Ballast inspection goes digital

TTCI evaluates a new approach to inspecting ballast and assessing ballast condition.

by Mike McHenry, senior engineer II, Transportation Technology Center, Inc.; Erol Tutumluer, professor, Paul F. Kent Endowed Faculty Scholar; John M. Hart, principal research engineer; Maziar Moaveni, post-doctoral research associate, University of Illinois at Urbana-Champaign

Railroad ballast provides stability and drainage for tracks that carry freight and passenger traffic. As a granular material, the ballast layer becomes degraded and finer in size with use. This is commonly related to particle abrasion and breakage or intruding subgrade soil fines. Degraded ballast may lead to poor drainage, settlement and eventually, track instability. Ballast degradation is typically quantified by Selig's Fouling Index (FI) or Percentage Fouling.[1] Both values describe the quantity of fine material present in the ballast relative to the overall sample size.

Assessing ballast condition usually involves identifying particle size distribution based on subjective expert visual inspection or using ballast sampling and laboratory sieve (gradation) analysis. Human visual inspection is qualitative, conducted primarily by looking at the surface of the ballast. However, underneath the surface, ballast degradation varies based on its three-dimensional location with respect to the rail and ties. Because of this, physical sampling/sieving efforts can be subjective and resource intensive and representative samples can be difficult to obtain.

Transportation Technology Center, Inc. (TTCI), recently supported research to develop a new approach to inspecting ballast and measuring its condition in the field. The University of Illinois at Urbana-Champaign (UIUC), an Association of American Railroads (AAR) affiliated laboratory, has developed a novel technique that uses cross-section digital images of ballast and a machine vision system to measure the size of ballast particles and estimate ballast degradation.[2] Through the AAR's Technology Outreach research program, TTCI has performed investigative field work using this system at the Facility for Accelerated Service Testing (FAST) near Pueblo, Colo.

Figure 1: Seven images were stitched together to provide a panorama of the ballast cross-section below a concrete tie at FAST.

Figure 2: For each image, samples corresponding to the area imaged were collected and later sieve analyzed. The photo shows a trench wall below a tie where a sample was collected.

Research overview

The research team at UIUC developed a Ballast Imaging Kit consisting of a camera, a tripod and calibration tools, including a 1-inch sphere calibration ball, for use in acquiring field images of ballast. Images and corresponding physical ballast samples were collected during multiple visits to both FAST's High Tonnage Loop (HTL) and various BNSF Railway revenue lines. Images were processed through UIUC's machine vision algorithm and ballast samples were sieved to obtain ground truth data on actual ballast degradation.

Field imaging and ballast sampling

To obtain in-service ballast cross-sections for imaging, trenches were dug perpendicular to the track across the ballast profile in existing test zones on the HTL.[3] Seven images were taken across the width of the ballast shoulder profile below the tie. Figure 1 is a stitched panoramic image of one of the trench walls showing the 1-inch calibration ball.

For each image, samples corresponding to the area imaged were collected and later sieve analyzed, as shown in Figure 2.

In addition to the collection of the FAST HTL transverse section images, vertical and horizontal images taken across longitudinal ballast cross sections—simulating those made by a ballast shoulder cleaner—were also collected on BNSF revenue service lines.

Image processing and analysis

Figure 3 follows the various steps associated with processing a ballast cross section image. A machine vision method for image segmentation was used to identify and separate individual ballast particles and degradation zones.[4] Segmentation algorithms primarily detect the rock particle boundaries to determine the locations of distinct particles.

The Vincent and Soille's watershed algorithm[5] was selected based on its reliable performance for extracting particles that are touching each other. Various pre-processing procedures were used to amplify the relative difference in light and dark pixels, increase the contrast of borders and reduce the internal texture on individual ballast particles.[6,7] Once segmented, particles can be extracted from the image and analyzed for size, shape and angularity.

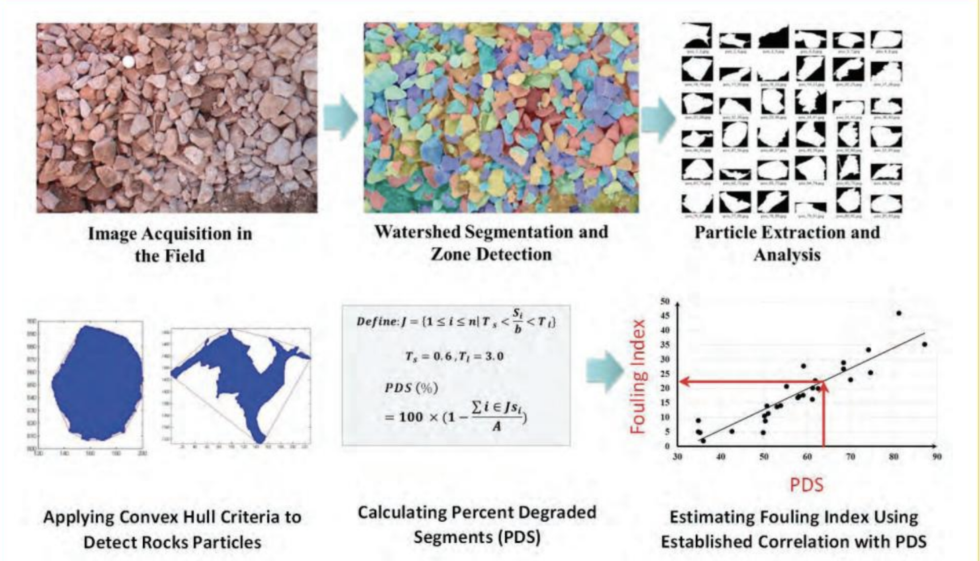

Figure 3: The various steps associated for estimating ballast degradation using the PDS index.

A critical step in the algorithm for determining the extent of ballast degradation in an image involves separating out "non-rock" segments, which are finer particles either filling voids or comprising large degraded areas in the image. To accomplish this, the ballast particles are generally expected to be convex in shape. Therefore, a convex hull is constructed around each segment found and the ratio of the area of the segment and the area of the convex hull is computed. The figure shows the difference between ballast particle and "non-rock" segments extracted from an image.

The analysis of each segmented image is conducted using an area-based approach. The area of a 1-inch calibration ball, in pixels, is estimated and then used to compute the area of each particle segment. According to area, these segments are partitioned into three classes: typical, small and large. The small category represents severely degraded particles, the typical category represents average sized ballast particles and the large category represents oversized regions with particles too small to be identified individually, such as fine grains. These categories are determined by normalizing the areas with respect to the area of the calibration ball.

THIS MACHINE-VISION SYSTEM OFFERS AN OBJECTIVE AND ON-TRACK METHOD TO EVALUATE BALLAST CONDITION

A score for each image, referred to in this research as the Percentage of Degraded Segments (PDS), determined the percent of the image that contained degraded ballast. Figure 4 shows the correlation of the PDS values computed for the various images collected at FAST and BNSF revenue sites to their measured FI values obtained in the laboratory from analyzing the corresponding samples collected from the trenches.

Moving forward

More details related to this research project can also be found in various other works.[8] Ultimately, this machine-vision system offers an objective and on-track method to evaluate ballast condition that is faster and less labor-intensive than the traditional sampling and sieving process.

The correlation shown in Figure 4 demonstrates the promise of such an approach in estimating ballast degradation and relating it back to Selig's FI — the most common parameter used by field practitioners to evaluate their ballast.

Additionally, future research is planned on the implementation of this type of imaging system on shoulder ballast cleaners. Automating the inspection of ballast offers the railroad industry yet another means of objective, data-driven maintenance decisions for ballast rehabilitation.

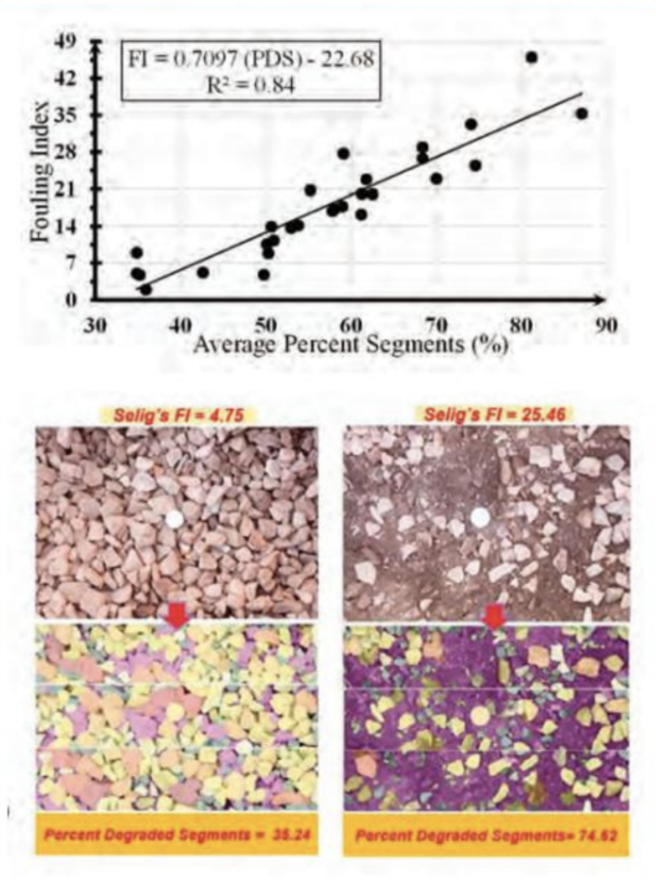

Figure 4: PDS values from ballast image segmentation were computed for the images collected at FAST and BNSF revenue sites and correlated to their Selig FI values as obtained from laboratory sieve analysis. This resulted in 28 images of ballast cross sections collected from field.

References

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