Development of Machine Vision Technology for Railcar Safety Appliance Inspection

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Summary: Before North American trains depart a terminal or rail yard, many aspects of the 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. The current inspection process is primarily visual and is labor intensive, redundant, and generally lacks "memory" of the inspection results. The effectiveness and efficiency of safety appliance inspections can be improved by use of machine vision technology. This paper describes a research project investigating the use of machine vision technology to perform railcar safety appliance inspections. Thus far, algorithms have been developed that can detect deformed ladders, handholds, and brake wheels on open-top gondolas and hoppers. Visual learning is being used to teach the algorithm the differences between safety appliance defects that require immediate repair, and other types of deformation that do not. Field experiments under natural and artificial lighting have been conducted to determine the optimal illumination needed for proper functioning of the algorithms. Future work will consist of developing algorithms that can identify deformed safety appliances across the spectrum of North American railcars under varied environmental conditions. The final product will be a wayside inspection system capable of inspecting safety appliance defects on passing railcars.

Index Terms: Machine Vision, Railcar Mechanical Inspection, Railroad Safety Appliances, Freight Wagons, Automated

1. INTRODUCTION

North American railroad rolling stock is required to be equipped with various types of equipment known as "safety appliances." These serve as the human/ machine interface for operation of railcars and 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 U.S. railcars since 1893 when the Interstate Commerce Commission (ICC) passed the Safety Appliance Act. This 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. The objective was to provide railroad transportation employees with a set of safe, standardized features to mount and dismount, or couple and uncouple, the car. Safety appliances are currently regulated under U.S. Federal Railroad Administration (FRA) regulations that specify their location, number, material, configuration, and means of securement [1].

Under the regulations, safety appliances must be kept in proper working order and in compliance with a set of standards regarding their location and geometry. Safety appliances undergo condition inspection by railroad personnel in rail yards and at other FRA-required locations. The process is labor intensive and a single inspector may see hundreds of cars during a shift, therefore monotony and fatigue may affect the efficiency of inspections [2, 3]. Inspection results for specific vehicles are not recorded unless they need repair and even in this case, if the repair can be made without moving the car to a repair track, neither the damage nor repair are typically recorded [4].

Use of machine vision lends itself to a number of railcar inspection tasks [5, 6, 7], and can improve the effectiveness and efficiency of safety appliance inspections as well. As a train passes a machine vision inspection site, digital video of the train is recorded. Machine vision algorithms then identify the safety appliances on railcars and detect defects. If implemented, such a system would lead to more efficient use of labor, more effective inspections, and potentially improve rail yard capacity. The system should be able to categorize defects in terms of the appropriate level of action required. It would also facilitate development of a database for each car that enabled trends to be detected and allow better planning and management of railcar maintenance.

2. METHODOLOGY

2.1 Quantification of Safety Appliance Defects

Data for the period 1995-2004 showed that 59% of defects occurred on ladder treads, handholds, and sill steps [8] and the annual cost of safety appliance repairs is over $5,000,000 [9]. However, this figure substantially understates the total cost of safety appliance repairs because it does not include all repair types and only includes inspections of cars not owned by the inspecting railroad. Additional costs more difficult to quantify are the opportunity cost of a car out of service for repairs and the loss of capacity in rail yards due to the use of space by cars awaiting inspection.

2.2 Methods of Improving the Efficiency and Effectiveness of Safety Appliance Inspections

Comparison of Human Vision and Machine Vision

Humans are capable of analyzing complex and dynamic situations. However, they are not as good at performing repetitive inspections. Additionally, for many tasks, humans are often not as objective and consistent as machine vision [10]. Compared to humans, machine vision systems have a higher first cost associated with the initial implementation, but can have a lower unit 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. Currently, the majority of car inspections are completed manually using human vision and the results are not recorded. Addition of memory to the inspection process could enhance the effectiveness and value of the machine vision system by improving maintenance scheduling and efficiency.

2.3 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 this section we describe a new image acquisition system, algorithms, and a portable field setup used to record images and test the algorithms.

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 sufficiently above ground level, it was difficult to adapt to situations where it was not. Additionally, use of a variable focal length lens made precise replication of a given focal length difficult. Subsequent use of a fixed focal length lens and proper setup protocols provided better repeatability.

The camera and lens need to provide high enough resolution to accomplish all the recognition and evaluation tasks required to satisfy inspection requirements. The camera is located below rail level angled upward and at a 45-degree angle to the track. This view allows most of the safety appliances to be seen and their condition assessed with regard to FRA regulations. In the portable setup, the camera is mounted upside down below the tripod head, close to the substrate supporting the tripod [2], and remains outside the clearance plate for rail equipment [11]. The resolution of the most distant safety appliance is generally the top ladder rung and this was the deciding factor in resolution selection. The noise threshold for this recognition task is two pixels and use of a resolution of 480x640 met this performance requirement.

Frames are generated at a rate of 30 frames per second and are converted to an AVI format. This frame rate ensures that at least one image will be captured within the tolerance window of ±20 pixels relative to the center of the image (Fig. 1).

A B C

Figure 1. Image sequence for one corner of a railcar showing, A) an image taken too early, B) at the optimal 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. 1), 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. 2). 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 accomplished 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.

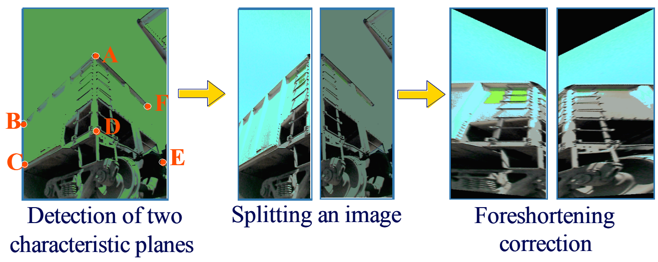

Figure 2. Perspective correction by specifying two planes A-B-C-F and A-E-D-F. As the final result, two views of the car are obtained, as if two cameras perpendicular to the side and end of the car were available

The 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. 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 (Fig. 3).

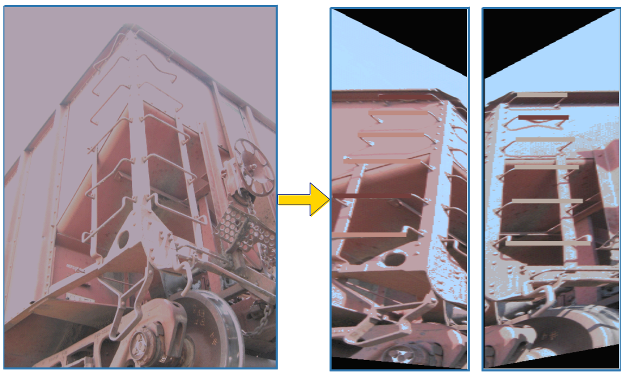

Figure 3. Detection of ladder rungs and handholds; yellow indicates no exception and red indicates deformed appliances

The algorithm correctly identified the deformation to the top and second from bottom side-ladder rungs, as well as deformation to the ladder rung that is second from the top on the end of the car. These examples of safety appliance deformation, like those seen in Fig. 3, were imaged after being inflicted on cars at the Transportation Technology Center (TTC) Facility for Accelerated Service Testing near Pueblo, CO.

In the future, additional parameters, appliances, and car types will be examined, as well as difficult lighting conditions. A particularly challenging parameter to identify using machine vision is the proper securement of safety appliances. This includes checking that bolts are present and securely fastened. Even though a bolt is lose, the appliance may 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.

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. 4).

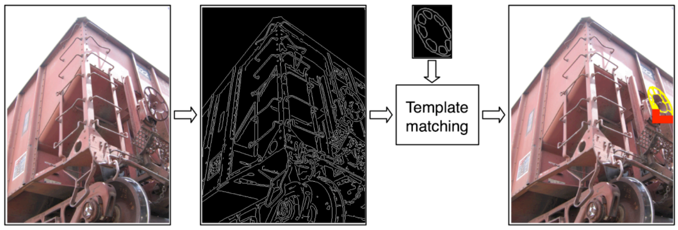

Figure 4. Brake-wheel detection; yellow indicates no exception and red indicates deformation of the brake-wheel

2.4 Methods of Obtaining Images of Deformed Railcar Safety Appliances

Because of the relatively low rate of safety appliance defects and deformation, acquisition of a sufficient number of images needed to develop the algorithm would take a long time. To accelerate this process we are using other methods. In addition to creating deformations on a test car at TTC, we have developed a virtual model of a railcar. This model provides several useful capabilities for the overall machine vision development project. Besides allowing us to "create" safety appliance deformation it also allows testing under varying lighting conditions, on multiple car types, and from differing camera views and angles.

2.5 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 5.

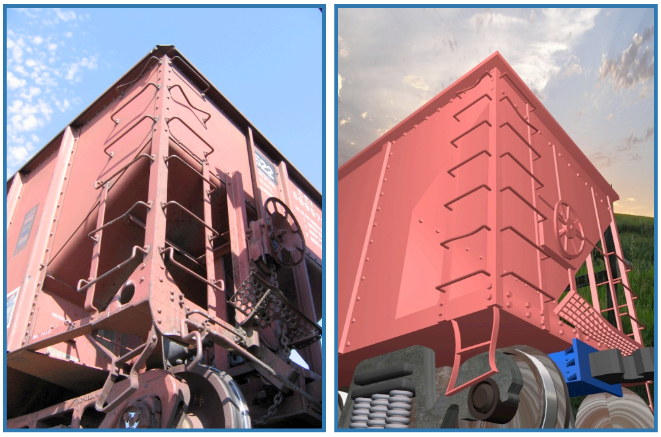

Figure 5. Views of a railcar with deformed safety appliances (left) and the corresponding 3D model showing the deformation (right)

Lighting and Camera Specifics

Within 3DS MAX, cameras can be located at any user-defined location within the model space. Resolution of the scene, the camera's field of view, and other camera parameters can be defined within the program. The model allowed us to refine our understanding of the preferred 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 allowed imaging of ladder rung and handhold clearances – 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 recorded in the field we obtain a large number of images of which only a small percentage, one percent or less, contain safety appliance deformations. Using the model, it is not only possible to simulate the railroad environment lighting, but also to generate all possible types of deformation. These would be difficult to gather by imaging real trains. Information regarding typical types of safety appliance deformation is being gathered from railroad mechanical personnel ensuring that the algorithms will be tailored to the recognition tasks that it will be facing.

The use of a virtual model increases the robustness of the machine vision algorithm by allowing generation of images under varying lighting conditions. 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, skylight is analogous to sunlight in that the intensity does not decrease as the distance from the light source to the target increases. We have also used the Illuminating Engineering Society sunlight system that allows us to simulate the correct sun altitude and azimuth for any day and location we specify. If the model is verified on one car type it can be extrapolated to other car types, saving time and expense compared to fieldwork.

Figure 6 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.

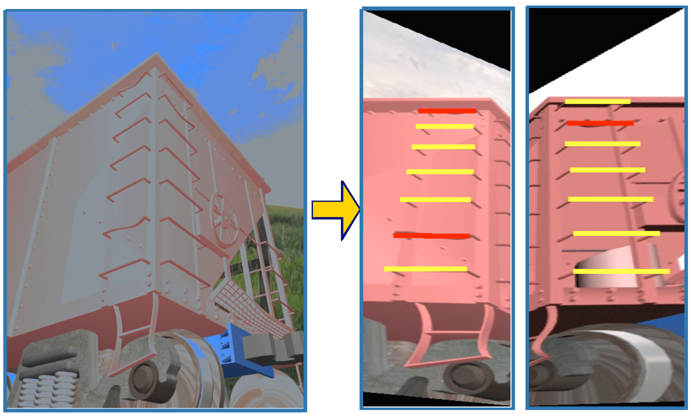

Figure 6. Validation of algorithm performance on the model image that replicates the deformation in the actual image in Figure 5.

An algorithm was developed that dynamically modifies the car model to represent typical safety appliance defect types. The algorithm is fed the two extremes of a given type of safety appliance deformation and incrementally generates images of deformation that fall between the two extremes (Fig. 7). This is being used to generate a large number of systematically varied images that are being used to train the learning algorithms.

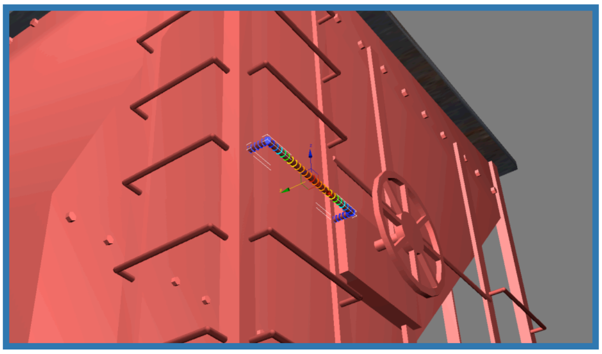

Figure 7. Virtual car model image indicating how deformation will be used to systematically create a library of deformations of a ladder rung

2.6 Field Testing of Under Artificial Lighting

Detection of safety appliances under artificial lighting in nighttime requires additional consideration of light intensity and direction. These parameters are less of a concern for video recorded in daylight, because light intensity is usually sufficient to properly adjust the aperture opening, and reflected light from the surroundings provides diffused light thereby reducing most of the negative effects of sun position. The exception to this is the strong shadowing from direct sunlight at certain angles.

By contrast, artificial light has much lower intensity and is more directional because there are no auxiliary reflections and therefore may introduce undesirable shadowing effects. For example, each ladder rung lit by an artificial light will cast a shadow. This may confuse the detection algorithm causing it to identify the shadows as rungs, since they may appear similar in the video frames. We needed to find the light intensity and direction that will allow similar performance of the safety appliance detection algorithms under both artificial and sun-lit conditions. This will be affected by various aspects of the artificial lighting configuration including: the number of light sources used, their height, and the angle of incident light on the car.

We conducted a series of nighttime tests in which we systematically varied the artificial light configuration, took detailed measurements of the light intensity at each safety appliance location on the car side and end, and tested the machine vision algorithm to verify that it was able to properly recognize and interpret the pertinent features in the images. Two portable lighting systems were used that allowed flexibility in the light configuration. Each system had four independently controlled 1,000-watt lights. They could be raised and lowered and had a pan and tilt bracket for angle control. Three pairs of lights were positioned above one another in horizontal groups of two. The light sets were placed parallel to the track with one light of each set directed straight toward the car side, and the other angled approximately 20 degrees from normal to the track, facing toward the car end. The uniformity of the illumination was adjusted by moving each light individually with the pan and tilt brackets while measuring different locations on the railcar using a light meter.

The combined effect was relatively consistent illumination of the car side and end from top to bottom. The variation across the surfaces of interest ranged from approximately 1,500 to 2,000 foot-candles. This degree of homogeneity in light intensity eliminated hotspots while providing sufficient illumination of all the safety appliances.

The camera system was set up and videos recorded under various lighting configurations. The shutter speed was fixed at 500 (calculated to accommodate a moving train without blurring) and the opening of the aperture maximized. The lighting was adjusted until the edge images showed the proper detection of all of the safety appliances of interest (Fig 8).

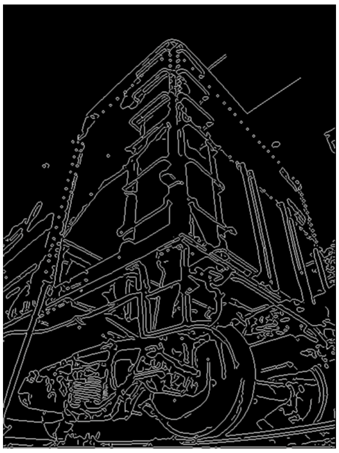

Figure 8. Images showing the edges detected on the corner of a freight car illuminated at night.

Figs. 9 shows the artificially illuminated railcar and the algorithm results. The tests were repeated with railcars of differing color. The final configuration had the fewest shadows and gave satisfactory image recording and detection results. The results of the nighttime illumination tests will be used as the basis for design of a semi-permanent machine-vision installation currently being planned.

A B

Figure 9. A) Nighttime image of BL corner of railcar illuminated by six 1,000-Watt lights B) foreshortened view with algorithm identification of ladder rungs

3. CONCLUSION

Machine-vision-enhanced inspection systems have the potential to substantially improve both performance and speed of inspections while also reducing cost. Although the capital cost of a machine vision system will be higher than the incremental addition to the labor force; the cost per unit will often be lower, depending on the number of cars to be inspected at a particular location.

Implementation of these types of systems will enable reallocation of personnel to tasks for which their capabilities are better suited, such as railcar repair. System memory could also be incorporated to enable better railcar maintenance planning. The combined effect will be more effective detection of defects and more efficient repair resulting in a railcar fleet with fewer defects.

A machine vision safety appliance inspection technology could be integrated into the Integrated Railway Remote Information Service (InteRRIS) developed by the Transportation Technology Center Inc. This system 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 [12, 13]. Another wayside machine vision inspection system is already being linked to InteRRIS. Known as FactIS, it inspects railcar mechanical components including wheels, brake shoes, and other components. A system for safety appliance inspection would link Automatic Equipment Identification (AEI) data that are 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. This will provide advance notice of cars in need of repair as they approach a terminal thereby allowing them to be more rapidly and effectively repaired.

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