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IMPROVING THE EFFICIENCY AND EFFECTIVENESS OF RAILCAR SAFETY APPLIANCE INSPECTION USING MACHINE VISION TECHNOLOGY

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ABSTRACT

Before a train departs a yard, many aspects of the freight cars and locomotives undergo inspection, including their safety appliances. Safety appliances are handholds, ladders and other objects that serve as the interface between humans and railcars during transportation. Federal safety rules govern the design and condition of safety appliances. The current car inspection process is primarily visual making it laborious, redundant, and generally lacking of memory. There exists a potential to increase both the effectiveness and efficiency of safety appliance inspections by utilizing machine vision technology to enhance the railcar inspection process. Machine vision consists of capturing digital video and using algorithms capable of detecting and analyzing the particular objects or patterns of interest. Computer algorithms can objectively inspect railcars without tiring or becoming distracted and can also focus on certain parts of the railcar not easily seen by an inspector on the ground. Thus far, algorithms have been developed that can detect deformed ladders, handholds, and brake wheels on open-top gondolas and hoppers. Next, visual learning will be employed to teach the algorithm the differences between Federal Railroad Administration (FRA) safety appliance defects and other types of deformation not requiring a car to be bad ordered. The final product will be a wayside inspection system capable of detecting safety appliance defects on passing railcars.

INTRODUCTION

Safe and efficient movement of trains and execution of railroad employee duties are critically important to the railroad industry. Consequently, any means of providing additional productivity, efficiency, and safety benefits is of great interest to railroads. Currently, before a train departs a rail yard it is inspected for a variety of defects, including safety appliances. Safety appliances on railcars act as the interface between man and machine when it comes to the movement of railcars. They consist of handholds, sill steps, brake steps, ladders, running boards, uncoupling levers, and brake wheels as well as other car specific appliances.

Safety appliances have been required on railcars since 1893 when the Interstate Commerce Commission (ICC) passed the Safety Appliance Act [1]. The Safety Appliance Act focused mostly on the need for automatic couplers and power brakes but also called for what we now consider safety appliances by requiring secure grab irons or handholds on cars [1, 2]. The objective was to provide railroad transportation employees with a set of safe, standardized features to mount and dismount the car or couple and uncouple the car. Safety appliances are currently regulated by the Federal Government through the Railroad Safety Appliances Standards, Code of Federal Regulations (CFR) Part 231, that specify the location, number, material, configuration, and means of securement of all safety appliances [3].

Safety appliances are inspected by railroad carmen primarily using visual cues with some tactile and auditory means for certain tasks. Carmen are trained to inspect cars for many types of defects that may cause the car to be unsafe for movement. In addition to inspection, their duties include repair and re-railing of railcars. At certain points, train and engine personnel are expected to inspect cars for defective safety appliances and determine if the car is safe for movement. Cars are generally inspected each time they are added to a train, even though they may have satisfactorily passed multiple inspections prior to the current inspection. Much of the success of current process is due to the redundancy of inspections. As carmen inspect hundreds of cars during their shift, monotony and fatigue may affect the efficiency of inspections.

Inspection results are not recorded by specific vehicle therefore a specific railcar's safety appliance health cannot be tracked over time, making planned maintenance and monitoring defect trends difficult. Defect trends could be used as a means of locating industries that consistently damage railcars, or be used to suggest future design changes for railcar safety appliances. Inspections are undertaken while inbound and outbound trains are on receiving and departure tracks. Capacity in yards is increasingly at a premium, therefore improving inspection efficiency also has the potential to increase yard throughput.

One way that the effectiveness and efficiency of safety appliance inspections can be increased is through the implementation of machine vision technology. As a train passes a machine vision inspection site, digital video of the train is captured. Machine vision algorithms then identify the safety appliances on railcars and detect defects. A system of this type would lead to better utilization of labor, more effective inspections, and potentially improve utilization of yard space. The system should be able to categorize defects in terms of the appropriate level of action required. The system would also lend itself to development of a database for each car that would enable trends to be detected and allow better planning and management of railcar maintenance.

NOMENCLATURE

Federal Railroad Administration, Code of Federal Regulations, Machine Vision, Railcar Inspection, Railroad Safety Appliance Standards, Safety Appliance.

QUANTIFICATION OF SAFETY APPLIANCE DEFECTS

We used several sources of data to quantify the occurrence of safety appliance defects; data from FRA safety appliance inspections and bad order data obtained from individual railroads. Additionally, car repair data from the Association of American Railroads (AAR) were used to estimate the magnitude of costs associated with safety appliance repairs.

The FRA maintains a database of all inspections conducted by both federal and state inspectors. The data are grouped by numeric codes specified in the CFR signifying the reason for the violation, and also by type of inspector; state or local. The data for Part 231 are divided into major rules. Each major rule pertains to a specific appliance. Analysis of these data for the period 1995-2004 showed that 59% of defects occurred on ladder treads, handholds, and sill steps [4] (Fig. 1).

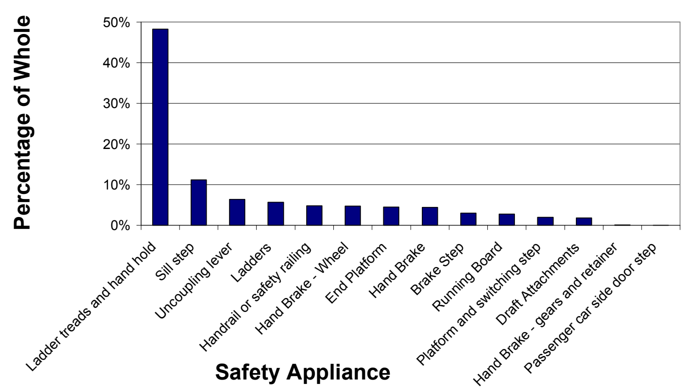

Figure 1. FRA Safety Appliance Defects found by FRA inspectors between 1995 and 2004 grouped by major rule of CFR Part 231, The Railroad Safety Appliance Standards

Between 1995 and 2003, 21% of FRA Motive Power and Equipment (MP&E) inspections focused on the Safety Appliance Standards. These inspections revealed 32% of the total defects detected by MP&E inspectors. The defect rate, or percentage of defective units (railcars) to the number of units inspected, is also given in the FRA database. The rate varies from 5.4% to 7.4% for the years 1995-2004, averaging 6.6%. This rate does not account for multiple defects on a single car. These data are critical in monitoring the rates at which safety appliance violations occur from the FRA standpoint as well as in evaluating the difference between FRA defect ratios and railroad safety appliance bad order ratios.

In order to determine the number of defects that are found by carmen, an analysis of bad order data was conducted for the fourth quarter of 2004 at two major Class I railroad yards. The percentage of cars bad ordered due to safety appliance defects was 0.6% and 1.5% at the two yards. However, these numbers underestimate the actual occurrence of defects because many cars are repaired in the yard without moving the car to the repair shop or facility, often referred to as a RIP track. One Class I railroad mechanical manager estimated that as many as 75% of the safety appliance repairs were completed in this way. In these cases there is no requirement to record the repair unless it was billable under the AAR Interchange Rules [5]. If 0.6% to 1.5% of cars are bad ordered for safety appliance defects, and only 25% of safety appliance defects are actually bad ordered to the shop, the percentage of cars with safety appliance defects could be as much as four times higher than the bad order numbers show. This would result in 2.4% to 6.0% of cars having safety appliance defects, a figure comparable to the FRA average of 6.6%. In addition, the differences between the FRA defect rates and the railroad bad order rates are a result of differing amounts of inspection scrutiny. FRA inspectors spend considerably more time inspecting a railcar than do railroad carmen. They may climb over a car, checking all the handholds and running boards, whereas railroad carmen are not expected to, nor do they have time to, inspect to this extent on a routine inspection.

Interestingly, there are considerable differences between the distributions of safety appliances defects in the two yards (Fig. 2). Yard A sees more sill steps and operating lever defects whereas Yard B sees over 35% of its defects on crossover steps alone. According to management at one Class I railroad, the percentage of safety appliance defects is affected by the amount of interchange traffic and the differing distribution of car types due to different yard and traffic make-up.

AAR repair data were analyzed to determine the monetary value of safety appliance repairs. In 2003, there were 195,242 repairs reported to AAR on ladders, handholds, brake wheels, and uncoupling levers [6]. This represents $5,177,415 in repair costs billed to railroads and private car owners, or 1.35% of all repairs made in interchange [6]. This number substantially understates the total cost of repairs made to safety appliances because the AAR car repair billing data statistics only include foreign car repair billing not repairs to system cars. Additionally, many safety appliance repairs are not billable under the AAR Interchange Rules unless the safety appliance is replaced or removed for straightening [5]. An additional cost that is more difficult to quantify is the opportunity cost while the car is out of service for repairs.

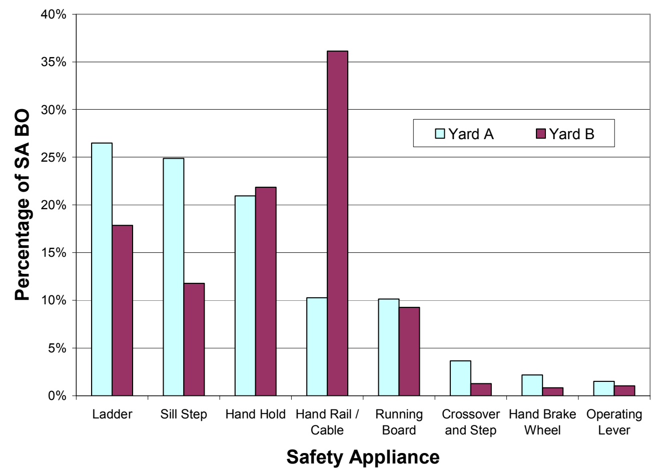

Figure 2. Comparison of Safety Appliance Defects at two Class 1 Rail Yards

CURRENT INSPECTION PROCEDURE

The current inspection process relies primarily on human vision to accomplish the task of identifying railcars with defective safety appliances. Car inspectors are tasked with identifying not only safety appliance defects, but a number of other mechanical defects as well. The most common car inspections single out the brake system on the train, and occur at FRA mandated intervals. Brake inspections occur at the train's initial terminal and at 1,000-mile intervals among other locations. The Safety Appliance Standards do not specify an inspection frequency, but railcars are expected to be inspected at each opportunity per the Safety Appliance Statute, Part 203 [7]. Carmen inspect trains by walking or riding alongside the train. There are many methods by which trains are inspected for safety appliance defects. Figure 3 depicts three Class I railroads inspection processes for three flat-switched yards.

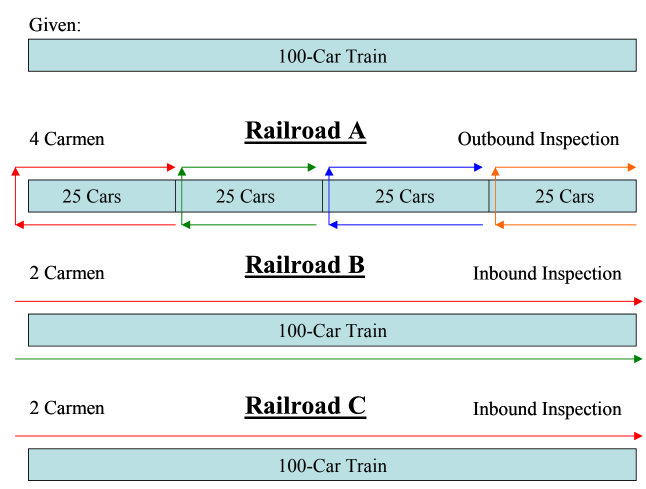

Figure 3. Three different approaches to inspection

Railroad A uses four carmen to inspect trains. Each train is broken up into four blocks, and the carman couples the air hoses on each car before crossing over and inspecting the opposite side of his or her portion of the train. Railroad B uses two carmen to inspect a train. The two carmen start at the same end of the train and walk down opposite sides of the train, allowing for communication between carmen across the train. Like Railroad B, Railroad C uses two carmen to inspect a train, but they start from opposite ends of the train. All three methods use the same number of person-hours, but result in different turnaround times. The amount of traffic dictates how many inspectors are on hand at a given yard and may also dictate whether or not the cars are inspected on the inbound or the outbound. Railroad A inspects cars upon outbound inspection, whereas Railroads B and C inspect cars at the time of inbound inspection.

Relationship Between Inspection Rate and Defect Detection

The functional relationship between the number of defects escaping inspection and inspection rate is not as simple as intuition might suggest. Audited studies of inspection effectiveness in a manufacturing environment indicate a more complex relationship [8]. Figure 4 shows the percent of defects escaping detection for a typical inspector completing 100% inspections at differing inspection speeds.

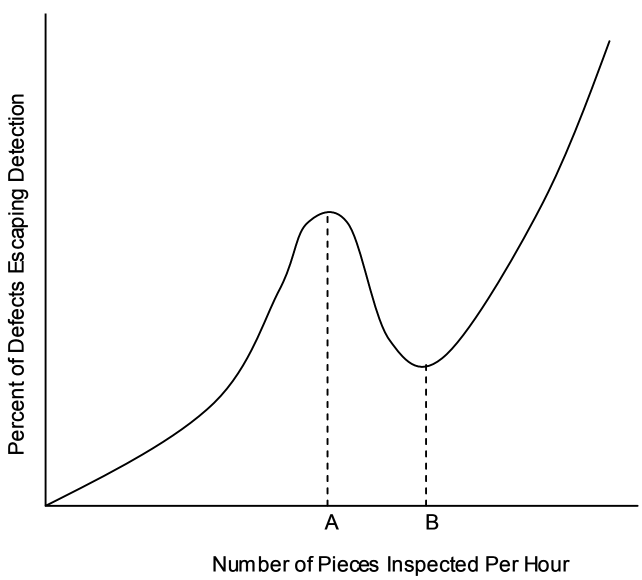

Figure 4. Functional relationship between percent of defects escaping detection and inspection rate of a human inspecting using 100 percent inspection [8]

When inspection rate is low, the number of missed defects is also low (Fig. 4) [8]. As inspection rate increases, so does the percentage of defects that are missed until a local maximum is reached at point A. As the inspection rate continues to increase after point A, the percentage of defects escaping detection actually decreases due to reduction in monotony until it reaches a minimum at point B. Beyond point B, the percentage of defects missed increases once again as fatigue and the limits of human cognitive ability begin to have a greater effect and the percent conformance decreases.

It should be noted that the functional relationship described in Fig. 4 applies to inspections of like pieces inspected under consistent conditions. This is not the case with railroad safety appliance inspections. With respect to safety appliance inspection it is also important to consider the varying levels of difficulty inspecting different safety appliances using the current visual methods. For instance, a handhold that violates the 2" clearance rule may be more easily detected than a brake wheel that violates the 4" clearance rule. Beyond this, different parameters for the same safety appliance have varying levels of difficulty in identification. Finally, different locations of a given safety appliance may have different levels of detection difficulty. For example, if a ladder at eye level is deformed it may be easily detected, but if the top ladder rung on a car is deformed, it may be very difficult for the inspector to detect.

METHODS OF IMPROVING THE EFFICIENCY AND EFFECTIVENESS OF SAFETY APPLIANCE INSPECTIONS

Machine Vision

As mentioned above, one means by which the efficiency of car inspections can be increased is through use of technology to enhance inspection effectiveness. Machine vision lends itself to a number of railcar inspection tasks [9, 10, 11], including many aspects of safety appliance inspections. Machine vision consists of capturing digital images and using algorithms to detect certain attributes in these images. In the context of this work, these images are of railcar safety appliances and the attributes are various forms of defects or deformation.

Comparison of Human Vision and Machine Vision

An understanding of the strengths and weaknesses of human and machine vision leads to a more realistic view of the possibilities of machine vision. Humans are capable of analyzing complex and dynamic situations. However, humans are not as good at performing repetitive inspections without suffering from boredom and fatigue. Additionally, for many tasks, humans are not as reliable at judging objects with the level of objectivity and consistency that is inherent in machine vision [12]. Machine vision systems have a higher first cost associated with the initial implementation of the system than does a human counterpart, but may have a lower operating cost, depending on the number of units to be inspected. Machine vision does not easily adapt to unforeseen events, but for certain types of consistent, repetitive tasks – precisely the ones humans become ineffective at – machine vision may offer more reliable, lower cost inspection.

Inspection Memory

Inspections can occur either with or without some type of memory. Currently, the majority of car inspections are completed manually and the results are not recorded. The addition of memory to the current system is possible through the use of a Personal Data Assistant (PDA). Carmen would enter defect information into their PDA's, which would be downloaded and used later as a means of tracking defects or planning maintenance.

Utilizing technologies without memory is useful in the short term, aiding mechanical personnel in the detection of defects, but it does not provide a means of tracking a railcar's health through time. This would have the advantage of making the system less memory intensive from a data storage perspective. However, addition of memory to the inspection process could enhance the effectiveness and value of the machine vision system by improving maintenance scheduling and efficiency. While all FRA safety appliance defects must be repaired before a train can depart a yard, there are other forms of deformation that could be repaired as time allows. For instance, if a ladder is deformed, but not a FRA defect, it would likely be repaired in its next visit to a repair facility. Memory in the inspection of railcars could lead to better scheduling of upcoming maintenance on a railcar, and ensure the needed parts are in stock or on the way before the car arrives at the facility. Examples of system memory could range from storing digital images for image correlation purposes, or matching safety appliance data with car numbers and storing this information in a database.

MACHINE VISION DETECTION OF SAFETY APPLIANCE DEFECTS

The University of Illinois at Urbana-Champaign is developing machine vision technology to detect defective safety appliances. In the next section we describe a new image acquisition system, algorithms, and preliminary portable field setup.

Image Acquisition System

This project is being conducted using a digital video camera with a ½" color Charge-Coupled Device (CCD) camera. Initially, a 6-12 mm lens with a variable focal length was used. While this lens provided adequate images where the track was well ballasted and elevated above ground level, the setup proved difficult at locations where the rails were not significantly higher than ground level. Additionally, use of a variable focal length lens can make replication of a given focal length difficult. Use of a fixed focal length lens and proper setup protocols provided better repeatability.

In the initial, portable setup, the camera is mounted upside down below the tripod head, close to the substrate supporting the tripod, and remains outside the clearance plate for rail equipment [13]. The clearance plate represents the maximum cross section that railcars and their loads must fit within while moving within North American interchange. These dimensions also provide a guide as to the barrier that no trackside objects should penetrate. The resolution of the most distant safety appliance, generally the top ladder rung, is the limiting factor in resolution selection. Resolution refers the number of pixels in an inch, with a higher resolution resulting in greater detail available for algorithmic recognition. Use of a resolution of 480x640 enabled the top ladder rung to be distinguished without being considered noise. The noise threshold for this recognition task is two pixels.

Frames are generated at a rate of 30 frames per second and are converted to an AVI format. This frame rate ensures that an image will be captured within the tolerable window of 40 pixels relative to the center of the image (Fig. 5).

A B C

Figure 5. Image sequence for one corner of a railcar showing, A) an image taken too early, B) at the optimum time, and C) too late

This frame rate is satisfactory for train speeds up to 25 miles per hour. At higher speeds the frame rate must be increased to ensure that images of the appropriate part of the car at the proper angle are obtained.

Machine Vision Algorithm

The goal of the machine vision algorithm is to detect ladder rungs, handholds and brake-wheels, and to classify the detected appliances as FRA defects, non-FRA deformation, or no deformation. From the input video it is first necessary to select an optimal frame that provides the best view of a car passing by the camera. Note that in a video sequence the position of the moving car is displaced in each consecutive frame by a small but not necessarily constant amount. In the optimal frame (Fig. 5B), the car position is such that the car's two top edges meet at the center of the image.

In the next module of the machine vision system, the selected frame is analyzed. Due to a foreshortening effect caused by the camera position and angle from which the railcar is viewed, parts of the car that are farthest away from the camera appear smaller and distorted. Therefore, we conduct a perspective correction that yields two views of the car that each appear as if they were taken by two cameras perpendicular to the car's side and ends (Fig. 6). This procedure not only saves the costs of mounting two cameras, but more importantly provides the perpendicular view of the end of the car that an additional camera, irrespective of position, would be unable to obtain. The perspective correction is done by using homography, where all the points belonging to a specified plane are transformed so that the foreshortening effect is corrected. The specification of the two planes in the image is done automatically by finding the intersection of the top edge of the car with the image boundaries. Once the planes are specified, homography projects them onto the image plane.

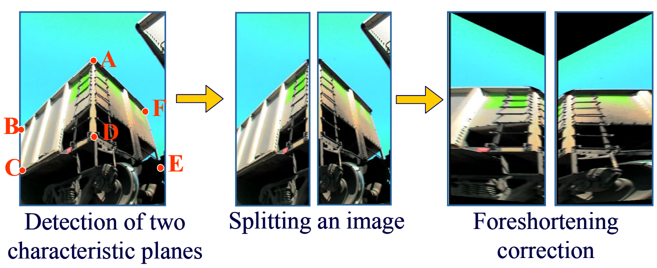

Figure 6. Perspective correction by specifying two planes A-B-C-F and A-E-D-F. As the final result, two views of the car are obtained, as if two cameras perpendicular to the side and end of the car were available

Such corrected images are more amenable to detection and assessment of safety appliance condition. In the next module, each corrected part of the selected frame is analyzed to detect safety appliances. To detect ladder rungs, edges are detected using a Canny detector (Fig. 7A). Then starting from the top edge of the car, the algorithm searches for periodically spaced, horizontal, parallel lines to define the area where the ladder and handholds are most likely to be. The straight-line edges in the specified area are classified as compliant (no exception) ladder rungs and handholds; the edges that are curves are classified as deformed appliances. Note that the algorithm correctly identified the deformation to the top and second from bottom side ladder rungs as well as deformation to the end ladder rung that is second from the top (Fig. 7A). These examples of safety appliance deformation, like those seen in Fig. 7A, were imaged after being inflicted on cars at the Transportation Technology Center Facility for Accelerated Service Testing (FAST) near Pueblo, CO. Two more examples of detected ladder rungs and handholds are presented in Fig. 7B.

In the future, additional appliances, appliance parameters, and car types will be examined, as well as difficult lighting conditions. One particularly challenging parameter to identify using machine vision is the securement of safety appliances. Checking for securement includes checking that bolts are present and securely fastened. Even though a bolt is lose, it may still be secure, and the machine vision algorithms must be robust enough to differentiate between the two scenarios. This recognition task may require additional camera views.

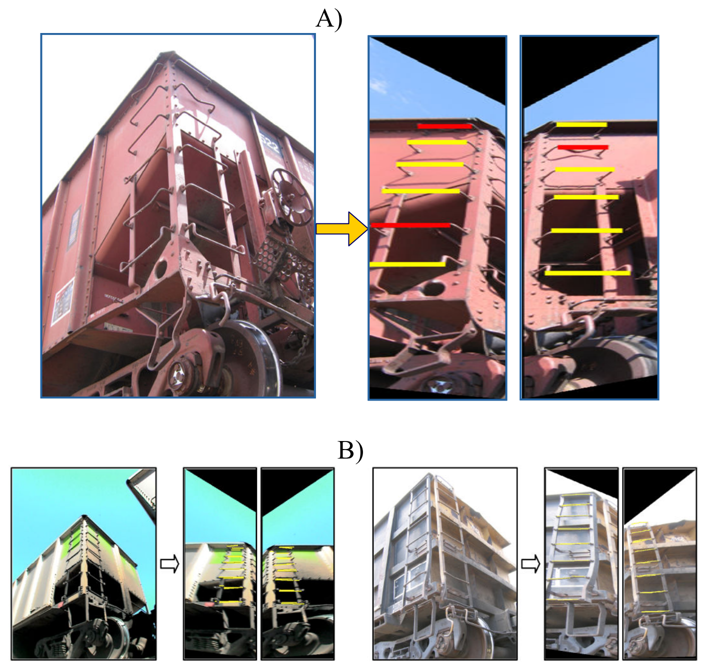

Figure 7. (A) Detection of ladder rungs and handholds; yellow indicates no exception and red indicates deformed appliances. (B) Additional examples of detected ladder rungs and handholds

Detection and assessment of a brake-wheel does not require the perspective correction. Due to the fact that the brake-wheel differs from the background in appearance, direct analysis of the original image is satisfactory. We perform template matching of an ideal brake-wheel model from a set of templates developed based on known brake wheel designs. The area in the image for which the correlation with the template yields the highest value represents the detected brake-wheel. If part of the detected area differs from the template it is classified as deformed (Fig. 8).

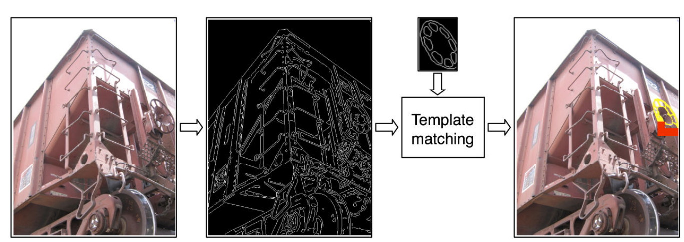

Figure 8. Brake-wheel detection; yellow indicates no exception and red indicates deformation of the brake-wheel

METHODS OF OBTAINING IMAGES OF DEFORMED RAILCAR SAFETY APPLIANCES

Because of the relatively low rate of SA defects noted above, acquisition of a sufficient number of images showing deformed safety appliances needed to develop the algorithm would take a long time. To accelerate this process other collection methods are being pursued. One of these was damaging an open-top hopper car under controlled conditions at TTC and imaging it as a part of a test train. Another method is through the use of a virtual model that allows for modeling of safety appliance deformation 1) under varying lighting conditions, 2) on multiple car types, and 3) from differing camera views and angles.

THREE DIMENSIONAL MODELING OF RAILCAR SAFETY APPLIANCES

Autodesk's® 3DS MAX 8 computer modeling software was used to create a three dimensional model of an open-top hopper car. 3DS MAX allows the user flexibility in depicting different camera views and angles, as well as in depicting realistic lighting conditions. Additionally, the program provides a means of generating both still images and AVI files of the railcar model. A comparison of an actual camera and an image from the 3D model is shown in Figure 9.

Lighting and Camera Specifics

Within 3DS MAX, cameras can be located at any user defined location within the model space. The resolution of the camera is set by the user and the field of view is set by changing the camera's distance from the railcar. The model allowed us to pinpoint the precise optimal camera angle once the view was selected. The camera view refers to the portion of the railcar that is being imaged whereas the camera angle is the specific angle between the lens and the target. The process of determining the camera angle was accomplished by running the algorithm on numerous images taken from angles that were below the top-of-rail. All of the images tested were at a 45-degree angle with respect to the track. Locating the camera below the top of rail allows for imaging of ladder rung and handhold clearance – key elements of the Railroad Safety Appliance Standards.

Model Uses

Visual learning is being used to categorize deformation to a railcar's safety appliances. Using this approach, it is necessary to gather hundreds of images representing defective safety appliances to teach the algorithm the difference among the various defect classes. Gathering these images in the field is tedious and labor intensive. Each time a train is imaged in the field we obtain a large number of images of which only a small percentage, one percent or less, contain safety appliance defects. Using the model, it is not only possible to simulate the railroad environment lighting, but also generate hundreds of types of deformation that would be difficult to gather by imaging real trains. Information regarding typical types of safety appliance deformation will be gathered from railroad mechanical personnel ensuring the algorithms will be tailored to the recognition tasks that it will be facing.

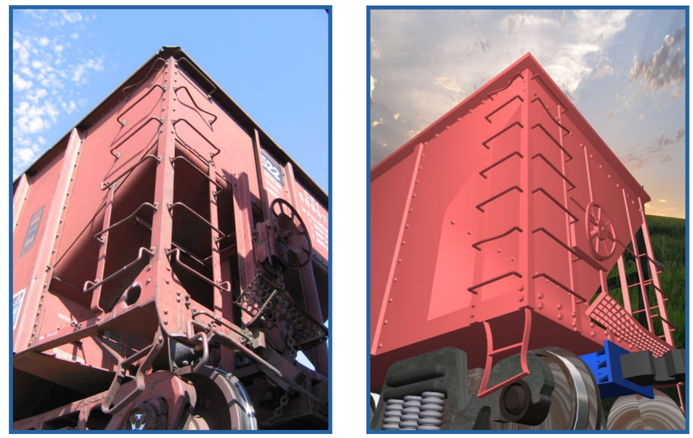

Figure 9. Views of a railcar after deformation was inflicted in a controlled environment (left) and the corresponding 3D model showing the deformation (right)

The use of a virtual model increases the robustness of the machine vision algorithm by allowing generation of images under varying lighting conditions. Out of the many lighting types provided within 3DS, two types are of interest to this project. The first is omni light, and consists of light having an intensity that is inversely proportional to the distance between the light and target. Omni light is the best representation of what an artificial spotlight would provide for this application. Secondly, sky light is analogous to sunlight in that the intensity does not decrease as the distance from the light source to the target increases.

Additionally, if the model is verified on one car type it may be extrapolated to be used on other car types, saving time and expense compared to field work.

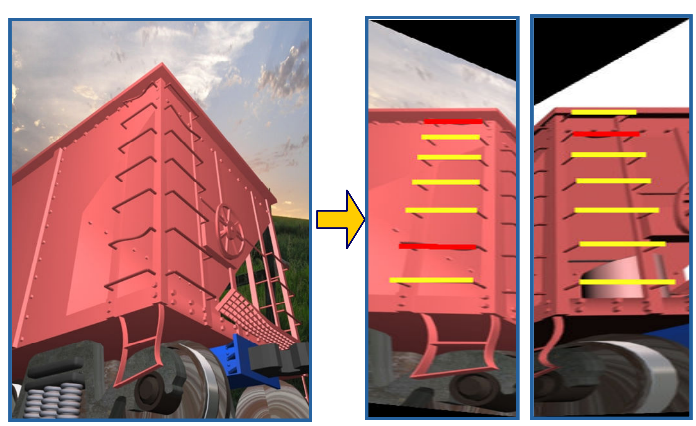

Figure 10. Validation of algorithms on the model image which replicates the deformation seen in the actual image in Figure 7A.

Figure 10 shows the algorithmic result from the model car. The second ladder rung from the bottom is not an FRA defect, but does have deformation. The sensitivity of the algorithm can be adjusted to either recognize or filter out these types of minor deformation.

Model Limitations

The limitations of the computer model should be recognized and considered as safety appliance recognition algorithms are developed. All edges of the railcar will appear crisper than the actual edges on the car. This gives the Canny detectors an easier task than the one that occurs in reality due to rust, minor irregularities and other aspects inherent in the railroad environment. Altering the surface of the railcar in the model reduces the effects of this limitation.

DISCUSSION & CONCLUSIONS

Since the installation of safety appliances was first required on railcars in 1893, inspections have been carried out visually. However, technologies have been developed that would allow for increased inspection effectiveness. A machine-vision-enhanced inspection process could improve performance and speed while reducing cost.

The capital cost of a machine vision system will be higher than incremental addition to the labor force; however, the cost per unit inspected may be lower, depending on the number of cars to be inspected at a particular location. Additionally, the system would enable reallocation of labor to tasks for which they are uniquely qualified, such as railcar repair. To take further advantage of the system, some type of system memory should be incorporated because it would enable better planning of railcar maintenance.

There are many examples of wayside rail vehicle health monitoring systems that have been installed or are in the research and development stages. An example of one wayside rail vehicle health monitoring system that includes a memory capability are Wheel Impact Load Detectors (WILD). These detect vertical loads at wayside installations and report the information back to a central system that monitors the vehicles' performance [11, 14]. This monitoring system was developed by the Transportation Technology Center Inc. (TTCI) and is known as Integrated Railway Remote Information Service (InteRRIS) and stores health information on a multitude of railcar parameters. InteRRIS provides rail vehicle condition and performance monitoring that is transferable to car owners and railroads via the internet (16). Another wayside vehicle monitoring system which is linked with InteRRIS are Truck Performance Detectors (TPDs) that detect poorly performing trucks by monitoring lateral loads. TTCI is also deploying a new visual inspection system known as FactIS to inspect railcar truck components including wheels, brake shoes, and other mechanical components. The FactIS system relies primarily on machine vision as a means of determining the health of a railcar. A system for safety appliance inspection would link Automatic Equipment Identification (AEI) data that is digitally encoded on tags located on all North American railcars to the information from the machine vision system in a similar manner, and provide input to the InteRRIS database as well as to railroad personnel at nearby repair facilities.

An additional benefit of a machine-vision-enhanced inspection system is that it has the potential to alleviate congestion in rail yards. Because much of the inspection process will occur along the line of road or at the entrance to a yard, railcars may not need to occupy yard trackage for as long while they await and undergo inspection. Instead, based on the outcome of the machine-vision results certain cars requiring a closer look or minor repair could be promptly inspected and repaired, while the remainder could be switched directly to either their appropriate outbound track, or to a major repair track. In conclusion, the prototype systems described here have the potential to improve rail transportation safety and efficiency in several ways, including improving the efficacy and efficiency of the inspection process as well as improving railyard productivity.

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