

Condition Monitoring of Railway Turnouts and Other Track Components Using Machine Vision

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Luis Fernando Molina^{1, 3}, Esther Resendiz², J. Riley Edwards¹, John M. Hart²,
Christopher P. L. Barkan¹, Narendra Ahuja²

¹*Railroad Engineering Program
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign
205 N. Mathews Ave., Urbana, IL 61801*

²*Computer Vision and Robotics Laboratory
Beckman Institute for Advanced Science and Technology
405 N. Mathews Avenue, Urbana, IL, 61801*

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Luis Fernando Molina¹
molinacl@illinois.edu
(217) 244-6063

Esther Resendiz²
eresendi@illinois.edu
(217) 244-4174

J. Riley Edwards¹
jedward2@illinois.edu
(217) 244-7417

John M. Hart²
j-hart3@illinois.edu
(217) 244-4174

Christopher P. L. Barkan¹
cbarkan@illinois.edu
(217) 244-6338

Narendra Ahuja²
ahuja@illinois.edu
(217) 333-1837

³ Corresponding author

ABSTRACT

Individual railroad track maintenance standards and the Federal Railroad Administration (FRA) Track Safety Standards require periodic inspection of railway infrastructure to ensure safe and efficient operation. This inspection is a critical, but labor-intensive task that results in large annual operating expenditures and has limitations in speed, quality, objectivity, and scope. To improve the cost-effectiveness of the current inspection process, machine vision technology can be developed and used as a robust supplement to manual inspections. This paper focuses on the development and performance of machine vision algorithms designed to recognize turnout components, as well as the performance of algorithms designed to recognize and detect defects in other track components. In order to prioritize which components are the most critical for the safe operation of trains, a risk-based analysis of the FRA Accident Database was performed. Additionally, an overview of current technologies for track and turnout component condition assessment is presented.

The machine vision system consists of a video acquisition system for recording digital images of track and customized algorithms to identify defects and symptomatic conditions within the images. A prototype machine vision system has been developed for automated inspection of rail anchors and cut spikes, as well as tie recognition. Experimental test results from the system have shown good reliability for recognizing ties, anchors, and cut spikes. This machine vision system, in conjunction with defect analysis and trending of historical data, will enhance the ability for longer-term predictive 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. In addition to internal railroad inspection procedures, periodic track inspections are required under the Federal Railroad Administration (FRA) Track Safety Standards. The objective of this research is to investigate the feasibility of developing a machine vision system to make track inspection more efficient, effective, and objective. In addition, interim approaches to automated track inspection are possible, which will potentially lead to greater inspection effectiveness and efficiency prior to full machine vision system development and implementation. Interim solutions include video capture using vehicle-mounted cameras, image enhancement using image-processing software, and assisted automation using machine vision algorithms (1).

The primary focus of this research is inspection of North American Class I railroad mainline and siding tracks, as these generally experience the highest traffic densities. High traffic densities necessitate frequent inspection and more stringent maintenance requirements, and leave railroads less time to accomplish it. This makes them the most likely locations for cost-effective investment in new, more efficient, but potentially more capital-intensive inspection technology. The algorithms currently under development will also be adaptable to many types of infrastructure and usage, including transit and some components of high-speed rail (HSR) infrastructure.

The machine vision system described in this paper was developed through an interdisciplinary research collaboration at the University of Illinois at Urbana-Champaign (UIUC) between the Computer Vision and Robotics Laboratory (CVRL) at the Beckman Institute for Advanced Science and Technology and the Railroad Engineering Program in the Department of Civil and Environmental Engineering.

CURRENT TRACK INSPECTION TECHNOLOGIES USING MACHINE VISION

The international railroad community has undertaken significant research to develop innovative applications for advanced technologies with the objective of improving the process of visual track inspection. The development of machine vision, one such inspection technology which uses video cameras, optical sensors, and custom designed algorithms, began in the early 1990's with work analyzing rail surface defects (2).

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, intermodal loading efficiency, railcar structural components, and railcar safety appliances (1, 3-21, 23). 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), BNSF Railway, NEXTRANS Region V Transportation Center, and the Transportation Research Board (TRB) High-Speed Rail IDEA Program (6-11).

In this section, we provide a brief overview of machine vision condition monitoring applications currently in use or under development for inspection of railway infrastructure. Railway applications of machine vision technology have three main elements: the image acquisition system, the image analysis system, and the data analysis system (1). The attributes and performance of each of these individual components determines the overall performance of a machine vision system. Therefore, the following review includes a discussion of the overall

machine vision system, as well as approaches to image acquisition, algorithm development techniques, lighting methodologies, and experimental results.

Rail Surface Defects

The Institute of Digital Image Processing (IDIP) in Austria has developed a machine vision system for rail surface inspection during the rail manufacturing process (12). Currently, rail inspection is carried out by humans and complemented with eddy current systems. The objective of this machine vision system is to replace visual inspections on rail production lines. The machine vision system uses spectral image differencing procedure (SIDP) to generate three-dimensional (3D) images and detect surface defects in the rails. Additionally, the cameras can capture images at speeds up to 37 miles per hour (mph) (60 kilometers per hour (kph)). Although the system is currently being used only in rail production lines, it can also be attached to an inspection vehicle for field inspection of rail.

Additionally, the Institute of Intelligent Systems for Automation (ISSIA) in Italy has been researching and developing a system for detecting rail corrugation (13). The system uses images of 512x2048 pixels in resolution, artificial light, and classification of texture to identify surface defects. The system is capable of acquiring images at speeds of up to 125 mph (200 kph). Three image-processing methods have been proposed and evaluated by IISA: Gabor, wavelet, and Gabor wavelet. Gabor was selected as the preferred processing technique. Currently, the technology has been implemented through the patented system known as Visual Inspection System for Railways (VISyR).

Rail Wear

The Moscow Metro and the State of Common Means of Moscow developed photonic system to measure railhead wear (14). The system consists of 4 CCD cameras and 4 laser lights mounted on an inspection vehicle. The cameras are connected to a central computer that receives images every 20 nanoseconds (ns). The system extracts the profile of the rail using two methods (cut-off and tangent) and the results are ultimately compared with pre-established rail wear templates.

Tie Condition

The Georgetown Rail Equipment Company (GREX) has developed and commercialized a crosstie inspection system called AURORA (15). The objective of the system is to inspect and classify the condition of timber and concrete crossties. Additionally, the system can be adapted to measure rail seat abrasion (RSA) and detect defects in fastening systems. AURORA uses high-definition cameras and high-voltage lasers as part of the lighting arrangement and is capable of inspecting 70,000 ties per hour at a speed of 30-45 mph (48-72 kph). The system has been shown to replicate results obtained by track inspectors with an accuracy of 88%.

Since 2008, Napier University in Sweden has been researching the use of machine vision technology for inspection of timber crossties (16). Their system evaluates the condition of the ends of the ties and classifies them into one of two categories: good or bad. This classification is performed by evaluating quantitative parameters such as the number, length, and depth of cracks, as well as the condition of the tie plate. Experimental results showed that the system has an accuracy of 90% with respect to the correct classification of ties. Future research work includes evaluation of the center portion of the ties and integration with other non-destructive testing (NDT) applications.

In 2003, the University of Zaragoza in Spain began research on the development of machine vision techniques to inspect concrete crossties using a stereo-metric system to measure different surface shapes (17). The system is used to estimate the deviation from the required dimensional tolerances of the concrete ties in production lines. Two CCD cameras with a resolution of 768x512 pixels are used for image capture and lasers are used for artificial lighting. The system has been shown to produce reliable results, but quantifiable results were not found in the available literature.

Ballast

The ISSIA has also been developing a system capable of reconstructing 3D surfaces of the ballast section (18). The objective of the system is to detect anomalous conditions within the ballast surface that are indicative of situations that could result in a loss of track stability. The system finds the depth of ballast voids from a set of 2D images. Next, the system uses high definition cameras of 2048 pixels per line and uses stereo matching techniques to generate the 3D images. Since the method employed to process images requires significant computational power, future work will be aimed at improving the analysis technique in order to make the system feasible for revenue service.

Fastening Systems

Visual Inspection System for Railways (VISyR) is a patented commercial system that has been developed for detecting hexagonal bolts in European fastening systems (19). VISyR collects real-time image data at a maximum speed of 125 mph (200 kph). Cameras capture images of 1,024 pixels per line and artificial lighting (OSRAM 41 850 FL) is used to provide adequate illumination for image capture. The image processing system uses discrete wavelet transforms for bolt detection in real-time. VISyR also includes a module for detecting rail surface defects. The system has an accuracy of 99.6% for detecting visible bolts and 95% for detecting missing bolts. It has also been tested for the detection of elastic fasteners with similar accuracies.

The University of Loughborough (England) has developed a machine vision system capable of detecting missing elastic fastening clips on concrete ties (20). The system was tested using a camera mounted near a train wheel and it also incorporated artificial lighting. The images were obtained using a resolution of 384x288 pixels. Experimental results showed accuracies of 84.7% in detecting missing clips and 95.3% in clip recognition.

General Track Structure Inspection

The University of Central Florida has been developing a system for measuring track gauge and inspecting fasteners (21). The system uses high-speed CCD cameras with a resolution of 1,024x768 pixels. The camera is synchronized with strobe lights to minimize the difference in contrast during the day. Additionally, sun shields were mounted in the cart to eliminate the effect of shadows in the images. The system detects the edges of the rails, and by exploiting the known distance between the two cameras, provides an estimate for track gauge. Future work includes the implementation of the system for revenue service and the development of algorithms to detect other type of track component defects.

The FRA and ENSCO began development of a machine-vision-based joint bar inspection system in 2002 (22). The system uses high-resolution cameras with high-powered xenon lights to capture images of joint bars. It collects images at a maximum speed of 65 mph (105 kph). ENSCO has incorporated this technology into their VisiRailTM Joint Bar Inspection System. The

system primarily finds external cracks in joint bars. Currently, the system requires manual interpretation of image data to determine true joint condition. Experimental results showed an accuracy of 98%, but under non-ideal track conditions the joint detection accuracy rate declines to 85%. ENSCO is continuing work on improving their algorithms to increase the crack detection rate without increasing the number of false positives.

Cybernétix, in conjunction with the French National Railways (SNCF), has developed a commercial system for inspecting rails, fastening systems, the rail gap in joint bars, and reconstructing the ballast profile (23). The system uses an optical system and machine vision algorithms to capture data at speeds of up to 200 mph (320 kph). The system is currently being used by SNCF for track inspection.

Summary of Inspection Technologies

Many machine vision techniques have been investigated and systems developed throughout the world to inspect railroad track components including: rail, ties, fastening systems, joint bars, and ballast. These systems have demonstrated the potential for machine vision to enhance the inspection of railway infrastructure. In many cases, experimental results have shown accuracies greater than 80% and measurement speeds of up to 200 mph (320 kph). Future work includes further experimentation with variable lighting conditions, especially adverse situations such as weather-related events and darkness. Additionally, more research is needed to improve algorithm-processing speeds and study the integration of machine vision with other NDT systems to perform real-time data analysis and improve reliability.

RISK-BASED PRIORITIZATION OF TURNOUT COMPONENTS

Safe and efficient network operation is of utmost importance to the rail industry. 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 (3, 4, 24). Previous research direction and prioritization was based on the frequency of derailments, available technology, severity of defects and their potential contribution to accident prevention, and input from railway industry experts (3, 4, 5). This approach provided the following initial priorities for machine vision inspection of railway infrastructure:

1. Raised, missing, or inappropriate patterns of cut spikes
2. Displaced, missing, or inappropriate patterns of rail anchors
3. Turnout component inspection

Although the initial approach is valid, other variables, such as the number of cars derailed, can provide additional information on the risk associated with specific derailment causes and track component failures (25). Therefore, a risk-based prioritization approach was used to select the turnout components that are most critical to the safe operation. It should also be noted that none of the aforementioned machine vision railway applications addressed turnout component inspection, hence our interest in researching this area of the railway infrastructure.

Analysis of the FRA Accident Database

The initial data analysis for the risk-based prioritization of track components used track-caused derailment data from 1998 to 2009. The data were classified into five FRA-established derailment cause categories (Figure 1). Some components, such as those associated with roadbed and geometry, are currently being inspected by other technologies including autonomous track geometry cars and ground penetrating radar (GPR). Additionally, defects

related to category one (rail, joint bar, and rail anchoring) were taken into account in the initial prioritization and subsequent research. For this reason, category three (frog, switches and track appliances) was selected for further evaluation. Most of these components are currently inspected using manual, visual inspection and may be amenable to machine vision inspection (1, 4).

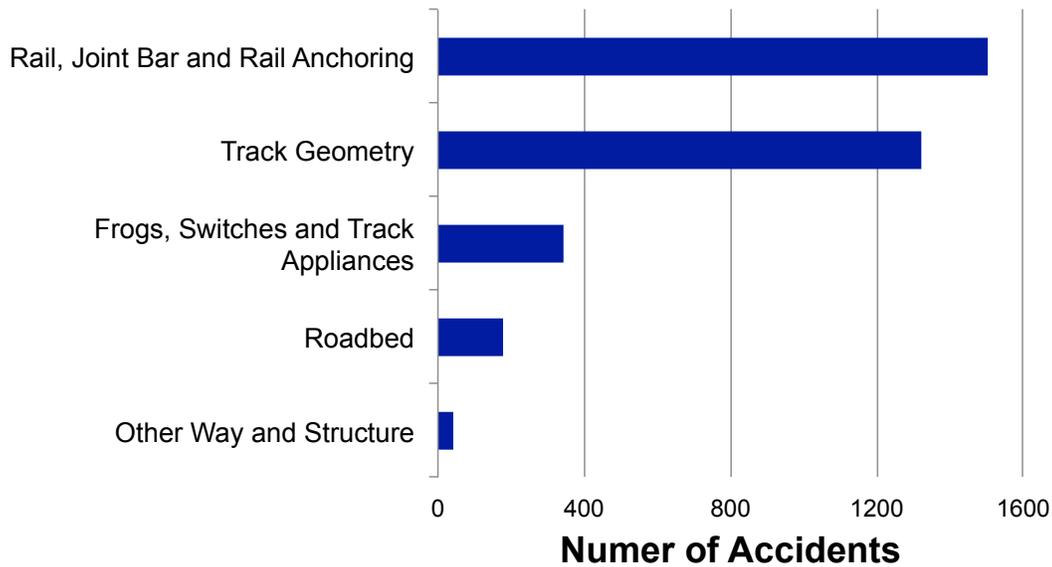


FIGURE 1 Top Track-Related Derailment Causes by Track Category from 1998-2009, Used for Track Component Inspection Prioritization.

Risk-Based Turnout Component Inspection Prioritization

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. Risk can be defined as the probability of an accident occurring multiplied by its consequence (25). With this being said, we selected the number of cars derailed as a proxy for consequence.

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. Figure 2 was divided into four quadrants based on the average value of each axis. The vertical dotted line represents the average derailment frequency and the horizontal dotted line represents the average number of cars derailed for all turnout-related derailment causes.

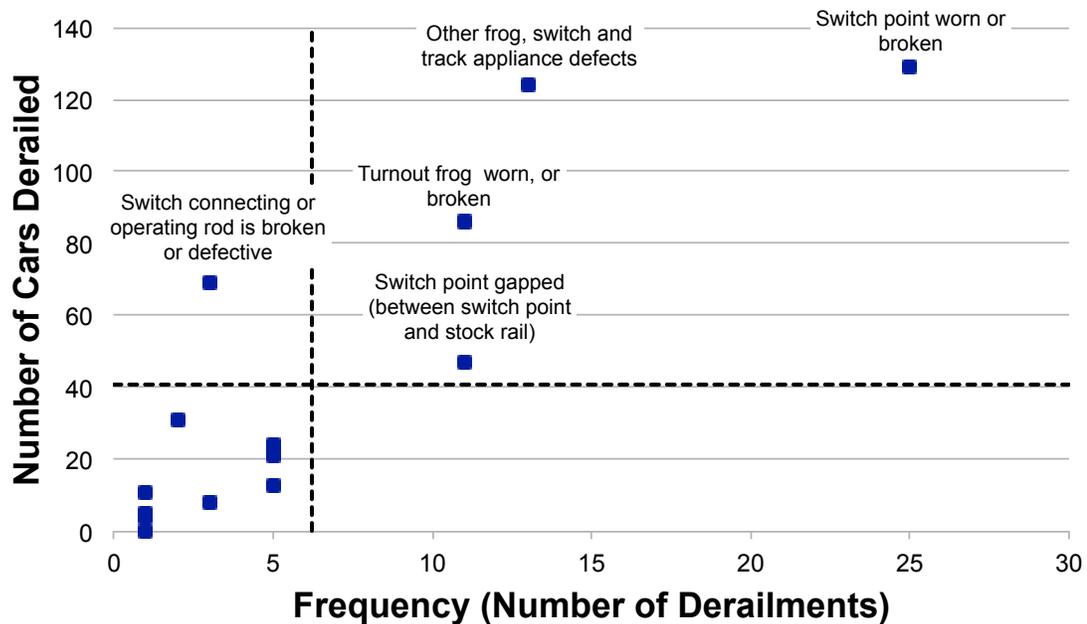


FIGURE 2 Railroad Track-Caused Derailments by Cause Severity on Track Classes 4 and 5, from 1998 – 2009.

Each quadrant in Figure 2 has a different meaning, and provides valuable insight into the prioritization of turnout components for machine vision inspection. For example, the lower left quadrant represents infrequent accident causes that result in low consequence derailments. The causes contained in the upper left quadrant are also rare, but their consequences are higher than average. The values in the lower right quadrant are more common but they are associated with low-consequence derailments. Of greatest importance are the accident causes in the upper right quadrant, as they occur at above-average frequencies and result in high-consequence derailments.

The causes contained in the upper quadrants were included in our priorities for inspection primarily due to the severity of these types of defects. Additionally, they account for almost 80% of turnout derailments on track classes 4 and 5. It is interesting to note that no causes were classified in the lower right (high frequency / low severity) quadrant. 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

In addition to the five tasks selected for inspection, missing bolts and cotter pins were included into our initial turnout inspection priority, since the inspection of these components in turnouts is conducted primarily using visual means and they are suitable candidates for inspection using machine vision.

Track inspection requirements for turnout components

The FRA Track Safety Standards (26) contain specific regulations for the inspection of track and turnout components, and provide guidance as to which components should be inspected using machine vision. According to the regulations for worn or broken switch points (section 213.135(h)): “Unusually chipped or worn switch points shall be repaired or replaced” (26). For this particular case, the criterion for the allowable magnitude of cracks is not established. This is partially because these defects may cause a derailment in conjunction with other conditions, such as the improper wheel/rail interaction, thus it is harder to define an acceptable defect threshold. Therefore, experience of the inspector and railway management must be used to determine specific conditions that should be repaired to reduce the risk of derailments (27). Alternatively, in the case of frogs points (section 213.137(b)), regulations are more specific and frogs worn or broken more than 5/8 inch downward and 6 inches back from the point of frog are not allowed for track classes with speeds greater than 10 mph (16 kph). Moreover, it is required that the flangeway may not be less than 1 1/2” in depth and width for FRA track classes 2 through 5. Finally, section 213.137(c) restricts the maximum operational speed over a frog to 10 mph (16 kph) if the tread is worn more than 3/8”.

Additionally, the FRA Track Safety Standards provide regulatory guidance as to how to maintain the switch stand and rods and state that: “Each switch stand and connecting rod shall be securely fastened and operable without excessive lost motion” (26). In this case, a broken or defective connecting switch rod could generate (in conjunction with the train movement) a gap between the switch points and the stock rail, resulting in a possible derailment. Specific defects are dependant on the switch stand design, thus different types of conditions and component designs should be incorporated into the machine vision inspection system.

Finally, the FRA requires that the switch points fit securely against the stock rail when the switch is operating in either position. This will allow the wheels to pass safely through the switch points. A mandated range of values for measuring the gap between switch point and stock rail is not provided, but the FRA Track Safety Standards Compliance Manual (27) states that most industry standards have defined 4¾ inches between switch point and stock rail measured at rod number 1 as acceptable.

In addition to the FRA Track Safety Standards, Class I track engineering standards and the Track Safety and Condition Index (TSCI) were used to determine guidelines and procedures for turnout component inspection (28, 29, 30). Similar considerations were made in previous work (1, 3, 4, 5) focusing on anchor and cut spike inspection, taking into account the expertise of track inspectors, researchers, and track maintenance managers at Class I railroads.

OVERVIEW OF PREVIOUS WORK

Collecting images and video of track components is a critical part in the development of a machine vision system. There are important trade-offs between where the candidate components are located in the view, how many components can be seen in a single view, and how many unique views are required to perform the desired inspections. Views of the components must not only show the entire component in its functional position(s), but also be conducive to distinguishing the component from background objects and be oriented properly for obtaining necessary measurements during the inspection of these components. In addition, the cameras must be placed to provide views that permit the machine vision algorithms to consistently and reliably detect the track components of interest under various conditions.

Experimental Data Acquisition System

Securing time to test the image acquisition system on active track during the developmental phases proved difficult, thus a Virtual Track Model (VTM) was created using North American recommended practices for track design (1, 31).

Initial experimentation with the VTM camera angles resulted in the selection of two camera views for inspection: the lateral view (Figure 3A) and the over-the-rail view (Figure 3B) (1, 3, 4, 5). The lateral view provides a suitable view of tie plates, spikes and anchors. The over-the-rail view provides perpendicular views of the spike and anchors. In addition, virtual views were used to generate synthetic images from these views for initial development of machine vision algorithms. They provided insight into challenges such as non-uniform lighting, variation in component design, and defect recognition (1).

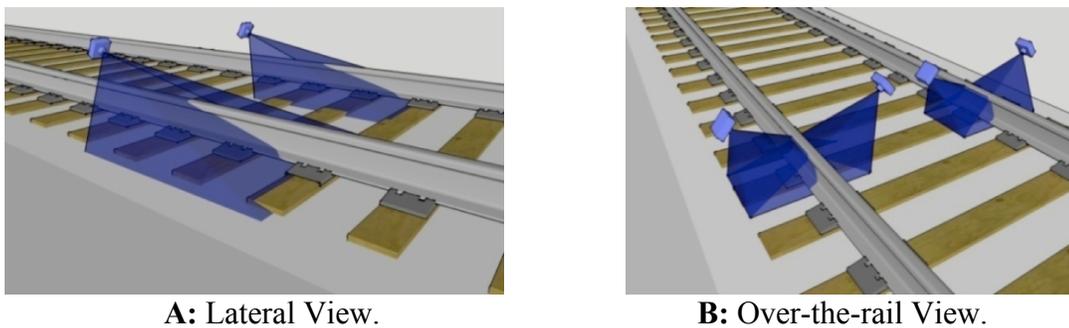


FIGURE 3 Camera Views.

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 development of the machine-vision inspection algorithms. For this reason an experimental data acquisition system called the Video Track Cart (VTC) was designed for collecting continuous video of track sections of interest on low-density track (1).

Three main components were considered in developing the experimental video acquisition system: the camera, lens, and imaging hardware. A detailed evaluation of different factors (1) led to the selection of a Dragonfly®2 DR2-COL camera for video data collection. This camera has an image resolution of 640x480 pixels (VGA) and can record video at up to 60 frames per second (fps) with shutter speeds as fast as 1/100,000 seconds (32). The camera is equipped with a 6 mm (wide-angle) lens. The laptop selected uses a Microsoft Windows XP Professional operating system, has 4 GB of RAM, an Intel® Core™ 2 Duo P9600 2.66 GHz processor, and a High Performance Solid State Drive.

Additional considerations are being studied in the approach to lighting. Currently, we are investigating low-wattage LED lighting, which will be powered by our VTC on-board battery system. The addition of lighting should improve the consistency and reliability in detecting the components of interest against a background of similar color and texture (e.g. steel).

Field Work

The VTC has been used on low-density track, where track occupancy time is easier to obtain. Video recording sessions have taken place at the Monticello Railway Museum in Monticello, IL as well as Class I track. During these field visits, we captured video 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, ballast types, and levels of ballast fouling in order to develop statistics on consistent component recognition under realistic field conditions. Additionally, experimentation to identify the transition between the tangent and turnout sections of track was performed in order to invoke the appropriate inspection algorithms (1).

Early Algorithm Development and Spike and Anchor Inspection

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 (1, 3, 4, 5).

The spikes are located using spatial correlation with a previously developed template (1, 3, 4). 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 rail meets the ballast. Anchors are detected by identifying their parallel edges (1, 3, 4, 5).

Experimental Results for Spikes, Anchors and Ties

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, but localization is only possible after the components are first detected.

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).

APPROACH FOR TURNOUT INSPECTION USING MACHINE VISION

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 (Figure 4A).



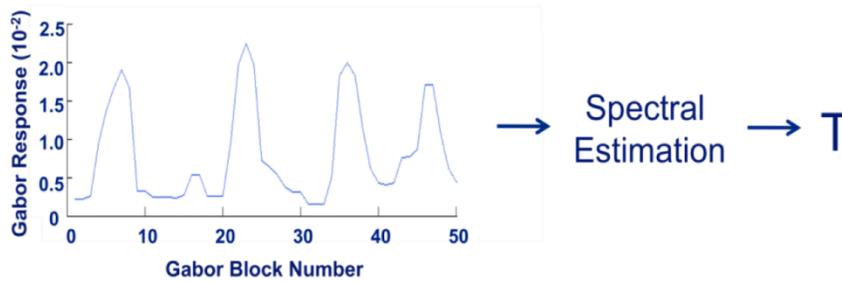
A: Original Image Switch Point Bolts.



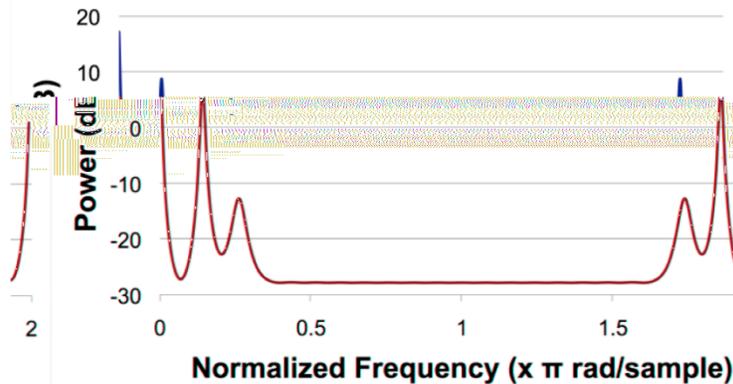
B: Panoramic Mosaic from the Mid-rail Area.



C: Gabor Frequency of the Panoramic Mosaic.



D: One-dimensional Signal from Gabor Frequency of Panoramic Mosaic.



E: Spectral Analysis on One-dimensional Signal.

FIGURE 4 Turnout Component Recognition.

The estimation of periodic component location within turnouts is carried out by converting the middle portion of the video, containing the rail web, into a panoramic mosaic (Figure 4B). The periodicity of the components in the panoramic mosaic is then estimated, and

the components subsequently localized. 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 (33).

The image is transformed in a block-wise manner into the Gabor frequency domain (Figure 4C). Each block's height is identical to the height of the rail web area shown in Figure 4B, and each block's response is computed using an overlapping width with its right neighboring block (Figure 4C). This block-wise Gabor response is then processed as a one-dimensional signal (Figure 4D). Spectral analysis is subsequently performed to find periodic components (Figure 4E). Spectral analysis is a technique in which a received signal is analyzed for the frequency components that it contains. We use the Multiple Signal Classification (MUSIC) algorithm due to its ability to extract frequencies from a signal containing multiple superimposed signals of different frequencies (34).

The MUSIC algorithm outputs a frequency analysis, in which the input signal's frequency response is computed for each frequency (Figure 4E). Dominant frequencies are then detected. The output of Figure 4E shows the power at each radial frequency, ω . Each radial frequency relates to the period, T , by the formula $\omega=2\pi/T$. Hence, when the peak is located at $T=0.14\pi$, the component repeats every $T=14.3$ blocks (35). This is a satisfactory approximation since the distance between bolts is not always constant (Figure 4A), and can vary depending on the turnout angle, component and turnout design, and turnout manufacturer. Nevertheless, this approximation allows us to reliably identify the switch area in a section of track (Figure 4B).

Spectral estimation provides frequency detection, but not phase estimation. Because of this, we are able to detect the presence of a turnout, but we are not able to localize the repeating component using only spectral estimation. In the future, if localization is needed, then autocorrelation can be performed on the blocks in the Gabor frequency domain. Candidate blocks would be proposed that have a strong Gabor frequency response (Figure 4C). The autocorrelation between a candidate block and all blocks that are nT blocks apart would be measured, where n is a positive integer. Blocks that yield a strong Gabor response and that are highly correlated to blocks nT away are considered repeating components.

The use of this periodicity detection algorithm, which can identify specific sections of track based on the appearance of periodic component locations, will be key to invoking distinct machine vision algorithms to identify and inspect unique components found in track.

FUTURE WORK

Future work involves refinement of the machine vision algorithms to improve the reliability of spike and anchor detection. Also, we will experiment with several machine learning methods to perform component detection in the presence of anomalies such as leaves. Additionally, since machine vision algorithms require previously stored models of the textures and components, we will research methods of dynamically updating the models. Once the algorithms and lighting for inspection of spikes, anchors and turnout components have been refined, the system will be adapted for testing on a high-rail vehicle.

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 problems. Based on analysis of railroad derailment statistics and input from subject-matter experts, we have focused our research efforts on inspection of cut spikes, rail anchors, 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.

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