Development of a Machine Vision System for the Inspection of Heavy-Haul Railway Turnout and Track Components

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Abstract

North American railroads and the United States Department of Transportation (US DOT) Federal Railroad Administration (FRA) require periodic inspection of railway infrastructure to ensure safe railway operation. The primary focus of this research is the inspection of North American Class I railroad mainline and sidings, as these generally experience the highest traffic densities. Tracks that are subjected to heavy-haul traffic necessitate frequent inspection and have more intensive maintenance requirements, leaving railroads with less time to accomplish these inspections. To improve the current (primarily manual) inspection process in an efficient and cost effective manner, machine vision technology can be developed and used as a robust alternative. The machine vision system consists of a video acquisition system for recording digital images, a mobile rail platform for allowing video capture in the field, and custom designed algorithms to identify defects and symptomatic conditions from these images. Results of previously developed inspection algorithms have shown good reliability in identifying cut spikes and rail anchors from field-acquired videos. The focus of this paper is the development of machine vision algorithms designed to recognize turnout components and inspect them for defects. In order to prioritize which turnout components are the most critical for the safe operation of trains, a risk-based analysis of the FRA accident database has been performed. From these prioritized turnout components, those that are best suited for vision-based inspection are being further investigated. Future analysis of the machine vision system results, in conjunction with a comparison of historical data, will enhance the ability for longer-term proactive assessment of the health of the track system and its components.

INTRODUCTION

Railroads conduct regular inspections of their track in order to maintain safe and efficient operation. Tracks that are subjected to heavy-haul traffic necessitate frequent inspection and more stringent maintenance requirements, leaving these railroads with less time to accomplish these inspections. This makes them the most likely locations for cost-effective investment in new, more efficient, but potentially more capital-intensive inspection technology. Machine vision systems are currently in use or under development for a variety of railroad inspection tasks, both wayside and mobile, including inspection of joint bars, surface defects in the rail, rail profile, ballast profile, track gauge, etc [1]. The University of Illinois at Urbana-Champaign (UIUC) has been involved in multiple railroad machine-vision research projects sponsored by the Association of American Railroads (AAR) Strategic Research Initiative and Technology Driven Train Inspection, BNSF Railway, NEXTRANS Region V Transportation Center, and the Transportation Research Board (TRB) High-Speed Rail IDEA Program [2-7]. These machine vision systems have been developed through interdisciplinary research collaboration between the Computer Vision and Robotics Laboratory (CVRL) at the Beckman Institute for Advanced Science and Technology and the Rail Technology Engineering Center (RailTEC) in the Department of Civil and Environmental Engineering. The objective of the research presented here is to investigate the feasibility of developing a machine vision system to inspect track fastening and turnout components in a more efficient, effective, and objective manner.

RISK-BASED PRIORITIZATION OF TURNOUT COMPONENTS

In order to determine which infrastructure components are most critical to the safe operation of trains, an analysis of the FRA Accident Database was conducted [8]. Previous research provided the following initial priorities for machine vision inspection of railway infrastructure: Raised, missing, or inappropriate patterns of cut spikes, displaced, missing, or inappropriate patterns of rail anchors and turnout component inspection. Although the initial approach is valid, other variables can provide additional information on the risk associated with specific derailment causes and track component failures [9]. Therefore, a risk-based prioritization approach was used to select the turnout components that are most critical to the safe operation.

Using data from the FRA Accident Database, a detailed evaluation of derailment data for track classes 4 and 5 was performed to quantify the risk of derailments at turnouts. For the period of 1998 through 2009, the number of derailments (derailment frequency) was plotted against the number of cars derailed (consequence) for each derailment cause [1]. The end result of the analysis was the selection of the following rank-ordered turnout components/defects for inspection using machine vision:

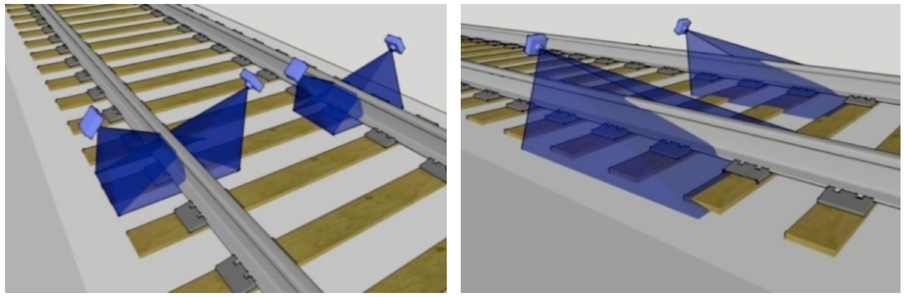
1. Switch point - worn or broken
2. Other frog, switch, and track appliance defects
3. Turnout frog - worn or broken
4. Switch connecting or operating rod - broken or defective
5. Switch point - gap between switch point and stock rail

With this new prioritization of inspection tasks, the following section describes the procedures used for determining and/or reevaluating the methods for obtaining images of these components.

IMAGE ACQUISITION SYSTEM DEVELOPMENT ON A MOBILE TEST PLATFORM

The collection of images and video of track components under inspection is a critical part in the development of a machine vision system and gives rise to several requirements. The image acquisition system consists of cameras that must be properly oriented to provide views of the components of interest. The system must also be capable of obtaining images under various environmental conditions in order for the machine vision algorithms to reliably detect the track components. Finally, it must be able to traverse the track while recording videos of the components under actual field conditions. These requirements have been addressed and are briefly described in this section, which is concluded with current experiments involving lighting to improve image capture.

The cameras selected must be oriented to provide views that permit the machine vision algorithms to consistently and reliably detect the track components of interest under various conditions. These views of the components must not only show the entire component in its functional position, but also be conducive to distinguishing the component from background objects and be oriented properly for obtaining necessary measurements of these components. Obtaining images with defective components under real-world circumstances has proven to be challenging. Prior to the development of an image acquisition system, a Virtual Track Model (VTM) was created [11] using North American recommended practices for track design [10]. This model of tangent and curved track provided a virtual environment that could be modified to suit particular experiments. Initial experimentation with virtual cameras in the VTM resulted in the selection of two camera views for inspection: the lateral view and the over-the-rail view [11]. The lateral view provides a suitable view of tie plates, spikes and anchors, Figure 1(a). The over-the-rail view provides perpendicular views of the spike and anchors, Figure 1(b). In addition, these virtual views were used to generate synthetic images for initial development of machine vision algorithms. These experiments with the VTM also provided insight into challenges such as non-uniform lighting, variation in component design, and defect recognition [11].



(a) (b)

Figure 1: Camera Views: (a) Lateral View, (b) Over-the-rail View

Beyond the virtual images, a method to capture video that would be representative of future cameras attached to a track inspection vehicle was needed for further the development of the machine-vision inspection algorithms. A system consisting of a digital camera, a laptop, and image acquisition software was developed so the system would be portable allowing it to be taken out in the field to capture actual track conditions. However, securing time and equipment to test the image acquisition system on active track throughout the developmental phases proved difficult. Therefore, a mobile data acquisition system called the Video Track Cart (VTC) was designed for automated collection of continuous video of entire sections of track [12]. The VTC has been extensively used on low-density track such as the Railway Museum in Monticello, IL as well as Class I track in Champaign, IL. During these field visits, video was captured of tangent track as well as turnouts of varying designs and conditions. In addition, we captured video under a variety of natural lighting conditions, levels of vegetation, and ballast types in order to develop detection statistics on consistent component recognition under realistic field conditions.

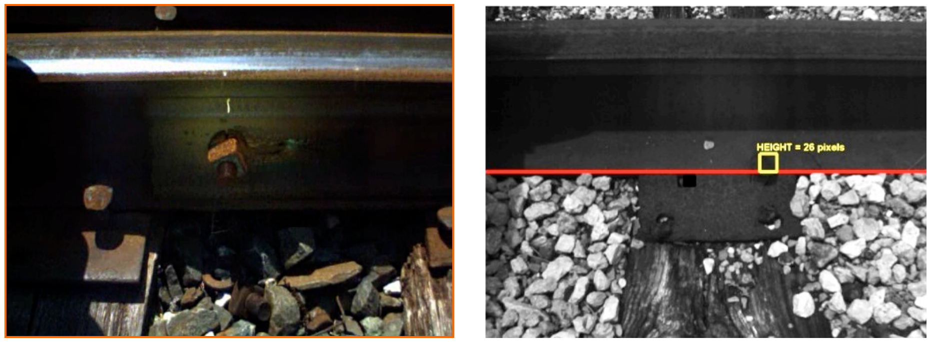
Lighting Experimentation for Proper Exposure of Components

During the capture of track videos, under various environmental conditions, several difficulties with properly exposing different parts of the camera view were encountered. For example, the lack of contrast between the steel spikes against the steel rail provides challenges for the automatic identification of these components. As a solution, the exposure level of the images was increased to provide better contrast between the two, which was successful. However, this compensation resulted in overexposed ballast when it was made up of light colored aggregate, causing difficulty in tie plate identification [12]. This indicated that, even in daylight situations, additional lighting may be required to properly expose all of the desired components in a single image.

Currently, we are investigating low-wattage LED lighting, which can be powered by our VTC on-board battery system. The lighting is intended to illuminate the web of the rail without overexposing the ballast section at the bottom of the image, Figure 2(a).

Test runs with the VTC were conducted on Class 1 track using the lighting system during video acquisition. A similar method for the algorithm evaluation testing, described in the following section, was used to evaluate the impact of the lighting approach. The proper identification and measurement of raised spikes showed the successful use of the initial lighting setup, Figure 2(b). The addition of lighting to the image acquisition system should further improve the consistency and reliability in detecting components of interest against a background of similar color and texture (e.g. steel).

Additional lighting considerations have been studied in the approach to lighting for the VTC, including a review of the lighting methods currently being used on other systems under development [1]. However, these methods are highly correlated to the type of camera or the specific application and no common solution has emerged.



(a) (b)

Figure 2: VTC Lighting Setup: (a) Handheld Camera Image of Light Illuminating the Web of the Rail, (b) Lateral View Image Showing Successful Measurement of Raised Spike Using Illuminated Image Captured from VTC

DEVELOPMENT AND TESTING OF SPIKE AND ANCHOR INSPECTION ALGORITHMS

Early algorithm development focused on spike, anchor, and tie detection and defect recognition. These algorithms can be summarized as a coarse-to-fine approach for detecting objects. We first locate the track components with low variability in appearance and predictable locations (e.g. the rail), and then locate objects that are subject to high appearance variability (e.g. spike heads and anchors) in subsequent stages. To increase robustness to changing environmental conditions and changes in object appearance, local features such as edges and texture information were also included in the model [11]. The spikes are located using spatial correlation with a previously developed template [11]. The search area for the spikes is limited after the tie plate and rail are both delineated given that spikes will only be found in certain positions. The search area for the anchors is restricted to where the base of rail meets the ballast. Anchors are detected by identifying their parallel edges [11].

To measure the system's performance, we monitor the accuracy of the system as it identifies raised spikes. In order to identify raised spikes, the distance from the base-of-rail to the spike head is measured. This requires that both the spike head and the base-of-rail are correctly localized. Since our algorithms identify defects in components that are near or over a tie (e.g. spikes and anchors) it is important to detect the tie and tie components reliably before localizing the exact parts of the components that will be used in distance measurements. For evaluating the detection algorithms, we differentiate between precision and recall, since precision penalizes the erroneous detection of an object that is not present (i.e. false positives), and recall penalizes the missed detection of an object that is in fact present (i.e. false negatives). We also measure the accuracy of the localization of certain parts of the components. Our goal is to correctly localize the base-of-rail and the edge of the spike head. Detecting the base-of-rail is trivial since all rails will have a base, but accurately localizing the exact line in the image that corresponds to the base-of-rail is more challenging.

Experimental results show an accuracy of 100% for the base-of-rail localization using the lateral view, and 76% for the over-the-rail-view. In the case of spikes, both views resulted in 71% accuracy for spike head localization. For individual components, 93% of the ties were detected without false positives in the lateral view. For over-the-rail view, all ties were detected, however 8% of the detected ties were false positives. Finally, 100% of the anchors were detected (100% recall), however only 80% of objects that were detected as "anchors" were in fact anchors (80% precision).

METHOD FOR TRACK TYPE IDENTIFICATION USING PERIODICITY DETECTION

Track components in turnouts differ in both size and shape from those found in normal tangent or curved track. For this reason we must correctly identify the specific section of the track the system is inspecting and whether it contains special trackwork. To accomplish this, we have developed algorithms to look for periodic components (T) indicative of turnouts, such as frog bolts or joint bar bolts [1]

(a)

(b)

Figure 3: Turnout Component Recognition: (a) Original Image Switch Point Bolts, (b) Panoramic Mosaic from the Mid-rail Area

The estimation of periodic component location within turnouts is carried out by converting the middle portion of the video, containing the rail web seen in Figure 4(a), into a panoramic mosaic, Figure 4(b). The periodicity of the components in the panoramic mosaic is then estimated. Detecting periodicity in the spatial domain is unreliable due to the variability of component appearances and the sporadic noise from non-periodic components (or similar components in other areas of the track structure – e.g. insulated rail joints). Alternatively, it is more reliable to investigate periodicity in a domain of texture responses, since each component typically has a characteristic shape that is captured as a texture response in the Gabor frequency domain [13]. This was reported in [1], and we successfully isolated the frames of the video that contained the periodic switch point bolts, which are indicative of a turnout.

APPROACH FOR TURNOUT COMPONENT INSPECTION

Once the turnout area has been isolated in the inspection video, we identify important components within the turnout. Components are identified in order of robustness. The switch rod is easily identifiable in both over-the-rail and lateral viewpoints, so we detect it first using spatial template filters to detect strong horizontal gradients in the over-the-rail viewpoint, and spatial filters to detect the round switch rod bolts in the lateral viewpoint. The heel of the switch is also found easily using a spatial template.

Both viewpoints are then registered with each other by aligning them temporally with the frames containing the switch rod and heel. The ties are then detected, and each detection aligns the videos in another temporal location. Once this is accomplished, the switch point is detected and any chips on the switch point are detected and measured.

Switch Point Chip Inspection

Our goal in turnout component inspection is to detect the end of the switch point, and subsequently measure the amount of chipping. We accomplish this through an algorithm that involves (1) detection of the turnout area within the field-acquired video, (2) detection of the end of the switch point, (3) delineation of the end point of switch boundaries (which, in the case of severe chipping, would be a hypothesis of the boundary), and (4) measurement of any chipping by measuring the detected point with respect to the hypothesized boundary.

This detection and measurement algorithm is demonstrated on the point of the switch shown in Figure 4. The initial step, (1) detection of the turnout area, was already described in the previous section. The remaining steps are illustrated in Figure 4(b) - (d).

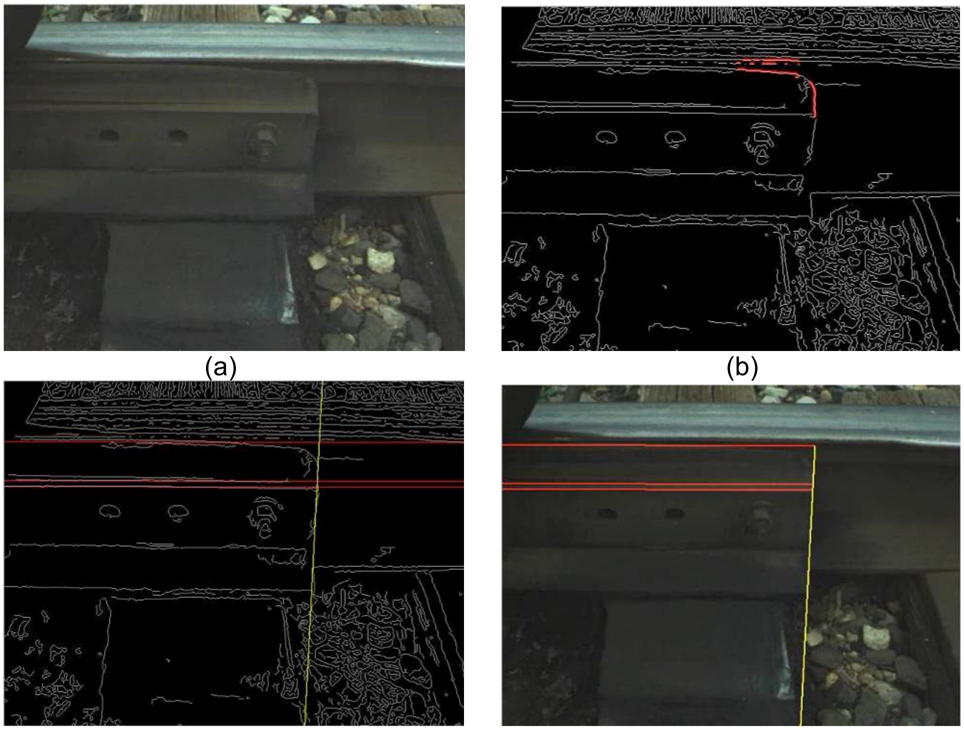


Figure 4: Algorithm for detection and measurement of end of the switch point, (a) original image of the switch point, (b) detection of the end of the switch point, (c) line detection for delineation, (d) delineation of the hypothesized end of the switch point

In Figure 4(b), the result of the Canny edge detection algorithm is shown [13]. A filter was created to detect the part of the image where a corner is formed by the edges, and where the inside of the corner contains few edges. This filter achieved a maximum response in the area that contains the red edges.

In Figure 4(c), the boundary lines of the point of the switch are inferred. We use a line detection algorithm that proposes candidate lines in the vertical and horizontal directions, and then finds the candidate lines that achieve the lowest sum of absolute differences with respect to the black and white Canny edge image. The resulting detected lines are shown. In Figure 4(d), these lines are truncated at the corner where they intersect so that the end of the switch point is delineated.

For the final step in the algorithm, the red (actual) edges that were detected in Figure 4(b) are measured with respect to the lines shown in Figure 4(d) to determine how much chipping is present at the end of the switch point.

FUTURE WORK

Future work involves refinement of the machine vision algorithms to improve the reliability of spike and anchor detection. We will experiment with various lighting and environmental conditions, and once the algorithms and lighting conditions for inspection of spikes, anchors and turnout components have been refined, the system will be adapted for testing on a high-rail vehicle.

When we detect turnout components, it is typically known which components we are looking for (e.g. switch rods, switch rod bolts, etc). For an autonomous system, it may be useful to detect and segment periodic components when no prior information is known about the components. Spectral estimation provides frequency detection, but not phase estimation. We propose using autocorrelation in addition to periodicity detection to detect and segment the periodically occurring components.

CONCLUSION

The inspection of most railroad track components is currently conducted using manual, visual inspections. These inspections are labor intensive and lack the ability to easily record and compare data to perform adequate trend analyses. Moreover, they are subject to variability and subjectivity in different inspectors' abilities and interpretation of what they observe. Additionally, it is impractical to manually catalog the condition of such a large number of track components, thus it is difficult to develop a quantitative understanding of exactly how the non-critical or symptomatic defects may contribute to the occurrence of critical defects or other track health problems.

Based on analysis of railroad derailment statistics and input from subject-matter experts, we have focused our research efforts on inspection of track fasteners and turnout components. Our algorithms use edge detection and texture information to provide a robust means of detecting track components, which narrows the search area. Within this restricted area, knowledge of probable component locations allows the algorithms to determine the presence of spikes and rail anchors even when there are variations in the appearance of the components.

Experimental results using this approach have shown good reliability for component inspection using machine vision. Recent work on periodicity detection methods, for automatically identifying transitions from tangent or curved track into special trackwork (e.g. turnouts), can now be used to initiate specialized machine vision algorithms to inspect particular components critical to these areas. In addition, current work on inspecting switch points for chips, described here, can also be invoked when the system determines it has entered a turnout.

ACKNOWLEDGEMENTS

This project is sponsored by a grant from the Association of American Railroads (AAR) Technology Scanning Program and funding from the NEXTRANS Region V Transportation Center. The authors are grateful to David Davis of the Transportation Technology Center, Inc. and the AAR Technology Scanning committee for their assistance and technical guidance. The Norfolk Southern (NS) Corporation and Monticello Railway Museum were instrumental in providing track access for initial data acquisition and field-testing. The Federal Railroad Administration (FRA), BNSF Railway, CN, NS, and Union Pacific Railroad provided additional material, technical input and support. We also thank Larry Milhon, Mike Iden, Rodriguez Sullivan, Donald R. Uzarski, David P. White, Gary Carr, Ali Tajaddini, Matthew D. Keller, Hank Lees, David Ferryman, and David Connell for their advice and assistance. We would also like to thank Mark Asmuth and Matt Toussaint for their assistance in the further development of the video track cart during their internships sponsored by NEXTRANS. J. Riley Edwards has been supported in part by grants to the UIUC Railroad Engineering Program from CN, CSX, Hanson Professional Services, Norfolk Southern, and the George Krambles Transportation Scholarship Fund.

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