Accepted for Presentation and Publication at the 92nd Annual Meeting of the Transportation Research Board Washington, DC, January 2013

by

Maziar Moaveni, Ph.D. Student, Graduate Research Assistant
Department of Civil and Environmental Engineering
Phone: (217) 778-2503 / Email: moaveni1@illinois.edu

Shengnan Wang, Ph.D. Student, Graduate Research Assistant
Department of Electrical and Computer Engineering
Phone: (217) 244-4392 / Email: wang403@illinois.edu

John M. Hart, Senior Research Engineer
Beckman Institute for Advanced Science and Technology
Phone: (217) 244-4147 / Email: jmhart3@illinois.edu

Erol Tutumluer, Professor (Corresponding Author)
Paul F. Kent Endowed Faculty Scholar
Department of Civil and Environmental Engineering
Phone: (217) 333-8637 / Fax: (217) 333-1924 / Email: tutumlue@illinois.edu

Narendra Ahuja, Professor
Donald Biggar Willet Professor of Engineering
Department of Electrical and Computer Engineering
Phone: (217) 333-1837 / Email: n-ahuja@illinois.edu

University of Illinois at Urbana-Champaign
205 North Mathews, Urbana, Illinois 61801

November 2012

Word Count: 4,739 words + 4 Tables (4*250) + 7 Figures (7*250) = 7,489
ABSTRACT

Morphological properties of mineral aggregates are known to affect pavement and railroad track mechanistic behavior and performance significantly in terms of strength, modulus and permanent deformation. With imaging technology, an objective and accurate measurement of aggregate particle size and shape properties can be obtained in a rapid, reliable and automated fashion. Yet, there is a need to bring these advances in aggregate imaging to project sites and quarries in the field. This paper introduces field image acquisition and processing techniques for extraction and analyses of individual aggregate particle size and shape properties. Referred to as segmentation techniques, image processing methods developed in this study analyzed 2-D field images of aggregates captured by a Digital Single Lens Reflex (DSLR) camera. The segmented aggregate images were fed into the validated University of Illinois Aggregate Image Analyzer (UIAIA) to quantify particle size and shape properties by means of its image processing algorithms for Flat and Elongated Ratio (FER), Angularity Index (AI), and Surface Texture Index (STI). The developed method successfully determined the properties of coarse aggregate samples collected from various depths in a railroad track ballast layer. The promising preliminary results indicate that these segmentation techniques can be considered in the field to capture several aggregate particles rapidly and reliably in a single image so that individual particle size and shape properties can be analyzed and further, both spatial property variability and property changes with layer depth and usage, i.e., property degradation in time, can be evaluated under service loading.

Key Words: Mineral aggregates, shape, texture, angularity, image analysis, field practice, image segmentation, image acquisition, machine vision
INTRODUCTION

As the transportation infrastructure continues to age and grow, the need for repairs, reconstruction and new construction grows, and the demand for aggregates expands. Nevertheless, high quality aggregate materials are becoming increasingly scarce and expensive in many parts of the country because gravel mines and rock quarries are being lost to other land uses. These aggregate materials are classified for use and placed in quantities based on specifications and testing techniques that are not always linked to the application of the aggregate resource. The most commonly used aggregate property, which makes a certain aggregate material to pass agency specifications for a certain transportation application, has typically been the grain size distribution or gradation.

The morphological or shape properties of mineral aggregates used in asphalt concrete, cement concrete, and unbound subbase/base/ballast layers can affect highway pavement as well as railroad track performance significantly in terms of strength and permanent deformation (1-4). Imaging technology provides an objective and accurate measurement of aggregate particle size and shape properties in a rapid, reliable and automated fashion when compared to traditional manual methods/tools, and has been successfully used as a research tool in the last decade for quantifying aggregate particle shape properties (5,6). Each available imaging system uses a specific mathematical procedure in calculating a validated index to evaluate form, angularity, and texture properties of aggregates. Among the most widely used techniques in aggregate shape characterization, the Flat and Elongated Ratio (FER), Angularity Index (AI), and Surface Texture Index (STI) were recognized as key indices from national studies such as NCHRP 4-30 and the TPF-5(023) pool fund study. These indices were determined using the University of Illinois Aggregate Image Analyzer (UIAIA) (7-9). A recent Minnesota Department of Transportation research project at the University of Illinois showed that incorporating the aggregate parameters FER, AI, and STI improved considerably the ability of the regression based predictive models in estimating the modulus and strength properties of commonly used aggregates in highway pavement construction (10). Further, railroad track ballast layers constructed from angular aggregate particles were determined from laboratory tests as well as Discrete Element Modeling (DEM) simulations to have higher strength properties and thus improved lateral stability when compared to rounded aggregate particles due to better stone on stone contact and aggregate interlock (11).

Designing and utilizing different types of aggregate image analyzers have been recognized as a promising method in evaluating aggregate shape properties. However, there are difficulties in implementing this method in the field. These include aggregate sampling in project sites/quarries for shipping to the laboratory, the slow speed of one at a time single particle image scanning/processing and finally the cost needed for building the image analyzer frame and camera mounts. Recently, low cost, high-resolution digital cameras have been available for everyday use by practitioners. A fast, simple, and cost effective procedure using user friendly hardware and software components needs to be developed to facilitate quantifying aggregate shape properties in project sites/quarries using high resolution color images captured by commercially available digital handheld cameras.

To analyze individual aggregate particle shape properties, one way is to apply image segmentation techniques to the field-captured images of aggregate samples. Image
segmentation is the process of partitioning a digital image into multiple sets/classes of pixels ("superpixels"). Each segmented set/class should correspond to a well-defined object or a coherent region in the image. The segmentation results are commonly used to recognize regions and objects of interest in the scene. This aids in subsequent image analysis or annotation (12). There are many approaches for image segmentation (13); they are either completely automatic or are based, to different degrees, on user interaction.

A basic technique for image segmentation is “thresholding”. The thresholding technique seeks to find boundaries between different regions in the image according to the difference in intensity/color. Usually, the threshold value(s) are either preset or adaptively (automatically and iteratively) chosen, and are used to partition pixels into different sets based on their intensities/colors (14). Clustering is another widely used technique for image segmentation (15,16). In this technique, a feature vector, which records pertinent information about the pixel such as its spatial coordinates, intensity/color, gradient, and so on, is first generated for each pixel in the image. It is then used as an input to a clustering method (such as k-means) (17). Thus, the image is segmented according to the clusters in the high dimensional feature vector space. Another major technique in image segmentation is region growing (18). This technique begins with a selection of a set of seed pixels by the user. After that, comparison tests are run in order to find pixels bearing similarity to the seed pixels. The process is then iterated until convergence. Region growing techniques provide users with better control of the process and output segmented regions that the users define with clear edges. Graph based approaches are also popular for image segmentation. A graph is constructed where every pixel corresponds to a node and every pair of neighboring pixels is connected by an (weighted) edge. The technique then aims to cut the graph into certain connected components so that the total weight of the edges that are cut is minimal. Many cutting algorithms are suggested in the literature, such as, the graph-cuts algorithm (19) and normalized-cuts algorithm (20). Note that the graph-cut techniques are minimizing an underlying energy/cost functional. There is a multitude of other segmentation techniques that are also based on the minimization of a suitable cost functional.

This paper describes aggregate image analysis and segmentation techniques that combine a Markov Random Field (MRF) approach for modeling, graph cut for optimization and user interaction for enforcing hard constraints (21,22). The methodology is intended to demonstrate image acquisition and processing for extraction and analyses of individual aggregate particle size and shape properties from 2-D field images of multi-aggregate samples captured using a Digital Single Lens Reflex (DSLR) camera. A case study involving collected field images of railroad ballast aggregate samples is also used to demonstrate the effectiveness of the field imaging and segmentation approach in producing single aggregate particle images, which are subsequently analyzed for size and shape properties through the use of image processing algorithms of an enhanced, second generation UIAIA.

**OBJECTIVE AND SCOPE**

The primary objective of this study is to provide a capability to characterize aggregate size and shape properties by developing a customized machine vision system designed to operate in the field. The scope of initial research tasks described in this paper deals with aggregate
image acquisition and processing through field imaging and laboratory UIAIA analyses. Field imaging involves capturing color photos of multiple aggregate particles in single 2-D images using a high-resolution DSLR camera. Separate small images of single aggregate particles are then extracted by applying the appropriate segmentation techniques to the field image containing multiple aggregate particles (23,24). The size and shape properties of each particle are subsequently analyzed based on image processing algorithms of an enhanced, second generation UIAIA.

AGGREGATE IMAGE ACQUISITION

Capturing the images of aggregate samples can be performed either using aggregate image analysis systems such as the UIAIA utilizing one at a time aggregate particle scanning option or a handheld camera that can capture multi-aggregate images. More details about each method are described in this section.

Procedure for Field Imaging Using DSLR Camera

This section describes the procedure developed to capture images of aggregate particles out in the field, to enable the desired image processing techniques to perform successfully. Key elements in the capture of the images of aggregate particles under ambient conditions are the following: appropriate contrast between the background and the edge of the particles, proper exposure to avoid having any areas in the image that are overexposed, a specified resolution (pixels/inch), and elimination of any shadows caused by the sun or the camera’s flash; these are necessary in order to successfully perform the segmentation procedure described. A Canon EOS Rebel T1i camera with 15.1-megapixel resolution, Complementary Metal–Oxide–Semiconductor (CMOS) sensor technology, and 18-55 mm lens was used in this study (see Figure 1). Camera settings to achieve proper aggregate images are summarized in Table 1. Other factors affecting field imaging, such as depth of field and lens distortion, were also addressed for the image acquisition system.

Enhanced University of Illinois Aggregate Image Analyzer (E-UIAIA)

Recently, an enhanced, second generation UIAIA has been designed and manufactured at the University of Illinois with many improvements over the old system. Figure 2 illustrates this new system featuring an aggregate particle with three orthogonal views captured using high resolution progressive scan digital color cameras. These views are used to quantify imaging based FER, AI, and STI morphological indices.
FIGURE 1. Camera setup developed for aggregate imaging in an outdoor setting
(Left: front view of camera and tripod, Right: top view camera screen)

TABLE 1. Developed camera setting for field imaging

<table>
<thead>
<tr>
<th>DSLR camera setting parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance from camera lens to object</td>
<td>28 inches</td>
</tr>
<tr>
<td>Shutter speed</td>
<td>1/30 sec</td>
</tr>
<tr>
<td>Aperture</td>
<td>f/4</td>
</tr>
<tr>
<td>Light sensitivity</td>
<td>ISO-100</td>
</tr>
</tbody>
</table>

Unlike the old version of UIAIA, which was limited to taking black and white images, the new system is equipped with three high resolution (1,292 x 964 pixels) Charge Coupled Device (CCD) progressive scan cameras to capture digital color images of aggregate particles. Since black and white images are generally used for texture analysis, the majority of texture details are lost during converting gray scale images into black and white. Therefore, the influence of natural color variation of the aggregate on grayscale intensities, which directly affects the texture, needs to be addressed by using color images rather than black and white ones. An advanced color thresholding scheme is utilized in Enhanced-UIAIA (E-UIAIA) processing software. Therefore, different types of mineral aggregates with a wide range of colors can be scanned with this system. Four LED illumination lights with dimmer controls assist the operator to achieve the best contrast and sharpest possible aggregate images by optimizing light intensity as well as minimizing shadows. An enhanced calibration adjustment interface also makes it possible to change the spatial resolution corresponding to the size of aggregate particle scanned by using the zooming capability of the camera lenses. After calibration process, ‘saved configurations files” are used in accurate size and shape property analyses for each batch of aggregate with different colors. Some of the new features of Enhanced-UIAIA in comparison to the old version of UIAIA are summarized in Table 2.
Table 2. Comparison of the old and enhanced versions of UIAIA

<table>
<thead>
<tr>
<th>Feature description</th>
<th>Old-UIAIA</th>
<th>Enhanced-UIAIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thresholding scheme</td>
<td>Black and white</td>
<td>Color</td>
</tr>
<tr>
<td>Image processing speed</td>
<td>1 particle/second</td>
<td>20 particles/second</td>
</tr>
<tr>
<td>Camera resolution</td>
<td>640 x 480</td>
<td>1292 x 964</td>
</tr>
<tr>
<td>Image format</td>
<td>bmp / monochrome</td>
<td>png / color</td>
</tr>
<tr>
<td>Light intensity control</td>
<td>Constant</td>
<td>Dimmer control</td>
</tr>
<tr>
<td>Magnification level</td>
<td>Constant</td>
<td>Variable</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>160 pixels/inch (0.1875 pixels/mm)</td>
<td>450 pixels/inch (0.0564 pixels/mm)</td>
</tr>
<tr>
<td>Calibration method</td>
<td>Constant</td>
<td>Variable for each aggregate batch</td>
</tr>
<tr>
<td>Camera triggering method</td>
<td>Laser sensor</td>
<td>Live video (30 frames/second)</td>
</tr>
</tbody>
</table>

Associated with color captured images, user friendly shape property analysis software application has been developed for the Enhanced-UIAIA. Figure 3 shows a screenshot of this user interface, which exports all the computed shape indices in a MS Excel file for further post processing and statistical analysis.
AGGREGATE IMAGE PROCESSING

Image Segmentation Technique

The Markov Random Field (MRF) technique is widely used for pixel labeling problems in computer vision. When only two labels exist, they are labeled as “foreground” and “background”. Pixels that belong to the foreground (object) are usually labeled as 1 while pixels that belong to background are labeled as 0.

The specific algorithm used in this study begins with the user drawing strokes on the images to select a small number of pixels for each label. The MRF is then invoked in order to learn and associate the foreground with a probability distribution of its pixel intensity/color. The user interface used in this paper is given in reference (25). A Gaussian mixture models the color probability distribution. A similar process is performed for the sampled background pixels. Then, given a new pixel in the image, the probabilities of the underlying intensity in each of the two probability models are evaluated. The results, therefore, at a pixel \( p \), are two probability values \( R_p(0) \) and \( R_p(1) \) discussed in detail in reference (22).

The algorithm continues by associating the image with a graph. An illustration of such graph that corresponds to an arbitrary \( 3 \times 3 \) image is given in Figure 4. Each pixel in Figure 4(a) corresponds to a node (pixel node) in the graph shown in Figure 4(b). In addition to pixel node, the graph contains a pair of nodes corresponding to the background and the foreground/object labels. They are marked as node S and T. The horizontal edges \( (n\text{-link}) \) connect neighboring pixels while the vertical edges \( (t\text{-link}) \) connect each pixel node to the label nodes. In Figure 4, the weight of an edge is shown in proportion to the thickness of the link. Only neighboring pixels are connected; the weight of the edge, however, varies. In Figure 4, the user identifies pixel \( v \) as a background pixel. Therefore, pixel \( v \) is connected to the background by a very thick edge. Similarly, pixel \( p \) is marked by the user belonging to...
the object. In the absence of such user input, the weight of t-links depends on the probabilities $R_p(0)$ and $R_p(1)$. Thus, the inspection of edges between label nodes and pixel nodes in Figure 4 shows that pixel $q$ is more probable to be background while pixels $w$ and $r$ are more likely to belong to the object. The segmentation is then done via a graph-cut optimization technique.

![Graph](image)

**FIGURE 4. Illustration of the graph-cut algorithm**

In the mini example of Figure 4, the optimal graph cut shown here is trivial. In general, the algorithm tends to cut the edges with small weight while preserving edges with large weight. The result is shown in Figure 4(c) by the dotted line and the corresponding segmentation result is shown in Figure 4(d) in which the black pixels are the background and the white pixels are the object. Usually, the optimal graph cut is robust to contamination of the image by noise.
Naturally, the selection of this algorithm is guided by considering several factors, such as the color of the pixels in the aggregate images, to distinguish between foreground (particles) and background. The color of the foreground is to some extent uniform and at the same time distinct from the background. Additionally, enforcing neighborhood constraints makes sure that the foreground particles are solid and their shape is not sensitive to acquisition noise.

Once the image is segmented into foreground and background regions, the connected components of the foreground need to be determined. Each such connected component is a single particle or a small cluster of particles. The algorithm examines each row in the image and finds the intervals of foreground pixels and cluster intervals from adjacent rows. Each cluster is hence a connected component thus corresponds to a single particle. An illustration of the process is depicted in Figure 5 for different color coarse aggregate particles segmented individually into smaller single-particle images.

![Figure 5](image-url)

**FIGURE 5. Illustration of segmentation technique for particle detection and binary image generation**
The newly Enhanced-UIAIA system uses the binary images of aggregates to measure imaging indices including Flat and Elongated Ratio (FER), Angularity Index (AI), and Surface Textures Index (STI). This section gives details about the algorithms involved in computing these indices.

**Flat and Elongated Ratio (FER)**

According to ASTM D 4791 (26), the FER of an aggregate particle is defined as the ratio of the maximum dimension of the particle to the minimum dimension. Using the three views, the longest dimension and shortest dimension are determined for each particle tested. After a suitable number of particles are tested, the FER values are averaged for a certain aggregate sample (7).

**Angularity Index (AI)**

To approximate the profile of each 2-D image of a particle, the coordinates of the profile are extracted first. Then, the outline is approximated by an n-sided polygon as shown in Figure 6. An optimum n value of 24 was determined to best separate the typical AI values of the crushed particles from those of the uncrushed gravel (7,8). The angle subtended at each vertex of the polygon is computed next. A relative change in slope of the n sides of the polygon is subsequently estimated by computing the change in angle $\alpha$ at each vertex with respect to the angle in the preceding vertex. The frequency distribution of the changes in the vertex angles is established in 10-degree class intervals. The number of occurrences in a certain interval and the magnitude are then related to the angularity of the particle profile.

![FIGURE 6. Replacing an aggregate particle with an n-sided polygon](image)

Equation 1 is used for calculating Angularity of each projected image. In this equation, $e$ is the starting angle value for each 10-degree class interval and $P(e)$ is the probability that change in angle $\alpha$ has a value in the range $e$ to $(e+10)$. From its definition as given in Equation 1, the Angularity has units of degree. The final AI value is a weighted average value of its Angularity determined from three views (front, top, side).
Surface Texture Index (STI)

The STI is defined based on the image analysis technique “erosion and dilation.” One erosion cycle processes each 2-D image by removing boundary pixels off an object surface to leave the object less dense along its outer boundary. However, dilation is the reverse process of erosion and a single dilation cycle increases the particle shape or image dimension by the same pixels around its boundary. Erosion cycles followed by the same number of dilation cycles tend to smooth the surface of a particle by trimming the peaks and corners and patching the sharp dents on the boundary. The imaging pixel count based area difference of the 2-D image before and after the erosion and dilation cycles of the same number of cycles is directly related to the surface micro-irregularities (9). Equation 2 defines the STI for each particle image.

\[
STI = \frac{A_1 - A_2}{A_1} \times 100
\]  

where

- \(STI\) = Surface texture parameter of the 2-D image of particle;
- \(A_1\) = Area (in pixels) of the 2-D image of particle;
- \(A_2\) = Area (in pixels) of the particle after performing a sequence of “\(n\)” cycles of erosion followed by “\(n\)” cycles of dilation.

To set up an STI index independent of particle size, the optimum number of cycles of erosion and dilation, \(n\), to be applied can be obtained as follows:

\[
n = \frac{L}{\beta}
\]

where

- \(L\) = Longest or maximum intercept of a particle in image;
- \(\beta\) = Scaling factor for erosion and dilation operations.

The optimal \(n\) value is determined as 20 at which STI of a set of smooth surface coarse aggregate is recognized as significantly separated from the STI of a set of rough surface coarse aggregate (9). The final STI value is a weighted average value of its individual image STI values determined from three views (front, top, side images).
Performance of Color Thresholding Feature in Enhanced-UIAIA

In the new Enhanced-UIAIA, 24 bits/pixel color images of aggregates are used as an input for the color thresholding algorithm. The performance of Enhanced-UIAIA in determining the size and shape property indices, i.e., FER, AI and STI, is demonstrated by the image processing and analysis stages applied on different colored aggregates in Table 3. For example, the black and gray colored aggregates with much higher AI and STI values in Table 3 were successfully analyzed using the E-UIAIA system.

<table>
<thead>
<tr>
<th>Aggregate color</th>
<th>Pink</th>
<th>Gray</th>
<th>Light brown</th>
<th>White</th>
<th>Black</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Image</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
</tr>
<tr>
<td>Binary Image</td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
</tr>
<tr>
<td>AI</td>
<td>350</td>
<td>620</td>
<td>380</td>
<td>510</td>
<td>690</td>
</tr>
<tr>
<td>FER</td>
<td>1.51</td>
<td>1.2</td>
<td>1.56</td>
<td>1.18</td>
<td>1.2</td>
</tr>
<tr>
<td>STI</td>
<td>1.29</td>
<td>2.08</td>
<td>1.67</td>
<td>1.2</td>
<td>2.4</td>
</tr>
</tbody>
</table>

CASE STUDY AND DISCUSSION

Each year, a large portion of the US freight railroad operating budget, to sustain the railway track system, goes into maintenance and renewal of mineral aggregates used as track ballast. These large sized aggregates; with a maximum size of 3 in., are used as the ballast layer in the track substructure, which distributes the train load to the subgrade soil and also provides drainage for the track with its uniform gradation. Unlike subbase/base layers in pavement structures, ballast aggregates tend to break down, powder and deteriorate under many repeated wheel loadings from heavy freight trains. This ballast degradation not only reduces particle sizes but also changes the physical shape properties of aggregate particles, resulting in accumulation of finer material causing ballast fouling. The intensity of the ballast degradation is a function of aggregate source properties, load levels, as well as track geometry and environmental conditions. Fast and reliable field ballast assessment methods using machine vision and image processing techniques are needed to monitor changes in ballast properties.

To evaluate the performance of the field imaging and segmentation methods developed in this study, aggregate samples were collected at different ballast depths from a mainline freight railroad in Mississippi. Figure 7(a) shows the aggregate samples collected at
the surface (0 in.) as well as 8-in. and 16-in. ballast depths. Figure 7(b) is a photo of the sampling track location showing clean ballast on top and gradually fouling ballast with depth.

The shape properties of the ballast aggregate particles were measured using the field imaging/segmentation and the laboratory E-UIAIA methods described in this paper to investigate the effects of train loading and the resulting ballast deterioration levels with depth. Table 4 summarizes the results of the morphological analyses with imaging based shape indices determined using both the E-UIAIA and the field segmentation techniques. It should be noted that 215 pixels/in. resolution was used in scanning the aggregates by both methods.

From Table 4, a comparison of the maximum aggregate dimensions and FER values proves that both the field imaging/segmentation and the laboratory E-UIAIA methods agree quite well in determining aggregate particle sizes (with averages ranging from 0.97 to 2.22 in.) obtained from different ballast depths. Furthermore, good level of repeatability is observed with both methods from a comparison of trials 1 and 2 and the standard deviation values. The AI values determined by the field imaging/segmentation are consistently lower than those computed in the laboratory from the E-UIAIA image scanning and processing method. On the other hand, the STI values are determined slightly higher using the field imaging/segmentation method. Since the camera sensor technologies as well as the natural lighting conditions vary considerably between two methods, it is conceivable that the pixel intensities of the captured aggregate images are not quite similar although the pixel calibrations are the same. In other words, digitization error can be considered as a factor for not achieving identical binary images by the two methods. Nevertheless, considering the ranges of AI and STI values and the similar magnitudes of standard deviations, the results from the two methods are closely matching and quite acceptable for practical field applications.

It is interesting to note that both methods could successfully detect the gradual demise in the aggregate size with ballast depth due to degradation and particle breakdown under...
repeated train loading. This is with the understanding that old ballast, which is more
degraded and broken down, is found in deeper sublayers. The particles sampled from the 8 in.
depth have slightly higher FER values as determined by the two methods. The FER values
also match closely between the two methods due to the same pixel resolution used. For both
methods, the measured AI and STI values indicate somewhat increasing trends with ballast
depth, which can be explained with the size reduction and breakage of older ballast under
train loading. Interestingly, as the aggregate size gets smaller with depth, these more recently
crushed particles at greater depths possess higher angularities and rougher surfaces.

### TABLE 4. Ballast aggregate shape indices computed from E-UlAIA in the laboratory
and field imaging/segmentation

<table>
<thead>
<tr>
<th>Depth (in.)</th>
<th>No. of particles</th>
<th>AI (degrees)</th>
<th>Max dimension (in.)</th>
<th>FER</th>
<th>STI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>E-UlAIA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Trial 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>34</td>
<td>420</td>
<td>112</td>
<td>2.19</td>
<td>0.55</td>
</tr>
<tr>
<td>8</td>
<td>54</td>
<td>438</td>
<td>116</td>
<td>1.29</td>
<td>0.37</td>
</tr>
<tr>
<td>16</td>
<td>42</td>
<td>432</td>
<td>108</td>
<td>0.96</td>
<td>0.33</td>
</tr>
<tr>
<td><strong>Trial 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>34</td>
<td>421</td>
<td>125</td>
<td>2.2</td>
<td>0.54</td>
</tr>
<tr>
<td>8</td>
<td>54</td>
<td>459</td>
<td>120</td>
<td>1.28</td>
<td>0.35</td>
</tr>
<tr>
<td>16</td>
<td>42</td>
<td>468</td>
<td>114</td>
<td>0.97</td>
<td>0.32</td>
</tr>
</tbody>
</table>

| **DSLR Camera and Segmentation** |              |                     |     |     |
| **Trial 1** |                  |              |                     |     |     |
| 0           | 34               | 385          | 77                  | 2.22| 0.6 |
| 8           | 54               | 417          | 108                 | 1.41| 0.38|
| 16          | 42               | 435          | 119                 | 1.07| 0.39|
| **Trial 2** |                  |              |                     |     |     |
| 0           | 34               | 379          | 81.4                | 2.21| 0.56|
| 8           | 54               | 402          | 105                 | 1.4 | 0.39|
| 16          | 42               | 441          | 97                  | 1.03| 0.36|

TRB 2013 Annual Meeting

Paper revised from original submittal.
SUMMARY AND CONCLUSIONS

Aggregate image processing/segmentation techniques have been developed and used in this study to analyze the 2-D images of aggregate samples captured by a commonly used DSLR camera in the field for extraction and analyses of individual aggregate particle size and shape properties. The segmented individual particle images were fed into the validated University of Illinois Aggregate Image Analyzer (UIAIA) processing algorithms to compute particle size and shape properties using the imaging based indices of Flat and Elongated Ratio (FER), Angularity Index (AI), and Surface Texture Index (STI). An enhanced, second generation UIAIA was also introduced in this paper with many improvements over the old system. The Enhanced-UIAIA uses high resolution aggregate color images, similar high resolution to those obtained from the DSLR camera, captured from three orthogonal views using progressive scan digital color cameras with improved lighting conditions and advanced color thresholding schemes to quantify imaging based aggregate size and FER, AI, and STI morphological indices.

The performance of field imaging and segmentation methodology was evaluated by means of a case study involving field images of railroad aggregate samples collected from various ballast depths in a mainline freight railroad track. The results of ballast aggregate size and morphological analyses, i.e., the computed imaging based size and shape indices, using both the laboratory Enhanced-UIAIA and the field imaging/segmentation methods matched quite closely. Further, both methods could successfully detect the gradual decrease in the aggregate size due to higher degradation and particle breakdown with ballast depth as evidenced by higher AI and STI values measured at greater depths. These promising preliminary results therefore indicate that these imaging and segmentation techniques can be considered in the field to rapidly and reliably capture several aggregate particles in a single image so that individual particle size and shape properties can be analyzed and further, both spatial property variability and property changes with layer depth and usage, i.e., property degradation in time, can be evaluated under service loading.

Future research will be directed towards establishing more validation cases involving statistical analyses with different ranges of size and shape property indices for different types of aggregate using both the field imaging/segmentation and laboratory E-UIAIA methods. Future successful applications of the developed field imaging/segmentation methodology hold the potential to provide optimized aggregate resource selection/utilization, better aggregate quality control/quality assurance, improved material specifications, and associated significant economic benefits for a sustainable construction and renewal of transportation infrastructure.

ACKNOWLEDGEMENT

The support for this research study was provided partially by the Association of American Railroads (AAR) and the BNSF Railway Company. The authors would like to acknowledge the help and advice of David Davis with Transportation Technology Center, Inc. (TTCI) and Henry Lees with BNSF Railway. The authors would like to thank Dr. Bruce Ammons from Ammons Engineering for his assistance in LabView programing. Special thanks go to
Mr. Dong Zhang, a visiting PhD student from Southeast University in China, for his help during the railroad field trip for aggregate sampling in Mississippi.

REFERENCES


25. Neo imaging. [www.neoimaging.cn](http://www.neoimaging.cn)