Machine-Vision Inspection of Railroad Track

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ABSTRACT
Railroad engineering practices and Federal Railroad Administration (FRA) regulations require track to be inspected for physical defects at specified intervals, which may be as often as twice per week. Most of these inspections are conducted visually by railroad track inspectors and include detecting defects relating to the ballast section, ties, fasteners, rail, and special trackwork. Enhancements to the current manual inspection process are possible using machine-vision technology, which consists of recording digital images of track elements of interest and analyzing them using custom algorithms to identify defects or their symptoms.

Based on analysis of FRA accident data, discussion with railroad track engineering experts and consultation with Association of American Railroads researchers, this project focuses on using machine vision to detect irregularities and defects in wood-tie fasteners, rail anchors, crib ballast, and turnout components. Development of a machine-vision-based inspection system will permit more efficient, effective, and objective inspection of these track elements. The system will be adaptable to inspect in accordance with FRA track safety regulations as well as railroad-specific track standards that may involve additional parameters of interest. Also, because data will be stored digitally, recall and quantitative comparative analysis is possible thereby enabling relative comparisons and trend analysis. This will enhance the ability for longer-term predictive assessment of the health of the track system and its components, and lead to more informed preventative maintenance strategies and a greater understanding of track structure degradation and failure modes.

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 Federal Railroad Administration (FRA) regulations. Although essential, track inspection requires both financial and human resources as well as consuming track time. The objective of the research described in this paper is to investigate the feasibility of using machine-vision technology to make track inspection more efficient and effective.

The focus of this project is inspection of Class I railroad mainline and siding tracks, as these generally experience the highest traffic densities. Heavy traffic leads to more frequent inspection and maintenance requirements and less time to accomplish it. The cost associated with removing track from service due to inspections or the repair of defects is most pronounced on these lines. This makes them the most likely locations for cost-effective investment in new, more efficient, but potentially more capital-intensive inspection technology.

REVIEW OF RELATED INSPECTION TECHNOLOGIES

We first conducted a survey of existing technologies for non-destructive testing of railroad track and track components. This provided insight regarding which tasks were best suited to vision-based inspection for which technology was not already under development. This survey encompassed well-established inspection technologies (e.g. ultrasonic rail flaw testing) and more experimental technologies currently under development (e.g. inertial accelerometers). In this section, we provide a brief review of the technologies currently in use or development that are of greatest relevance in the determination of the scope of our research.

Light Detection and Ranging (LIDAR)

Light Detection and Ranging (LIDAR) uses a light source, such as laser, that reflects off objects. The properties of the scattered light are then analyzed to determine the object's distance. LIDAR systems in use by the railroads employ a rotating laser emitter that has high cross-sectional resolution due to the large number of sampling points along the inspection arc. However, the longitudinal resolution along the track is dependent on the speed of the inspection vehicle (*1*). To allow for greater resolution at high speeds, LIDAR systems have been improving their laser emitters to use multiple beams or to rotate at higher speeds; however, these features also increase the cost. An advantage of this technology is the ability to accurately measure an entire cross section at high speed irrespective of light level. Disadvantages include the relatively low longitudinal resolution, and the inability to obtain measurements from objects at oblique angles or from the surface of water.

Clearance/Ballast Measuring System

Plasser American has developed a clearance/ballast measuring system that uses LIDAR to measure tunnel clearances and the shoulder ballast section (*1*). Their system currently uses a laser mirror scanner that operates using an electro-optical range detection method and has an accuracy of 25 mm (0.98 in). This rotating laser array covers a 350 degree range, with a ten-degree gap in the measurements at the center of the track that is used for system recalibration purposes. It is currently being used by the New York City Transit Authority, Long Island Rail Road, Taipei Transit, Union Pacific Railroad, and CSX Transportation.

Machine Vision

Machine-vision systems are currently in use or under development for a variety of inspection tasks, both wayside and mobile, including inspection of joint bars, surface cracks in the rail, rail profile, gauge, intermodal loading efficiency and railcar structural components and safety appliances. Machine-vision systems have three main elements. The first element involves the data acquisition system, in which digital cameras are used to obtain images or video in the visible or infrared spectrum. The next component is the image analysis system, where the images or videos are processed using machine-vision algorithms to detect and identify items of interest and assess particular aspects of the condition of the detected items. The last component is the data analysis system that can compare and verify whether the condition of items complies with the appropriate specified parameters.

The advantages of machine vision include greater objectivity and consistency compared to manual, visual inspection, and the ability to record and organize large quantities of visual data in a quantitative format. These features, combined with data archiving and recall capabilities, provide powerful trending capabilities in addition to the enhanced inspection capability itself. Some disadvantages of machine vision include difficulties in coping with unusual or unforeseen circumstances and the need to control and augment lighting conditions.

Joint Bars

The FRA began development of a machine-vision-based joint bar inspection system in 2002 (*2*). The system uses high resolution, line scan cameras along with high-powered xenon lights to capture images of joint bars at inspection speeds of up to 65 mph (105 km/hr). ENSCO has incorporated this technology into their VisiRail™ Joint Bar Inspection system, which is currently undergoing development and testing. The system primarily finds external cracks in joint bars, and under good track conditions, can detect joints with 98% accuracy and cracks with 80% accuracy. However, under non-ideal track conditions, especially when the rail is wet, the joint detection accuracy rate declines to 85%, and false-positive crack detections increase, although half of these are due to the increase in false joint detections. The system currently in use requires manual interpretation to determine true joint condition. ENSCO is continuing to work on improvements to their algorithms to increase the crack detection rate without also increasing false positives. Planned enhancements to this system include the capability to inspect for missing bolts, rail-gap width, and rail batter.

Elastic Rail Clips

The National Taiwan University of Science and Technology, in cooperation with the Taiwan Ministry of Transportation and Communications, is developing a machine-vision system to inspect elastic rail clips (*3*). The goal is to improve the safety, comfort, and efficiency of mass transit in Taiwan. This system is capable of inspecting the German VOSSLOH clip, which is the most prevalent type in use on Taiwanese rapid transit lines. The system uses area scan cameras with a resolution of 640x480. It can inspect clips on concrete or ballasted track to determine if they are broken and has a 77% recognition rate for broken clips. Future work includes improving the lighting system and image processing algorithms, and inspection of the bolts that secure the elastic rail clips.

Rail and Track

A variety of machine vision systems have been developed to inspect rail and track, including systems from the University of Central Florida, Georgetown Rail Equipment Company and MER MEC. The University of Central Florida, in association with the Florida Department of Transportation, is developing a machine-vision system for the inspection of surface cracks in the rail, missing or misaligned tie plates, presence of fasteners, and improper gauge (*4*). Initially, they used a small, self-propelled track cart to gather video data and are now adapting the system for use on a high-rail vehicle. A downward-facing, high frame rate, 640x480 area scan camera is used in combination with strobe lights, lasers, and sun shields to gather the video data. Images are recorded approximately every 1.5 feet, with the exact interval determined using Global Positioning System (GPS) data.

Georgetown Rail has developed their AURORA system for inspection of wood ties, rail seat abrasion, presence of fasteners, and improper gauge (*5*). This system is mounted on a high-rail vehicle and can be operated at speeds of up to 30 mph (48 km/hr). Wood tie inspection includes determination of the size, length and location of cracks, as well as an estimation of tie "roughness" and a measurement of vertical plate cutting. Fastener detection can recognize and catalog cut spikes as well as Pandrol E-clips, Fast Clips and Safelock clips with 85%-90% accuracy.

MER MEC has developed a track inspection system, known as the "Track Surface Detection System", which uses line-scan cameras and has three separate modules that can be installed to detect different track defects (*6*). The system can be installed on any track vehicle and can be operated at speeds of up to 160 km/hr (99mph). With all three modules installed, the system can detect tie type and movement, inspect and classify rail fastenings and surface defects, measure rail gap, check for ballast irregularities and vegetation and determine tie plate condition and the structural condition of several pieces of on-track equipment (e.g. transponders for the European Train Control System).

Wheel and Rail Profile

Wheel and/or rail profile measurement systems are offered by several companies, such as ENSCO and Beena Vision (*7, 8*). The profile measurement systems operate by projecting a laser line onto the wheel or the rail, and using cameras to record the shape of the object from which the light is reflected. The shape of the line is then used to determine the profile. Most rail-profile systems also have the ability to measure gauge as well as information on rail profile. Wheel-profile systems are generally designed for use in the shop, as an expensive array of cameras and lasers would be necessary to capture the entire profile of a wheel in a track-based system.

Air Hoses and Coupler Height

Progressive Rail Technologies has developed a system that detects low-hanging air hoses, as well as coupler height mismatches (*9*). It uses a single wayside camera enclosure, and has the ability to distinguish between air hoses and auxiliary hoses to minimize false alarms. ENSCO also has developed a system to detect low-hanging and worn air hoses (*10*). There are two major elements to this system, the first is an above-grade, wayside optical array that detects both the presence and height of air hoses. The second element is below-grade imaging system that has an upward view that can detect the oval-shaped wear pattern on the underside of air hoses caused by dragging.

Wheel and Journal Bearing Temperature
Several systems have been developed to measure the temperatures of wheels and hot journal bearings. Those that are machine-vision-based use infrared cameras (*11*). The video taken from these cameras is analyzed to determine the temperature of wheels or journals and bearings. Wheels that are too cold relative to other wheels on the car indicate poor brake performance. Wheels that are too hot indicate a locked-up wheel caused by a stuck brake. Locked wheels are detected by determining if the heat distribution across the edge of the wheel is even, indicative of normal braking, or if it is concentrated at the wheel/rail interface. For hot bearings, the concern is simply whether they are overheating. This condition is symptomatic of bearing failure, which can cause a derailment.

Railcar Performance
Wayside Inspection Devices Inc. developed a wayside machine-vision and laser-based system to measure the angle of attack and track the position of the wheels in relation to the rail (*11*). The measurement is accomplished by projecting a line of dots using a laser onto the side of the wheel, and analyzing the profile recorded by the camera. If multiple systems are used to measure several wheels simultaneously, they have the ability to detect hunting.

University of Illinois Machine Vision Systems
The University of Illinois at Urbana-Champaign (UIUC) has been involved in several railroad machine-vision projects sponsored by the Association of American Railroads, BNSF Railway and the Transportation Research Board High-Speed Rail IDEA Program. A number of the concepts, algorithms and hardware systems are being adapted for the track inspection project, so it is worth briefly reviewing their prior work here.

Railcar Trucks The first UIUC machine-vision project was inspection of the condition of several components on railcar trucks (*12*). This system has the ability to locate the brakes, bearings and spring set. Images of railcar trucks were taken using a view that was perpendicular to the cars and encompassed half of the truck. Several algorithms were developed that could identify the wheel, the angle of compression of the spring set, and the presence or absence of the bearing end-cap bolts.

Safety Appliances A system was developed to inspect safety appliances on railcars, such as ladder rungs, handholds, and brake wheels (*13*). An area scan camera was placed alongside the track, and recorded images of cars passing by at up to 25 mph (40 km/hr) at 30 fps. A virtual model of an open-top hopper car was used to “train” the algorithms. Use of the virtual model provided a large quantity and variety of simulated safety appliance defects thereby enabling more rapid training of the algorithms. Data were also gathered in the field, with video taken under differing natural and artificial lighting conditions. The algorithms that were developed could identify deformed ladder rungs, handholds, and brake wheels; preliminary work on sill steps and uncoupling levers was also completed.

Undercarriages A system was developed that used visible and infrared cameras to enable multi-spectral, machine-vision inspection of passenger car undercarriages *(14)*. The system focused on detection of overheated, missing or damaged components and foreign objects. Both the visible and infrared spectrum cameras were area scan cameras. These cameras were placed below rail level, between the rails in inspection pits and video was recorded as trains passed overhead. The videos were then separated into individual frames that were used to create panoramic images of the undercarriage in both spectra. Machine-vision algorithms were then used to process the train panoramas to separate them into individual car and locomotive panoramas through identification of the couplers. Then each vehicle was analyzed to detect visible and thermal anomalies, which include incipient failures not normally detected during manual inspections.

Intermodal Loading Efficiency Another project used machine vision to monitor the aerodynamic efficiency of intermodal train loading (*15*). As with the undercarriage inspection, it created a panoramic image, but in this case, it is necessary to first separate the train from the background in the images. This posed a significant challenge due to the dynamic nature of the natural background. Algorithms were used to determine the length of the gaps between the different intermodal loads in trains. The system automatically records trains passing at up to 70 mph (113 km/hr) and provides information to the railroad that allows them to assess the aerodynamic properties of the train to determine if the loading pattern could be improved to enhance energy efficiency.

DETERMINATION OF INSPECTION TASKS

Prioritization Based on Accident Statistics

In order to prioritize the tasks that are most conducive to machine-vision inspection, the FRA Accident Database was analyzed to identify the most frequent causes of track-related railroad accidents from 2001-2005 (*16*). The three most frequent causes are broken rail, wide gauge, and cross-level. However, several existing technologies are already being used by railroads to detect these defects. The principal defects that contribute to the next three most common, buckled track, switch points, and other turnout defects, are currently inspected primarily using manual, visual inspection. Therefore, these may be amenable to the use of machine vision inspection and were selected for further consideration.

Defect Severity Levels

In order to characterize the level of severity of track-component defects and determine the required action, we grouped defects into three categories (listed in decreasing order of severity): critical, non-critical, and symptomatic.

Critical Defects

We define critical defects as those that pose either an immediate or near-term hazard to safe and efficient operation. They represent a potentially severe condition such as a track buckle. These types of defects are what preventative maintenance and periodic track inspection are intended to prevent.

Non-critical Defects

Non-critical defects are those that cause sub-optimal track structure conditions but do not present an immediate hazard to train operations. An example of a non-critical defect would be low crib ballast between a single pair of ties. Such a condition may result in a small degradation in the longitudinal stability of the track, but is unlikely to pose an immediate hazard. However, if there is low crib ballast along an extended portion of track, longitudinal stability may be lost to the point where, in combination with high thermal stresses, a track buckle might occur.

Symptomatic Defects

Symptomatic defects do not necessarily represent deficiencies per se, but they may be indicators of a possible problem. An example of a symptomatic defect would be shiny spots on the base of the rail near anchors or other rail fastening devices. These are not defects, but they indicate possible rail running due to excessive longitudinal forces in the rail, another possible precursor to a track buckle.

Selected Inspection Tasks

In the initial selection of the inspection tasks to be developed in this project, we took into account the lack of available technology, severity of defects, and their potential contribution to accident prevention. We then sought and reviewed input from Class I railroad track-engineering and maintenance managers, track inspectors, and experts in track-related research. The result of this process was the selection of the following inspection tasks:

1. Raised, missing or inappropriate patterns of cut spikes
2. Displaced, missing, or inappropriate patterns of rail anchors
3. Insufficient level of crib ballast
4. Condition of switch points and other turnout components

DATA COLLECTION

Determination of Camera Views

Track Simulation Model

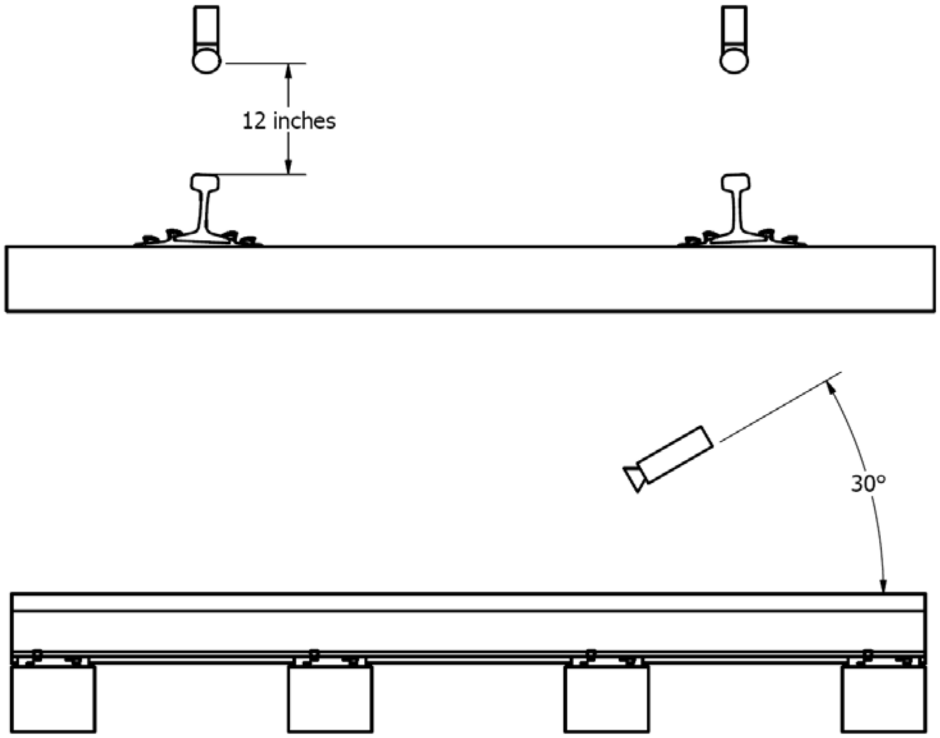
A track simulation model was developed to evaluate camera views and to provide images for initial machine-vision algorithm development (Figure 1).

FIGURE 1 Synthetic Track Image Created Using Simulation Model

This enabled virtual, laboratory experimentation on varying the camera location used to view and record images of track components of interest. The simulation model was developed based on AREMA track specifications (*17*) and representative Class I railroad track standards (*18, 19*). Association of American Railroads (AAR) clearance plate diagrams were incorporated into the simulation model to ensure that cameras were not being placed in infeasible positions while obtaining the desired views of the track (*20*). The virtual cameras were then adjusted until they enabled the viewing of the relevant components of the track and allowed assessment of the conditions of interest that were conducive to algorithm development.

Selected Camera Views

Three camera views are being used to record images of components on each side of the rail: an over-the-rail view and gauge and field-side lateral views. The over-the-rail view is captured parallel to the longitudinal axis of the track from 12 inches above the top of the rail head (TOR), at a 30 degree angle (Figure 2a). Field and gauge-side spikes are visible in this view as well as the level of crib ballast (Figure 2b).

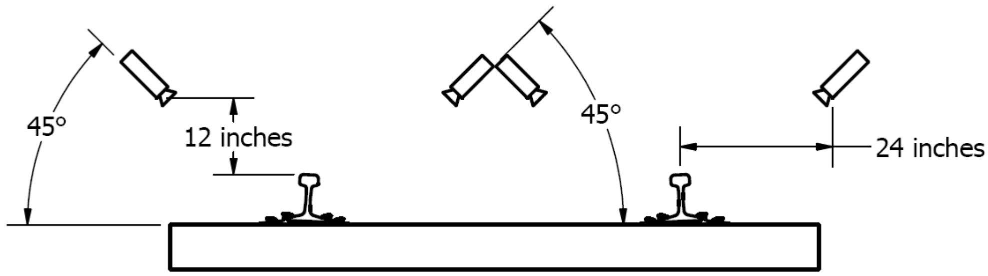


(a)

(b)

FIGURE 2 Over-the-rail Camera View Specifications: (a) Placement of Cameras, (b) Image from Camera View

The field and gauge-side lateral views are taken perpendicular to the rail from a point 24 inches laterally from the center of the rail and 12 inches above the TOR at a 45 degree angle (Figure 3a). The base of the rail and fastening system are visible from this view (Figure 3b and 3c).



(a)

(b)

(c)

FIGURE 3 Lateral Camera View Specifications: (a) Placement of Cameras, (b) Image from Gauge-side View and (c) Image from Field-side View

Preliminary Data Collection
In our initial collection of digital images, we used handheld cameras to take photographs at the selected camera views. These photographs were taken at various representative locations, and provided insight into challenges such as lighting and the degree of variation in components. This was an iterative process that helped us find a more effective view that had not been evident in the initial track simulation.

Video Acquisition Cart
A small track cart was modified to support the image acquisition equipment used in our initial field data acquisition. Experiments on camera views and lighting are being conducted using this cart on low density trackage during system development. Ultimately, the system will be adapted for vehicles suitable for use on mainline track such as detector cars or high-rail vehicles.

Lighting Challenges
As with many vision-based inspection systems, optimizing lighting is a challenge, especially for our over-the-rail view. We reviewed lighting arrangements of other machine-vision systems to

gain insight into possible solutions. ENSCO's Joint Bar Inspection system uses high-powered xenon lights that eliminate the need for sun shields. However, unlike our system, they use line scan cameras that require a much smaller area of illumination, so this method could not be directly adapted to our system (*2*). The University of Central Florida's track inspection system uses a strobe light that operates synchronously with the camera, and has sun shields to limit the surrounding light. Like our system, they use area scan cameras; however, our cameras are farther from the components than theirs. Consequently we may encounter difficulty using sun shields. Methods to control and augment light levels are one of the areas we are continuing to study and experiment with.

ALGORITHM DEVELOPMENT

Inspection Guidelines

It is important to understand the specific track components and defects associated with them when developing the algorithms. We used the FRA Track Safety Standards, Class I track engineering standards, and the Track Safety and Condition Index (TSCI) to determine guidelines used for inspection procedures (*18*, *19*, *21*, *22*). Our guidelines for the algorithms are currently under development and include the height that would constitute a raised spike, and how many need to be raised before they would be considered critical.

Track Simulation Model

The track model was used to produce images and video of simulated component defects. This enabled rapid comparison of various detection algorithms. Defects such as raised spikes, moved anchors, and low ballast were all simulated, along with varying environmental conditions that could affect detection reliability.

Track Inspection Algorithms

Algorithm development to date has focused on spike and anchor detection. Our algorithms can be summarized as a coarse-to-fine approach for detecting objects. We first locate the track components with little 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. This increases robustness of component detection by restricting the search space for the smaller components, whose appearances can vary.

To further increase robustness to changing environmental conditions and changes in object appearance (e.g. differing types or material corrosion), we have selected features that do not rely on a specific spatial description, but rather a configuration of simple, local features that are known to be valuable in classification. The spatial templates that are used are restricted to the final stages, and since the location of the objects have been isolated by then, it is not necessary that the objects have a strong response to the template in order to be detected.

The simple, local features that we use include edges and Gabor features. Edges are frequently used to detect objects in machine vision since object boundaries often generate sharp changes in brightness (*23*). Image gradients (edges) should be consistent among differing ties and rails, but unanticipated track obstacles could create unanticipated edges, causing confusion for the algorithms. For this reason, texture information from the ballast, tie, and steel was incorporated into an edge-based algorithm to improve its robustness. This approach relied on texture classification using Gabor filters, which produced low-level texture features. Gabor filtering is used to summarize two-dimensional spatial frequencies, and this can be used in texture discrimination (*23*).

Image Decomposition

Since we operate using a coarse-to-fine approach, we decompose the image beginning with the rail, which is the largest, most consistently detectable object. The strong gradients of the rail make it the most distinct and detectable object in all of the camera views. However, gradients alone do not consistently detect ties, so texture classification is used to detect the tie closest to the camera.

We reliably differentiated ballast texture from non-ballast texture using Gabor filtering. Labeled examples of ballast, tie, and steel textures were created using previously stored images. Gabor filtering is applied to analyze the spatial frequencies, and the results are stored for each texture example. When presented with a previously unseen image, texture patches are extracted and classified as either “ballast” or “non-ballast”. Though the “non-ballast” area may contain edge noise due to occluding objects (e.g. leaves or ballast on ties), this method robustly provides a region that is centered on the tie. The rail is isolated, as is the part of the tie visible on the field-side of the rail (Figure 4). Though the boundaries are inexact, in all test images, the area is reliably isolated for subsequent processing.

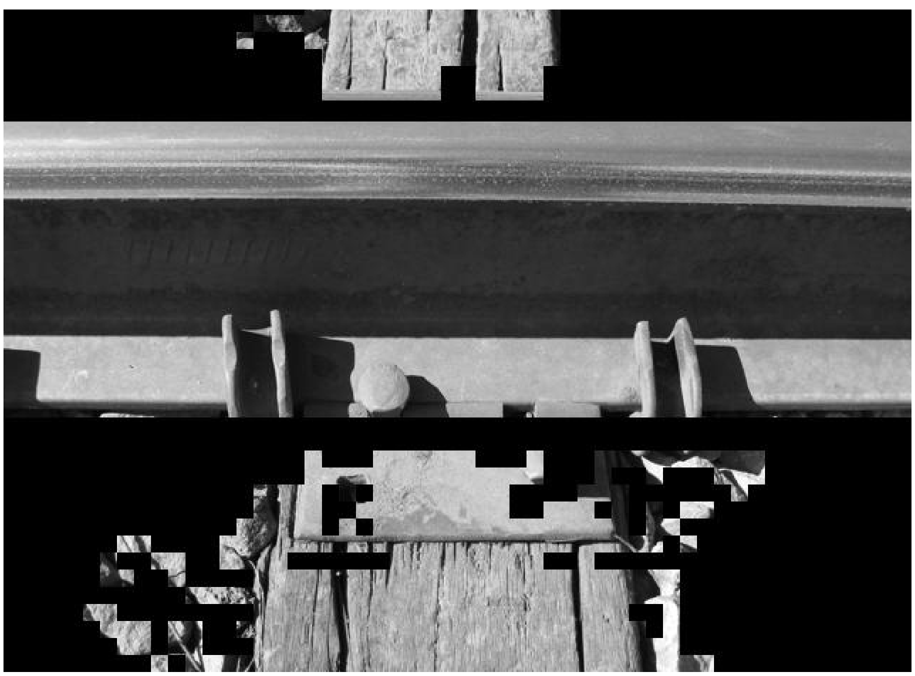


FIGURE 4 Isolated Non-Ballast Objects from FIGURE 3b

Anomalous objects from unforeseen circumstances, such as leaves, could interfere with this initial texture classification phase. For this reason, we will experiment with several machine learning methods to perform our texture classification in the presence of anomalies. We will experiment with Gaussian Mixture Models, which are a weighted combination of Gaussian probability distributions, to enforce a confidence-level on our texture classifications. As a result, a previously unseen object on the track will appear as an unknown/anomalous texture.

After isolating the foreground portion of the tie, an accurate boundary for both the tie plate and tie must be obtained to determine if an anchor has moved from its proper position. Also, if the tie plate is delineated (Figure 5), prior knowledge of the known dimensions of a tie plate can be compared to the image to calibrate its scale.

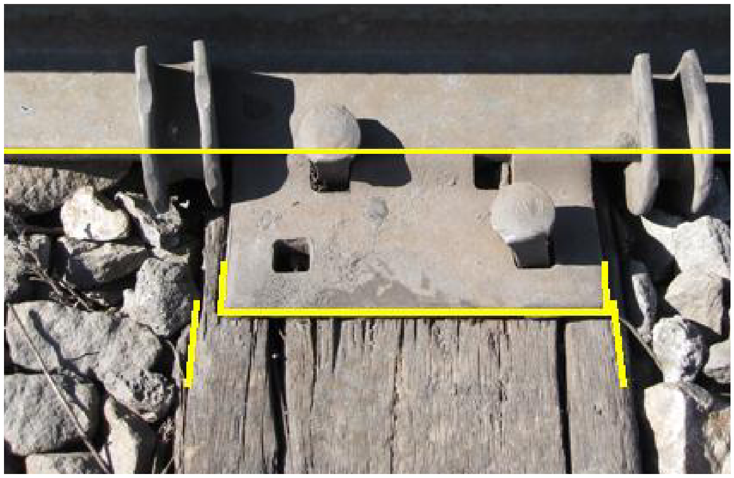


FIGURE 5 Delineated Tie Plate and Tie

Texture information is used to ensure that the rail-to-tie plate edge separates two steel textures, and that the tie plate-to-tie edge separates steel and tie textures. After delineation of the two horizontal edges, the vertical edges are found since they are reliably detected only if their search space is restricted. A restricted search space is needed because shadows, occlusions, and other unforeseen anomalies will cause unanticipated edges and shapes. The vertical tie edge is the dominant gradient that exists on both sides of the tie plate-to-tie edge, while the vertical tie plate edge is the dominant gradient that exists only above the tie plate-to-tie edge.

We will experiment with refining our classifiers based on the appearance of the specific type of track under inspection to further improve robustness to anomalous component appearances. The training on an initial set of videos will be done using labeled texture data and labeled components provided by a user through a process known as supervised learning. In the field, without the benefit of user-labeled data and user interaction, we will experiment with updating our model based off of the appearance of the components that we detect (i.e. unsupervised learning). For example, as ties are detected, Gabor features can dynamically update our tie texture model. This way, the feature values for the ties, tie plates and other components are accurate for that particular piece of track, since deteriorating conditions should affect several ties in the same location. To ensure that we are not accepting erroneous updates, we will only update after subsequent components have been successfully identified in a group. Then the features of the low-confidence texture areas can be added to the particular component model to increase its robustness.

Spike Inspection

The spikes are located with spatial correlation using a previously developed template (Figure 6). The search area for the spikes is limited after the tie plate and rail are both delineated because within this area, spikes will only be found in certain positions. These locations include a row of gauge spikes next to the base of the rail and another row of line spikes further from the rail. Since the search space is restricted for finding spikes, a low threshold can be set for the template response. Therefore, a spike with an anomalous appearance will be detected, since we have lowered the threshold for a template match. Missing spikes are detected by a two-dimensional filter that consists of a dark square surrounded by a steel-colored square. The color of the steel is extracted from the isolated tie plate. Our detection of spike heads is not yet robust due to environmental variability and different wear conditions, but when the search area is limited, the accuracy improves.

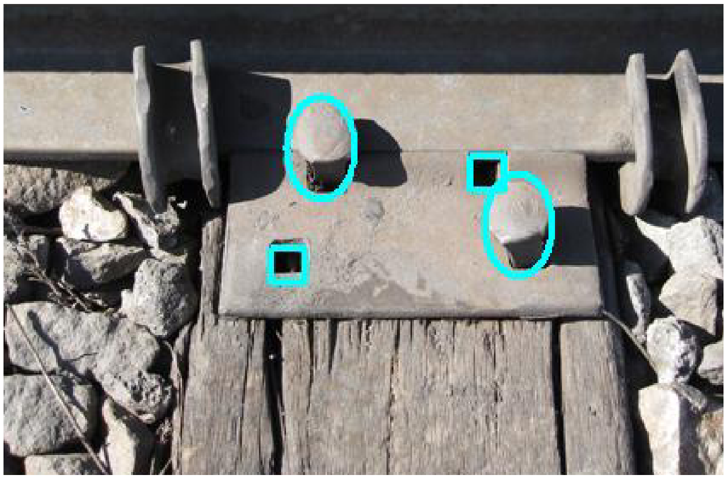


FIGURE 6 Spike Detection Results

Anchor Inspection

Rail anchors, when installed correctly, have more distinctive visual characteristics when viewed from the gauge-side compared to the field-side (Figures 3b and 3c), therefore, our anchor inspection primarily uses this view. The anchors are identified and the distance to both the tie and tie plate are measured (Figure 7). The search area for the anchors is restricted to where the rail meets the ballast on either side of the tie plate. Anchors are detected by identifying their parallel edges. Color intensity information is also included to ensure that parallel edges have similar intensity distributions. This scheme is robust to shadows, since shadows will result in similar intensity distributions for parallel edges in the same anchor. It is also robust to anchor rotation and skewing, since the parallel edges that we detect need not be vertical.

FIGURE 7 Anchor Detection Results

DISCUSSION

In order to obtain information needed for trending, diagnosis, and prediction of problems, inspections must be conducted at regular intervals. The duration of these intervals will vary depending on the particular component. We anticipate that the system we are developing could be mounted on one of three commonly used track inspection vehicles: track geometry cars, detector cars, or high-rail inspection trucks, each of which is operated at different intervals.

Determining the inspection frequency depends on a variety of factors. The two principal ones are the rate of track deterioration, which is generally estimated based on annual gross tonnage, and the normal track speed, which in turn determines the FRA track class. The FRA defines nine track classes, ranging from the lowest, Class 1, to the highest, Class 9 (*21*). Each class is defined by allowable operating speeds and maintenance tolerances relating to gauge, cross-level, and various other parameters.

Most Class I railroad mainline trackage is FRA Class 4 or 5 (*24*), so we first considered the FRA requirements for the most restrictive case, Class 5 track. High-rail inspections are required at least twice a week, with one calendar day in between inspections. Detector cars must be run at least once for every 40-million gross tons of traffic, and no less than once per year. There are no regulations pertaining to operation of geometry cars on Class 4 or 5 track. Railroads may run any of these inspection vehicles more frequently than required, based on the rate of track deterioration and their own criteria for safety and efficiency.

For an initial implementation, the inspection frequency provided by a detector car would be sufficient, and as an operational platform has an advantage over high-rail vehicles in that the crews that operate these are more accustomed to and have greater training with advanced inspection systems technology. Furthermore, these vehicles are already equipped to handle the large amount of data upload and storage that would be necessary for a machine-vision system. Once the system has been proven on detector cars, it will be adapted for use on high-rail vehicles.

CONCLUSIONS

The inspection of most railroad track components is currently conducted using manual, visual inspections. These are labor intensive and lack the ability to easily record and compare data needed for trend analysis. Moreover, they are subject to variability and subjectivity in different inspectors' abilities and interpretation of what they see. Also, it is impractical to catalog in detail the large number of track components manually, so 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.

The goal of this machine-vision system for track inspection is to supplement current visual inspection methods, allowing consistent, objective inspection of a large number of track components. Based on analysis of railroad accident statistics and input from subject-matter experts, we are focusing our initial research and development efforts on inspection of cut spikes, rail anchors, crib ballast, switch points, and other turnout components.

Our algorithms use edge detection and texture information to provide a robust means of detecting rail, ties and tie plates, which narrows the search area. Within this restricted area, knowledge of probable component locations allow the algorithms to determine the presence of spikes and rail anchors.

Future work involves refinement of the algorithms to improve the reliability of spike and anchor detection. In addition, we will conduct lighting experiments to achieve better results from the algorithms in adverse lighting conditions. Once the algorithms and lighting for inspection of spikes and anchors have been refined using the video acquisition cart, we intend to begin working on adapting the system for testing on a rail detector car.

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