

Automated Inspection of Railcar Underbody Structural Components Using Machine Vision Technology

09-2863

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Word Count: 250 (Abstract) + 4,784 (Text) + 7 Figures = 6,784 Words

Submitted November 15, 2008

ABSTRACT

Monitoring the structural health of railcars is important to ensure safe and efficient railroad operation. The structural integrity of freight cars depends on the health of certain structural components within their underframes. These 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, they can still develop a variety of structural defects. As a result, Federal Railroad Administration (FRA) regulations and individual railroad mechanical department practices require periodic inspection of railcars to detect mechanical and structural damage or defects. These inspections are primarily a manual process that relies on the acuity, knowledge and endurance of qualified inspection personnel. Enhancements to the process are possible through machine vision technology, which uses computer algorithms to process digital image data of railcar underframes into diagnostic 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. A preliminary image acquisition system has been developed, field trials conducted and algorithms developed that can analyze the images and identify certain underframe components, assessing aspects of their condition. The development of this technology, in conjunction with additional preventive maintenance systems, has the potential to provide more objective information on railcar structural condition, improved utilization of railcar inspection and repair resources, increased train and employee safety, and improvements to overall railroad network efficiency.

INTRODUCTION

In the United States, railcars undergo regular mechanical inspections as required by Federal Railroad Administration (FRA) regulations and as dictated by railroad mechanical department practices. These mechanical inspections address numerous components on the railcar including several underbody components that are critically important to the structural integrity of the railcar. The primary structural component, the center sill, runs longitudinally along the center of the car, forming the backbone of the underframe and transmitting buff and draft forces through the car (*1*). In addition to the center sill, several other structural components are 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 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 camber and structural integrity of the car.

Mechanical Regulations and Inspection Procedures

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, as well as other selected inspection items (*2*). Over 1.6 million freight cars are in service throughout North America. Each time one of these cars departs a yard, terminal, or industrial facility it is required under Federal Railroad Administration (FRA) regulations to be inspected by either a qualified mechanical inspector, referred to as a carman, or a train crew member for possible defects that would adversely affect the safe operation of the train. The current railcar inspection process is tedious, labor intensive, and in general lacks the level of objectivity that may be achievable through the use of new technology. In order to effectively detect structural defects, car inspectors would need to walk around the entire car and crawl underneath with a flashlight to view each structural component. Due to time constraints associated with typical pre-departure mechanical inspections, cars are only inspected with this level of scrutiny in car repair shops before undergoing major repairs. In addition to the inherent safety concerns and efficiency challenges of manual inspections, records of these inspections are generally not retained unless a billable repair is required, making it difficult to track the health of a car over time or to perform a trend analysis. As a result, the maintenance of railcar structural components is almost entirely reactive rather than predictive, making repairs and maintenance less efficient. To address these concerns, a number of automated systems have been developed to inspect various railcar components through the use of cameras, sensors, and other non-destructive inspection methods. These technologies have the potential to improve inspection efficiency and reduce the time that car inspectors are exposed to the hazards of the rail yard environment.

Technology Driven Train Inspection (TDTI)

The Association of American Railroads (AAR) along with the Transportation Technology Center, Inc. (TTCI) has initiated a program intended to provide safer, more

efficient, and traceable means of rolling stock inspection (3). The object of the Technology Driven Train Inspection (TDTI) program is to identify, develop, and apply new technologies to enhance the efficiency and effectiveness of the railcar inspection, maintenance, and repair process. Examples of these new technologies include the automated inspection of railcar trucks, safety appliances and passenger car undercarriages (4, 5, 6). The ultimate objective of TDTI is to implement a network of automatic wayside inspection 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. In order for this automated inspection initiative to improve safety and enhance the efficiency of current railcar mechanical inspections, the final wayside inspection systems must be holistic in scope. As a result, TDTI has initiated the development of separate automated inspection technologies that will address each aspect of the federally-mandated freight car inspection.

Automated Inspection of Structural Components (AISC)

One aspect of the TDTI initiative is the development of the system known as Automated Inspection of Structural Components (AISC), which is currently underway at the University of Illinois at Urbana-Champaign (UIUC). AISC focuses on developing technology to aid in the inspection of freight car underbodies for defective structural components through the use of machine vision. A machine vision system acquires data using digital cameras, organizes and analyzes the images using computer algorithms, and outputs useful information, such as the type and location of defects, to the appropriate repair personnel. The 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. While manual inspections are subject to inaccuracies and delays due to time constraints and human fatigue, AISC will work collectively with other automated inspection systems (e.g. machine vision systems for inspecting safety appliances, truck components, brake shoes, etc.) to inspect freight cars efficiently and objectively and will not suffer from monotony or fatigue. AISC will also maintain health records of every car that undergoes inspection, allowing potential structural defects to be monitored so that components are repaired prior to failure. Additionally, applying these new technologies to the inspection process has the potential to enhance safety and efficiency for both train crew members and mechanical personnel.

A primary benefit of AISC and other automated inspection systems is the facilitation of preventive, or condition-based, maintenance. Condition-based maintenance involves the monitoring of certain parameters related to component health or degradation and the subsequent corrective actions taken prior to component failure (7). Despite the advantages of condition-based maintenance, current structural component repair and billing practices engender corrective maintenance, which does not occur until after a critical defect is detected. Due to the reactive nature of corrective maintenance, repairs cannot be planned as effectively, resulting in higher expenses and less efficient repairs. For example, it is more economical to patch a cracked crossbearer before it breaks than to replace a fully broken crossbearer. Having recognized the need for preventative maintenance, railroads have begun implementing other technologies similar to AISC that monitor subtle indicators of railcar component health (e.g. Truck

Performance Detectors and the AAR's Fully Automated Car Train Inspection System - FactIS™) (8).

REGULATORY COMPLIANCE

The FRA regulations for freight car bodies form the basis for which components will be inspected by AISC. Section 215.121 of Title 49 in the U.S. Code of Federal Regulations (CFR) governs the inspection of freight car bodies and two of the six parts in this section pertain to the inspection of structural components (2). 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 established for the allowable magnitude of cracks or buckling because these defects may undermine the integrity of the sill, resulting in a center sill failure (9). Therefore, these regulations are intended to identify potentially hazardous cars so that they will be repaired before an in-service failure. During FRA motive power and equipment (MP&E) inspections, inspectors have multiple enforcement options for railroads operating railcars with defective structural components. The inspector may take exception to the condition of a structural component and issue a warning of possible monetary penalties if the defect is not repaired immediately. When deemed necessary, inspectors can also issue violations having monetary penalties ranging from \$2,500 to \$6,000 depending on the type, severity, and location of the defect (2). Structural component inspection data from the FRA Office of Safety from 2000 to 2007 shows that on average 59% of the structural component defects are comprised of broken, cracked, bent, or buckled center sills, while the remaining 41% represent defective sidesills, body bolsters, or crossbearers (Figure 1).

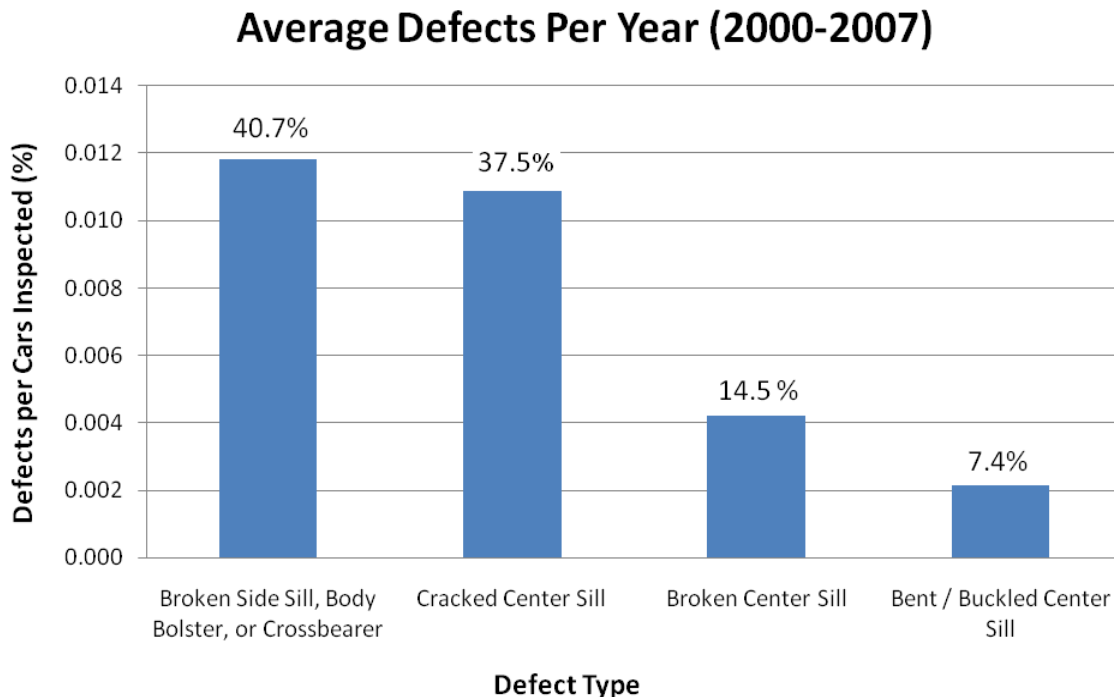


FIGURE 1 Average number of yearly structural defects recorded by FRA inspectors as a percentage of all cars inspected in a year.

Based on these data and guidance from the AAR, the primary focus of AISC will be on the inspection of center sills and the secondary focus will be on the inspection of the other structural components. The final goal of AISC is to provide data and trending information for the implementation of condition-based maintenance on all four categories of freight car structural components. These components, although infrequently defective, are critical to the structural integrity of the freight car. As a result, the fines assessed by FRA inspectors due to a broken center sill are among the highest for CFR 215.121, and are matched only by violations due to loose or broken axles. Beyond the structural importance of these components, the automated inspection of freight car underbodies is an essential aspect of improving network efficiency. If structural components are not inspected through automated inspection systems, the potential economic gains of other inspection technology will be greatly reduced because the train will still need to be stopped for manual inspection. AISC constitutes one important element in the overall automated freight car inspection process.

BACKGROUND

Multi-spectral Machine Vision Inspection of Passenger Car Undercarriages

Previous research demonstrated the feasibility of detecting defects and other anomalies on the underbody of passenger cars (6). Machine-vision techniques were developed to record images and inspect rolling stock and locomotive undercarriages. 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 in-service trains were recorded as they moved over a stationary camera mounted between the rails 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 in the course of their routine visual inspections. This research addressed the issues associated with 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.

Mechanical Component and Safety Appliance Inspection

The feasibility of using machine vision for inspection of mechanical components and safety appliances has also been demonstrated. A machine vision system was developed to inspect railcar truck components using wayside cameras with a perpendicular view of the truck (4). Computer algorithms were developed to detect the locations of the brake components, spring sets, and bearing end cap bolts. This research laid the groundwork for developing additional automated freight car inspection systems using machine vision. One of these systems was the Automated Safety Appliance Inspection System (AS AIS), which detected deformed ladders, handholds, and brake wheels using machine vision algorithms (5). AS AIS also used visual learning techniques to determine the difference between FRA defects that need to be repaired immediately and deformations that were less critical. The results and methods developed in both of these projects have been incorporated into other aspects of the AAR's TDTI program and the knowledge gained from these research initiatives has been applied to the underbody of freight rolling stock in the current project.

METHODOLOGY

AISC focuses on demonstrating the feasibility of an automated structural underbody inspection system to assess the structural health of railcars using machine vision algorithms. The goal of this project is to develop a system that is capable of recording digital images of railcar underframes, analyzing them for structural component defects and deformations, and reporting the defects to railroad mechanical personnel. Once defects are reported by AISC, potentially defective cars will be addressed through follow-up inspections.

The initial stages of this project focused largely on collecting images of representative railcar structural components. Digital video was acquired from underneath healthy railcars to assess the feasibility of capturing structural components and determine the proper approach to underbody illumination. A previously-developed algorithm was adapted to convert the series of digital images into a panoramic image showing the entire railcar underbody. Subsequent algorithms are being developed to analyze the panorama to detect components of interest and the location of defects. In order to develop and train algorithms capable of detecting cracks and other defects, a large sample of real-world images containing defects is required.

Prior to recording images of defective railcars, data were analyzed to determine the frequency that structural defects are identified by FRA inspectors. FRA data from the past ten years shows that the average percentage of cars experiencing structural component defects is less than 0.03% of all freight cars inspected per year by FRA MP&E. This percentage represents only the number of defective units (railcars) found by FRA MP&E inspectors as a percentage of the total number of units inspected per year, and does not include defective units identified by private car owners or individual railroads. However, due to the scarcity of structural defects as suggested by this data, a considerable field image acquisition effort will be required to amass sufficient data to develop representative and robust algorithms.

Data collection for this project will primarily occur at Class I Railroad mechanical repair facilities, but an initial feasibility study was conducted at the Monticello Railway Museum in Monticello, Illinois. The initial lighting and image acquisition approach was adapted from the previous project on multi-spectral machine vision inspection of passenger cars (6). However, new lighting and image acquisition methods were developed specific to freight car underbodies. Freight cars exhibit more variability in underbody designs than passenger cars and thus provide more illumination challenges due to the varied heights and orientations of the structural members. Initial tests were run on an Illinois Central, 1950 era AAR-standard-design hopper car, running the car over a locomotive pit while recording videos using various lighting arrangements (Figure 2).

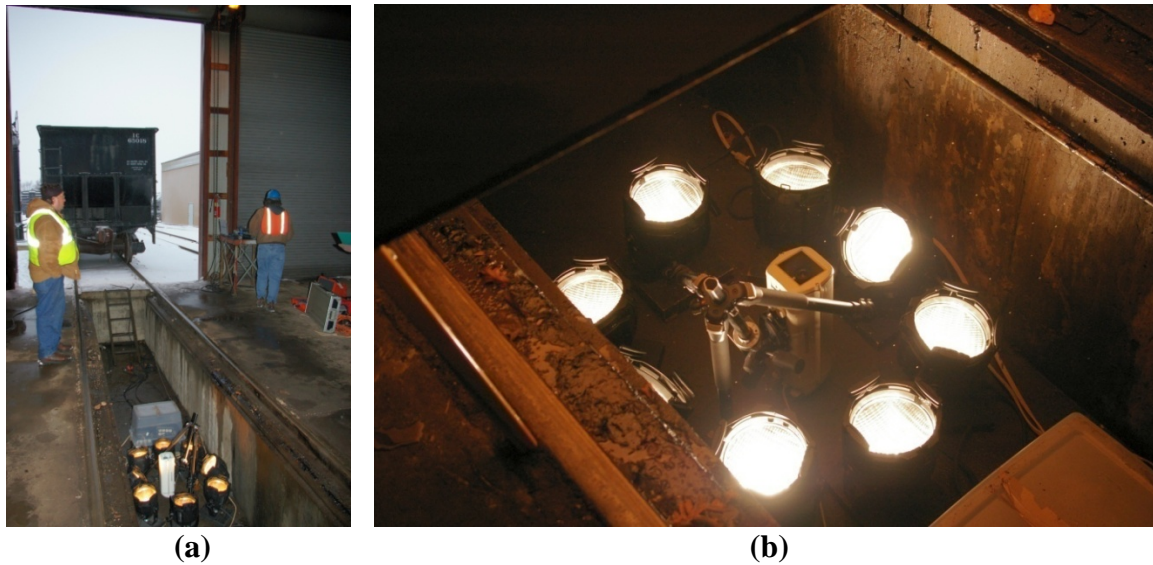


FIGURE 2 (a) Experimental set-up at Monticello and (b) lighting and camera arrangement in the pit.

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 track. Videos were taken with varying train speeds and lighting conditions. After recording these data, a panoramic image was developed in the lab to provide a proof-of-concept for this data collection approach. The resulting panoramic image offered confidence in the feasibility of this method of automated structural component inspection (Figure 3), displaying an unobstructed view of both the center sill and crossbearers.



FIGURE 3 Panoramic image of the underbody of a hopper car taken at the Monticello Railway Museum.

In addition, many other railcar mechanical components are 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. Detailed views of the inner side of the wheels are also visible (including the raised letters and numbers along the wheel plate). Due to the large field of view of the wide-angle lens, the wheels appear distorted: measurement accuracy in these areas of the image will be addressed through future refinement of the algorithm. Other areas of improvement include the development of lighting methods that provide even illumination of the entire underframe, the introduction of new camera views, and the addition of higher resolution cameras for detecting cracks.

DATA ANALYSIS

Given a panoramic image of the car underbody, the algorithms must detect and localize the center sill in the image 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 inspection of the center sill needs to be rapid: with a processing speed close to real-time. This requirement, 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. Multiscale image segmentation provides access to pixel neighborhoods of varying size, which can be further 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 all degrees of inter-region versus intra-region homogeneity of 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 that identify the center sill to measure their deviation from the model, and thus the degree of the sill's bending and buckling; and Fourth, recursively analyze sub-regions embedded within image 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, and can be used to evaluate the magnitude of the discovered defect.

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 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 (Figure 4).

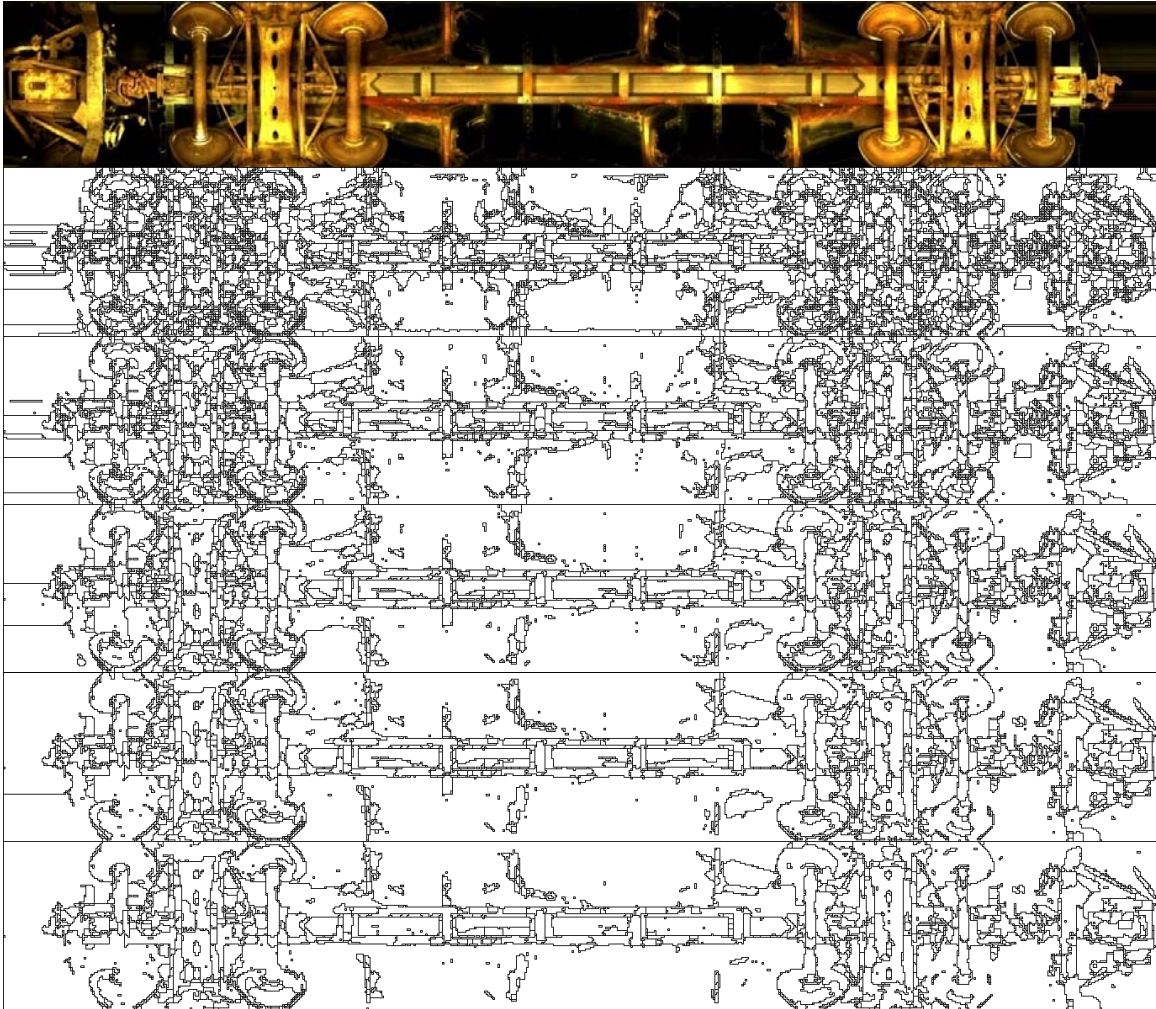


FIGURE 4 Multiscale segmentation of the hopper car image showing the car underbody with the segmentation scale increasing from top to bottom.

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. As the scale increases, smaller regions strictly merge to form a larger region, which means that the segmentation algorithm is hierarchical. Since the scale parameters of image regions are previously unknown, all the regions can be detected by exhaustively varying the scale across the entire range (e.g. using a range of gray-level intensity from 1 to 255) (Figure 4).

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 5).



FIGURE 5 (a) Digital picture of a broken crossbearer with (b) a multiscale segmentation of the image.

The obtained regions can be organized in a tree structure referred to as a segmentation tree. The root of the segmentation tree represents the whole image, the nodes closer to the root represent large regions, and their children nodes represent smaller details embedded within the corresponding parent regions. Each subset of tree nodes represents one possible segmentation of the image. Figure 6 illustrates image segmentations that are obtained by considering different subsets of tree nodes each of which are at a constant hierarchical depth from the root.

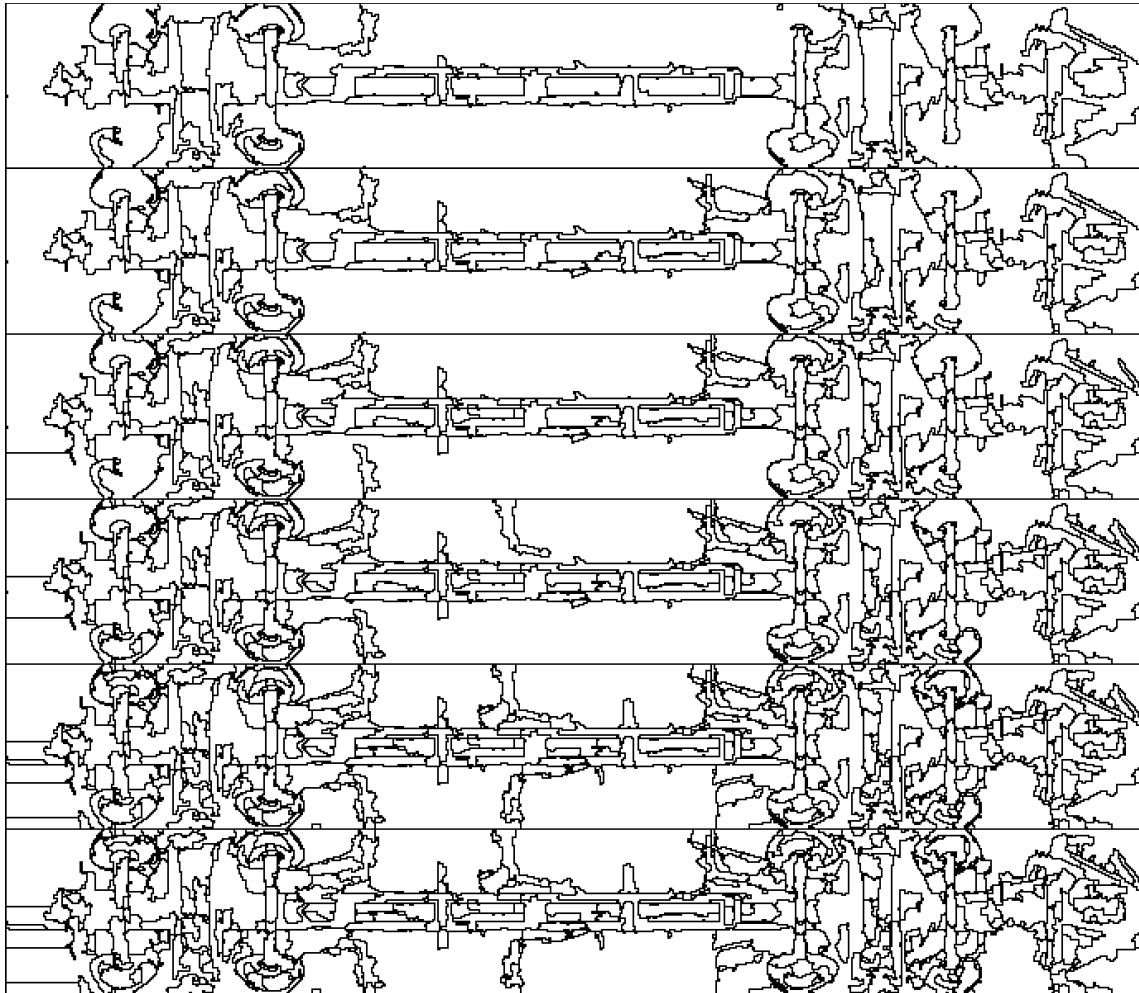


FIGURE 6 Segmentation tree containing all image regions represented as nodes.

The figure shows image segmentations obtained by considering subsets of nodes in the segmentation tree that are at increasingly larger hierarchical depths from the root. The scale changes from the coarsest at the top to the finest at the bottom. Each subset of nodes closer to the leaf nodes introduces new fine details that are embedded within the parent regions present at the previous scale. Since the center sill occupies a large area in the image relative to other objects, the coarsest cutset of the segmentation tree is used for detection of the center sill.

Detection of the Center Sill

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. Since the center sill's contrast with the surroundings is large, the coarsest-scale segmentation of the image is used for detection. To detect the center sill, the algorithm first searches for two prominent, parallel edges in the coarsest segmentation of the image. These edges should be located near the middle of the image, and the contrast across these edges should be large. Once identified, the edges are interpreted as contours of the center sill (Figure 7a).

The identified edges are also taken as the general direction in which the center sill extends across the image. However, some parts of the center sill are partially occluded, and some other parts appear in the cluttered areas around the trucks. These parts cannot be detected directly by using the aforementioned strategy. Therefore, the detected edges must be used to guide a further search for these remaining parts of the center sill. Specifically, it is assumed that the amount of possible deformation of partially occluded parts is relatively small, so that these parts occur in the vicinity of the identified general direction of the center sill. The remaining visible parts can thus be detected by analyzing a finer scale segmentation and identifying edges that lie along the identified general direction of the center sill (Figure 7b).

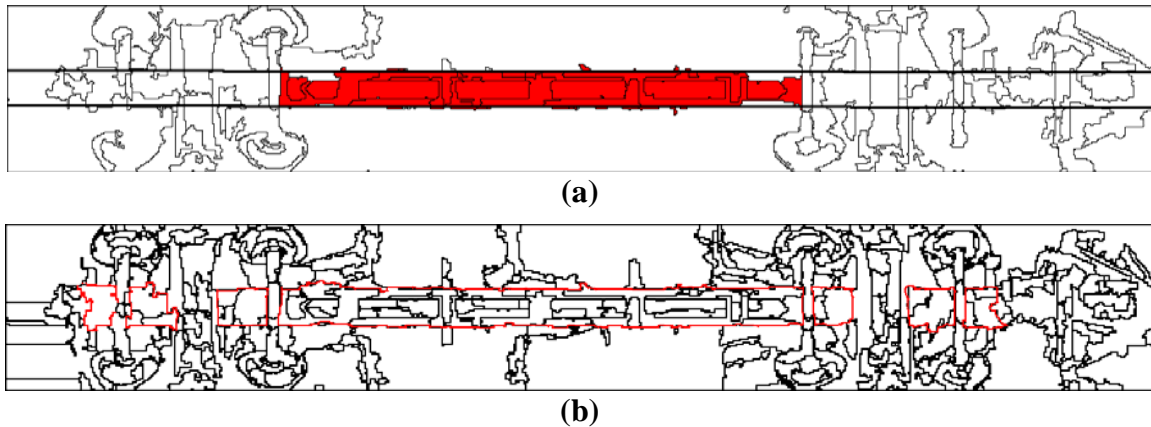


FIGURE 7 (a) Center sill detection using the coarsest-scale segmentation, and (b) the identification of the boundaries of the center sill using fine-scale segmentation.

Inspection of the Center Sill

Once the contours of the center sill are identified, they are compared with the ideal rectangular shaped model (template). Any deviation from the model is interpreted as deformation. 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 current accuracy of segmentation for the center sill is high. Experimental evaluation by visual inspection demonstrates that the average error of identified contours of the center sill is two pixels. By using the aforementioned calibration, this error corresponds to 0.75 inches, which is tolerable considering the center sill must be bent more than 2.5 inches to be in violation of the FRA regulations. Improved camera resolution should reduce this error.

Identification of Cracks and Breaks in the Center Sill

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 and the implementation and experimental evaluation of these ideas are beyond the scope of this paper. However, a multiscale process has been proposed as a potential approach to this phase of inspection. Both cracks and breaks will 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 of parts of the center sill's contours.

To identify breaks and cracks, a multiscale strategy will be used that recursively searches smaller subregions embedded within the region occupied by the center sill, and contrasts them against the models of breaks and cracks. 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 it will be feasible.

Data Collection Techniques

The need for field data combined with analysis of FRA data showing the infrequency of structural defects indicated that alternative solutions to data acquisition were necessary. Consequently, a portable rolling image-acquisition cart, equipped with lights and a camera, was developed that can be rolled underneath a car between the two trucks. Another cart has been developed to record a 45 degree side-angle shot capturing both the sidesills and center sill of a stationary car. Using these portable image acquisition carts, panoramic images of both healthy and defective cars have been analyzed to provide a basis for detecting structural component defects. Lighting methods will continue to be refined and improved and higher resolution cameras for crack detection will be considered in order to collect the maximum amount of data in each panorama. As AISC is further developed, new machine vision algorithms will be implemented to inspect other railcar structural components including crossbearers and sidesills.

DISCUSSION & CONCLUSIONS

Initial data collection and analysis has demonstrated the feasibility of AISC for the improvement of the effectiveness and efficiency of car inspections. The initial machine vision system parameters needed to inspect and evaluate the health of railcar structural underbodies have been determined and field investigations are underway in cooperation with local Class I railroads and car repair facilities to collect digital images of real-world structural component defects. These data will be used to further develop and refine algorithms capable of detecting various structural defects on multiple types of underbodies. When complete, AISC will be capable of inspecting the undercarriage of an entire train, identifying areas of concern, and reporting the suspected defects to qualified inspection personnel for further review or repair. After implementing algorithms for

structural component inspection, the system will provide a basis for future systems capable of addressing other mechanical component issues visible from the bottom of the car (e.g. missing coupler pins, broken or missing coupler retaining pins, and broken train line trolleys).

The ultimate goal 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. In this way, freight cars will be inspected more thoroughly and efficiently and the safety risks associated with manual car inspection will be minimized through the reduced exposure to potential yard hazards. Additionally, reducing inspection time will increase yard efficiency and improve overall network capacity by reducing the time needed to process inbound and outbound trains. In order to improve network efficiency by reducing the duration of car inspections, a majority of freight car inspection tasks will need to be automated. The AISC system brings TDTI and the railroad mechanical departments closer to achieving fully-automated car inspection. As a result of implementing machine vision technology and other automated inspection systems, North America's railroads will be poised to improve system-wide safety and efficiency by taking advantage of preventative maintenance strategies and by reducing network costs associated with the current inspection process.

ACKNOWLEDGEMENTS

This research is sponsored by a grant from the AAR's Strategic Research Initiative Program. The authors thank Jim Robeda and Semih Kalay at the Transportation Technology Center, Inc. (TTCI) for their support and oversight of this research and members of the TDTI committee for providing technical guidance for this project. Charles Powell at TTCI provided images and resources for initial data collection. Thanks to Gary Nelson, Chuck Sloan, Jacob Bilthuis, Bob Maloney, Dan Trimmer, and Michael Gay at Norfolk Southern and Darrell Iler, John Geary, David Beer, and Bill Bruns at CN for providing railcar mechanical inspection expertise and for the use of their facilities for field work and testing. Additional data and technical input was provided by the Federal Railroad Administration and Railinc. The authors are also grateful to the Monticello Railway Museum for the use of their facilities and equipment for testing. Finally, the authors would like to thank Esther Resendiz at the Machine Vision and Robotics Laboratory of the Beckman Institute for her work on the panorama development and Mike Wnek and Brennan Caughron in the Railroad Engineering Program at UIUC for their photographs and assistance during field testing.

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