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Machine Vision for Evaluating In-Service Ballast Condition

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Summary

The University of Illinois at Urbana-Champaign (UIUC), an Association of American Railroads (AAR) affiliated lab, and Transportation Technology Center, Inc. (TTCI) are developing improved ballast inspection techniques. The investigative and field work described here recommends a novel method for automatic inspection of the condition of ballasted track using machine vision, eliminating the need for sampling and laboratory sieve analyses. Current results of this investigation include the development of the following:

- Image capture and calibration equipment, provided in a Ballast Imaging Kit (BIK), for railroad investigators to acquire the images of ballast cross sections;
- Field acquisition procedures for determining appropriate parameters, such as view, exposure, spatial resolution, etc., are critical for obtaining high quality images;
- Image preprocessing and enhancement methods for refining images prior to the application of machine vision algorithms for analysis;
- Image segmentation algorithms to extract particles and degraded zones visible in field images of ballast;
- Percentage of Degraded Segments (PDS) scoring system to quantify the level of ballast degradation in the field;
- Validation of PDS results using a field test underway at the Transportation Technology Center, Inc., (TTCI).

Railroad ballast provides stability and drainage for tracks that carry freight and passenger traffic. In-service ballast, as a granular material, degrades into finer particles resulting from abrasion, breakage and polishing. Degraded ballast may lead to poor drainage, settlement and eventually track instability. Ballast condition assessment methods usually involve the task of identifying particle size distribution, based on subjective expert visual inspection or using ballast sampling and transport for laboratory sieve analysis. Human visual inspection is 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. This phenomenon also makes sampling/sieving efforts subjective as well, based on the location where the sample is taken.

Ultimately, this automatic inspection approach can provide objective machine vision analysis of ballast degradation underneath and in between the ties. This method is envisioned to be applied to a continuous longitudinal cross section of the shoulder near the end of the ties, such as that created by a shoulder ballast cleaner along the length of the track. This work is being conducted as part of an ongoing AAR Technology Outreach Program project to help evaluate the design and deterioration of ballasted track and provide predictive service life and failure analysis for improving the safety and network reliability of AAR member railroads.

INTRODUCTION AND BACKGROUND

Maintaining ballasted track requires periodic evaluation of the ballast condition to detect excessive degradation, which can lead to track instability and possible track failures. Fouling Index (FI) and Percentage Fouling (PF)[1] are two commonly used indices for quantifying ballast degradation. To estimate these indices, one needs to perform ballast sampling and subsequent sieve analysis on acquired samples, which are labor intensive and time consuming. To counter these difficulties, an objective and automated methodology for determining levels of degradation is being developed with the aid of a machine vision system to be integrated on regularly used ballast maintenance equipment. This configuration provides a method for capturing and analyzing images of the ballast as the maintenance equipment traverses the track. The degraded ballast condition results from this system can assist in determining proper maintenance strategies and prediction of the ballast service life cycle.

This *Technology Digest* describes the recent results of the machine vision inspection system under development. To estimate the degradation levels, the system uses an image segmentation algorithm to extract particles and degraded zones from high resolution images that were captured in the field.

Initial image data, for early development of the segmentation algorithm,[2] was acquired in the laboratory using ballast samples placed in a transparent Plexiglas box. This method allowed the fabrication of mock ballast cross sections similar to those observed in the shoulder or underneath the track in the field. The clear sides of the box allowed images of the ballast to be captured in the laboratory under controlled conditions.

Key requirements for capturing images, in the laboratory or the field, include obtaining proper exposure, consistent spatial resolution, and minimization of distortion across the entire image of the ballast cross section. To ensure these requirements are achieved, equipment was assembled into a Ballast Imaging Kit (BIK) with a multiple-step procedure for allowing railroad personnel to acquire images suitable for machine vision segmentation algorithms.

Several trips to both in-service and test track sites were made to remove ballast by hand to capture images of undisturbed ballast layers in the shoulder. Results of the segmentation algorithm in these test cases showed good performance by properly segmenting approximately 80 percent of the particles in the images (Figure 1).

Obtaining an adequate number of images showing ballast cross sections under different levels of degradation in the field was challenging. To obtain further images and alleviate the preparation of cross sections by hand, the authors collaborated with the Improved Tie and Fastener System Performance Strategic Research Initiative (SRI) being conducted at the Facility for Accelerated Service Testing (FAST). Ballast trench cross-sections were imaged at FAST as a field application for initial validation of the ballast inspection system.

(a) (b) (c)

Figure 1. (a) Original cross section image (b) Image segmented into colored areas, and (c) Individually extracted particles for analysis

LATERAL TRENCHING AND FIELD IMAGING

The aforementioned SRI project includes evaluation of different concrete tie designs and their effects on ballast degradation and track geometry.[3] As part of scheduled research activities, trenches are made laterally across the track so the condition of the ballast within and underneath the various tie zones can be visually observed (Table 1).

Table 1. Crosstie information for trenches image analyzed

Trench ID (Crosstie #)	Zone #	Type of Concrete Crosstie	Under Tie Pads	Crosstie Spacing (inch)
1100	1	Half-Frame	Yes	24
1177	1	Half-Frame	Yes	24
1274	2	Conventional	No	24
1388	3	Conventional	Yes	24
1477	4	Conventional	Yes	24

These various tie types presented an opportunity for imaging trenches with several different levels of degradation for testing the machine vision algorithms and identifying any correlation between ballast degradation and the types of crossties used. Using the BIK and imaging procedure developed, seven images were captured along five trenches by TTCI personnel (Figure 2).

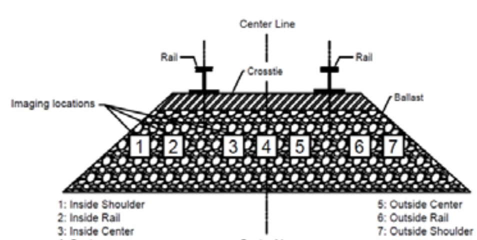


Figure 2. Trench cut underneath tie shows imaging locations

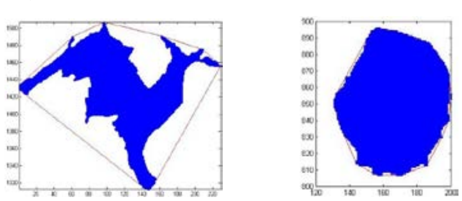
FIELD IMAGE ANALYSES OF BALLAST PARTICLES AND DEGRADED ZONES

For identifying and separating individual ballast particles and degradation zones, the process of image segmentation was used. Segmentation algorithms primarily detect the rock particle boundaries to determine the locations of distinct particles. The Watershed algorithm[4] was selected based on its good performance for extracting particles that are touching each other. This process is still challenging and often requires preprocessing of the images to improve the performance of the segmentation.

The first step in the image preprocessing is image enhancement. Gamma adjustment[5] can be used to enhance the image by rebalancing the relative intensities of pixels, if the image is predominantly too bright or too dark, thus amplifying the visual differences between the bright or dark pixels, respectively. Histogram equalization[5] can also be used to increase the image contrast if the intensity of the pixels are concentrated in small band of values. Both methods can improve the boundary detection.

Images of ballast provide a challenge for the segmentation algorithm due to the excessive amount of texture on ballast particles. The segmentation algorithm confuses the internal texture on the surfaces of the rocks with their true boundaries. Bilateral Filtering[6] is employed to reduce the internal texture while preserving the actual boundaries between touching particles. Once the particles are segmented, they can be extracted from the image and further analysis involving size, shape, and angularity can be performed, see Figure 1c.

An additional step involves separating out non-rock segments, which are either finer particles filling voids or rocks from underneath the surface layer. To accomplish this, the ballast particles are assumed to be mostly 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 (Figure 3).



(a) (b)

Figure 3. (a) Convex hull (boundary) of non-rock (area ratio = 0.4803) (b) Convex hull of rock particle (area ratio = 0.9718) (Note: axes are pixel locations in the image)

Those segments with high ratio values are considered to be normal rock particles, thus reducing the number of false positive particle detection.

SEGMENT ANALYSIS AND CALCULATION OF DEGREDATION PERCENTAGE

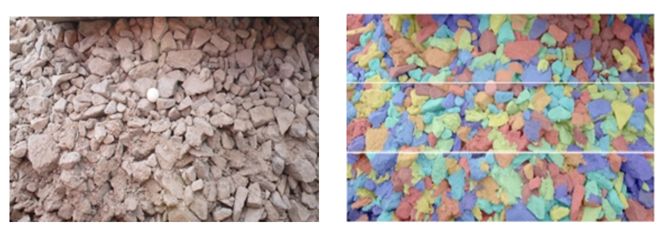
The analysis of each segmented image is conducted using an area-based approach. The area of a 1-inch calibration ball, in pixels, is estimated and then used to calibrate the area of each particle segment. According to area, these segments are then partitioned into three classes, *typical*, *small*, and *large*. The *typical* category represents average size ballast particles, the *small* category represents severely degraded 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, setting thresholds at <60 percent for *small* and >300 percent for *large*. The later categories are labelled as Degraded Segments.

A score for each image, Percentage of Degraded Segments (PDS), is defined as the percentage of the total area of the *large* and *small* segments compared to the total area of the ballast image. Let S_i ($i = 1, \ldots, n$) be the areas of the segments 1, ..., n in the image. Let b be the area of the calibration ball and A be the area of the image. All areas are measured in number of pixels.

Define: $J = \{1 \leq i \leq n \mid threshold_s < S_i/b < threshold_l, threshold_s = 0.6, threshold_l = 3\}$

Then, $PDS(\%) = 100 \text{ x } (1 - \sum i \in J S_i / A)$

Figure 4 shows the segmentation result of a typical trench image, taken by TTCI, divided into three sub-images of equal height for processing. The PDS score for each sub-image is 55, 41, and 40, respectively. These values are averaged to determine an overall PDS score of 45.3.



(a) (b)

Figure 4. (a) Original trench image (b) Image segmented into colored areas in the three sub-images after processing

All 35 images taken in the trenches were processed and the results are presented in Table 2. To test the validity of the PDS values, estimated degradation level rankings were made by human visual judgments for each trench (1 = low degradation, 5 = high degradation), as listed in Table 2.

Table 2. PDS values and visual rankings for TTCI trench images

Inside Shoulder Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1477	1177	1274	1100	1388
PDS (%)	48.9	52.5	50	65.4	65.4
Inside Rail Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1177	1100	1477	1388	1274
PDS (%)	45	73.4	73.9	93.1	63.54
Inside Center Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1177	1100	1388	1274	1477
PDS (%)	74.4	63.1	77.94	86.4	87.84
Center Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1177	1100	1388	1477	1274
PDS (%)	75.94	42.97	90.27	83.24	89.87
Outside Center Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1177	1100	1274	1477	1388
PDS (%)	45.40	53.5	79.76	81.54	79.45
Outside Rail Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1177	1100	1274	1388	1477
PDS (%)	58.37	63	67.13	75	77
Outside Shoulder Imaging Location					
Visual Ranking	1	2	3	4	5
Trench ID	1100	1177	1477	1274	1388
PDS (%)	62.1	55.94	66.57	66.8	85.17

When compared, the majority of the PDS rankings are comparable to the visual rankings. One explanation for those not comparable is that direct sunlight, which causes shadows and highlights, creates artificial discrepancies in pixel intensities in these images. In addition, the human visual rankings are of course subjective. Note that images with high levels of degradation and those with low levels have high and low PDS scores, respectively.

Both the visual and PDS rankings for trenches ID1100 and ID1177 had the lowest levels of degradation. These trenches correspond to locations of the half-frame tie, which is a larger concrete tie with greater ballast contact area. The half-frame tie appears to be reducing ballast degradation compared to a conventional concrete tie.

Segmentation results for PDS values were presented as part of SRI Tie Project at the 2014 International Crosstie Fastening System Symposium at UIUC and at the 20th AAR Annual Research Review in 2015.

CONCLUSIONS AND RECOMMENDATIONS

Initial results in generating PDS values show great promise in replacing the tedious and time-consuming method of sampling and sieving ballast samples. For further validation of this method, ballast samples are being collected from the area imaged by the camera and analyzed (sieved) to obtain the ground truth required to correlate the PDS values to the Selig's FI. Ultimately, the system will be installed on Shoulder Ballast Cleaners for ballast quality and condition assessments during operations and incorporated into a Ballast Maintenance System to determine proper maintenance and rehabilitation strategies.

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