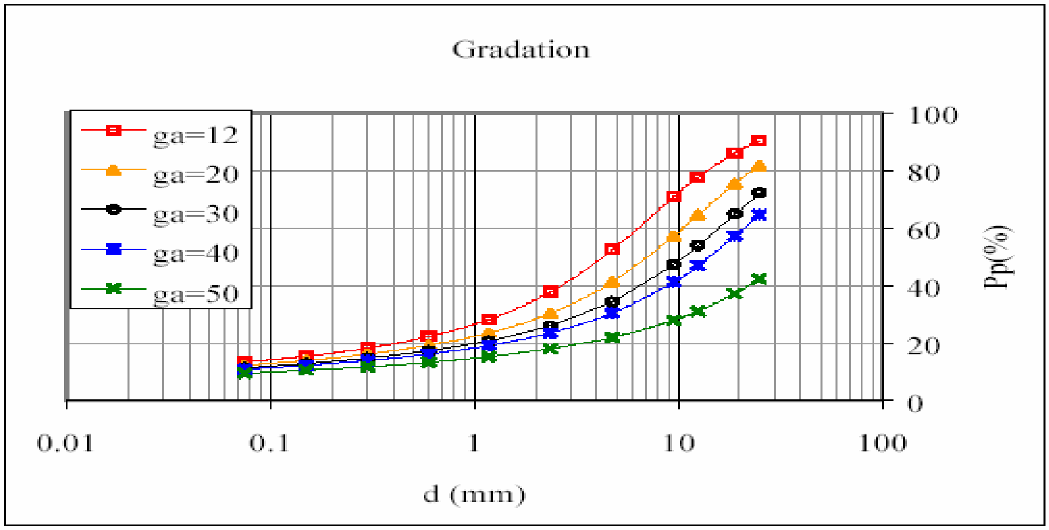

Fig.5. 1. Sample plot with gn =1.544 and gm = 0.9644, and ga varies (Kim et al. 2004)

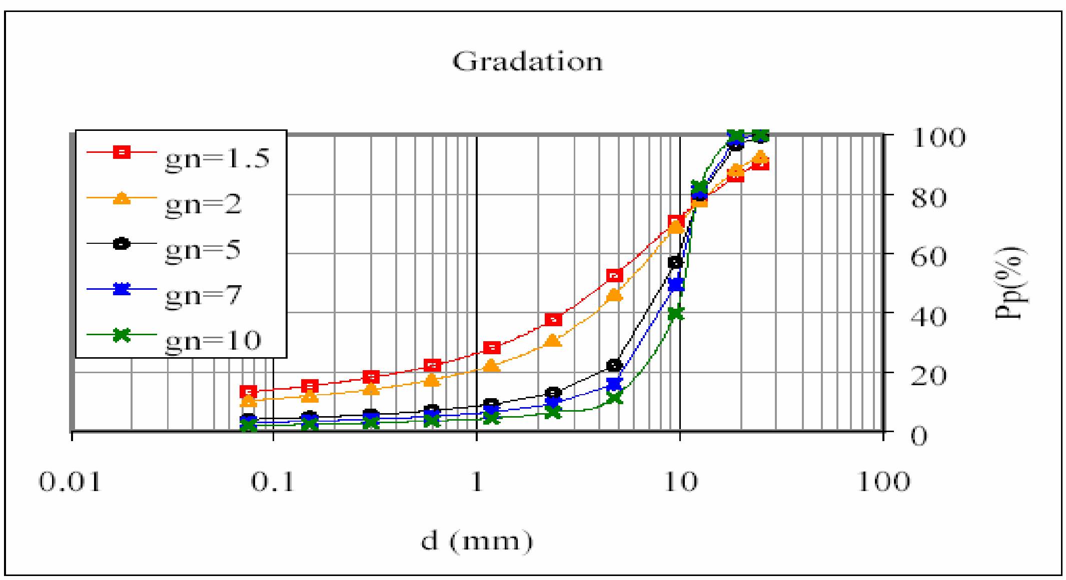

Fig.5. 2. Sample plot with ga =11.997 and gm = 0.9764, and gn varies (Kim et al. 2004)

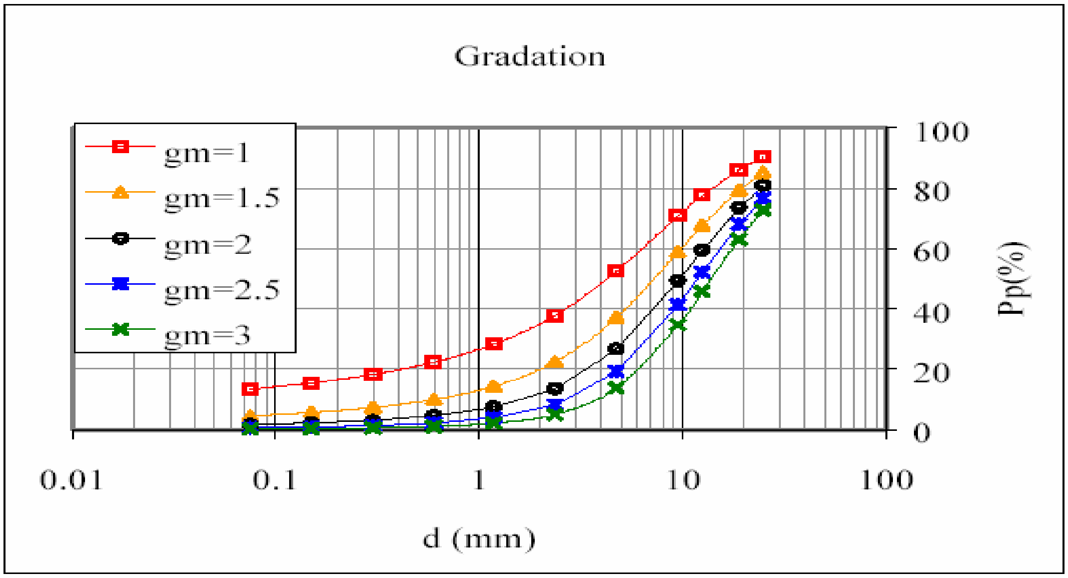

Fig.5. 3. Sample plot with gn = 1.544 and ga = 11.997, and gm varies (Kim et al. 2004)

Table 5.1. Parameters of Equation- I for Radius Angularity

Aggregate	g_a	g_m	g_n
1	7.346	2.584	3.913
2	8.527	1.817	5.818
3	11.107	1.858	4.871
4	11.603	2.088	5.014
5	9.706	2.554	4.885
6	9.980	1.940	5.474
7	11.487	1.550	5.802
8	7.917	2.064	4.241
9	11.067	1.568	5.948
10	7.095	4.368	3.367
11	11.318	1.974	6.662
12	10.387	2.214	5.455
13	10.304	2.089	5.957

Table 5.2. Parameters of Equation- I for Gradient Angularity

Aggregate	g_a	g_m	g_n
1	3098.936	1.304	3.855
2	3250.317	1.624	3.746
3	3261.117	1.313	4.605
4	3254.526	1.195	5.152
5	4138.848	1.075	6.415
6	2644.119	1.612	3.854
7	3402.386	1.607	3.727
8	2592.482	1.553	3.437
9	4279.870	0.981	5.626
10	3366.467	1.571	3.842
11	2882.511	1.879	2.993
12	3518.215	1.258	3.951
13	3396.672	2.029	4.103

Table 5.3. Parameters of Equation- I for Form- 2D

Aggregate	g_a	g_m	g_n
1	5.992	2.219	5.648
2	6.328	2.640	7.257
3	6.433	5.831	5.933
4	7.238	3.982	6.030
5	7.733	2.439	9.032
6	7.482	2.052	7.801
7	7.238	3.186	6.214
8	5.378	2.719	4.427
9	7.631	2.194	6.540
10	7.467	1.997	7.316
11	8.134	1.859	9.253
12	4.939	11.831	4.836
13	6.721	4.220	6.070

Table 5.4. Parameters of Equation-I for Sphericity

Aggregate	g_a	g_m	g_n
1	0.716	1.910	15.786
2	0.765	1.931	16.856
3	0.619	4.209	12.346
4	0.613	2.303	9.161
5	0.760	1.052	19.443
6	0.699	2.315	14.072
7	0.686	1.554	13.111
8	0.760	1.453	15.559
9	0.675	1.707	12.016
10	0.727	1.188	15.645
11	0.681	2.022	16.366
12	0.690	1.928	10.277
13	0.576	4.242	9.377

Table 5.5. Parameters of Equation-I for Texture

Aggregate	g_a	g_m	g_n
1	70.4518	1.2537	3.1190
2	84.3497	1.9397	2.9502
3	311.8152	3.8945	4.1998
4	150.9904	3.0865	2.6993
5	387.5927	1.4210	8.8276
6	230.7379	2.2327	3.5851
7	130.8074	2.5230	2.5904
8	85.2174	3.1624	2.3227
9	556.9411	1.8097	7.7035
10	416.7835	1.6567	5.7845
11	292.8944	1.5297	8.8148
12	97.1651	2.0821	4.0456
13	252.7719	3.1148	4.0793

The parameters g_a, g_m, and g_n are observed for their variation for different aggregates. Each property measured has been evaluated individually. In order to observe the effect of each of the parameters g_a, g_m, and g_n on the measured distribution curves the values of g_a, g_m, and g_n for all aggregates should be independent and significantly different from each other. Hence the confidence interval has been calculated for the mean difference of each of the parameters for all the combinations of aggregates. The mean difference has been found at a confidence level of 95 percent. The confidence interval calculated below is for the mean difference between any two aggregates for each parameter g_a, g_m, and g_n and for the values to be independent the confidence interval should not contain zero.

The confidence interval is calculated as shown

$$\left(X_i - X_j\right) \pm 1.96\sqrt{\left(\sigma_i^2 + \sigma_j^2\right)} \tag{5.2}$$

where

X_i = estimated value of the parameter for aggregate, i

X_j = estimated value of the parameter for aggregate, j

σ_i = standard error in the estimation of the parameter, X_i and

σ_j = standard error in the estimation of the parameter, X_j

The confidence intervals have been found for all the aggregate combinations for all the three parameters g_a, g_m, and g_n for each property measured individually. The parameters are found to be different for all the aggregates in measurement of texture except for one aggregate combination of aggregate 6 and aggregate 13 (Table 3.1). In measurement of form, radius angularity, gradient angularity, and sphericity, in some cases aggregate combinations were not different at 95 percent confidence level for the parameters. Tables 5.6-5.10 show all aggregate combinations and it can be determined whether or not the combination has parameters g_a, g_m, and g_n that are significantly different or not. The shaded cells indicate that the aggregates do not have different parameters. For example, in case of texture aggregates 6 and 13 do not have different parameters.

Table 5.6. Aggregate Combinations for Texture (Equation- I)

Texture	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.7. Aggregate Combinations for Radius Angularity (Equation- I)

Radius Angularity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.8. Aggregate Combinations for Gradient Angularity (Equation- I)

Gradient Angularity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5. 9. Aggregate Combinations for Form (Equation- I)

Form	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.10. Aggregate Combinations for Sphericity (Equation- I)

Sphericity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

GAMMA DISTRIBUTION

It is desirable to use a standard distribution function to describe the shape characteristics of an aggregate sample. Such a standard function has well defined parameters with known relationships to changes in the distributions. For this purpose, the BestFit 4.5 software was used and several standard distribution functions were fitted to the distributions of shape, angularity and texture. Each of the standard distribution function fitted for an aggregate sample was ranked according to the root mean squared error (RMS) value. There were 13 aggregate samples and 5 properties measured (texture, radius angularity, gradient angularity, form, and sphericity), hence each of the standard distribution function was fitted to 65 distribution curves. All the standard distribution functions were fitted to the aggregate distribution curves to check if they could model all the 65 aggregate distribution curves. Many of the distribution functions, such as the lognormal and beta general, fitted the data well but only the gamma distribution fitted all the 65 aggregate distribution curves with good RMS values. The RMS values for all aggregates fitted to the gamma distribution are attached in the appendix. Hence the aggregate distribution curves for AIMS follow the gamma distribution. The parameters are shown in Table 5.11 for all the aggregates.

The CDF of the gamma distribution is given by

$$F(x) = \int_0^x \frac{y^{\alpha-1} e^{-\frac{Y}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)} dy \tag{5.3}$$

Where Scale parameter, β

Shape parameter, α>0 and Γ(α) is the gamma function

Table 5.11. Shape and Scale Parameters of the Gamma Distribution for all Aggregates

Aggregate	Form		Texture		Sphericity		Radius Angularity		Gradient Angularity	
	Shape	Scale	Shape	Scale	Shape	Scale	Shape	Scale	Shape	Scale
1	11.000	1.837	1.906	0.033	75.382	107.788	6.204	0.788	2.967	0.001
2	20.657	3.181	2.939	0.035	82.940	110.683	9.446	1.166	3.803	0.001
3	20.260	2.584	8.684	0.023	77.889	118.622	7.165	0.677	3.989	0.001
4	17.851	2.184	3.297	0.017	30.187	49.395	8.292	0.724	4.086	0.002
5	29.217	3.755	17.013	0.048	48.008	68.616	9.467	0.936	5.635	0.002
6	19.371	2.646	4.781	0.020	69.281	99.472	9.004	0.933	3.996	0.002
7	16.681	2.142	2.810	0.019	41.233	63.345	8.101	0.776	3.690	0.001
8	8.218	1.428	2.727	0.024	52.417	72.796	6.000	0.766	2.981	0.001
9	14.464	1.910	17.166	0.032	38.668	59.908	8.638	0.856	3.329	0.001
10	16.705	2.302	8.823	0.023	38.473	57.397	5.849	0.622	3.754	0.001
11	25.843	3.304	17.988	0.066	84.403	126.079	14.357	1.309	2.861	0.001
12	14.470	1.947	5.574	0.058	32.854	49.119	10.531	1.015	2.782	0.001
13	19.428	2.537	7.251	0.025	44.284	70.866	11.718	1.157	5.571	0.002

It was of interest to evaluate the variations in the parameters of the gamma distribution with various aggregate types. The confidence interval for each parameter was calculated to determine if the mean difference between any two aggregates is zero at 95 percent confidence level. The confidence interval calculated in Eq. (10) below is for the mean difference between any two aggregates. For the shape and scale parameters to be different for all combinations of aggregates the confidence interval should not contain zero.

$$\left(X_i - X_j\right) \pm 1.96\sqrt{\left(\sigma_i^2 + \sigma_j^2\right)} \tag{5.4}$$

where

X_i = estimated value of the parameter for aggregate, i

X_j = estimated value of the parameter for aggregate, j

σ_i = standard error in the estimation of the parameter, X_i and

σ_j = standard error in the estimation of the parameter, X_j

The confidence intervals for the mean difference of the parameters for all the combinations of aggregates were calculated. Tables 5.12-5.16 show all aggregate combinations, and these results indicate whether the combination has parameters (shape and scale) that are significantly different or not. The shaded cells indicate that the aggregates do not have significantly different parameters with 95 percent confidence. In case of texture, all aggregates were found to have significantly different parameters at 95 percent confidence level except for one aggregate combination of aggregate 3 and aggregate 10 (Table 5.12). In measurement of angularity and form some aggregate combinations were found to have parameters that are not significantly different at 95 percent confidence level (Tables 5.13 – 5.16). More aggregate combinations were found to have significantly different shape and scale parameters for texture compared with form and angularity. This indicates that aggregates exhibit more variation in texture than the other characteristics. This finding emphasizes the important of measuring texture, and relating to the performance of pavement layers.

Table 5.12. Aggregate Combinations for Texture (Gamma Distribution)

Texture	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.13. Aggregate Combinations for Radius Angularity (Gamma Distribution)

Radius Angularity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.14. Aggregate Combinations for Gradient Angularity (Gamma Distribution)

Gradient Angularity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.15. Aggregate Combinations for Form (Gamma Distribution)

Form	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

Table 5.16. Aggregate Combinations for Sphericity (Gamma Distribution)

Sphericity	1	2	3	4	5	6	7	8	9	10	11	12	13
1													
2	X												
3	X	X											
4	X	X	X										
5	X	X	X	X									
6	X	X	X	X	X								
7	X	X	X	X	X	X							
8	X	X	X	X	X	X	X						
9	X	X	X	X	X	X	X	X					
10	X	X	X	X	X	X	X	X	X				
11	X	X	X	X	X	X	X	X	X	X			
12	X	X	X	X	X	X	X	X	X	X	X		
13	X	X	X	X	X	X	X	X	X	X	X	X	

CATEGORICAL UNITS FOR AIMS

AIMS is capable of measuring the physical characteristics of various sizes of coarse and fine aggregates. The AIMS test results consist of a cumulative distribution function for each of the characteristics. Al-Rousan (2004) has developed aggregate shape classification system based on the cluster analysis of wide range of aggregates (Al-Rousan 2004). In this system, aggregates within a sample are divided into categories as shown in Table 5.17. For example, texture is divided into (percent polished, percent smooth, percent low textured, percent medium textured, percent high textured).

Table 5.17. Categorical Units for Aggregate Imaging System (AIMS)

Measured Property	**Sub Class**				
	1	**2**	**3**	**4**	**5**
Texture	% Polished	% Smooth	% Low Roughness	% Medium Roughness	% High Roughness
Radius Angularity	% Rounded	% Sub Rounded	% Sub Angular	% Angular	
Gradient Angularity	% Rounded	% Sub Rounded	% Sub Angular	% Angular	
Form 2D	% Circular	% Semi Circular	% Semi Elongated	% Elongated	
Sphericity	% Flat and Elongated	% Low Sphericity	% Medium Sphericity	% High Sphericity	

In this study, it is proposed to employ the “categorical units” in the evaluation of differences between aggregates. The chi-square goodness of fit test is used to find significant differences in the categorical data of aggregates. To check the applicability of categorical units to assess differences among aggregates, four different cases were evaluated. In each case chi-square goodness of fit test was adopted to test differences among the aggregates compared. In the first case two aggregate samples were compared. This case helps to demonstrate differences when two aggregate samples are to be compared. In the second case, many aggregate samples were evaluated so as to help in comparing one aggregate sample to a database of measurements of aggregates. In the third case one, one aggregate sample was measured three times. This helps to identify the ability of the methods to capture the differences or similarities between samples from the same aggregate versus from different aggregates. The fourth case evaluated was for samples prepard by mixing different proportions of two aggregates. This helps to quantify the sensitivity of categorical units to different distributions of aggregate characteristics. Thus the four cases selected help in comprehensively evaluating the application of categorical units to find differences among aggregate shape distributions measured by AIMS.

Two-Aggregate Samples

This test can be used when comparison is needed between two different aggregate samples measured by AIMS. The chi-square goodness of fit test was adopted to test the differences between aggregate 1 and aggregate 10 (Table 3.1), and the p-value of the pearson chi-square tests the null hypothesis.

- Null hypothesis: Two aggregates are not different in at least one subclass.
- Alternative hypothesis: Two aggregates are different in at least one subclass.

Table 5.18 shows the chi-square test results for the measurement of texture. The pearson chi-square p-value is 0.000 and less than 0.05. Hence we reject the null hypothesis with 95 percent confidence and aggregates 1 and 10 are different using the categorical units in measurement of texture.The standard residual can be observed for the differences between aggregates in all the subclasses. If the standard residual is greater than 1.96, then we can ascertain that differences exist in the respective subclasses for the two aggregates. In the case of texture aggregates 1 and 10 have standard residuals greater than 1.96 in subclasses 1, 2, 3, and 4. Hence aggregates 1 and 10 are different in all the subclasses. Also in measurement of all the parameters (texture, radius angularity, gradient angularity, form and sphericity) for aggregates 1 and 10, the pearson chi-square p-value is found to be less than 0.05. Hence aggregates 1 and 10 are different in all the parameters measured by AIMS. Also the differences in each parameter can be observed as discussed above. Thus the categorical units can be used to define differences between two aggregate samples. Also the graphical representation can be used to define differences among aggregates as shown in Fig. 5.4 for texture.

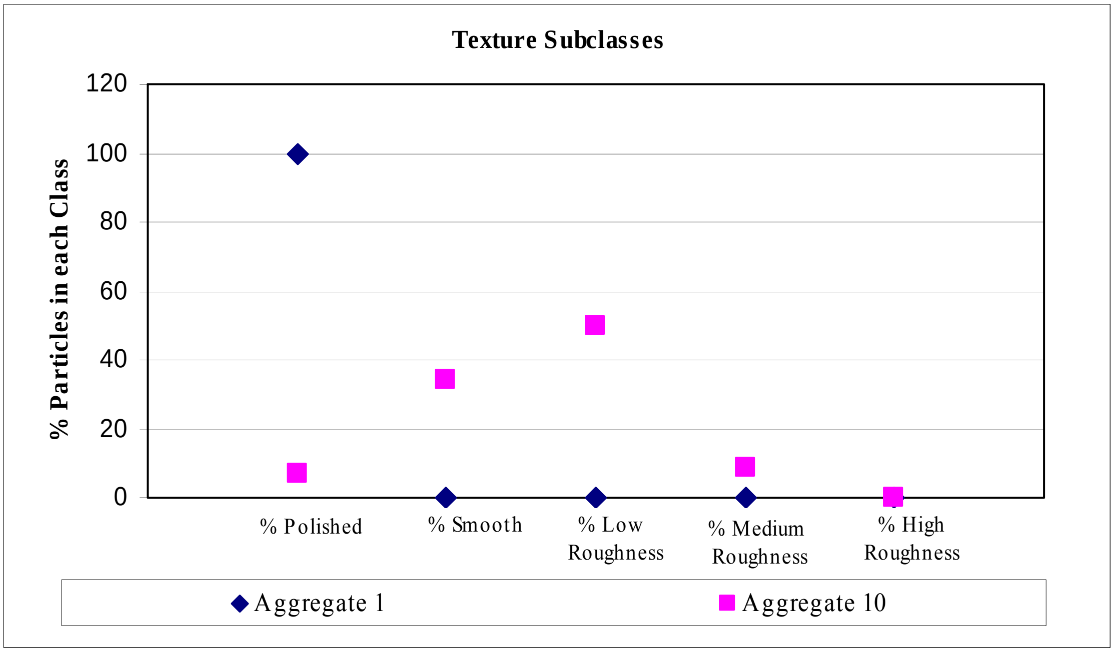

Fig.5. 4. Graphical representation of categorical units for texture

Table 5.18. Chi Square Test for Aggregates 1 and 10

Aggregate Sample Descriptions	**Measured Property**	**Standard Residual**				**Chi-Square P- value**
		SubClass				
Two Aggregate Samples		1	2	3	4	
1	Texture	6.4	-4.1	-5	-2.1	0.000
10		-6.4	4.1	5	2.1	
1	Gradient Angularity	2.1	-0.8	0.8	-1.5	0.008
10		-2.1	0.8	-0.8	1.5	
1	Sphericity	-1	-1.9	1.1	0	0.009
10		1	1.9	-1.1	0	

Several Aggregate Samples

When many aggregate samples are measured using AIMS the chi-square test can also be used to test the differences among the aggregates. For this purpose all 13 aggregate samples are compared (Table 3.1).

- Null hypothesis: All the aggregates are not different in at least one subclass.
- Alternative hypothesis: All the aggregates are different in at least one subclass.

The test statistic is determined from pearson chi-square test statistic. In all the parameters compared (texture, radius angularity, gradient angularity, form and sphericity) the p-value is less than 0.05.Hence we reject the null hypothesis and all the 13 aggregates are different from each other in at least one subclass.

Same Aggregates with Repeated Measurements

The same aggregate sample (aggregate 1) is repeatedly measured three times. The repeated measures of aggregate 1 should not be different and the pearson chi-square test statistic is used for this purpose.

- Null hypothesis: All three aggregates are not different in at least one subclass.
- Alternative hypothesis: All three aggregates are different in at least one subclass.

In all the parameters compared (texture, radius angularity, gradient angularity, form and sphericity) the p-value is greater than 0.05. Hence with 95 percent confidence we do not reject the null hypothesis. All the aggregates are not different in at least one subclass.

Blends of Aggregates

The sensitivity of AIMS was evaluated in chapter III where the mean values of measurements were used to evaluate the sensitivity. The same four aggregate samples used in chapter III were observed to see if they are different in categorical units.

- Null hypothesis: All four aggregates are not different in at least one subclass.
- Alternative hypothesis: All four aggregates are different in at least one subclass.

The p-value was observed to be less than 0.05 in all the parameters measured by AIMS. Thus we reject the null hypothesis, and all the aggregates are different using categorical units. Thus AIMS is sensitive in measuring aggregates using categorical units. The summary Table 5.19 describes the chi-square p-value for all the properties measured by AIMS for all the four cases discussed above (All the chi-square test results for all the cases are attached in the appendix for all cases.)

Table 5.19. Chi-Square Test Results for Categorical Units

Aggregate Sample Descriptions	Measured Property	Chi-Square P- value
Two Aggregate Samples	Texture	0.000
	Radius Angularity	0.009
	Gradient Angularity	0.008
	Form 2D	0.000
	Sphericity	0.009
Many Aggregate Samples	Texture	0.000
	Radius Angularity	0.000
	Gradient Angularity	0.000
	Form 2D	0.000
	Sphericity	0.000
Same Aggregates (Repeated)	Texture	1.000
	Radius Angularity	0.931
	Gradient Angularity	0.489
	Form 2D	0.607
	Sphericity	0.889
Sensitivity	Texture	0.000
	Radius Angularity	0.000
	Gradient Angularity	0.001
	Form 2D	0.004
	Sphericity	0.000

SUMMARY

This chapter presented statistical methods for the analysis of aggregate shape characteristics. The gamma distribution function was found to describe the distribution of all shape characteristics of the aggregates used in this study. The statistical difference between the gamma function parameters was most pronounced in the texture measurements. This finding confirms that aggregates differ the most in their texture. A statistical method based on the “Categorical Units” is used in this study to analyze the differences among aggregate samples. This method is able to capture the significant differences between aggregates. The statistical analysis methods presented in this paper can be used in a number of applications:

- The parameters of the distribution function can be determined for a certain aggregate source, and be used to detect changes in aggregate physical characteristics as part of the quality assurance (QA) and quality control (QC) procedures.
- The parameters of the distribution function can be related to the performance of pavement layers. It is expected that performance will have better correlation with the distribution parameters than with average parameters of aggregate characteristics.
- The analysis methods presented in this paper can be used to compare the results from different crushing techniques, and to assist in deciding on the techniques that produce the most desirable characteristics.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

The quality of the AIMS measurements was studied using statistical analysis. It was evaluated for its repeatability, reproducibility, and sensitivity on a wide range of coarse and fine aggregate samples. AIMS was found to be highly repeatable with a maximum coefficient of variation (C.V) of 13.9 percent in measuring random samples and 4.9 percent in measuring the same samples. The reproducibility of the test method was found to have a maximum C.V equal to 16.3 percent in measuring random samples and is expected to decrease significantly in measuring the same samples. AIMS was found to be sensitive to changes in the distributions of shape, angularity and texture.

The statistical parameters of AIMS repeatability and reproducibility were compared with other test methods. AIMS has been found to have excellent repeatability and reproducibility for all measured parameters when compared with many other test methods.

Two distribution functions “Equation -I” and “Gamma distribution” were studied for their applicability to represent the AIMS test results. It was found that Equation -I fitted

AIMS test results well in all the parameters measured. The equation-I parameters were found to be significantly different in describing the texture of the majority of aggregates. However, aggregates were found to have less variation in the angularity and shape parameters compared with the texture parameters. It was found that there are no distinct relationships between the parameters of Equation-I and the distributions of aggregate physical characteristics. Hence standard distribution functions that have well defined parameters were studied for their applicability to describe AIMS test results. The gamma distribution was found to fit well all the distribution of shape characteristics for all the aggregates used in this study. The parameters of the gamma distribution were also found to be significantly different in describing the texture of the majority of aggregates. Less significant differences were found between the parameters that describe the angularity and shape of aggregates.

The gamma distribution function was found to describe the distribution of all shape characteristics of the aggregates used in this study. The statistical difference between the gamma function parameters was most pronounced in the texture measurements. This finding confirms that aggregates differ the most in their texture.

A statistical method based on the “Categorical Units” was used in this chapter to analyze the differences among aggregate samples. This method is able to capture the significant differences between aggregates.

RECOMMENDATIONS

This thesis studied the quality of measurements by AIMS. It was identified that the test method had high repeatability, reproducibility and sensitivity. The test method is recommended for use in the pavement industry in measuring the shape, angularity and texture of aggregates. The statistical analysis methods presented in this chapter can be used in a number of applications:

- The parameters of the distribution function can be determined for a certain aggregate source, and can be used to detect changes in aggregate physical characteristics as part of the quality assurance (QA) and quality control (QC) procedures.
- The parameters of the distribution function can be related to the performance of pavement layers. It is expected that performance will have better correlation with the distribution parameters than with average parameters of aggregate characteristics.
- The analysis methods presented in this chapterr can be used to compare the results from different crushing techniques, and to assist in deciding on the techniques that produce the most desirable characteristics.

REFERENCES

Al-Rousan, T. M. (2004). "Characterization of aggregate shape properties using a computer automated system." PhD dissertation, Texas A&M Univ., College Station, Te-as.

American Association of State Highway and Transportation Officials, (AASHTO). (19-97) AASHTO Standard T304, "Uncompacted void content of fine aggregate." *Standard Specifications for Transportation Materials and Methods of Sampling and Testing,*18th Ed., Washington, D.C.

American Society of Testing and Materials (ASTM). (1999). ASTM D5821-95, "Standard test method for determining the percentage of fractured particles in coarse aggregate." *Annual Book of ASTM Standards, Vol. 04.03,* Philadelphia, Pennsylvania.

American Society of Testing and Materials (ASTM). (2000). ASTM D4791-99, "Standard test method for flat particles, elongated particles, or flat and elongated particles in coarse aggregate." *Annual Book of ASTM Standards,* Vol. 04.03, West Conshochocken, Pennsylvania.

Barksdale, R. D., and Itani, S. Y. (1994). "Influence of aggregate shape on base behavior."*Transportation Research Record 1227,* Transportation Research Board, Washington, D.C. 171-182.

Chowdhury, A., Button, J. W., Kohale, V., and Jahn, D. (2001). "Evaluation of superpave fine aggregate angularity specification," International Center for Aggregates Research (ICAR) Report 201-1, Texas Transportation Institute, Texas A&M Univ., College Station, Texas.

Fletcher, T., Chandan, C., Masad, E., and Siva Kumar, K. (2002). "Measurements of aggregate texture and its influence on HMA permanent deformation." *Journal of Testing and Evaluation*, *American Society for Testing and Materials,* ASTM, 30(6), 524-531.

Fletcher, T., Chandan, C., Masad, E., and Siva Kumar, K. (2003). "Aggregate Imaging System (AIMS) for characterizing the shape of fine and coarse aggregates." *Transportation Research Record 1832,* Transportation Research Board, Washington D.C., 67-77.

Folliard, K. J. (1999). "Aggregate tests related to performance of portland cement concrete pavements." *Phase 1 Interim Report*, *Project 4-20B,* National Cooperative Highway Research Program, Austin, Texas.

Fowler, D. W., Zollinger, D. G., Carrasquillo, R. L., and Constantino, C. A. (1996). "A-gregate tests related to performance of portland cement concrete." *Phase 1 Unpublished Interim Report*, *Project 4-20,* National Cooperative Highway Research Program (NCHRP), Lincoln, Nebraska.

Huber, G. A., Jones, J. C., and Jackson, N. M. (1998) "Contribution of fine aggregate angularity and particle shape to Superpave mixture performance." *Transportation Research Record 1609,* Transportation Research Board, Washington D.C., 28 – 35.

Kim S.H, Little, D.N., Masad E, Lytton,R.,(2004) "Determination of anisotropic moduli considering aggregate particle shape and gradation in unbound granular layer" A paper presented at the 83rd Transportation Research Board Annual Meeting, 2004, Washington, D.C.

Kosmatka, S. H., Kerkhoff, B., and Panarese, W. C. (2002) *Design and control of concrete mixtures.* 14th Ed., Portland Cement Association, Skokie, Illinois.

Masad, E. (2001). "Review of imaging techniques for characterizing the shape of aggregates used in asphalt mixes," A Paper Presented at the 9th Annual Symposium International Center for Aggregate Research (ICAR), Austin, Texas.

Masad, E. (2003). "The development of a computer controlled image analysis system for measuring aggregate shape properties." Final Report, *National Cooperative Highway Research Program NCHRP-IDEA Project 77*, Washington, D.C.

Masad, E. (2004). "Aggregate Imaging System (AIMS) basics and applications" *Report no. FHWA/TX-05/5-1707-01-1,* Texas Department of Transportation and Federal Highway Administration, Washington, D.C.

Masad, E., Al-Rousan, T., Button, J., and Little, D., Tutumuler, E. (2005). "Test methods for characterizing aggregate shape, texture and angularity." Final Report, *National Cooperative Highway Research Program,* (NCHRP) *Project 4-30A.* Transportation Research Board, National Research Council, Washington, D.C.

Masad, E., Olcott, D., White, T., and Tashman, L. (2001). "Correlation of fine aggregate imaging shape indices with asphalt mixture performance," *Transportation Research Record 1757,* Transportation Research Board, Washington, D.C., 148-156.

Meininger, R. C. (1998). "Aggregate test related to performance of portland cement concrete pavement." Final Report, *National Cooperative Highway Research Program Project 4-20A.* Transportation Research Board, National Research Council, Washington, D.C.

Mindness, S., and Young, J. F., (1981) *Concrete.* Prentice Hall Inc., Englewood Cliffs, New Jersey.

Monismith, C. L. (1970). "Influence of shape, size, and surface texture on the stiffness a-nd fatigue response of asphalt mixtures." *Highway Research Board 109 Special Rep-ort,* Transportation Research Board, National Research Council, Washington, D.C. 4-11.

Saeed, A., Hall, J., and Barker, W. (2001) "Performance-related tests of aggregates for use in unbound pavement layers." Report 453, *National Cooperative Highway Rese-arch Program* (NCHRP), Transportation Research Board, National Research Counc-il, Washington, D.C.

APPENDIX A

CHI-SQUARE TEST RESULTS

CASE 1: TWO AGGREGATE SAMPLES AGGREGATE 1 AND 10

TEXTURE

			Subclass				Total
			1	2	3	4	
Aggregate	1	Count	100	0	0	0	100
		Expected count	53.5	17.0	25	4.5	100.0
		Std Residual	6.4	-4.1	-5.0	-2.1	
	10	Count	7	34	50	9	100
		Expected count	53.5	17	25	4.5	100
		Std Residual	-6.4	4.1	5.0	2.1	
Total		Count	107	34	50	9	200
		Expected count	107.0	34.0	50.0	9.0	200.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	173.832[a]	3	.000
Likelihood Ratio	225.550	3	.000
Linear-by-Linear Association	139.116	1	.000
N of Valid Cases	200		

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 4.50.

CASE 1: TWO AGGREGATE SAMPLES AGGREGATES 1 AND 10.

GRADIENT ANGULARITY

			Subclass				Total
			1	**2**	**3**	**4**	
Aggregate	1	Count	25	22	30	23	100
		Expected count	16.5	26.0	26.0	31.5	100.0
		Std Residual	2.1	-0.8	0.8	-1.5	
	10	Count	8	30	22	40	100
		Expected count	16.5	26.0	26.0	31.5	100
		Std Residual	-2.1	0.8	-0.8	1.5	
Total		Count	33	52	52	63	200
		Expected count	33.0	52.0	52.0	63.0	200.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	15.806[a]	3	.001
Likelihood Ratio	16.309	3	.001
Linear-by-Linear Association	7.934	1	.005
No of Valid Cases	200		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.50.

CASE 1: TWO AGGREGATE SAMPLES AGGREGATE 1 AND 10

RADIUS ANGULARITY

			Subclass				Total
			1	2	3	4	
Aggregate	1	Count	20	21	36	23	100
		Expected count	13.5	23	32.5	31.0	100.0
		Std Residual	1.8	-0.4	0.6	-1.4	
	10	Count	7	25	29	39	100
		Expected count	13.5	23.0	32.5	31.0	100
		Std Residual	-1.8	0.4	-0.6	1.4	
Total		Count	27	46	65	62	200
		Expected count	27.0	46.0	65.0	62.0	200.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	11.490[a]	3	.009
Likelihood Ratio	11.806	3	.008
Linear-by-Linear Association	6.882	1	.009
No of Valid Cases	200		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.50.

CASE 1: TWO AGGREGATE SAMPLES AGGREGATE 1 AND 10

SPHERICITY

			Subclass 1	2	3	4	Total
Aggregate	1	Count	4	5	82	9	100
		Expected count	6.5	11.5	73.0	9.0	100.0
		Std Residual	-1.0	-1.9	1.1	0.0	
	10	Count	9	18	64	9	100
		Expected count	6.5	11.5	73.0	9.0	100
		Std Residual	1.0	1.9	-1.1	0.0	
Total		Count	13	23	146	18	200
		Expected count	13.0	23.0	146.0	18.0	200.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	11.490[a]	3	.009
Likelihood Ratio	11.998	3	.007
Linear-by-Linear Association	5.968	1	.015
N of Valid Cases	200		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 6.50.

CASE 1: TWO AGGREGATE SAMPLES AGGREGATE 1 AND 10

FORM 2D

			Subclass				Total
			1	2	3	4	
Aggregate	1	Count	54	30	16	0	100
		Expected count	40.0	37.5	20.5	2.0	100.0
		Std Residual	2.2	-1.2	-1.0	-1.4	
	10	Count	26	45	25	4	100
		Expected count	40.0	37.5	20.5	2.0	100
		Std Residual	-2.2	1.2	1.0	1.4	
Total		Count	80	75	41	4	200
		Expected count	80.0	75.0	41.0	4.0	200.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	18.776[a]	3	.000
Likelihood Ratio	20.568	3	.000
Linear-by-Linear Association	15.242	1	.000
N of Valid Cases	200		

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 2.00.

CASE 2: MANY AGGREGATE SAMPLES

RADIUS ANGULARITY

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	188.703[a]	36	.000
Likelihood Ratio	196.788	36	.000
Linear-by-Linear Association	23.636	1	.000
N of Valid Cases	1301		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 6.32.

Aggregate * Subclass Cross tabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	20	21	36	23	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	5.4	1.6	.3	-3.2	
	2.00	Count	14	18	46	21	99
		Expected Count	6.3	14.8	34.0	43.8	99.0
		Std. Residual	3.1	.8	2.1	-3.4	
	3.00	Count	0	21	25	54	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-2.5	1.6	-1.6	1.5	
	4.00	Count	2	7	25	66	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-1.7	-2.1	-1.6	3.3	
	5.00	Count	0	16	38	46	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-2.5	.3	.6	.3	
	6.00	Count	7	11	45	38	101
		Expected Count	6.4	15.1	34.7	44.7	101.0
		Std. Residual	.2	-1.1	1.7	-1.0	
	7.00	Count	5	11	30	54	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-.5	-1.0	-.7	1.5	
	8.00	Count	18	21	38	23	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	4.6	1.6	.6	-3.2	
	9.00	Count	4	16	29	52	101
		Expected Count	6.4	15.1	34.7	44.7	101.0
		Std. Residual	-1.0	.2	-1.0	1.1	
	10.00	Count	7	25	29	39	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	.2	2.6	-.9	-.8	
	11.00	Count	2	7	34	57	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-1.7	-2.1	-.1	1.9	
	12.00	Count	4	7	36	53	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-.9	-2.1	.3	1.3	
	13.00	Count	0	14	36	50	100
		Expected Count	6.4	15.0	34.4	44.3	100.0
		Std. Residual	-2.5	-.3	.3	.9	
Total		Count	83	195	447	576	1301
		Expected Count	83.0	195.0	447.0	576.0	1301.0

CASE 2: MANY AGGREGATE SAMPLES

GRADIENT ANGULARITY

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	82.399[a]	36	.000
Likelihood Ratio	85.167	36	.000
Linear-by-Linear Association	6.725	1	.010
N of Valid Cases	1299		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.49.

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	41	21	30	7	99
		Expected Count	30.8	26.8	27.9	13.5	99.0
		Std. Residual	1.8	-1.1	.4	-1.8	
	2.00	Count	27	30	30	13	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-.7	.6	.3	-.2	
	3.00	Count	29	36	27	9	101
		Expected Count	31.4	27.4	28.5	13.8	101.0
		Std. Residual	-.4	1.6	-.3	-1.3	
	4.00	Count	32	32	27	9	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	.2	.9	-.2	-1.3	
	5.00	Count	20	21	41	18	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-2.0	-1.2	2.4	1.2	
	6.00	Count	41	32	21	5	99
		Expected Count	30.8	26.8	27.9	13.5	99.0
		Std. Residual	1.8	1.0	-1.3	-2.3	
	7.00	Count	27	25	30	18	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-.7	-.4	.3	1.2	
	8.00	Count	48	23	20	9	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	3.0	-.8	-1.5	-1.3	
	9.00	Count	29	20	30	21	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-.4	-1.4	.3	2.0	
	10.00	Count	29	25	30	16	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-.4	-.4	.3	.6	
	11.00	Count	34	30	20	16	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	.5	.6	-1.5	.6	
	12.00	Count	33	27	24	16	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	.3	.0	-.8	.6	
	13.00	Count	14	30	36	20	100
		Expected Count	31.1	27.1	28.2	13.6	100.0
		Std. Residual	-3.1	.6	1.5	1.7	
Total		Count	404	352	366	177	1299
		Expected Count	404.0	352.0	366.0	177.0	1299.0

CASE 2: MANY AGGREGATE SAMPLES

FORM-2D

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	205.431(a)	36	.000
Likelihood Ratio	205.357	36	.000
Linear-by-Linear Association	11.396	1	.001
N of Valid Cases	1302		

a 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.25.

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	54	30	16	0	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	6.0	-1.9	-2.3	-2.3	
	2.00	Count	38	46	13	4	101
		Expected Count	24.6	42.4	28.6	5.4	101.0
		Std. Residual	2.7	.5	-2.9	-.6	
	3.00	Count	11	46	36	7	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-2.7	.6	1.4	.7	
	4.00	Count	9	43	39	9	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-3.1	.2	2.0	1.6	
	5.00	Count	11	52	34	4	101
		Expected Count	24.6	42.4	28.6	5.4	101.0
		Std. Residual	-2.7	1.5	1.0	-.6	
	6.00	Count	20	48	27	5	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-.9	.9	-.3	-.1	
	7.00	Count	14	45	32	9	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-2.1	.5	.7	1.6	
	8.00	Count	59	27	9	5	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	7.0	-2.3	-3.6	-.1	
	9.00	Count	25	38	32	5	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	.1	-.6	.7	-.1	
	10.00	Count	27	45	25	4	101
		Expected Count	24.6	42.4	28.6	5.4	101.0
		Std. Residual	.5	.4	-.7	-.6	
	11.00	Count	7	46	41	5	99
		Expected Count	24.1	41.6	28.1	5.2	99.0
		Std. Residual	-3.5	.7	2.4	-.1	
	12.00	Count	22	42	31	5	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-.5	.0	.5	-.1	
	13.00	Count	20	39	34	7	100
		Expected Count	24.3	42.0	28.3	5.3	100.0
		Std. Residual	-.9	-.5	1.1	.7	
Total		Count	317	547	369	69	1302
		Expected Count	317.0	547.0	369.0	69.0	1302.0

CASE 2: MANY AGGREGATE SAMPLES

SPHERICITY

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	186.743(a)	36	.000
Likelihood Ratio	175.918	36	.000
Linear-by-Linear Association	13.505	1	.000
N of Valid Cases	1302		

a 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.17.

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	4	5	82	9	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.5	-3.1	1.9	-.4	
	2.00	Count	4	18	73	5	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.5	-.1	.8	-1.6	
	3.00	Count	2	4	68	27	101
		Expected Count	5.3	18.5	66.9	10.3	101.0
		Std. Residual	-1.4	-3.4	.1	5.2	
	4.00	Count	14	32	46	7	99
		Expected Count	5.2	18.2	65.5	10.1	99.0
		Std. Residual	3.9	3.2	-2.4	-1.0	
	5.00	Count	7	11	71	11	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	.8	-1.7	.6	.2	
	6.00	Count	2	9	77	13	101
		Expected Count	5.3	18.5	66.9	10.3	101.0
		Std. Residual	-1.4	-2.2	1.2	.8	
	7.00	Count	7	25	63	5	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	.8	1.6	-.4	-1.6	
	8.00	Count	4	9	66	21	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.5	-2.2	.0	3.4	
	9.00	Count	5	27	63	5	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.1	2.0	-.4	-1.6	
	10.00	Count	9	18	64	9	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	1.7	-.1	-.3	-.4	
	11.00	Count	2	13	79	7	101
		Expected Count	5.3	18.5	66.9	10.3	101.0
		Std. Residual	-1.4	-1.3	1.5	-1.0	
	12.00	Count	4	25	62	9	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.5	1.6	-.5	-.4	
	13.00	Count	4	43	48	5	100
		Expected Count	5.2	18.4	66.2	10.2	100.0
		Std. Residual	-.5	5.8	-2.2	-1.6	
Total		Count	68	239	862	133	1302
		Expected Count	68.0	239.0	862.0	133.0	1302.0

CASE 2: MANY AGGREGATE SAMPLES

TEXTURE

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	761.686[a]	48	.000
Likelihood Ratio	788.213	48	.000
Linear-by-Linear Association	7.716	1	.005
N of Valid Cases	2599		

a. 13 cells (20.0%) have expected count less than 5. The minimum expected count is

Aggregate * Subclass Crosstabulation

			Subclass					Total
			1.00	2.00	3.00	4.00	5.00	
Aggregate	1.00	Count	104	5	82	9	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	7.1	-6.1	-.4	-1.6	-.4	
	2.00	Count	96	25	73	5	0	199
		Expected Cour	52.2	46.2	85.1	15.4	.2	199.0
		Std. Residual	6.1	-3.1	-1.3	-2.6	-.4	
	3.00	Count	5	52	105	38	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	-6.6	.8	2.1	5.7	-.4	
	4.00	Count	77	61	55	7	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	3.4	2.1	-3.3	-2.2	-.4	
	5.00	Count	16	50	118	16	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	-5.0	.5	3.5	.1	-.4	
	6.00	Count	45	52	91	13	0	201
		Expected Cour	52.7	46.6	85.9	15.5	.2	201.0
		Std. Residual	-1.1	.8	.5	-.6	-.4	
	7.00	Count	84	45	66	5	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	4.4	-.2	-2.1	-2.7	-.4	
	8.00	Count	89	20	70	21	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	5.0	-3.9	-1.7	1.4	-.4	
	9.00	Count	5	32	114	46	2	199
		Expected Cour	52.2	46.2	85.1	15.4	.2	199.0
		Std. Residual	-6.5	-2.1	3.1	7.8	4.7	
	10.00	Count	16	52	114	18	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	-5.0	.8	3.1	.6	-.4	
	11.00	Count	16	91	84	9	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	-5.0	6.5	-.2	-1.6	-.4	
	12.00	Count	104	25	62	9	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	7.1	-3.1	-2.5	-1.6	-.4	
	13.00	Count	25	93	77	5	0	200
		Expected Cour	52.5	46.4	85.5	15.5	.2	200.0
		Std. Residual	-3.8	6.8	-.9	-2.7	-.4	
Total		Count	682	603	1111	201	2	2599
		Expected Cour	682.0	603.0	1111.0	201.0	2.0	2599.0

CASE 3: SAME AGGREGATE (MEASURED REPEATEDLY 3 TIMES)

TEXTURE

AGGREGATE * SUBCLASS Crosstabulation

			SUBCLASS		
			1.00	2.00	Total
AGGREGAT	1.00	Count	98	2	100
		Expected Count	98.0	2.0	100.0
		Std. Residual	.0	.0	
	2.00	Count	98	2	100
		Expected Count	98.0	2.0	100.0
		Std. Residual	.0	.0	
	3.00	Count	98	2	100
		Expected Count	98.0	2.0	100.0
		Std. Residual	.0	.0	
Total		Count	294	6	300
		Expected Count	294.0	6.0	300.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	.000[a]	2	1.000
Likelihood Ratio	.000	2	1.000
Linear-by-Linear Association	.000	1	1.000
N of Valid Cases	300		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 2.00.

CASE 3: SAME AGGREGATE (MEASURED REPEATEDLY 3 TIMES)

RADIUS ANGULARITY

			Subclass				Total
			1	2	3	4	
Aggregate	1	Count	0.7	25	32	36	100.0
		Expected count	5.3	24.3	31.7	38.7	100.0
		Std Residual	0.7	0.1	0.1	-0.4	
	2	Count	5	23	34	38	100
		Expected count	5.3	24.3	31.7	38.7	100.0
		Std Residual	-0.1	-0.3	0.4	-0.1	
	3	Count	4	25	29	42	100
		Expected count	5.3	24.3	31.7	38.7	100.0
		Std Residual	-0.6	0.1	-0.5	0.5	
Total		Count	16	73	95	116	300
		Expected count	16.0	73.0	95.0	116.0	300.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1.867[a]	6	.931
Likelihood Ratio	1.853	6	.933
Linear-by-Linear Association	.852	1	.356
N of Valid Cases	300		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.33.

CASE 3: SAME AGGREGATE (MEASURED REPEATEDLY 3 TIMES)

GRADIENT ANGULARITY

			Subclass				Total
			1	**2**	**3**	**4**	
Aggregate	1	Count	27	23	34	16	100.0
		Expected count	26.7	27.3	30.3	15.7	100.0
		Std Residual	0.1	-0.8	0.7	0.1	
	2	Count	30	29	23	18	100
		Expected count	26.7	27.3	30.3	15.7	100.0
		Std Residual	0.6	0.3	-1.3	0.6	
	3	Count	23	30	34	13	100
		Expected count	26.7	27.3	30.3	15.7	100.0
		Std Residual	-0.7	0.5	0.7	-0.7	
Total		Count	80	82	91	47	300
		Expected count	80.0	82.0	91.0	47.0	300.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	5.442[a]	6	.489
Likelihood Ratio	5.621	6	.467
Linear-by-Linear Association	.019	1	.892
N of Valid Cases	300		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 15.67.

CASE 3: SAME AGGREGATE (MEASURED REPEATEDLY 3 TIMES)

SPHERICITY

			Subclass				Total
			1	**2**	**3**	**4**	
Aggregate	1	Count	0	26	70	4	100.0
		Expected count	0.3	24.3	71.0	4.3	100.0
		Std Residual	-0.6	0.3	-0.1	-0.2	
	2	Count	1	25	70	4	100
		Expected count	0.3	24.3	71.0	4.3	100.0
		Std Residual	1.2	0.1	-0.1	-0.2	
	3	Count	0	22	73	5	100
		Expected count	0.3	24.3	71.0	4.3	100.0
		Std Residual	-0.6	-0.5	0.2	0.3	
Total		Count	1	73	213	13	300
		Expected count	1.0	73.0	213.0	13.0	300.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.595[a]	6	.858
Likelihood Ratio	2.793	6	.834
Linear-by-Linear Association	.484	1	.487
N of Valid Cases	300		

a. 6 cells (50.0%) have expected count less than 5. The minimum expected count is .33.

CASE 3: SAME AGGREGATE (MEASURED REPEATEDLY 3 TIMES)

FORM 2D

			Subclass				Total
			1	**2**	**3**	**4**	
Aggregate	1	Count	46	32	20	2	100.0
		Expected count	45.7	32.0	20.3	2.0	100.0
		Std Residual	0.0	0.0	-0.1	0.0	
	2	Count	43	32	21	4	100
		Expected count	45.7	32.0	20.3	2.0	100.0
		Std Residual	-0.4	0.0	0.1	1.4	
	3	Count	48	32	20	0	100
		Expected count	45.7	32.0	20.3	2.0	100.0
		Std Residual	0.3	0.0	-0.1	-1.4	
Total		Count	137	96	61	6	300
		Expected Count	137.0	96.0	61.0	6.0	300.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4.310[a]	6	.635
Likelihood Ratio	5.856	6	.439
Linear-by-Linear Association	.258	1	.611
N of Valid Cases	300		

a. 3 cells (25.0%) have expected count less than 5. The minimum expected count is 2.00.

CASE 4: AGGREGATE BLENDS

TEXTURE

			Subclass					Total
			1	2	3	4	5	
Aggregate	1	Count	100	0	0	0	0	100
		Expected count	47.9	12.2	19.2	12.7	8.0	100.0
		Std Residual	7.5	-3.5	-4.4	-3.6	-2.8	
	2	Count	54	8	12	15	12	101
		Expected count	48.4	12.3	19.4	12.8	8.1	101.0
		Std Residual	0.8	-1.2	-1.7	0.6	1.4	
	3	Count	31	7	15	27	20	100
		Expected count	47.9	12.2	19.2	12.7	8.0	100.0
		Std Residual	-2.4	-1.5	-1.0	4.0	4.3	
	4	Count	7	34	50	9	0	100
		Expected count	47.9	12.2	19.2	12.7	8.0	100.0
		Std Residual	-5.9	6.2	7.0	-1.0	-2.8	
Total		Count	192	49	77	51	32	401
		Expected count	192.0	49.0	77.0	51.0	32.0	401.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	291.579[a]	12	.000
Likelihood Ratio	322.341	12	.000
Linear-by-Linear Association	83.441	1	.000
N of Valid Cases	401		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.98.

CASE 4: AGGREGATE BLENDS

GRADIENT ANGULARITY

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	41	21	30	7	99
		Expected Coun	33.2	31.3	23.1	11.4	99.0
		Std. Residual	1.3	-1.8	1.4	-1.3	
	2.00	Count	35	44	13	8	100
		Expected Coun	33.6	31.6	23.3	11.5	100.0
		Std. Residual	.2	2.2	-2.1	-1.0	
	3.00	Count	29	36	20	15	100
		Expected Coun	33.6	31.6	23.3	11.5	100.0
		Std. Residual	-.8	.8	-.7	1.0	
	4.00	Count	29	25	30	16	100
		Expected Coun	33.6	31.6	23.3	11.5	100.0
		Std. Residual	-.8	-1.2	1.4	1.3	
Total		Count	134	126	93	46	399
		Expected Coun	134.0	126.0	93.0	46.0	399.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	27.957[a]	9	.001
Likelihood Ratio	28.562	9	.001
Linear-by-Linear Association	6.721	1	.010
N of Valid Cases	399		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.41.

CASE 4: AGGREGATE BLENDS

RADIUS ANGULARITY

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	20	21	36	23	100
		Expected Coun	23.9	27.9	29.7	18.5	100.0
		Std. Residual	-.8	-1.3	1.2	1.1	
	2.00	Count	38	31	23	8	100
		Expected Coun	23.9	27.9	29.7	18.5	100.0
		Std. Residual	2.9	.6	-1.2	-2.4	
	3.00	Count	31	35	31	4	101
		Expected Coun	24.2	28.2	30.0	18.6	101.0
		Std. Residual	1.4	1.3	.2	-3.4	
	4.00	Count	7	25	29	39	100
		Expected Coun	23.9	27.9	29.7	18.5	100.0
		Std. Residual	-3.5	-.6	-.1	4.8	
Total		Count	96	112	119	74	401
		Expected Coun	96.0	112.0	119.0	74.0	401.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	71.130[a]	9	.000
Likelihood Ratio	75.909	9	.000
Linear-by-Linear Association	6.634	1	.010
N of Valid Cases	401		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 18.45.

CASE 4: AGGREGATE BLENDS

FORM 2D

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	54	30	16	0	100
		Expected Count	41.4	34.7	20.9	3.0	100.0
		Std. Residual	2.0	-.8	-1.1	-1.7	
	2.00	Count	50	29	17	4	100
		Expected Count	41.4	34.7	20.9	3.0	100.0
		Std. Residual	1.3	-1.0	-.9	.6	
	3.00	Count	35	35	26	4	100
		Expected Count	41.4	34.7	20.9	3.0	100.0
		Std. Residual	-1.0	.1	1.1	.6	
	4.00	Count	27	45	25	4	101
		Expected Count	41.8	35.0	21.2	3.0	101.0
		Std. Residual	-2.3	1.7	.8	.6	
Total		Count	166	139	84	12	401
		Expected Count	166.0	139.0	84.0	12.0	401.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	24.083[a]	9	.004
Likelihood Ratio	27.221	9	.001
Linear-by-Linear Association	16.824	1	.000
N of Valid Cases	401		

a. 4 cells (25.0%) have expected count less than 5. The minimum expected count is 2.99.

CASE 4: AGGREGATE BLENDS

SPHERICITY

Aggregate * Subclass Crosstabulation

			Subclass				Total
			1.00	2.00	3.00	4.00	
Aggregate	1.00	Count	4	5	82	9	100
		Expected Cou	16.0	20.1	51.4	12.5	100.0
		Std. Residual	-3.0	-3.4	4.3	-1.0	
	2.00	Count	21	25	38	15	99
		Expected Cou	15.9	19.8	50.9	12.4	99.0
		Std. Residual	1.3	1.2	-1.8	.7	
	3.00	Count	30	32	21	17	100
		Expected Cou	16.0	20.1	51.4	12.5	100.0
		Std. Residual	3.5	2.7	-4.2	1.3	
	4.00	Count	9	18	64	9	100
		Expected Cou	16.0	20.1	51.4	12.5	100.0
		Std. Residual	-1.8	-.5	1.8	-1.0	
Total		Count	64	80	205	50	399
		Expected Cou	64.0	80.0	205.0	50.0	399.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	92.586[a]	9	.000
Likelihood Ratio	100.675	9	.000
Linear-by-Linear Association	5.166	1	.023
N of Valid Cases	399		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.41.

APPENDIX B

RMS VALUES FITTING GAMMA DISTRIBUTION

Table B.1.RMS values for the fitted Gamma Distribution function

RMS Values: Aggregate	**Form 2D**	**Form 3D**	**Radius Angularity**	**Gradient Angularity**	**Texture**
1	0.000224	0.000428	0.0007419	0.001055	0.000825
2	0.000422	0.001311	0.0006178	0.000875	0.000665
3	0.000504	0.000567	0.0009023	0.001154	0.000653
4	0.000331	0.000395	0.0005734	0.001395	0.001449
5	0.000797	0.001988	0.0002064	0.001925	0.001449
6	0.000474	0.000639	0.0006546	0.000735	0.000631
7	0.001032	0.000608	0.0008403	0.00063	0.000483
8	0.000251	0.000826	0.0002808	0.000784	0.00057
9	0.001023	0.000641	0.0007948	0.002394	0.00039
10	0.000356	0.001689	0.0009196	0.000812	0.000616
11	0.00164	0.000305	0.0009021	0.000308	0.001026
12	0.001308	0.000849	0.0002898	0.001051	0.000599
13	0.000613	0.000981	0.0003446	0.000291	0.000865

VITA

Manjula Bathina was born in Hyderabad, India on July 22, 1979. She completed her bachelors in civil engineering from Jawaharlal Nehru Technological University, Hyderabad in 2002. She received her masters in civil engineering at Texas A&M University during 2003-2005. While working towards her master's degree, she worked as a research assistant at Texas Transportation Institute (TTI) in College Station, Texas.

Her permanent mailing address is

1-6-558

Dayar Market, Musheerabad,

Hyderabad-500020,

Andhra Pradesh,

India.