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**MACHINE VISION CONDITION MONITORING OF
RAILCAR STRUCTURAL UNDERFRAME COMPONENTS**

John M. Hart

Senior Research Engineer
Computer Vision and Robotics
Laboratory
Beckman Institute for Advanced
Science and Technology
University of Illinois at Urbana-
Champaign
405 N. Mathews Avenue,
Urbana, IL, USA 61801
Tel: (217) 244-4174
email: jmh@vision.ai.uiuc.edu

Bryan Schlake

Graduate Research Assistant
Railroad Engineering Program
Department of Civil and
Environmental Engineering
University of Illinois at Urbana-
Champaign
B118 Newmark Civil
Engineering Laboratory
205 N. Mathews Ave.,
Urbana, IL, USA 61801
Tel: (217) 244-6063
Fax: (217) 244-0815
email: schlake@illinois.edu

Sinisa Todorovic

Assistant Professor
School of EECS
2107 Kelley Engineering Center
Oregon State University
Corvallis, OR 97331
Tel: (541) 737-7268
Fax: (541) 737-1300
email:
sinisa@eecs.oregonstate.edu

J. Riley Edwards

Lecturer
Railroad Engineering Program
Department of Civil and
Environmental Engineering
University of Illinois at Urbana-
Champaign
1201 Newmark Civil Engineering
Laboratory
205 N. Mathews Ave.,
Urbana, IL, USA 61801
Tel: (217) 244-7417
Fax: (217) 333-1924
email: jedward2@illinois.edu

Narendra Ahuja

Professor
Department of Electrical and
Computer Engineering
Computer Vision and Robotics
Laboratory
2041 Beckman Institute for
Advanced Science and
Technology
University of Illinois at Urbana-
Champaign
405 N. Mathews Avenue
Urbana, IL, USA 61801
Tel: (217) 333-1837
Fax: (217) 244-8371
email: n-ahuja@uiuc.edu

Christopher P.L. Barkan

Professor
Director - Railroad Engineering
Program
Department of Civil and
Environmental Engineering
University of Illinois at Urbana-
Champaign
1203 Newmark Civil Engineering
Laboratory
205 N. Mathews Ave.,
Urbana, IL, USA 61801
Tel: (217) 244-6338
Fax: (217) 333-1924
email: cbarkan@illinois.edu

ABSTRACT

Monitoring the structural health of rolling stock is critical to ensuring safe and efficient railroad operation. The structural integrity of freight cars depends on the health of certain structural components within their underframes. These structural components serve two principal functions: supporting the car body and lading, and transmitting longitudinal buff and draft forces. Although railcars are engineered to withstand large static, dynamic and cyclical loads, various structural defects can still develop within their

underframes. As a result, both the United States Department of Transportation (USDOT) Federal Railroad Administration (FRA) regulations and individual railroad mechanical department practices require periodic inspection of railcars to detect structural damage and defects. These inspections are conducted manually and rely heavily on the acuity, knowledge and endurance of qualified inspection personnel. Enhancements are possible through machine-vision technology, which uses computer algorithms to convert digital image data into useful information.

This paper describes research investigating the feasibility of an automated inspection system capable of detecting structural defects in freight car underframes and presents an inspection approach using machine-vision techniques, including multi-scale image segmentation. Using field data from a preliminary image acquisition system, algorithms were developed to analyze images of railcar underframes and assess the condition of certain structural components. This technology, in conjunction with additional preventive maintenance systems, has the potential to provide more objective information on railcar condition, improve utilization of railcar inspection and repair resources, increase train and employee safety, and improve overall railroad network efficiency.

INTRODUCTION

Federal Railroad Administration (FRA) regulations require that every car placed in a train be inspected by a car inspector or train crew member before departing a yard or terminal. The current railcar inspection process is tedious, labor intensive, and relies on personnel with varied experience and training, performing their tasks under a wide range of environmental conditions. Additionally, there exists no practical means of recording and retaining inspection information unless a billable repair is required. This makes it difficult to track a car's condition over time or perform trend analyses. As a result, the majority of railcar maintenance is reactive, resulting in less efficient repair and maintenance processes. Consequently, the Association of American Railroads (AAR) and the Transportation Technology Center, Inc. (TTCI) initiated a program to develop and implement automated inspection technologies, called Technology Driven Train Inspection (TDTI).

Technology Driven Train Inspection

The goal of TDTI is to provide safer, more efficient, and traceable means of rolling stock inspection by automating the mechanical inspection process through a variety of technologies [1]. Examples of these technologies include the automated inspection of railcar truck components, safety appliances and passenger car undercarriages [2, 3, 4]. The ultimate vision for TDTI is a network of automatic wayside systems capable of inspecting and monitoring the North American freight car fleet in order to maintain compliance with FRA regulations and railroad-specific maintenance and operational standards. To reach this goal, the final wayside inspection systems must be comprehensive in scope, inspecting all aspects of the car. As a result, TDTI has initiated the development of separate automated inspection technologies that will address many aspects of the federally-mandated freight car inspections. One aspect of the TDTI initiative is the development of the system known as Automated Inspection of Structural Components (AISC), which will use cameras and computer algorithms to aid in the inspection of freight car underframes.

Structural Underframe Components

Structural underframe components contribute to the structural integrity of the railcar by supporting the car body and lading and transmitting longitudinal buff and draft forces. The

primary structural component, the center sill, runs longitudinally along the center of the car, forming the backbone of the underframe and transmitting the majority of buff and draft forces through the car [5]. Several other structural components are also critical to load transfer, including the sidesills, body bolsters, and crossbearers. The sidesills are longitudinal members, similar to the center sill, running along the entire length of the car on either side. Body bolsters are transverse members near each end of the car that transfer the car's load from the car body to the trucks. Crossbearers and crossties are transverse members that connect the sidesills to the center sill and help distribute the load between the longitudinal members of the car. These components work together as a system to help maintain the car's camber and structural integrity. Each of these components must be regularly inspected to ensure the safe and efficient operation of rolling stock.

FRA Mechanical Regulations require the inspection of center sills for breaks, cracks, and buckling, and the inspection of sidesills, crossbearers, and body bolsters for breaks [6]. To effectively detect structural defects, a car inspector must walk around the entire car, looking beneath it with the aid of a flashlight to view each structural component. Due to time constraints associated with typical pre-departure mechanical inspections, cars are typically inspected with this level of scrutiny only before undergoing major repairs in a car repair shop. To provide more efficient and effective mechanical inspections, the AAR and TTCI are investigating the use of machine-vision technology for inspecting underframe components through the development of the AISC system.

Machine Vision Technology

A machine-vision system acquires data using digital cameras, organizes and analyzes the images using computer algorithms, and produces useful information, such as the type and location of defects. Machine-vision algorithms use visual cues to locate areas of interest on the freight car and then analyze each component to determine its variance from the baseline case. AISC will work collectively with other automated inspection systems to inspect freight cars efficiently and objectively. Since inspection data is stored digitally, it will be possible to maintain historical health records for each car that undergoes inspection. Maintaining these records will allow potential structural defects to be monitored over time so that components are repaired prior to failure. Applying these new technologies to the inspection process has the potential to enhance rolling stock maintenance efficiency and safety.

Condition Based Maintenance

A primary benefit of AISC and other automated inspection systems is the facilitation of predictive, or condition-based, maintenance. Condition-based maintenance includes monitoring certain parameters related to component health and taking subsequent corrective action prior to component failure [7]. Instead of taking advantage of condition-based maintenance, current structural component inspection and repair practices rely primarily on corrective maintenance, which occurs only after a critical defect is detected. This approach maximizes component service life but makes repair

planning difficult. Furthermore, when repairs are needed, they can disrupt service, leading to higher repair expenses and reduced railcar utilization. Railroads have recognized the advantage of predictive maintenance and have begun implementing other technologies similar to AISC that monitor indicators of railcar component health (e.g. Truck Performance Detectors and the AAR's Fully Automated Car Train Inspection System - FactIS™) [8].

REGULATORY COMPLIANCE

According to Section 215.121 of Title 49 in the U.S. Code of Federal Regulations (CFR), structural underframe components must be inspected on each railcar placed in a train [6]. The specific regulations pertaining to freight car bodies form the basis for determining which components will be inspected by AISC. According to the regulations, the center sill may not be broken, cracked more than 6 inches, or bent/buckled more than 2.5 inches in any 6 foot length. Specific parameters are also established for the allowable magnitude of cracks and buckling because these defects may undermine the integrity of the sill, resulting in a center sill failure [9]. Fines assessed by FRA inspectors for a broken center sill are among the highest in CFR 215.121, matched only by violations due to loose or broken axles.

Inspection data from the FRA Office of Safety from 2000 to 2007 show that on average 59% of structural component defects are comprised of cracked, broken, bent, or buckled center sills (CS), while the remaining 41% represent defective sidesills (SS), body bolsters (BB), or crossbearers (CB) (Figure 1). Based on these data and guidance from the AAR, the primary focus of AISC is inspecting the center sill and the secondary focus is the inspection of other structural components. All of these components, although infrequently defective, are critical to the structural integrity of the railcar.

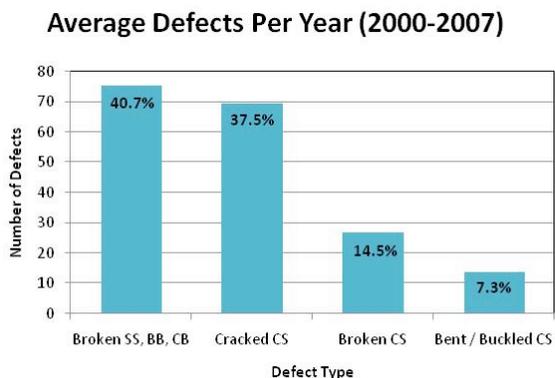


FIGURE 1: AVERAGE NUMBER OF STRUCTURAL DEFECTS RECORDED BY FRA MOTIVE POWER AND EQUIPMENT INSPECTORS PER YEAR

BACKGROUND

Previous research at UIUC has demonstrated the feasibility of using machine vision to detect defects and other anomalies on the underbodies of passenger cars and locomotives [4]. Algorithms using both the visible and infrared spectra demonstrated that missing, damaged, or overheated components could be detected as well as incipient failures and

foreign objects beneath the cars. Videos of trains were recorded as they moved over a stationary camera mounted in a pit beneath the tracks. The combination of information from both the thermal and visible spectra identified certain defects that might otherwise go unnoticed by human inspectors. This research addressed the difficulties of acquiring images from beneath a railcar: an inherently challenging location due to lighting requirements, space constraints, and the difficulties involved in keeping the equipment clean and protected.

Another machine vision system was developed to inspect railcar truck components using wayside cameras and a perpendicular view of the truck [2]. Computer algorithms were developed to detect the locations of brake components, spring sets, and bearing end cap bolts. This work laid the groundwork for developing additional automated freight car inspection systems using machine vision, such as the Automated Safety Appliance Inspection System (ASAIS) [3]. ASAIS detects deformed ladders, handholds, and brake wheels, and uses visual learning techniques to determine the difference between FRA defects needing immediate attention and deformations that are less critical. The results and methods developed in these projects have been incorporated into other aspects of the AAR's TDTI program, and knowledge gained from these research initiatives was applied to inspecting the underbody of freight rolling stock.

METHODOLOGY

The goal of the work done at UIUC was to demonstrate the feasibility of AISC. The initial stages of this project focused largely on collecting images of representative railcar structural components. Using computer algorithms, these images were converted from raw video data into full panoramas of the railcar underbody. Subsequent algorithms and approaches were developed to analyze the panoramas, detect components of interest, and locate defects.

Preliminary Image Acquisition

Initial tests were conducted at the Monticello Railway Museum in Monticello, IL on an Illinois Central, 1950 era AAR-standard-design hopper car. The car was rolled over a locomotive repair pit, which contained equipment for recording the car's underframe (Figure 2).

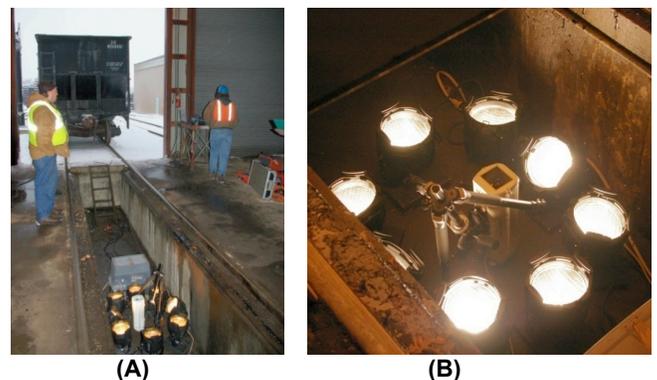


FIGURE 2: EXPERIMENTAL TEST SETUP AT MONTICELLO, IL (A); LIGHTING AND CAMERA ARRANGEMENT IN THE LOCOMOTIVE PIT (B)

The camera and lighting arrangement was placed at the bottom of the three-foot pit, and data were acquired via a laptop computer adjacent to the tracks. Videos were taken at varying train speeds and lighting conditions, and a panoramic image was developed from the video data (Figure 3).



FIGURE 3: PANORAMA OF HOPPER CAR UNDERFRAME USING PRELIMINARY IMAGE ACQUISITION METHODS

This image provided initial confidence in the feasibility of this method of automated structural component inspection, because the structural components, including the center sill and crossbearers, were clearly visible. Many mechanical components are also visible in the panorama, including the couplers, much of the draft gear, the truck bolsters, the brake rigging, brake beam, the interior springs in each spring nest, and the axles. Additionally, initial data acquisition efforts provided a basis for properly illuminating the railcar underbody.

Data Collection

After analyzing the preliminary image acquisition results and subsequent data collected using portable image acquisition carts, an experimental setup was developed (Figure 4) and data collection procedures were defined. This equipment arrangement was used during testing at the Norfolk Southern (NS) Locomotive Repair Facility in Decatur, IL (Figure 5). Tests were run on several different NS railcars by rolling them above the camera at 3-5 mph. As before, the videos were converted into panoramic images (Figure 6). Results from the testing at NS Decatur show much more even illumination for the hopper car image (Figure 6a) as compared to the previous hopper panorama (Figure 3). Only the center strip of each individual video frame is extracted to develop the panorama, so lighting improvements were made by focusing illumination on the center of the image. The panorama of the gondola underbody (Figure 6b) provides a clear view of the center sill,

crossbearers, and crosssties (thinner lateral members between the crossbearers).

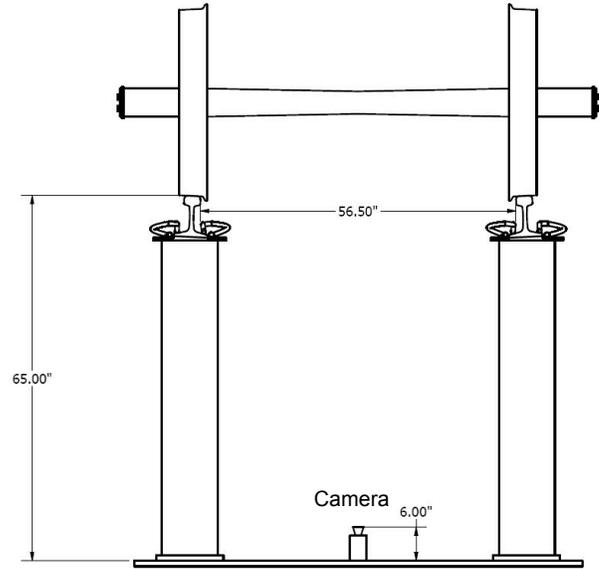


FIGURE 4: EQUIPMENT SETUP SHOWING THE 90° STRAIGHT-UP CAMERA VIEW



(A) (B)

FIGURE 5: LOCOMOTIVE REPAIR PIT USED FOR DATA COLLECTION (A); CAMERA AND LIGHTING SETUP (B)



FIGURE 6: PANORAMIC IMAGES OF A HOPPER CAR (A) AND A GONDOLA CAR (B) TAKEN FROM THE NS LOCOMOTIVE REPAIR FACILITY IN DECATUR, IL

Other components of the gondola that are clearly visible include the brake reservoir, brake cylinder, and the entire foundation of the braking system. In order to determine the resolution of the panoramic images, engineering drawings were acquired from Norfolk Southern for each of the cars that were tested. By measuring the length of components in the panoramic image in pixels and dividing by the actual lengths of the components, the pixel-to-foot ratio (i.e. the image resolution) was determined to be 92.3 pixels per foot.

DATA ANALYSIS

Given a panoramic image of the car underbody, the algorithms must detect and localize the center sill and inspect it for two types of defects: (i) deformation, caused by bending and/or buckling and (ii) the presence of breaks or cracks. The need to minimize processing speed, as well as the nature of the two types of defects being considered, necessitates a multiscale-analysis approach. The image area occupied by the center sill and the image region representing a crack differ significantly in size. As a result, the detection of the center sill requires analyzing large pixel neighborhoods; while the detection of breaks and cracks requires analyzing fine-resolution image details.

A computationally efficient strategy capable of addressing these two image-analysis extremes is known as multiscale image segmentation. This strategy provides access to pixel neighborhoods of varying size, which can be used for detection and inspection of the center sill.

The machine vision algorithm will consist of the following steps: First, parse the panoramic image into homogeneous-intensity regions, at various scales, based on the pixel values present in the image; Second, analyze regions obtained at the coarsest scale (showing limited detail) to detect the center sill by using a known model (e.g. a rectangular shaped object located at the center of the panoramic image); Third, inspect the contours of the image regions occupied by the center sill to measure their deviation from the model, and thus the degree of the sill's bending and/or buckling; and Fourth, recursively analyze sub-regions embedded within the region representing the center sill to detect cracks or breaks in the center sill by using known models (e.g., a crack typically appears in the image as an elongated, dark region that represents a discontinuity in brightness of the center sill). This recursive analysis is feasible due to the multiscale image segmentation algorithm previously developed at UIUC and noted in step one [10, 11, 12].

In this case, object detection immediately produces object segmentation since region boundaries generally coincide with boundaries of an object present in the image. That is, detection of the center sill in step two simultaneously delineates its boundaries, and thus localizes its position in the image. Similar to center sill detection, the identification of cracks and breaks in the center sill is based on known models of these defects. Identification of a crack or break simultaneously localizes its position, orientation, and length, so the magnitude of the discovered defect can be evaluated.

Multiscale Image Segmentation

The segmentation algorithm partitions the image into homogeneous regions of previously unknown shape, size, gray-level contrast, and topological context. A region is perceived to be homogeneous if variations in pixel intensity within the region are smaller than intensity variations of its surroundings, regardless of its absolute degree of variability. Consequently, image segmentation may be performed at a range of homogeneity values. At any scale, recursive segmentation may be performed to extract finer scale segments characterized by an increasing degree of homogeneity. This process continues until one obtains strictly constant intensity regions, yielding a multiscale segmentation of the image. The black pixels form the boundary lines of the segmented regions (Figure 7).

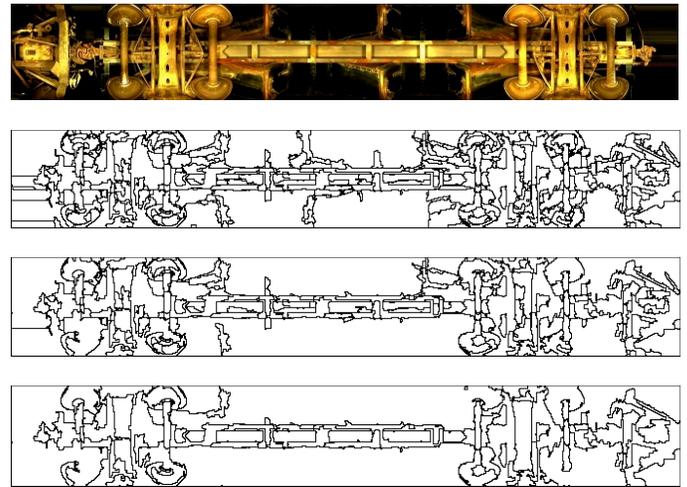


FIGURE 7: MULTISCALE SEGMENTATION HIERARCHY OF THE HOPPER CAR IMAGE SHOWING THE CAR UNDERBODY WITH THE SEGMENTATION SCALE INCREASING FROM TOP TO BOTTOM

As the scale increases, smaller regions strictly merge to form a larger region, meaning that the segmentation algorithm is hierarchical. The same multiscale segmentation algorithm can also be used for simultaneous inspection of other structural components in addition to the center sill. For example, analyzing the image segmentation at a finer scale than that used for center sill inspection, crossbearers can also be inspected for breaks, cracks, bending and buckling (Figure 8).

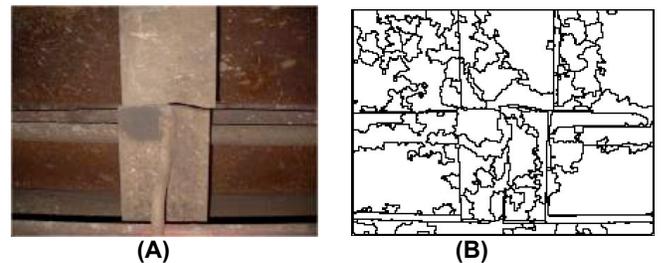


FIGURE 8: DIGITAL IMAGE OF A BROKEN CROSSBEARER (A) WITH A FINE-SCALE SEGMENTATION OF THE IMAGE (B)

Center Sill Inspection

All videos are taken from the same camera distance and viewpoint, so the train moves nearly parallel to one of the camera axes. This allows us to hypothesize that the center sill: (1) is centrally located in the corresponding panorama, (2) appears as a rectangle with possible embedded patterns within the rectangle, and (3) two longer edges of the rectangle lie along two image rows. Therefore, the center sill can be modeled as a large, rectangular-shaped object, prominently featured at the center of the panoramic image against the darker background. A template is developed based on the model parameters above or made from averaging templates created from panoramic images from cars of the same type. Then, starting with the coarsest levels of the segmentation hierarchy, the template is matched to the segmentation image to find the central location of the center sill between the trucks (Figure 9).

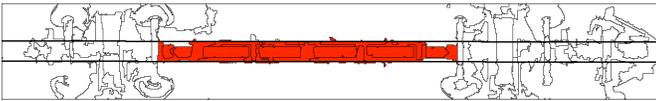


FIGURE 9: CENTER SILL DETECTION USING THE COARSEST-SCALE SEGMENTATION

Once identified, the matching edges are interpreted as contours of the center sill. These identified edges are also taken as the general direction in which the center sill extends across the image. Given that the camera view is along the surface perpendicular to and directly below the center of the car, the known physical width of the center sill in the scene can be immediately mapped to the number of pixels associated with this width in the image. This mapping technique serves to calibrate the measurement of deformation of the center sill in the image. The average error of identified contours of the center sill using multiscale segmentation is two pixels, which corresponds to 0.26 inches (1 pixel corresponds to 0.13 inches). Improved camera resolution should further reduce this error.

Pixel Summation

An alternative, less computationally intensive method could be used to find the location of the center sill. This method, based on pixel summation, is carried out by summing the pixels longitudinally for each row of the segmented image (or edge image) of the car panorama.

Along each horizontal row in the edge image (Figure 10a) we compute the number of pixels present (i.e., pixels belonging to longitudinal edge lines in the image). Prominent peaks in the histogram of the pixel summation (Figure 11) denote long, straight sections in the image. Since the center sill creates the longest edges in the panoramic image, the two largest peaks (rows 276 and 388) correspond to the outer contours of the center sill, while the four interior peaks in the histogram correspond to the inner contours of the center sill. The outer contours of the center sill are then denoted with parallel lines (Figure 10b). These detected edges can then be used to guide the search for the remaining parts of the center sill as described in the previous method. Once the contours of the center sill are identified, they are compared with the ideal template. Any deviation from the parallel lines is interpreted as deformation. Note that this method can be applied in the lateral direction as well to identify and inspect crossbearers and crosssties. In this way, pixel summation provides flexibility with reduced computational requirements. However, it does not provide the same level of accuracy or robustness as the multiscale segmentation approach when considering the constraints of the AISC system.

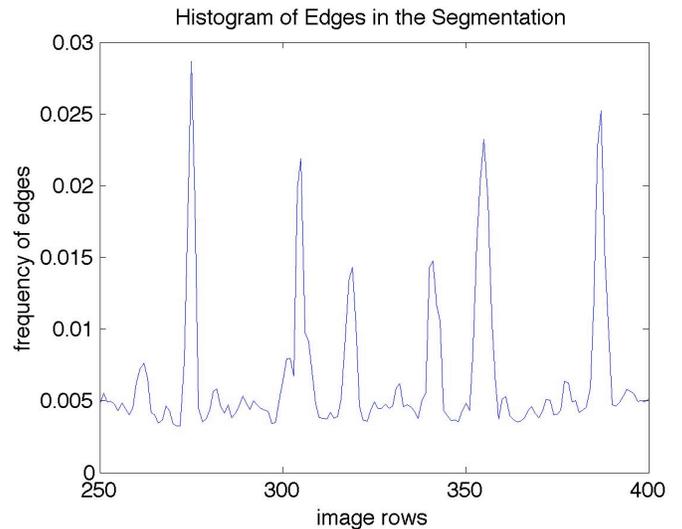


FIGURE 11: HISTOGRAM OF THE PIXEL SUMMATIONS BELONGING TO REGION BOUNDARIES

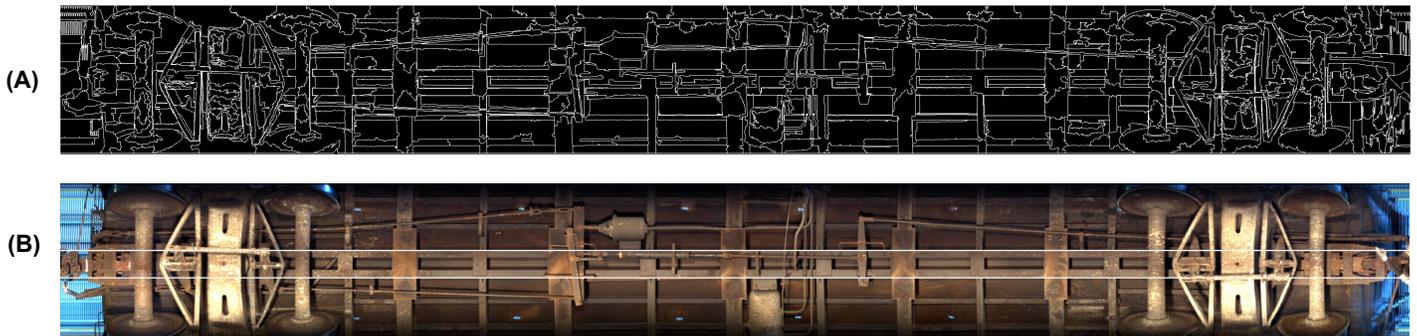


FIGURE 10: EDGE IMAGE OF GONDOLA CAR UNDERBODY PANORAMA (A), AND ORIGINAL PANORAMA WITH CENTER SILL DETECTED (B)

Inspection of Cracks and Breaks

The image region identified as the center sill will be analyzed to detect the presence of cracks and breaks. This phase of work is still in preliminary stages, but a multiscale process has been proposed as a potential approach to this aspect of inspection. Both cracks and breaks can be modeled as distinct objects that may occur in the image area occupied by the center sill. A crack can be modeled as a homogeneous, elongated region that appears darker than the center sill. Similarly, a break can be modeled as a dark region that represents a discontinuity in the following properties of the center sill: brightness, contiguity of the sill's contours, and co-linearity and parallelism with parts of the center sill's contours.

The algorithm will first identify the region that delineates the boundary of the center sill (Figure 9). To identify breaks and cracks (Figure 12), a multi-scale search strategy will be used that recursively searches smaller subregions embedded in the region occupied by the center sill. At each segmentation scale, the regions found will be compared to the models developed for breaks and cracks, identifying suspect regions like the one seen in Figure 12c corresponding to a center sill crack.

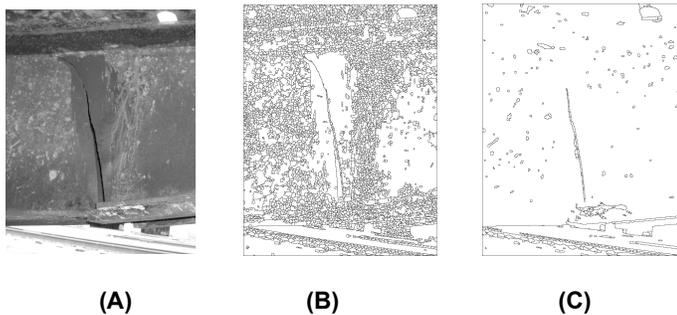


FIGURE 12: ORIGINAL DIGITAL IMAGE OF A CRACK (A), AND FINE TO COARSE SEGMENTATION IMAGES (B & C), FROM MULTISCALE SEGMENTATION, SHOWING CRACK ISOLATION

If any of these subregions exhibit properties defined by the models, they will be considered as potential cracks or breaks. In addition to detection, we will also be able to identify the position, orientation, length and other characteristics of cracks and breaks and thus assess the degree of damage. Since cracks, in general, appear at finer resolutions of the image segmentation, their detection is expected to be more difficult than breaks; however, preliminary field data indicate that it will be feasible.

DISCUSSION & CONCLUSIONS

Initial data collection and analysis has demonstrated the feasibility of AISC for the improvement of the effectiveness and efficiency of railcar underbody inspections. This study provides the basic system parameters needed to inspect and evaluate the health of railcar structural underbody components and provides several machine vision approaches for inspection and defect detection. As a result of this research, vendors have designed and implemented a field prototype and initiated testing

at mainline speeds. When complete, AISC will be capable of inspecting the undercarriage of an entire train, identifying areas of concern, reporting the suspected defects to qualified inspection personnel, and documenting the condition of structural components for the implementation of condition-based maintenance. AISC will also provide the basis for future machine vision systems capable of addressing other mechanical component problems visible from the bottom of the car (e.g. missing coupler pins, broken or missing coupler retaining pin bolts, and broken train line trolleys).

The ultimate goal for railcar inspection is a complete, automated inspection system that will inspect the entire car via a system of wayside cameras, including the AISC cameras located below the car. Using this system, freight cars will be inspected more thoroughly and efficiently and potential risks associated with manual car inspection will be minimized through a reduction in manual inspections. Additionally, reducing inspection time will increase yard efficiency and improve overall network capacity by reducing the time needed to process inbound and outbound trains. Although a holistic system for automated car inspection is still under development, the implementation of individual automated inspection systems will continue to improve both the safety and efficiency of railroad operations.

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NOMENCLATURE

Center Sill, Computer Vision, Freight Wagon, Multiscale segmentation, Predictive Maintenance.

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