Machine Vision Condition Monitoring of Heavy-Axle Load Railcar Structural Underframe Components

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ABSTRACT

To ensure the safe and efficient operation of the approximately 1.6 million freight cars (wagons) in the North American railroad network, the United States Department of Transportation (USDOT) Federal Railroad Administration (FRA) requires periodic inspection of railcars to detect structural damage and defects. Railcar structural underframe components, including the center sill, sidesills and crossbearers, are subject to fatigue cracking due to periodic and/or cyclic loading during service and other forms of damage. The current railcar inspection process is time consuming and relies heavily on the acuity, knowledge, skill and endurance of qualified inspection personnel to detect these defects. Consequently, technologies are under development to automate critical inspection tasks to improve their efficiency and effectiveness. Research was conducted to determine the feasibility of inspecting railcar underframe components using machine vision technology. A digital video system was developed to record images of railcar underframes and computer software was developed to identify components and assess their condition. Tests of the image recording system were conducted at several railroad maintenance facilities. The images collected there were used to develop several types of machine vision algorithms to analyze images of railcar underframes and assess the condition of certain structural components. The results suggest that machine vision technology, in conjunction with other automated systems and preventive maintenance strategies, has the potential to provide comprehensive and objective information pertaining to railcar underframe component condition, thereby improving utilization of inspection and repair resources and increasing safety and network efficiency.

Keywords: Center Sill, Computer Vision, Freight Wagon, Multiscale Segmentation, Automated Inspection, Condition-based Maintenance

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1 INTRODUCTION

There are approximately 1.6 million freight cars (wagons) operating in the North American railroad network and they are subject to wide ranging forms of wear and damage while in service [1]. The United States Department of Transportation (USDOT) Federal Railroad Administration (FRA) regulations require a car inspector or train crew member to inspect every car placed in a train before that train may depart from a yard or terminal [2]. The current railcar inspection process is tedious, labor intensive, and relies on personnel with varying degrees of experience and training who must perform their tasks under a wide range of environmental conditions. Additionally, there is currently no practical means of recording and retaining inspection information unless a billable repair is required. This makes it difficult to track the condition of an individual railcar's components over time, thereby preventing trend analyses and predictive maintenance. As a result, US railways have progressively moved away from reactive maintenance to planned and scheduled component replacement in order to improve efficiency and reduce costs [3]. Consequently, the Association of American Railroads (AAR) and the Transportation Technology Center, Inc. (TTCI) initiated the Advanced Technology Safety Initiative (ATSI) and a program called Technology Driven Train Inspection (TDTI) to develop and implement automated inspection technologies [4-6].

The objective of ATSI and 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. Examples of these technologies include wheel impact load detectors (WILDs), truck (bogie) performance detectors (TPDs), acoustic bearing detectors (ABDs), and machine vision inspection of truck components, safety appliances, and brake shoes [3, 5-14]. The plan for

TDTI is to implement an integrated network of automatic wayside (lineside) systems capable of inspecting and monitoring the North American freight car fleet with two principal objectives. The first goal is to cost-effectively maintain compliance with FRA regulations and railroad-specific maintenance and operational standards and the second is to improve the overall effectiveness and efficiency of the railcar inspection and maintenance process.

In order for TDTI to provide substantial improvement to the inspection process, each component and system on the railcar must be addressed. If not, railcars and trains will still need to stop in order to manually inspect the components excluded from automated inspection. An automated system that only addresses a limited selection of inspection tasks, or only inspects certain cars, would offer incremental and qualitative benefits, but it may not provide sufficient savings to cost justify the investment in these expensive technologies [13]. Consequently, the final wayside inspection systems should be comprehensive in scope, inspecting as many aspects of the car as possible [8]. In addition to the wide variety of components requiring inspection, there are also many variations in the nature of component defects, symptoms of interest, and the required means of ascertaining component condition. As a result, the requisite technologies capable of addressing these inspection demands must vary in design and application. The AAR has initiated research and development on a variety of different automated inspection technologies that will address many aspects of the federally mandated freight car inspections including brake application and release verification, brake shoe thickness measurement, safety appliance condition inspection, wheel defect inspection, and wheel profile measurement [3, 6, 8].

2 BACKGROUND

2.1 Structural Underframe Components

One component of the TDTI initiative is the development of a system known as Automated Inspection of Structural Components (AISC) that will use cameras and computer-aided image-search methods to inspect freight car underframes. Steel 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 (slack action) within the train. On many types of freight cars the principal structural member of the underframe is the center sill, extending longitudinally along the center from one end of the car to the other. The center sill is the largest element in the underframe structure, supporting vertical loads and also transmitting the majority of buff and draft forces through the car [15]. In addition to the center sill, several other components are needed to support vertical, longitudinal, static, and dynamic loads while the car is in transit. These components include sidesills, body bolsters, and crossbearers. Some cars also have smaller cross members (sometimes called crossties) and smaller longitudinal members known as stringers or floor supports. Unlike other underframe structural members, neither crossties nor stringers bear substantial loads. The sidesills are longitudinal members running along each side of the car. They are connected to the center sill by various cross members that run transversely from the sidesills to the center sill. The two body bolsters are the largest of these transverse members and are located near each end of the car. Besides their role as major transverse members of the underframe structure, they support the carbody atop its trucks (bogies). Crossbearers (and crossties) are additional transverse members connecting the sidesills to the center sill and further help to distribute and support vertical loads. All of these components combine to form a structural system that maintains the car's camber and structural integrity.

2.1.1 Structural Underframe Defects

Freight car structural underframe components are subject to cyclic loading, shock, and vibration while in service. Cyclic longitudinal loading, also called slack action, occurs in the form of buff and draft forces. The majority of these forces are absorbed by a car's draft system, but extreme loading in buff (compression) or draft (tension) must be absorbed by the center sill and accompanying structural components. Lateral cyclic loading occurs in curves as centripetal forces generate higher loads on one side of the railcar. A portion of these loads are carried by the sidesill and transferred to the center sill through the crossbearers. Damage and repeated loading and unloading can lead to fatigue-crack growth and ultimately result in fracture of structural members. When cars are overloaded or loaded unevenly, cyclic forces en route are higher, exacerbating fatigue stresses. In addition to cyclic loading, railcars are also subject to periodic "shocks" as a result of loading or coupling practices or track geometry deviations, that can lead to structural component defects. Examples may include: dropping lading into a gondola car rather than slowly lowering it or excessive coupling impact speeds during switching or classification yard operation. Due to these potential sources of structural component damage, the FRA and railroad mechanical department practices require railcar underframes to be regularly inspected to ensure the safe and efficient operation of rolling stock.

2.1.2 Structural Underframe Inspection

Due to the robust nature of railcar designs, frequent inspections, and AAR mechanical standards, serious problems with the structural elements are unusual and failures are rare. However, when failures do occur, they pose a high risk of causing a derailment. As a result, 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]. To detect defects in all of these structural elements with certainty, a car inspector must walk around the entire car, carefully looking beneath it (often with the aid of a flashlight) to adequately view each structural component. North American freight trains average approximately 70 cars in length [1] and are often over 100 cars long. Each car typically receives about 1-2 minutes for either in-bound or outbound mechanical inspections. Under these conditions, defects that are not easily seen may go undetected. Cars are typically inspected with the level of scrutiny necessary to detect structural component problems only when entering a railcar repair shop for major repairs. Machine vision technology for inspection of underframe components offers the possibility for inspections to be performed more efficiently and effectively, hence the rail industry's interest in development of the AISC system.

2.2 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 [3, 7, 8]. AISC will work collectively with other automated systems, leading to railcar inspections that are more efficient, effective and objective than current human-vision inspections. By storing digital inspection data, it will be possible to maintain historical health records for each car that undergoes inspection. Maintaining these records will enable condition monitoring of structural elements over time, allowing the repair of defects or damaged components to be appropriately scheduled prior to an in-service failure. As a result, applying machine vision technology to the railcar inspection process has the potential to enhance rolling stock maintenance efficiency and safety.

A primary benefit of machine vision and other automated inspection systems is the facilitation of predictive, or condition-based, maintenance. Condition-based maintenance (CBM) involves monitoring certain parameters related to component health or degradation and taking corrective action prior to component failure [16]. Despite the advantages of CBM, current railcar structural component repair and billing practices encourage reactive maintenance to correct extant defects, rather than prevention of incipient failures. One of the reasons for this is the lack of cost-effective technology and infrastructure to conduct thorough inspections of many railcar elements, especially underframes. Due to the reactive nature of corrective maintenance, repairs cannot be effectively planned, resulting in higher maintenance 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 CBM, railroads have begun implementing other technologies similar to AISC that monitor various indicators of railcar component health (e.g. Truck Performance Detectors and the AAR's Fully Automated Car Train Inspection System - FactIS™) [4, 7, 13].

2.3 Previous Machine Vision Research

Among the earliest research and development in North America on the use of machine vision for railroad inspection tasks was work conducted by Conrail who developed a system to detect low-hanging air hoses in the 1990s [17]. Since then, research on use of machine vision for a variety of other railroad inspection tasks has been conducted, including work sponsored by the AAR, FRA, BNSF Railway, NEXTRANS Center, and the Transportation Research Board (TRB) High-Speed Rail IDEA Program [3, 8-12, 18-20].

The University of Illinois at Urbana-Champaign (UIUC) has conducted several railroad machine vision research projects that have been an interdisciplinary collaboration between the Railroad Engineering Program in the Department of Civil and Environmental Engineering and the Computer Vision and Robotics Laboratory at the Beckman Institute for Advanced Science and Technology. The first of these was a project investigating wayside inspection of railcar truck components [8]. The experimental setup used a perpendicular view of the truck with respect to the track, and algorithms were developed to both detect the locations of brake components and spring sets and identify missing bearing end cap bolts. This research provided a basis for subsequent research on the Automated Safety Appliance Inspection System (ASAIS) [12]. 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 has been incorporated into the AAR's TDTI program and are currently being developed by technology companies and adopted by railroads for field testing.

Subsequent UIUC research demonstrated the feasibility of using machine vision to detect defects and other anomalies on the underbodies of passenger cars and locomotives [9-11]. Image acquisition and machine vision techniques were developed to record images and inspect rolling stock and locomotive undercarriages. Algorithms using images captured in 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 between the rails in a repair pit beneath the tracks. The combination of information from both the thermal and visible spectra identified certain defects that might have otherwise gone unnoticed by human inspectors in the course of routine visual inspections. This research addressed some of the problems associated with acquiring images from beneath a railcar: an inherently challenging location due to lighting requirements, space constraints, and difficulties involved with keeping the equipment clean and protected. Hardware, algorithms, and technical methodologies for image acquisition developed in these earlier projects was adapted and expanded to develop a system for machine vision inspection of freight car underframes in the AISC project described in this paper.

2.4 Regulatory Compliance

The FRA regulations for freight car inspection formed the basis for determining which components would 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 FRA regulations, the center sill may not be broken, cracked more than 15.24 cm (6 inches), or bent/buckled more than 6.35 cm (2.5 inches) in any 1.83 meter (6 foot) length. Specific parameters are established for the allowable magnitude of cracks and buckling because these defects may undermine the integrity of the center sill, resulting in a failure [21]. 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. The inspector may take exception to the condition of a structural component and issue a warning to the operating railroad 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].

2.5 Research Focus

In order to determine which structural elements should have the highest priority among AISC inspection tasks, railcar inspection data from the FRA Office of Safety were analyzed for the time period of 2000 to 2007. Inspection data pertaining only to railcar underframe components were considered in this analysis. 59% of all structural component defects identified by FRA MP&E inspectors, were broken, cracked, bent, or buckled center sills, while the remaining 41% were defective sidesills, body bolsters, or crossbearers (Fig. 1).

These data suggest that defects in the center sill are the most frequent type among freight car structural underframe components. This is consistent with FRA train accident data from 1999-2008. Over this ten-year period, bent or broken center sills were responsible for 75 train accidents on US Class I railroads in comparison to only 31 accidents due to broken side sills and only 1 accident due to a defective body bolster [22]. Given the importance of center sills in providing load bearing capacity and their role transmitting buff and draft forces, the consequence of center sill failures are higher than other structural components. Fines assessed by FRA inspectors due to a broken center sill are among the highest of those listed in CFR 215.121, matched only by violations due to loose or broken axles. Risk is typically defined as the product of frequency (or probability) and consequence [23]. Center sill defects are more frequent and have higher consequences than other structural components, thus the risk associated with center sill failure is the highest among railcar structural components. Therefore, the inspection of center sills is a primary focus of AISC and of this research.

3 METHODOLOGY

3.1 Preliminary Image Acquisition

The initial stage of this research focused on collecting images of representative railcar structural components. Preliminary tests were conducted at the Monticello Railway Museum in Monticello, IL on a 1950-era AAR-standard-design hopper car. The basic data recording system was adapted from UIUC's previous passenger car inspection research [9-11]. Camera and lighting equipment were mounted, facing upward, on the floor of a three-foot-deep inspection pit, and connected to a laptop computer adjacent to the pit. Eight halogen lights were arranged in a circle with the camera in the center and were manually adjusted in order to provide proper illumination of the railcar's center sill. Experiments were conducted in which the car was rolled over the pit track at various speeds, and images were recorded under various levels of light intensity. A panoramic image was developed using image data from the best (i.e. most clearly visible) trial. Using previously developed panoramic image creation algorithms, the central portions of each consecutive video frame were extracted and appended together to form a complete image of the entire railcar underbody [9] (Fig. 2).

The resulting panorama provided initial confidence in the feasibility of this method of automated structural component inspection. Several critical structural underframe components, including the center sill and crossbearers, are clearly visible in the panoramic image as well as other mechanical components such as the couplers, draft gear, truck bolsters, brake rigging, brake beam, interior springs in each spring nest, and axles. Results from these tests identified specific areas for improvement, including better illumination of the recessed portions of the underframe most distant from the camera (e.g. the tops of the hoppers).

3.2 Data Collection

After analyzing preliminary image acquisition results, a more precise experimental setup was developed using an additional camera (Fig. 3A), and data collection procedures were defined. This equipment arrangement was used during testing at the Norfolk Southern (NS) locomotive repair facility in Decatur, IL (Fig. 3B).

The test set-up included two cameras placed below the rails. In an arrangement similar to the setup used at Monticello, Camera 1 was located 1.65 meters (65 inches) below the top of rail, centered between the two rails and aimed straight upward, 90 degrees from horizontal (Fig. 3A). The video-image collection system for this camera view was a Dragonfly 2 camera recording at 15 frames per second, with a 4.8mm lens and an f/1.8 aperture. Illumination was provided by eight 575-watt (115 volt) halogen lights, each with parabolic reflectors and medium flood lenses. The lights were oriented on the floor of the pit in a circle around the camera, and the intensity of each light could be individually adjusted. Using a handheld light meter, the maximum luminous intensity of each light was determined to be 40,900 lux (3,880 foot candles at a distance of 3 ft.). The lights were aimed upward but adjusted inwardly at various angles to provide even illumination of the camera's entire field of view. Half of the lights were oriented to illuminate the center sill, while the other four lights were positioned at higher angles (closer to 90 degrees vertically) in order to illuminate the more distant portions of the underbody (i.e. the top sections of the hoppers).

Camera 2 was positioned 1.22 meters (48 inches) from the field side of the rail, 0.76 meters (30 inches) below the top of rail, oriented perpendicular to the track and aimed upward 45 degrees above horizontal (Fig. 3A). Equipment for this camera view included a Marlin camera recording at 15 frames per second and a 6mm lens with an f/1.4 aperture. Four individually adjustable halogen lights (with the same specifications as those used for Camera 1) provided illumination for Camera 2, each oriented at approximately 45 degrees above horizontal. Tests were run using two NS gondola cars and one NS covered hopper car by rolling them past the cameras at 5-8 km/h (3-5 mph). Fourteen different videos were recorded during testing, and the image data were converted into panoramic images (Fig. 4). Since the two gondola cars were almost identical to each other, images of only one of the cars are shown.

Results from the testing at Decatur show much more even illumination for the covered hopper car image (Fig. 4A) compared to the previously recorded hopper car panorama (Fig. 2). The panorama of the gondola underbody (Fig. 4B) provides a clear view of the center sill, crossbearers and crossties (thinner lateral members between the crossbearers). 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 NS for each of the cars that were tested. By measuring certain components in the panoramic image in pixels and dividing by the actual lengths of those components, the pixel-to-cm ratio (i.e. the image resolution) was determined to be 3.03 pixels per centimeter (~7.8 pixels per inch). Each panoramic image was developed by combining the center strips of over 400 video frames, with each strip having a mean strip size of approximately 12 pixels.

The panoramas from Camera 2 are much longer due to the fact that this camera was located closer to the track than Camera 1. As a result, the images in Fig. 4C and 4D only represent one half of each railcar. The images from this camera view are valuable because cracks or breaks in the side of the center sill would be visible from this angle. This view can also be used to inspect the camber of the car, to determine whether the center sill is sagging or deformed.

4 DATA ANALYSIS

4.1 Multiscale Image Segmentation

Given a panoramic image of the car underframe, 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 nature of the two types of defects being considered necessitates the development of a multiscale analysis approach, where defect search functions are performed at various scales, or levels, of image segmentation. The area occupied by the center sill differs significantly in size compared to the area encompassing a crack. As a result, the detection of the center sill requires analysis of large pixel neighborhoods, while the detection of breaks and cracks requires analysis of higher-resolution image details. A computationally efficient strategy capable of addressing these two image-analysis extremes is known as multiscale image segmentation [24-26]. Multiscale image segmentation provides access to pixel neighborhoods of varying size, which can be further used for detection and inspection of the center sill for defects.

The machine vision algorithm requires the following steps:

1. Using pixel values present in the image, parse the panorama into homogeneous-intensity regions at all degrees of inter-region versus intra-region homogeneity.
2. 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).
3. Inspect the contours of the image regions that identify the center sill to measure their deviation from the model, thus determining the degree of center sill bending and/or buckling.
4. Recursively analyze sub-regions at different scales of the segmentation, from fine to coarse, to detect cracks or breaks in the center sill. Use models developed from example images containing cracks or breaks (e.g. a crack typically appears in the image as an elongated, dark region that represents a discontinuity in brightness).

This recursive analysis is feasible due to the multiscale image-segmentation algorithm previously developed at UIUC and noted in step one [24-26]. 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 models of these defects. Identification of a crack or break simultaneously localizes its position, orientation, and length, and this information can be used to evaluate the magnitude of the discovered defect.

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 (Fig. 5).

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. 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.

4.2 Center Sill Inspection

The center sill is the largest and single most critical structural component in the railcar underbody; therefore its correct identification and inspection is the highest priority of the AISC inspection tasks. The consistency of the camera orientation and panorama development techniques allow 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) contains two long parallel edges that lie along two horizontal image rows. Therefore, the center sill can be modeled as a large, rectangular-shaped object, prominently featured at the center of the panoramic image. 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 wheelsets (Fig. 6A).

Once identified, the matching edges are interpreted as contours of the center sill. These identified edges also indicate the general direction in which the center sill extends across the image. However, some parts of the center sill (e.g. the portion above the truck bolster) are partially occluded, and other parts appear in the cluttered areas around the railcar truck (bogie). These parts cannot be directly detected using the aforementioned strategy. Therefore, the detected edges must be used to guide an additional search for the remaining portions of the center sill. It is assumed that the amount of possible deformation of the partially occluded parts is relatively small, so these portions of the center sill should occur in the vicinity of the previously identified general direction of the sill. The remaining visible parts can then be detected by analyzing a finer-scale segmentation and identifying the edges that lie along the general direction of the center sill. Nearby segmentation boundary pixels are identified to fill in missing parts of the center sill contour (Fig. 6B).

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 about 0.66 cm (1 pixel corresponds to 0.33 cm, or 0.13 inches). Improved camera resolution should further reduce this error. Additional errors could be generated by lateral motion of the train when passing the AISC system. These errors were not witnessed during testing, however, they could be remedied, should they prove to be a problem. By maintaining a tight track gauge and using guardrails that force the wheel flange against the gauge side of the rail at the inspection site, lateral motion could be substantially reduced or eliminated.

4.3 Pixel Summation

An alternative, less computationally intensive method can also 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. The number of pixels along each horizontal row is computed from the edge image (Fig. 7A). Long, straight sections in the panoramic image will appear as prominent peaks in the histogram of the pixel summation (Fig. 8A).

Since the center sill creates the longest edges in the panoramic image, the two largest peaks (a and f in Fig. 8A) correspond to the outer contours of the center sill, while the four interior peaks (b - e in Fig. 8A) in the histogram correspond to the inner contours of the center sill (see Fig. 8B). The outer contours along the length of the center sill are then denoted with white parallel lines (Fig. 7B and Fig. 8B). 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. This method can also be applied in the lateral direction to identify and inspect crossbearers and crossties.

Additionally, using the panoramas from Camera 2 (Fig. 4C and 4D), the same methods described above can be utilized to identify the location of the center sill from the side of the car. Using pixel summation, the bottom edge of the center sill can be identified and inspected for breaks or bends. As a result, the AISC system will detect whether or not the center sill maintains appropriate camber and could determine if a car has been overloaded to the point of causing the center sill to deform. Pixel summation provides detection and inspection flexibility with reduced computational requirements but does not provide the same level of accuracy or robustness as the multiscale segmentation approach.

4.4 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 (Fig. 6A). To identify breaks and cracks, 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 corresponding to a center sill crack (Fig. 9).

If any of these subregions exhibit properties defined by the models, they will be considered as potential cracks or breaks. In addition to detection, the AISC system 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, their detection is expected to be more difficult than breaks; however, preliminary field data indicate that it will be feasible.

5 DISCUSSION

The ultimate goal for an automated machine vision railcar inspection system is one that can inspect railcars using a series of integrated wayside cameras, including the AISC cameras located below the track. Through automated inspections, freight cars will be inspected more thoroughly and potential risks associated with manual car inspection minimized. A completely functional AISC will be capable of inspecting the underframes of an entire train of cars moving at mainline speeds, identifying areas of concern and reporting the suspected defects to railroad inspection personnel for further review or repair at terminals ahead. After implementing algorithms for structural component inspection, AISC will provide a basis for future systems capable of addressing other mechanical component defects visible from the bottom of the car (e.g. missing knuckle pins, broken or missing coupler retaining pins and broken train line trolleys).

In addition to the goals of TDTI, there are other advantages afforded by the use of this technology. The collection of high-quality images of railcar components, even without the use of machine vision and computer-aided defect detection, can provide benefits to the railroad industry. For example, a car inspector could be stationed in an office with the task of manually inspecting the digital images of railcar underbodies, as trains pass the inspection site. If used in this manner, benefits could be immediately realized, as car inspectors would have a much clearer and more comprehensive view of railcar underbodies than is currently possible. In addition, the collection of high-quality images of railcar underframes would also be helpful for security and liability purposes, as AISC could provide railroads the ability to detect "non-standard features" including contraband or explosive devices [8]. These images would also provide historical documentation of railcar underbody condition that has not been previously available. As machine vision systems develop further, software could be integrated to aid the human inspector by highlighting potential defects visible in the images. Models of humans and machines have been used to develop similar hybrid automation systems for other industries, which typically perform better than either humans or machines alone [27, 28]. In this way, railroads could benefit from the increased speed of an automated system while improving the quality of human decision making.

Finally, the use of automated inspection systems will eliminate wasted effort by allowing carmen to spend less time inspecting cars and dedicate more time to the value-adding task of making repairs. This will result in reduced inspection times and will potentially add capacity to receiving and departure tracks, thus improving the efficiency of an entire terminal [29]. As a result of the benefits in terminals, these technologies may also improve overall railroad network efficiency, since average train speed and service reliability are greatly dependant on terminal dwell [30-35]. In order to improve yard and terminal efficiency most effectively, all freight car inspection tasks will need to be automated. Since a railcar's physical features (including underframes) vary substantially among car types, extensive testing will be required to ensure appropriate inspection accuracy and minimal false alarm rates. Machine vision inspection capabilities will initially be most applicable to unit trains (i.e. those containing cars of nearly uniform design) due to the fact that component image templates (e.g. the shape of the center sill) will be consistent for the entire train. Over time, however, templates can be developed for all car types to extend the use of machine vision to manifest, or mixed freight trains. Although a partially automated inspection system (i.e. one that still required one or more cars or components to be manually inspected) would provide incremental benefits in effectiveness, terminal efficiency and/or labor utilization, the benefits would be disproportionately less. Therefore, the larger TDTI vision, of which AISC is a part, is being pursued by the North American railway industry.

The technical knowledge exists for the TDTI objective to become a reality, however additional work is required to develop and integrate the appropriate systems. Calibration and validation requirements will need to be determined for AISC and other machine vision systems similar to those developed for wheel impact load detectors (WILDs) and acoustic bearing detectors (ABDs) [36]. In addition, each location where AISC is installed will require site validation, which will likely be more extensive than what is required for either WILD or ABD sites, due to the large number of disparate components that AISC will inspect. Although the validation period may be longer for AISC and other machine vision systems, these technologies will benefit from the framework that has been established for previous wayside detector implementation.

6 CONCLUSIONS

The image acquisition system and machine vision inspection algorithms described in this paper have demonstrated the feasibility of AISC for the improvement of the effectiveness, efficiency and objectivity of railcar inspections. The initial machine vision system parameters needed to inspect and evaluate the health of railcar structural underframes have been determined and railway technology supply firms have built a subsequent test installation at TTCI. This installation currently collects images of railcar underbodies at speeds up to 40 miles per hour and provides the capability to further develop and refine the AISC system for use with multiple types of freight car underframes. As a result of implementing this machine vision technology and other automated inspection systems, railroads will be poised to improve inspection effectiveness, take advantage of the operation and management benefits of predictive maintenance strategies and improve system-wide network reliability and efficiency.

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A LIST OF FIGURES

Fig. 3 Diagram of equipment setup with measurements in meters (A) and locomotive repair pit used for data collection (B)

Fig. 4 Panoramic images of hopper car (A & C) and gondola car (B & D) from Camera 1 (A & B) and Camera 2 (C & D)

Fig. 5 Multiscale segmentation hierarchy of hopper car image showing car underframe with the segmentation scale increasing (i.e. becoming more coarse) from top to bottom

Fig. 6 Center sill detection using the coarsest-scale segmentation (A) and center sill boundary identification using finer scale segmentation (B), colors have been modified for document reproduction purposes

Fig. 7 Edge image of gondola car underbody panorama (A) and original panorama with center sill detected (B)

Fig. 8 Histogram of the pixel summations belonging to center sill region boundaries, with the row index of the image on the horizontal axis and the proportion of strong edges on the vertical axis (A); (B) is a close-up of Fig. 7B, showing the edges (a - f) corresponding to (A)

Fig. 9 Original digital image of a cracked center sill, provided courtesy of AAR (A) and fine to coarse segmentation images (B-F), showing the crack at various segmentation levels

Figure 1
Click here to download high resolution image

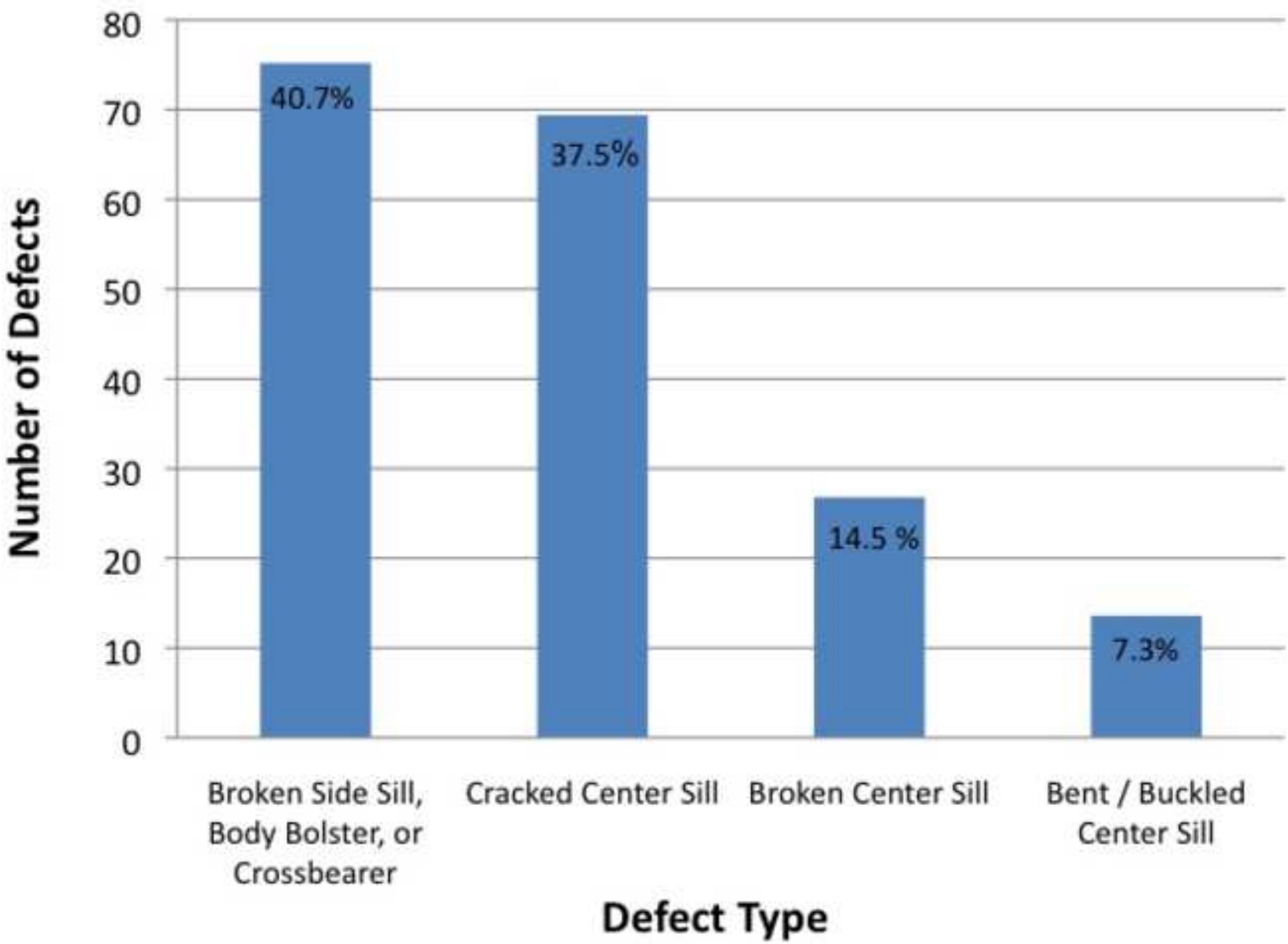

Figure 2
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Figure 3A

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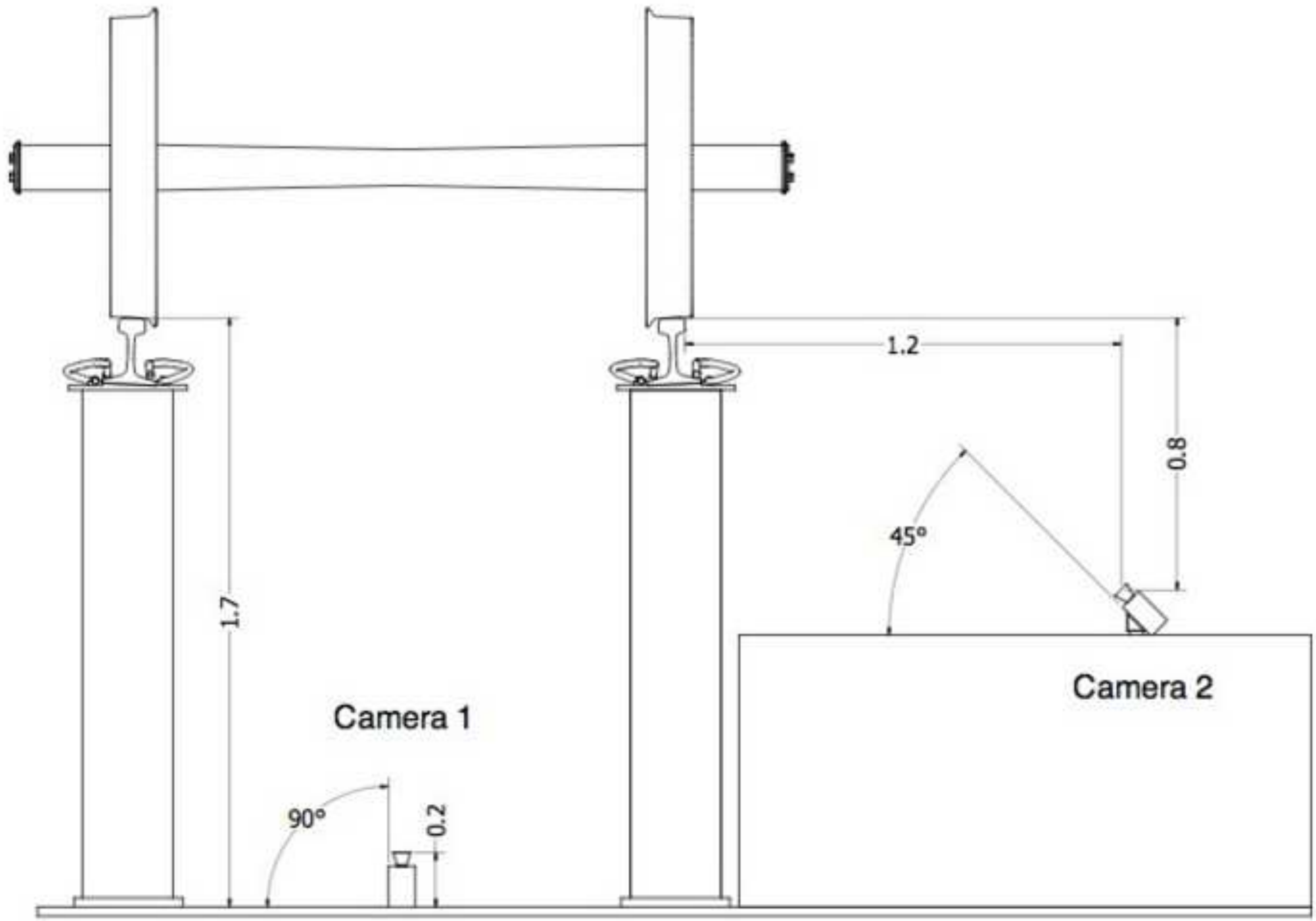

Figure 3B
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Figure 4

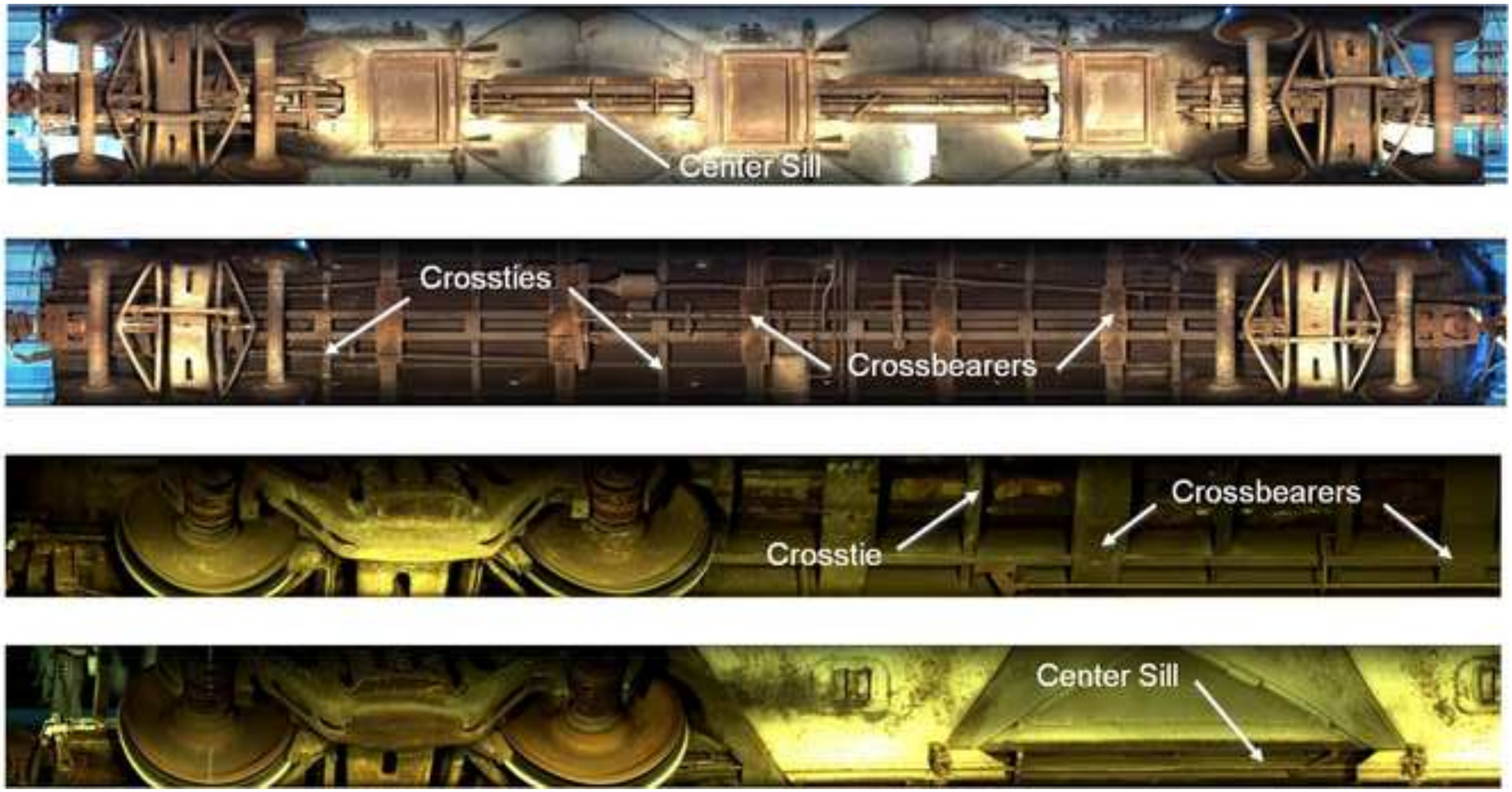
(A)
Center Sill
(B)
Crossties
Crossbearers
(C)
Crossbearers
Crosstie
(D)
Center Sill

Figure 5
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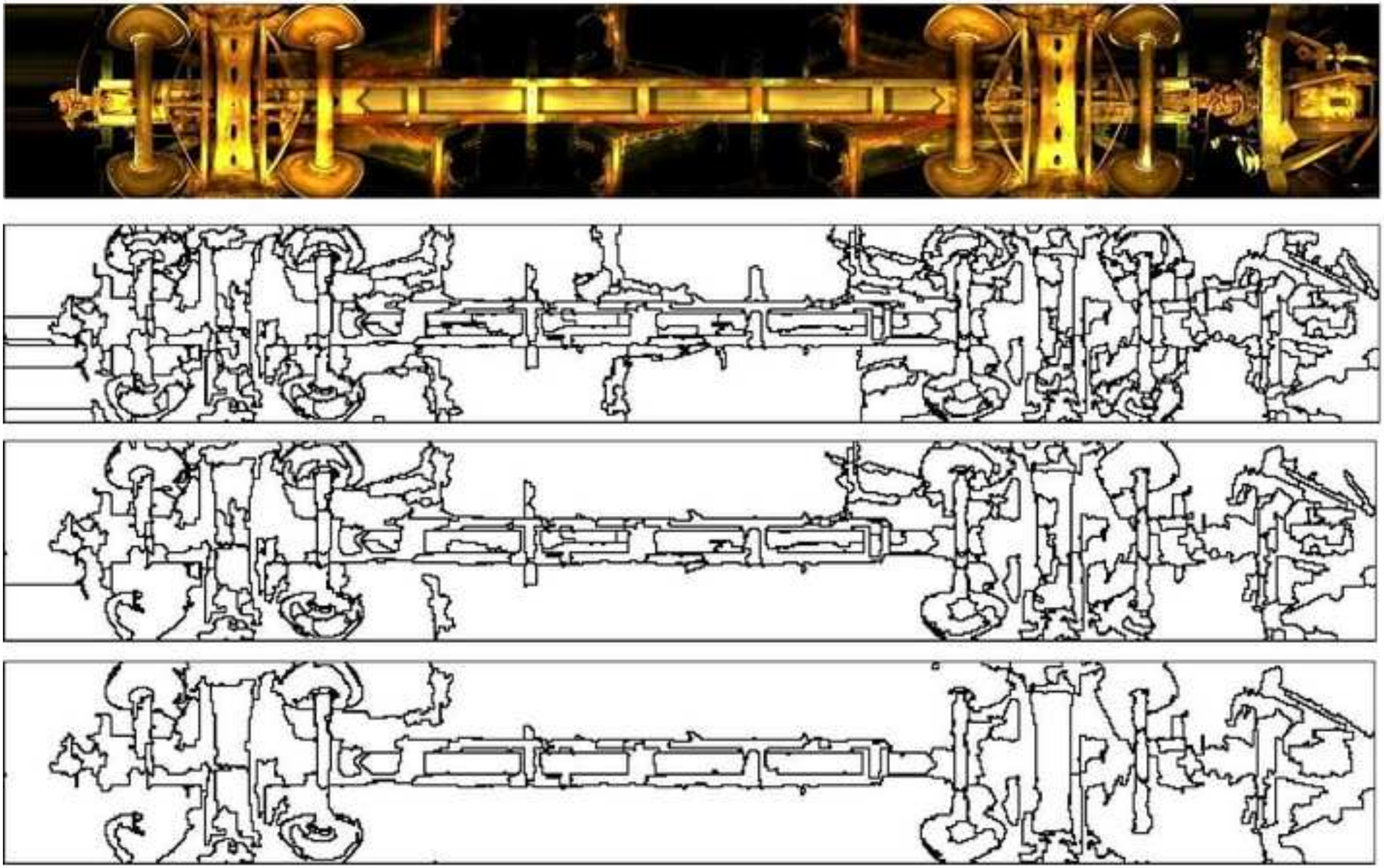

Figure 6

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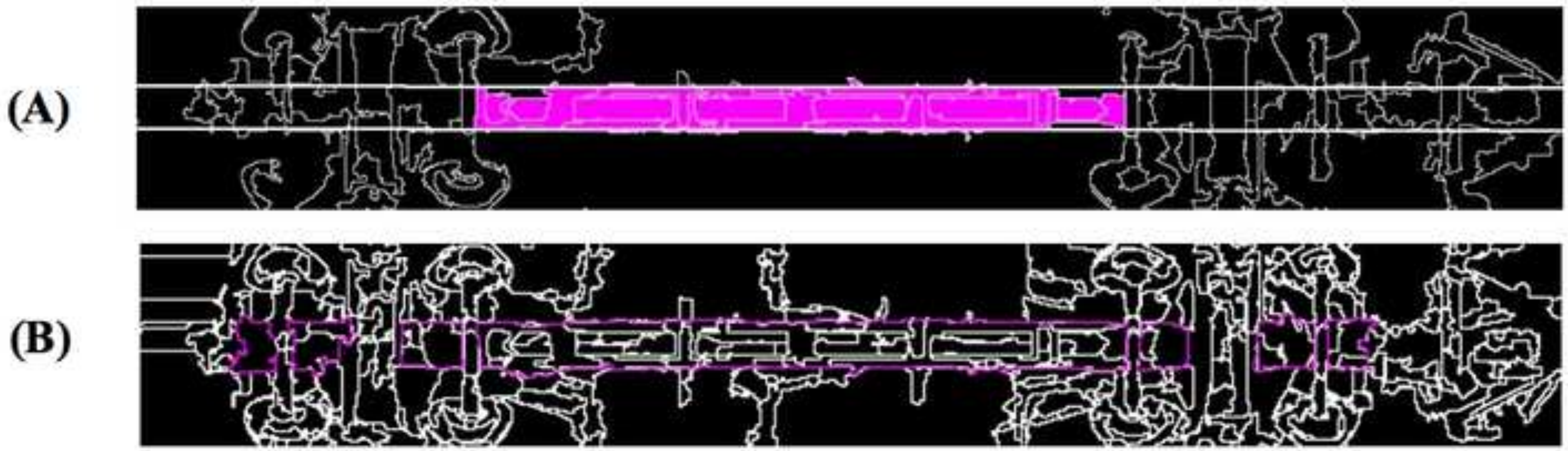

Figure 7
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(A)
(B)

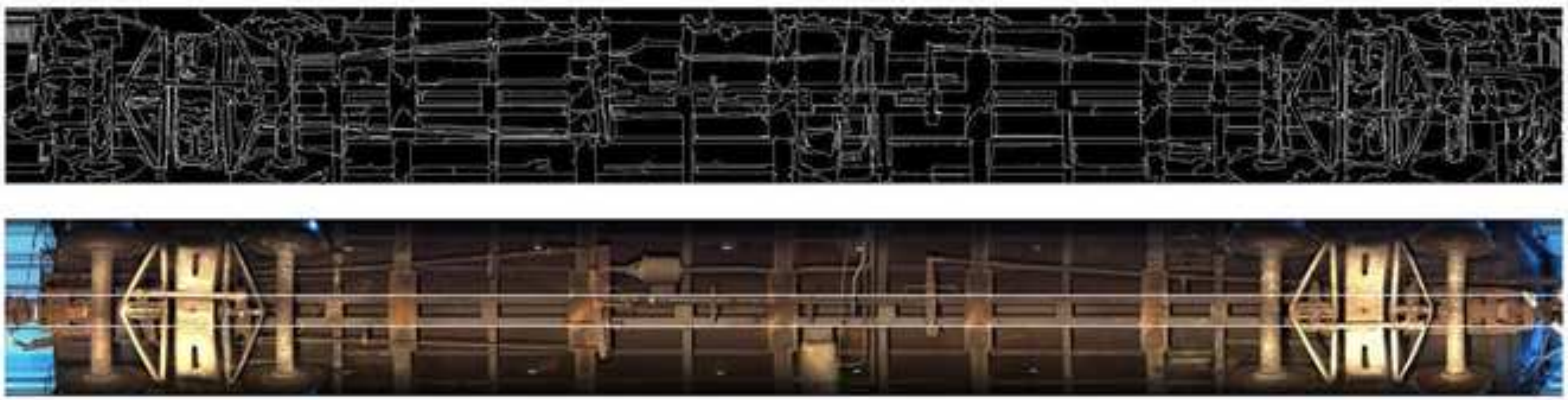

Figure 8
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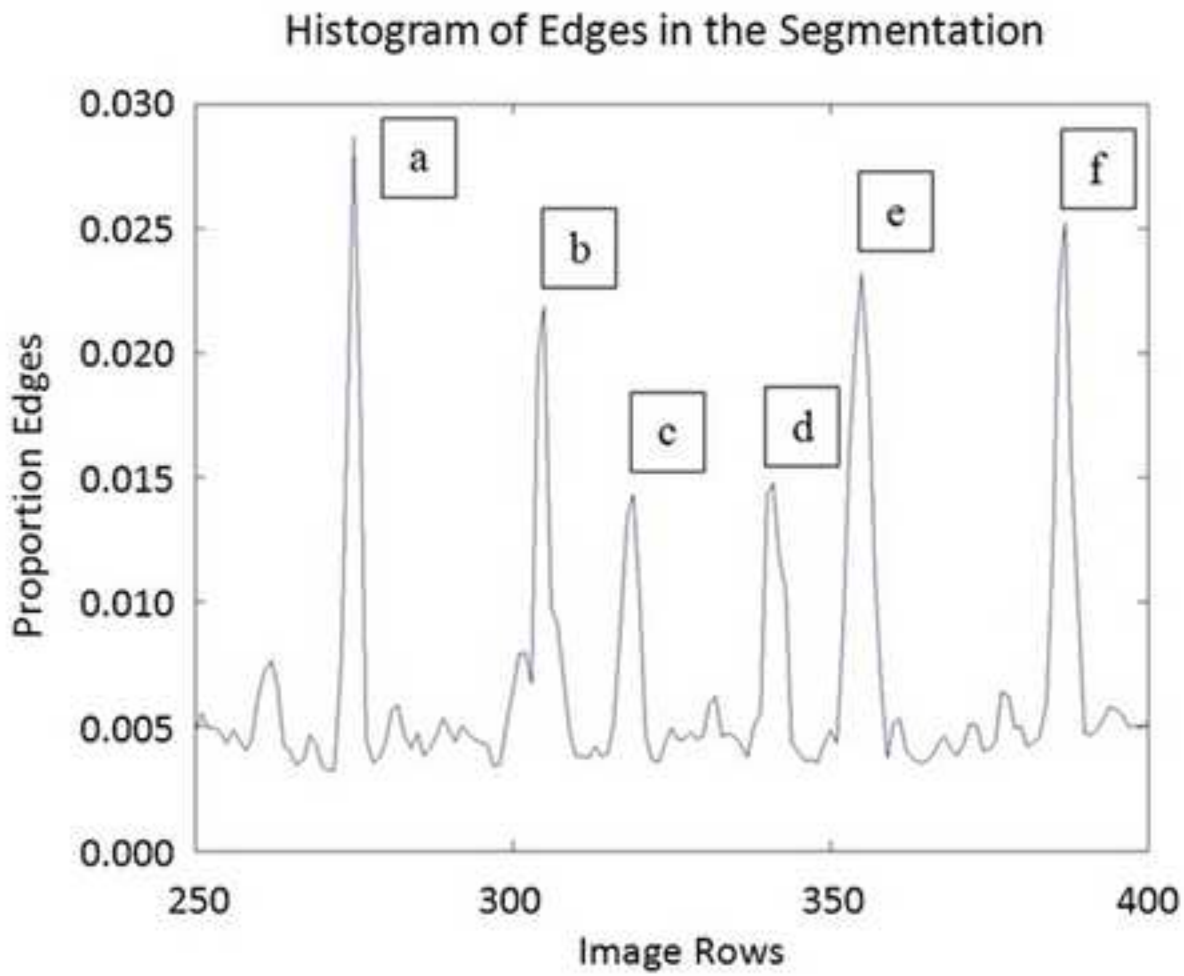
(A)



(B)

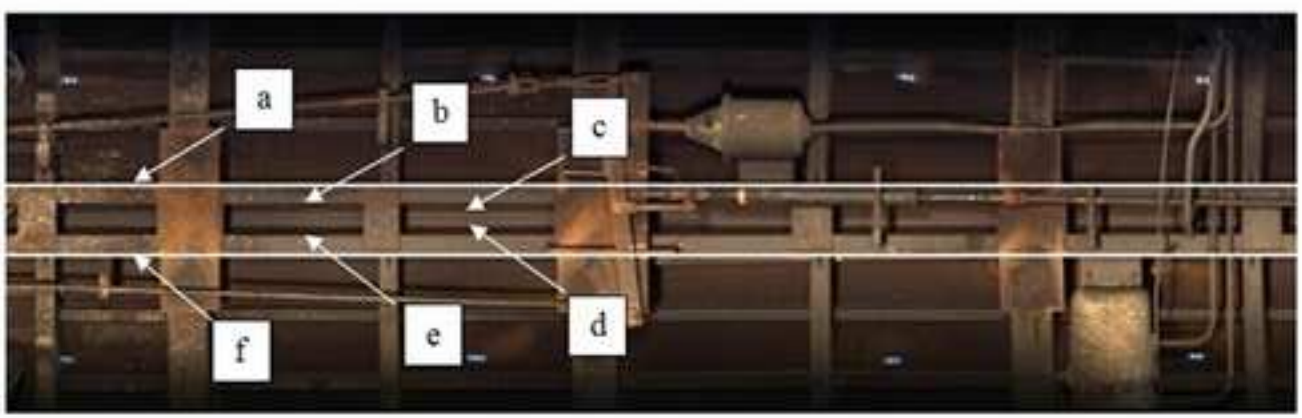


Figure 9

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