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Aggregate Classification by Using 3D Image Analysis Technique

Mahmut SİNECEN[1,♠], Metehan MAKİNACI[1], Ali TOPAL[2]

[1] *Dokuz Eylül University, Faculty of Engineering, Department of Electric-Electronic Engineering, İzmir*
[2] *Dokuz Eylül University, Faculty of Engineering, Department of Civil Engineering, İzmir*

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ABSTRACT:

Aggregate occupy approximately 80 percent of the total volume of concrete mix, and aggregate physical characteristics significantly affect the properties of concrete both fresh and hardened state. Selection of improper aggregates such as flat and elongated particles may cause failure or deterioration of a concrete structure. Therefore, selection process of aggregates for a specific job is very important. There is no standard test method for evaluating the aggregate physical properties effectively. The manual standard test methods (EN 933, ASTM D 4791, ASTM C 1252, and ASTM D 3398) are laborious, time consuming and tedious measurements. Trent to tighten specifications for aggregate properties along with recent technological advances in technology, availability of high performance computers, and low cost imaging systems support usage of image analysis methods for quantitative measurement of aggregate properties such as size, shape and texture with easy, fast, real-time and without human errors. In last decades, two dimensional (2D) and three dimensional (3D) image analysis techniques have been used to measure size, shape, and texture of aggregates. In this paper, shape and size parameters (features) of four different types of aggregates are calculated by 3D image analysis technique and aggregates are classified by three different artificial neural network models with using these parameters. Best classification performance is given by a multilayer perceptron method which is 90,84 % precision.

Keywords: *Aggregate, Shape, Image analysis, 3D, Classification*

1. INTRODUCTION

Since approximately 80 percent of the total volume of concrete mix consist of aggregate, their characteristics significantly affect the performance of fresh and hardened concrete and have an impact on the cost effectiveness of concrete [1-3]. Aggregate morphological characteristics of size, shape, and surface texture influence workability, finishability, bleeding, pumpability, and segregation of fresh concrete and affect strength, stiffness, shrinkage, creep, density, permeability and durability of hardened concrete. The flaky and elongated particles will have less strength and durability when compared with cubical, angular or rounded particles of the same aggregate. Flaky and elongated particles tend to produce harsh mixtures and affect finishability. An excess of poorly shaped particles could reduce the strength of concrete through the increase of mixing water requirement. To avoid these problems, some specifications limit the amount of flaky and elongated particles in concrete.

The manual methods of ASTM C 136, ASTM D 4791, ASTM C 1252, ASTM D 3398, EN 933, are indirect measurement of physical properties of aggregate particles which are lack both precision and repeatability, and they are labor-intensive and time-consuming procedures. Sieve analysis (ASTM C 136), has been commonly used to measure the aggregate size, but the sieve analysis which just measure the percent cumulative mass does not actually measure size distribution of an aggregate sample [4, 5]. Moreover, it is neither real-time sensing nor an on-line measurement [6-8]. ASTM D 4791 is the proportional caliper method for evaluating the flatness and elongation of coarse aggregate particles. Flaky and elongated grains

♠Corresponding author, e-mail: mahmutsinecen@gmail.com

are determined by the relation among the length, width and thickness of the grain. The length is defined as the longest axis of the grain. The width is the second longest axis of the grain and the thickness is the shortest axis. A grain is classified as *flaky* if width to thickness ratio is bigger than 2.0 and a grain is classified as *elongated* if length to thickness ratio is bigger than 2.5. A grain is classified as *cubic* if it is not flaky or elongated, that means: width to thickness ratio is smaller than 2.0 and length to thickness ratio is smaller than 2.5.

Lately, the methods using modern data acquisition equipment have been increasingly utilized. Image analysis methods have been utilized in widespread applications in many disciplines thanks to technological advance, increase of computer usage, cost reduction of imaging system, and high capacity storage devices. Image analysis is the process of extracting information from digitized image by analyzing the pixel array. In analysis, scene is captured by a digital camera, charge-coupled device (CCD), or even a 35 mm camera firstly. Second step is to digitize the scene directly by frame grabber or analog to digital converter. The digitized image is stored as an array of pixels. The last step is to feature extraction in the array of pixels by using image analysis techniques [9].

Recent advances in 2D and 3D image analysis applications to characterize aggregates have led to development of methodologies for size, shape and texture evaluation. Nor Ashidi Mat Isa and et al, used image processing techniques for finding absolute parameters of aggregates shape and size [9], Mora and et al, researched advantage of image processing techniques to mechanical techniques which were used to find size distribution of aggregates [10], Weixing Wang calculated shape and size parameter measures through image processing techniques with best Ferret methods [11]. Fernlund calculated length, width and height parameters in 3D coordinate plane by using two different images [12], Also Fernlund evaluated Los Angeles Test by using 3D image processing techniques [13], Erdogan and et al, analyzed aggregate shape by 3D image analysis techniques [14], and Garboczi and et al, used laser detection and ranging (LADAR) to characterize the 3D shape of aggregates [15].

In this study, 3D shape features of aggregates are calculated by using 3D image analysis and classification is performed by using 3 different artificial neural network models.

2. MATERIAL AND METHODS

2. 1. Aggregates

One type of aggregate provided from Famerit Company (Dalaman natural aggregate) was used which is used to produce washbeton. Dalaman natural aggregate is visually classified as angular, sphere, flat, and elongated which are shown in the Figure 1. Depending upon aggregates are taken from one source, they have the same surface texture property. Therefore, aggregates are classified using shape features provided that other variables (i.e. surface texture, color, etc.) were fixed.

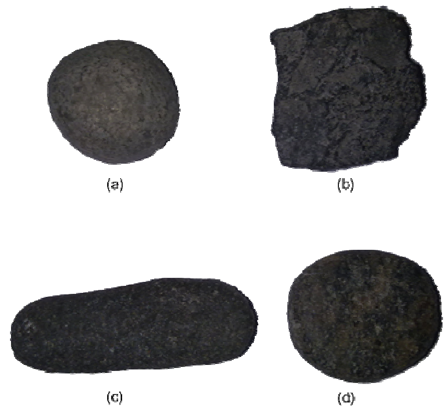


Figure 1. Images of different shaped aggregate types: (a) Sphere, b) Angular, (c) Elongated, (d) Flat

Table 1. The number of samples for different shaped aggregate types

Aggregate Shape	Number
Elongated	126
Sphere	156
Angular	160
Flat	174

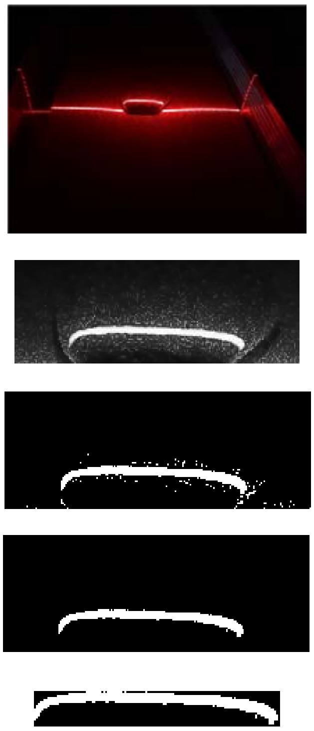
2.2. Imaging System

In this paper, a conveyor belt for imaging system is constructed, which is 25x30 cm in dimension (width, length), and drive with step motor (Figure 2). A laser source was used which is C13635-2-3(5) type and provided by Huanic Corporation, has 650 nm wavelength, red line module and thickness ≤1,5 mm that is made thin to 0.3 mm by using 5 number hypermetropic glass. Two cameras (Logitech® Quickcam Pro 9000 has 2-mega pixel, Carl-Zeiss optics and up to 30 frames per second video) are attached to two sides of conveyor belt. Each of them has 45^o ($\pm 45^o$) viewing angle according to laser source which is placed above at the middle of conveyor belt. Aggregates are moved on conveyor belt by step motor. Step motor has specific start (100 ms because of laser line thickness) and stop time (2 sec because of stabile conveyor belt). During the stop period, line of laser source falls on aggregate particle and at the same time two webcams capture images with 30 fps speed from both sides. In this way, two different images (one for each angle) are acquired for a single laser scan line on the aggregate surface.

Figure 2. Laser based 3D Imaging System.

2.3. Image Preprocessing

Preprocessing is applied on image slices by using Image Processing Toolbox of Matlab® software. First, the captured image (resolution of 960x720 pixels) is cropped to specific coordinate values for segmentation, after that, image is converted to gray tone and then threshold to convert to binary image. Noise artifacts are removed by eliminating areas having less than 50 pixels for not effecting labeling. Example output of the preprocessing section is given in Figure 3.



Capturing

Croping and Resizing

Background Substraction

Noise Elimination

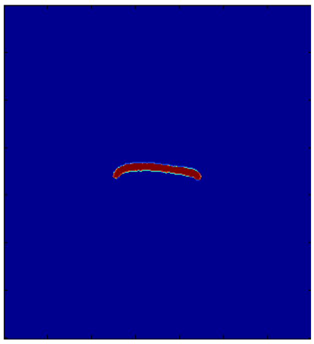
Image Slice

Figure 3. Image Preprocessing Steps

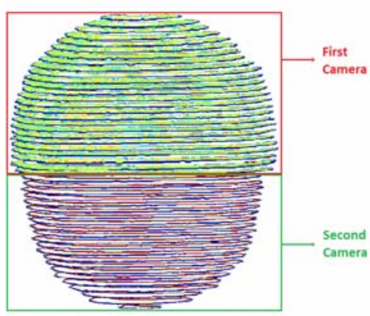
Image slices are only given us values of distance information for X-Y-Z coordinate plane. So, this study is independent to rotation, scale, transformation, etc.

After preprocessing, image slices are merged to form the upper part 3D image of the sample aggregate (Figure 4). The center line is found by subtracting the image slices taken from the both angles. For this operation, to takeimage from the left-camera was rotate 180^o horizontal direction because of its view point, and that was substracted the right-camera images. As shown in Figure 5, if the total number of pixels from obtaining the difference images less than 1% from belonging to that image slice, second part of aggregate was created images after from that images. This procedure is very important to calculate real size of the each aggregate sample.

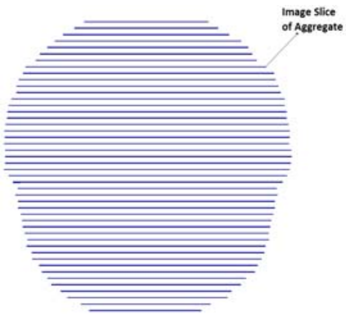
(a) Original Aggregate Shape



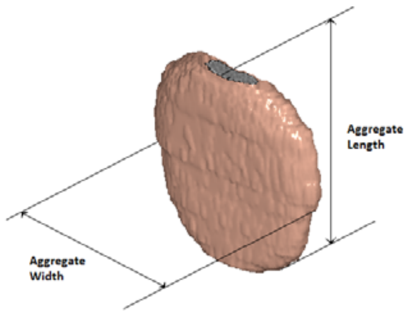
(b) Image Slice



(c) Merging of Image Slices



(d) Front View of Image Slices



(e) Patching of Image Slices

Figure 4. Merging slice image of an aggregate and patching on surface as 3D image

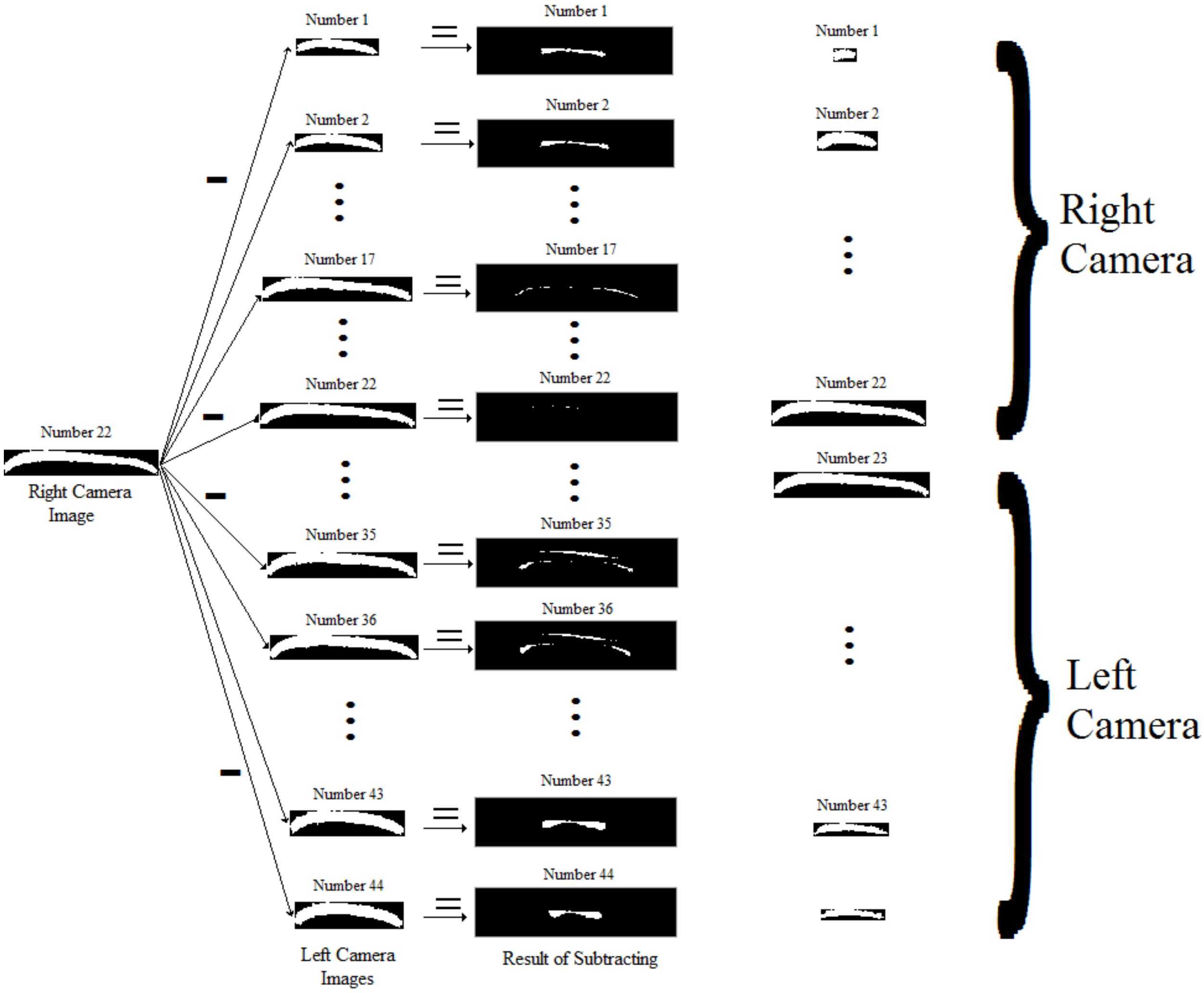


Figure 5. Finding center line from image slice

2.4. Feature Extraction

Shape properties are important for characterization of aggregates. Shape indexes for aggregates are mainly shape factor, sphericity, flatness, and elongation [5, 23, 24]. Three dimensional information (Long [L], Intermediate [I]), and Short [S] are needed for aggregate characterization. Although, these properties are not easily measured by mechanical or manual test methods, in this study 3D info can be calculated easily in a short period of time. Extracting features are independent from the most of the processing operations such as rotation, transformation, and etc. Because of the features are calculated as variations of L, I and S measurements. L is defined as the longest axis, I is the intermediate axis and the S is the shortest axis of the aggregate. The software which is written in C# for this study used to distinguish principal dimensions of the aggregate first, then calculate shape factor, sphericity, flatness, and elongation.

In this section, shape features are described and shown average of feature vectors values in Table 2 which are used for aggregate classification.

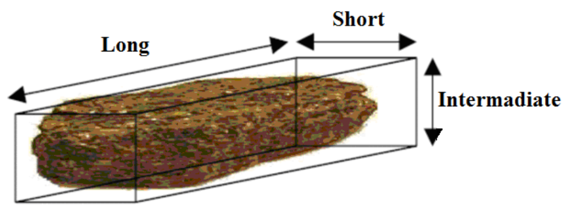


Figure 6.Principal dimensions of an aggregate Long (L), Intermediate (I), Short (S) [16]

- Sphericity is defined as the ratio of grain with sphere diameter of equivalent volume and smallest sphere diameter that is surrounding of grain [5, 17].

$$Sphericity = \sqrt[3]{\frac{SxI}{L^2}} \tag{1}$$

- Shape factor is a commonly used index but different researchers adopt different definitions for it to describe different aspects of shape [5, 17].

$$ShapeFactor = \frac{S}{\sqrt{LxI}} \tag{2}$$

- The elongation ratio is defined as the length to short ratio [5].

$$Elongation\ ratio = \frac{L}{S} \tag{3}$$

- Flatness ratio is defined as the thickness to short ratio [5].

$$Flatness\ ratio = \frac{S}{I} \tag{4}$$

Table 2. Average of Feature Vectors Values

	Sphericity	Shape Factor	Elongation Ratio	Flatness Ratio
Angular	1,159287807	0,511132361	3,407636038	1,590780664
Sphere	1,761346038	0,698089860	2,895562760	0,780748688
Elongated	0,934341701	0,309260780	4,866780756	2,519850012
Flat	0,780197986	0,224699792	6,007842944	3,695193455

3. CLASSIFICATION

The aim of classification is to discriminate 4 different aggregate shape types using aggregate features. Three different artificial neural network models (Multilayer Perceptron, Radial Basis Function and Learning Vector Quantization) are used for classification as shown Figure 7 [18 - 21]. Two different models are used in multilayer perceptron. One of these models has one hidden layer and node numbers are increased in hidden layer from 3 to 15 for finding best performance. Other model has two hidden layers, and node numbers are increased from 3 to 15 for each layer.

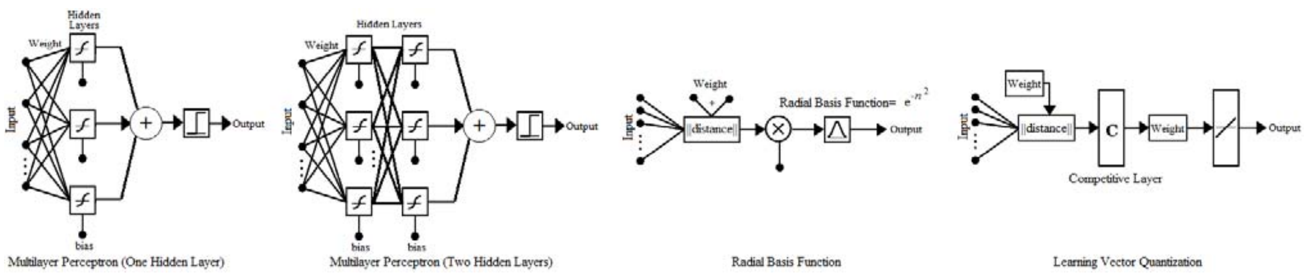


Figure 7. Artificial Neural Network Models

Multilayer perceptron (one and two hidden layers) parameters are tangent sigmoid transfer function for hidden layer and linear transfer function for output, Levenberg-Marquardt backpropagation for training, gradient descent with momentum weight/bias (0.95) for learning function and mean squared error with regularization (0.01) for performance function. Learning vector quantization parameters are learning rate 0,001. Radial basis function parameters are spread of RBF 1.0 and mean squared error goal 1.10^{-9}.

To find the artificial neural network model which has the highest performance among the selected topologies, so feature sets are formed by random selection from the sample set. Then, we use leave-one-out cross-validation method for finding performance error. Performance results are given in Table 3 and confusion matrix result is given in Table 4.

Table 3. Classification results

Network Type	Node Number (First Hidden Layer)	Node Number (Second Hidden Layer)	Performance (%)
FF1[a]	15	-	86.11
FF2[b]	10	14	90,84
RBF[c]	-	-	71,30
LVQ[d]	-	-	68,75

a. Feed Forward One Hidden Layer
b. Feed Forward Two Hidden Layers
c. Radial Basis Function
d. Learning Vector Quantization

Table 4. Confusion matrix of having best performance neural network

		Variables	Predicted Classes				Total
			Angular	Sphere	Elongated	Flat	
Actual Classes	Count	Angular	137	23	0	0	160
		Sphere	0	156	0	0	156
		Elongated	0	15	111	0	126
		Flat	0	0	14	160	174
	%	Angular	85,63	14,37	0	0	100
		Sphere	0	100	0	0	100
		Elongated	0	0	86,49	13,51	100
		Flat	0	0	8,75	91,25	100

4. CONCLUSION AND RECOMMENDATIONS

The aggregate shape properties are very important for concrete mix design. Irregular shapes such as; flat, elongated and irregular particles affect the fresh and hardened concrete properties negatively. Unable to obtain height parameters with the help of 2D image processing techniques on the classification of the aggregate makes difficult to distinguish in close resemblances to each other in the aggregate. However, in this study, a classifier has been designed for aggregates grouped under four basic shapes; with the help of 3D image processing extracted feature vectors. In this study, by using three-dimensional image analysis, faster and more reliable classification of types for aggregate is performed. Multilayer Feed Forward Perceptron Neural Network Type has had the highest discrimination performance in the model of four different classifiers. The first hidden layer offering 90,84% network performance ratio has 10 nodes and the second hidden layer has 14 nodes. It takes at most one minute to take image slice of an aggregate for distinction, to complete the image processing stage and classification.

This study constitutes the first step of developing automation systems that changes faster analysis system with software. The aim of the next phase of the study is to develop the study by including the surface roughness parameters in aggregate.

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