USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No. 0281Y02

Machine Vision Inspection of Railroad Track

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DISCLAIMER

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TECHNICAL SUMMARY

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Machine Vision Inspection of Railroad Track

Introduction

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. One of the objectives of the research underway at the University of Illinois at Urbana-Champaign (UIUC) is to investigate the feasibility of using machine-vision technology to recognize turnout components, as well as the performance of algorithms designed to recognize and detect defects in other track components. In addition, 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. This and other research on railway applications of machine-vision technology at UIUC are interdisciplinary collaborations between the Railroad Engineering Program in the Department of Civil and Environmental Engineering and the Computer Vision and Robotics Laboratory at the Beckman Institute for Advanced Science and Technology.

Findings

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 derailment statistics and input from subject-matter experts, we are focusing our initial research and development efforts on inspection of cut spikes, rail anchors, and turnout components.

A Virtual Track Model was designed to generate synthetic images for the initial development of the machine-vision inspection algorithms. This simulation also provided a test-bed for selecting specific camera views, which would capture the components of interest, using virtual cameras placed in the simulation at locations consistent with track regulations and vehicle mounting conditions.

An image acquisition system was designed to capture video recordings of track components from a moving vehicle. This system uses a CCD video camera and ruggedized computer to obtain and store video on the track. The system will be augmented by adding lighting for adverse daylight conditions.

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 allows the algorithms to determine the presence of spikes and rail anchors even when there are variations in the appearance of the components.

The machine-vision algorithms require previously stored models of the textures and components. Therefore, dynamic updates are needed for the situations where the part of the track that is being investigated changes and also other situations where the components are changing appearance based on environmental or manufacturing differences. Central to this update method is the ability to detect and localize the periodically repeating parts. Using periodicity detection, and then implement the additional component localization step that was proposed where autocorrelation is applied to the Gabor frequency domain. The models will be updated using the results of this, which are inherently robust, since the detected periodicity relies on some consistent component being repeated.

Recommendations

Future work involves refinement of the algorithms to improve the reliability of spike and anchor detection. Anomalous objects from unforeseen circumstances, such as leaves, could interfere with this initial texture classification phase. Consequently, experimentation with several machine-learning methods to perform component detection in the presence of anomalies is recommended. Work is continuing on processing the over-the rail view and merging results from this view with the lateral view to increase the accuracy of the identified defects and the estimated measurements. Once the algorithms and lighting for inspection of spikes and anchors have been refined using the video track cart, further experimentation will be needed on adapting the system for testing on a high-rail vehicle.

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CHAPTER 1. INTRODUCTION

1.1 Background and motivation

North American Railways and the United States Department of Transportation (US DOT) Federal Railroad Administration (FRA) require periodic inspection of railway infrastructure to ensure the safety of railway operation. This inspection is a critical, but labor-intensive task resulting in large annual operating expenditures and it has limitations in speed, quality, objectivity, and scope. A machine vision approach is being developed to automate inspection of specific components in the track structure. The machine vision system consists of a video acquisition system for recording digital images of track and custom designed algorithms to identify defects and symptomatic conditions from these images, providing a robust solution to facilitate more efficient and effective track inspection. The main focus of the system is the detection of irregularities and defects in wood-tie fasteners, rail anchors, and turnout components. An experimental on-track image acquisition system has been developed and used to acquire video in the field of different track classes. The machine-vision algorithms use a global-to-local component recognition approach, in which edge and texture-based detection techniques are used to narrow the search area where components are likely to be detected. The system will be designed to evaluate the railway infrastructure in accordance with FRA track safety regulations, but will be adaptable to railroad-specific track standards. In the future, defect analysis and comparison with historical data will enhance the ability for longer-term predictive assessment of the health of the track system and its components, more informed and proactive maintenance strategies, and improved understanding of track structure degradation and failure modes.

1.2 Study objectives

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 and consumes valuable track capacity. The objective of the 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. These interim solutions include video capture using vehicle-mounted cameras, image enhancement using image processing software, and assisted automation using machine-vision algorithms.

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. Heavy axle loads and high traffic volumes necessitate frequent inspection and more stringent maintenance requirements, but present railroads with less time to accomplish it. Additionally, 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. Although the primary focus of this research is the inspection of high-density track, algorithms are also being tested on lower track classes to ensure robustness to component variability and condition. The algorithms currently under development will also be adaptable to many types of track (and track components), including transit and some components in high-speed rail (HSR) infrastructure.

A machine vision system is being developed to automate, or enhance, the visual inspection of track and track components. Machine vision algorithms are being designed to recognize track components, identify their proper location and condition, and detect and quantify the extent of the defects found. Equipment to aid in the development of the this system consists of a virtual computer model of the track, image acquisition hardware, and a platform for obtaining video of actual components of in-service track from local railroads.

The machine vision system designed for this project was developed through an interdisciplinary collaboration 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, at the University of Illinois at Urbana-Champaign.

CHAPTER 2. DETERMINATION OF THE INSPECTION TASK

2.1 *Review of Related Inspection Technologies*

Prior to commencing work on this project, we conducted a survey of existing technologies for non-destructive testing of railroad track and track components (1, 2, 3, 4). This survey provided insight as to which tasks were best suited for vision-based inspection and were not already under development or in use within the railroad industry. This survey encompassed well-established inspection technologies (e.g. ultrasonic rail flaw and geometry car testing) and more experimental technologies currently under development (e.g. inertial accelerometers).

Out of the technologies we surveyed, machine vision is the most applicable technology to our present scope of work given the manual, visual nature of current track inspections. 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 cracks in the rail, rail profile, track gauge, intermodal loading efficiency, railcar structural components, and railcar safety appliances (1-10). 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 Center, and the Transportation Research Board (TRB) High-Speed Rail IDEA Program (6, 7, 8, 9, 10).

2.2 *Railway Machine-Vision Inspection Systems*

Railway applications of machine-vision technology that were previously developed or are under development at UIUC have three main elements (Figure 1). The first element is the image 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 that identify specific items of interest and assess the condition of the detected items. The final component is the data analysis system, which compares and verifies whether or not the condition of track features or mechanical components comply with parameters specified by the individual railroad or the FRA. This component will also record and compare data needed for trend analysis.

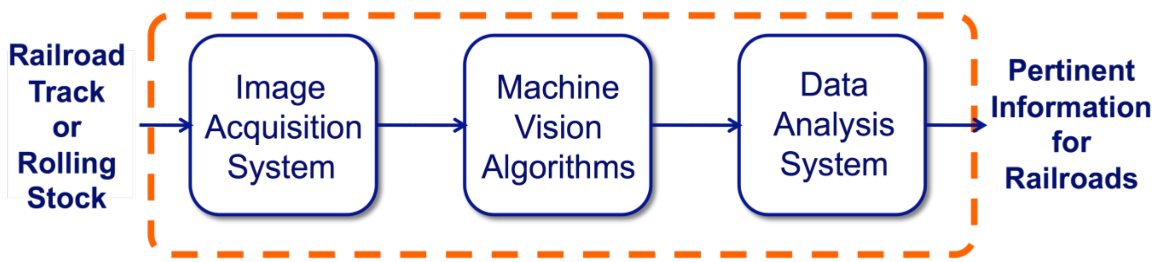


Figure 1. Primary Components of a Machine Vision System

The advantages of machine vision include greater objectivity and consistency as compared to manual (i.e. visual) inspection, and the ability to record and organize large quantities of visual data in a quantitative format. Gathering and organizing quantitative data facilitates analysis of the health of track or vehicle components over both time and space. 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 (e.g. unique track components) and the need to control or augment variable outdoor lighting conditions typical of the railroad environment.

2.3 *Determination Of Inspection Tasks*

2.3.1 **Prioritization Based on FRA Accident Statistics**

Safe and efficient network operation is of utmost importance to the rail industry. In order to determine which components are most critical to the safe operation of trains, an analysis of the FRA Accident Database was conducted (1, 2, 3, 4, 5, 11, 12). The initial approach, which was based on the frequency of derailments, revealed that the priorities for inspection with machine vision were buckled track, switch points, and other turnout defects (1, 2, 3). Although this approach is valid, other variables (e.g. the number of cars derailed) can provide additional information on the risk associated with a derailment caused by a specific track component (13). Therefore, we selected "number of cars derailed" as a proxy for the consequence of a derailment, and used these data in a risk-based prioritization approach.

The initial data analysis approach for this project used track derailment data from 1998 to 2009 and classified the data into five FRA-established categories (Figure 2). Some components, such as those associated with roadbed and geometry, are currently being inspected by other technologies including track geometry cars and ground penetrating radar (GPR). For this reason, defects associated with categories one (rail, joint bar and rail anchoring) and three (frog, switches and track appliances) were selected for further prioritization and inspection using machine vision. Most of these components are currently inspected using manual, visual inspection and may be amenable to machine vision inspection, thus they were selected for further consideration (1, 2, 3).

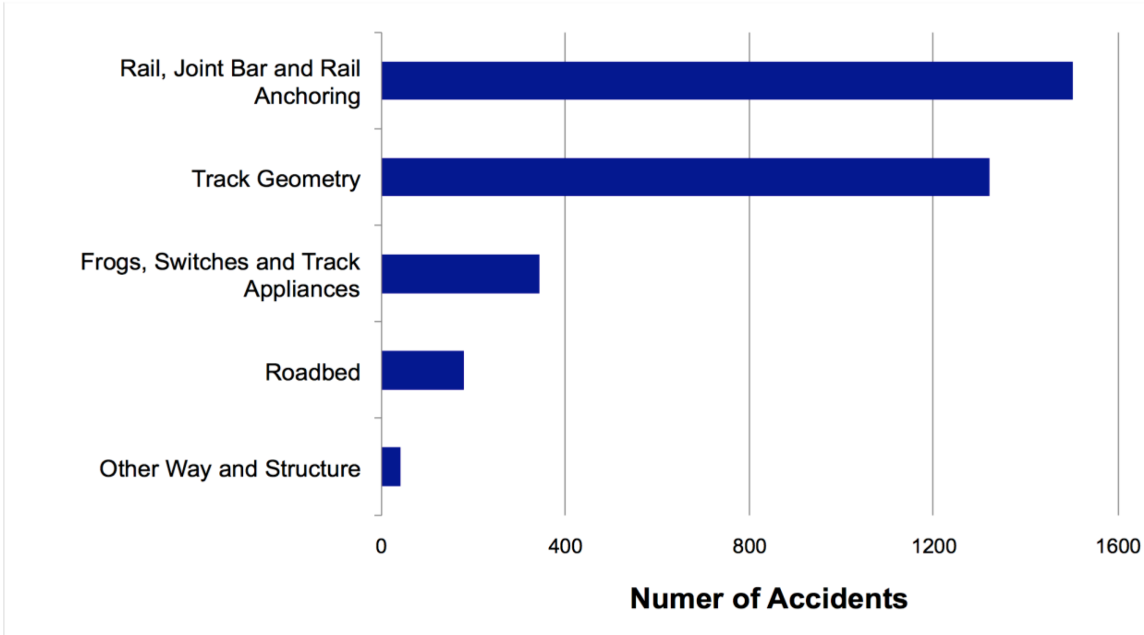


Figure 2. Top Track Related Derailment Causes by Track Category from 1998-2009

2.3.2 Track Component Inspection Prioritization

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

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

Beyond the current scope of work listed above, track components and inspection tasks that have been identified for future machine-vision research include measuring tie spacing, identifying insulated joint slippage, monitoring wayside rail lubricator performance, recording rail manufacturing markings, determining thermite weld integrity, and monitoring track circuit bond wire condition.

2.3.3 **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 (5, 13). 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 3 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.

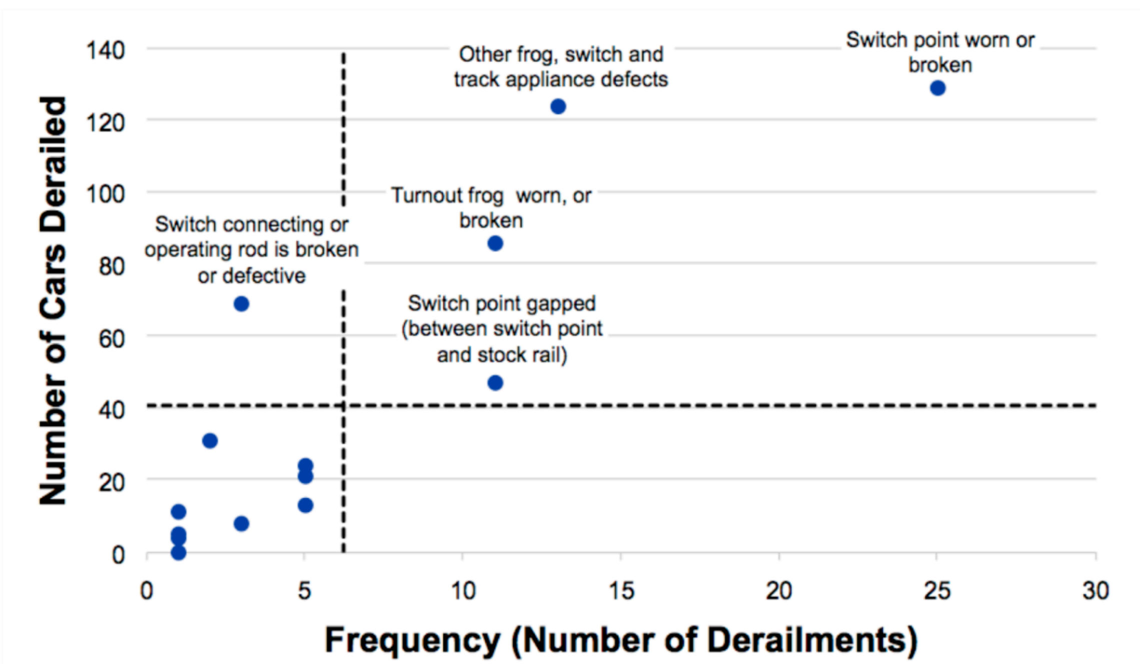


Figure 3. Railroad Track-Caused Derailments by Cause Severity on Track Classes 4 and 5, from 1998 – 2009.

Each quadrant in Figure 3 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 risk and 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.

2.4 Inspection Guidelines

A thorough understanding of the specific track components and defects associated with them was gained prior to developing the machine-vision algorithms. We used the

FRA Track Safety Standards, Class I track engineering standards, and the Track Safety and Condition Index (TSCI) to determine guidelines and procedures used for track inspection (14, 15, 16, 17). Example guidelines for the algorithms include the height of a spike above the base of rail that would constitute a raised spike and how many spikes need to be raised before they would be considered critical. Similar considerations were developed for inspection of anchors and turnout components, taking into consideration the expertise of track inspectors, researchers, and track maintenance managers at Class I railroads.

CHAPTER 3. DATA COLLECTION

3.1 Image and Video Acquisition

Collecting images and video of components to be inspected is a critical part in the development of the machine vision system. There are important trade-offs between where the components to be inspected are located in the view, how many components can be seen in a single view, and also what views are required to perform the desired inspections. Views of the components must not only show the entire component in its functional situation, but also be conducive to obtaining 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.

Once viewing angles are determined, another challenge is to collect images of components that are deformed or defective. However, due to the scarcity of defects, the number of violations that can be found locally are far fewer than the examples needed to properly develop a machine vision system. Therefore, methods for finding or creating these conditions must be addressed.

A final consideration is the need to obtain continuous video of the track sections of interest using equipment such as high-rail vehicles and geometry cars, which are two possible implementation vehicles for the final system. Long video sequences are also needed to develop the machine vision algorithms to extract images and test the component identification success rates under realistic environmental conditions, thus an experimental mobile camera system was envisioned.

3.1.1 **Virtual Track Model for Initial Algorithm Development**

An important consideration in the development of the image acquisition system is the placement of cameras to acquire suitable images of desired components in their functional settings. Securing time to test the image acquisition system on active track during the developmental phases proved difficult, so a virtual track model (VTM) was created. The VTM used American Railway Engineering and Maintenance-of-Way Association (AREMA) recommended practices for the design of track components to model FRA Class 4 and 5 track and included sections of both tangent and curved track (18). AAR clearance plates were incorporated into the VTM to ensure camera placements were in feasible locations (19).

The angles of the virtual cameras were then adjusted until they enabled viewing of the relevant track components and allowed assessment of the conditions of interest that were conducive to algorithm development. The VTM camera view experimentation resulted in the selection of two initial camera views: the lateral view (Figure 4A) and the over-the-rail view (Figure 4B) (1, 2). The lateral view provides a good view of tie plates, spikes and anchors. The over-the-rail view provides perpendicular views of the spike and anchors to combine with the lateral view for increasing the accuracy of the measurements. In addition, it also provides a view of the ties for future inspection tasks.

A: Lateral view showing view of simulated track and tie plate

B: Over-the-rail view showing both sides of the simulated tie plate and crib ballast

Figure 4. Virtual Camera Views

The virtual cameras were then used to generate synthetic images of the components in the simulation from the selected camera locations. These images were used for initial development of the machine-vision algorithms. They provided insight into challenges such as lighting and variation in component design, which allowed us to test the initial algorithm's ability to identify specific track components.

Using the VTM the brightness and direction of the simulated sunlight was adjusted to test the algorithm's effectiveness in the presence of over saturation and shadows. The over saturation condition caused problems in the algorithms that discriminate the ballast from the ties, since the brightness caused the ballast to lose its characteristic texture, thus making it difficult to discriminate the ballast and tie textures. When localizing the base of the rail in the lateral view, the shadows were problematic for initial algorithms that relied only on edge detection, since the shadows created edges at the shadow boundaries. However, algorithms incorporating texture identification into edge detection were developed and were more effective.

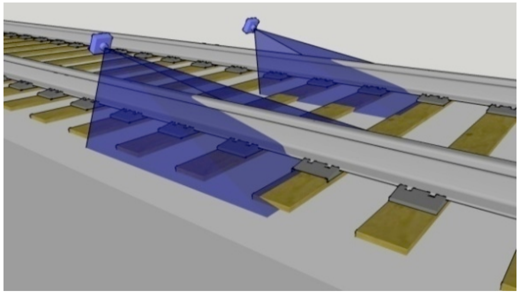
Defects were simulated with the VTM to understand how different camera views influenced the algorithm's ability to locate and detect these defects of differing types. On a stretch of simulated track, a series of spikes were raised to varying heights and anchors were moved out of position to simulate actual defect scenarios. These images were used to test the localization of out of place components and the measurement capabilities of the inspection algorithms. However, the amount of time devoted to the simulation development is significant, in order to provide the realism needed for robust detection in the field under environmental circumstances, so a system was developed for field video acquisition.

3.2 Track Cart for Field Video Acquisition

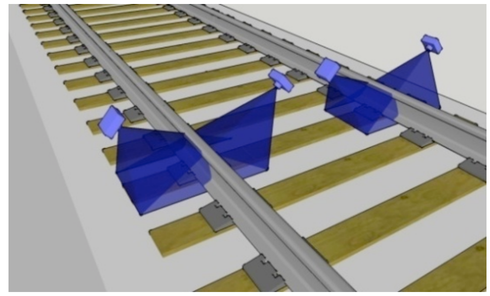
Beyond the virtual images, a method to capture video that would be representative of future cameras attached to a track inspection vehicle, was needed for further development of the machine-vision inspection algorithms. For this reason, and the need to minimize the use of high-rail vehicles and mainline track capacity, an experimental data acquisition system referred to as the Video Track Cart (VTC) was designed for collecting continuous video of track sections of interest on low-density track (**Error! Reference source not found.**). This additional track time allows for field adjustments of a variety of parameters, such as focus, shutter speed, and camera views.

Figure 5. a) The VTC Data Collection and Experimentation with Lighting at the Monticello Railroad Museum with NEXTRANS Interns Matt Toussaint ('09) left, and Mark Asmuth ('10) right, with John M. Hart, NEXTRANS Mentor ('09) and Advisor ('10), and b) Mark Asmuth, Matt Toussaint, and Luis Fernando Molina, NEXTRANS Mentor ('10), collecting data on Norfolk Southern track.

Two camera views are being used to record images of components on each side of the rail: an over-the-rail view and a lateral view. The over-the-rail view is captured parallel to the longitudinal axis of the track (Figure 6A). This view is used for measuring the distance between the spike head and the base-of-rail and verifying spiking patterns, also to measure the distance between switch points and stock rail, and identify worn or broken frog points. The lateral view is taken perpendicular to the rail (Figure 6B). The base of the rail and fastening system are visible from this view and is used for measuring the distance between the rail anchors and the edge of the ties and verifying anchor patterns. In addition, is also used to identify missing bolts/cutter pins and worn or broken switch points in turnouts.



A: Over-the-rail View



B: Lateral View

Figure 6. Initial Camera Views

3.3 Autonomous Imaging Hardware

There are three main components that were considered in developing a video acquisition system: the camera, lens, and computing hardware. In selecting a camera, the critical specifications are frame rate, shutter speed, and image resolution. The values necessary for frame rate and shutter speed are dependent on the speed at which the VTC is moving. For initial algorithm development at low speeds, a camera capable of 30 frames-per-second and a shutter speed of at least 1/500 seconds was sufficient. The required resolution is determined by the smallest component feature to be identified or the accuracy required in defect measurements. The close positioning of the cameras to the components, the large size of the components to be inspected, along with the 1/8 to 1/4-inch accuracies required, indicate a standard VGA resolution camera would be adequate.

Several factors are considered for the camera lens selection, such as distance of the camera from the subject, depth of field requirements, and the lens distortion. The depth of field suitable for use in the over-the-rail view is the most important consideration because the track appears in both the foreground and background in this view. The camera placement is restricted to the allowable areas found in the VTM, which are placed at a distance practical for track vehicle mounting and within the AAR-required clearance plates. This suggests a wide-angle lens that will provide a full view of the components of interest and their surrounding area, but can also be placed relatively close to the components themselves. However, the use of very wide-angle lenses can induce a significant level of distortion around the edges of the image, thus a trade-off is required.

Many factors were considered in the selection of the laptop computer used for recording data in the field to ensure adequate performance while moving along track in the outdoor environment. The most important factor was the ability to record video without dropping (or missing) video frames. For hard drive access, a high-performance, single-level-cell, solid-state hard drive is the optimal choice as it provides speed, reliability, low power consumption, and low access times. Standard hard drives also suffer from reduced performance when fragmented. A high-contrast screen was also necessary for viewing in bright outdoor environments. A degree of ruggedness is required to reliably use the equipment in track situations that induce vibration and shock and under a variety of environmental conditions, such as dust and rain.

The selected equipment for video data collection was a Dragonfly®2 DR2-COL camera. 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 (20). The camera is equipped with a 6 mm wide-angle lens. The laptop selected has Microsoft Windows XP Professional, 4 GB of RAM, an Intel® Core ™ 2 Duo P9600 2.66 GHz processor, and an Ultra Performance Solid State Drive (Figure 7).

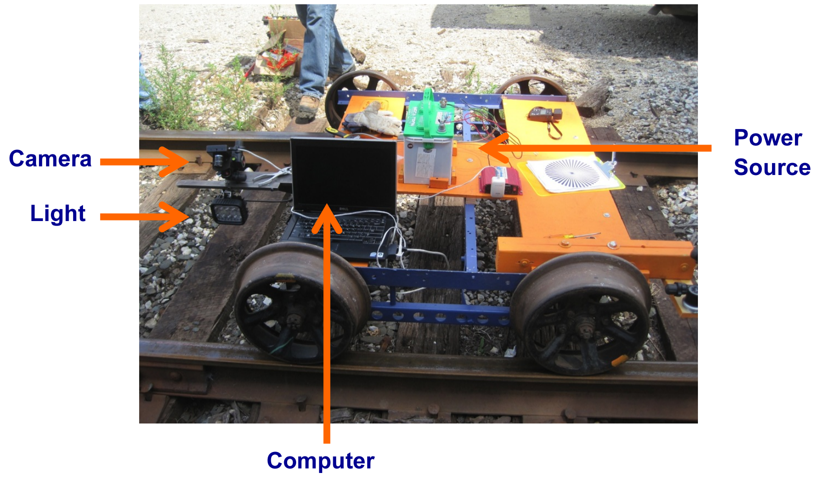


Figure 7. Autonomous Imaging Hardware

The initial field data collection required a mobile power source to provide power to the cameras and the laptop. A Mega-Tron SRM-27 marine deep cycle battery was selected that has the capability of steadily powering electronics drawing up to 10 amps of power for 4-5 hours. The power is supplied to the equipment through a DC to AC converter, which transforms the 12volts (battery) to 110VAC (regular North American outlets).

The VTC has been used on low-density track, where track occupancy time is easier to obtain. Many video recording sessions have taken place at a local railroad museum where the system was modified based on the results of field experimentation. A significant amount of videos were also collected on Class I railroad track. Long stretches of tangent track with varying conditions, including variations in natural lighting, vegetation, and differing ballast types were encountered and are valuable for determining statistics on consistent component recognition under these realistic field conditions. Substantial video of turnouts, with the VTC approaching the turnouts from each possible direction was obtained and is being used to experiment with identifying the transition between the tangent and turnout sections of track to invoke the appropriate inspection algorithm.

3.4 Approach to Lighting Challenges

In the lateral view, improvement in the contrast is needed to distinguish spikes more clearly from the background of the rail, which is the same color and texture. When spikes are raised they tend to blend in and are more difficult to identify and measure. This can be enhanced by increasing the exposure of the image during acquisition, however when the ballast is light in color (white or grayish) it tends to become overexposed, causing difficulty with the texture detection phase. Currently, we are experimenting by adding lights to the VTC to further illuminate only the upper area of the image where the rail and spikes are located, but not the lower area where the ballast is closest to the camera.

To achieve this we are investigating LED type lighting that will not require a significant amount of wattage, and will be able to be powered by our VTC on-board battery system (Figure 8). This should improve the consistency and reliably in detecting the components of interest against a similar type background (Figure 9).

A: Light off **B:** Light on

Figure 8. Effects of The Lighting on The Web Of The Rail

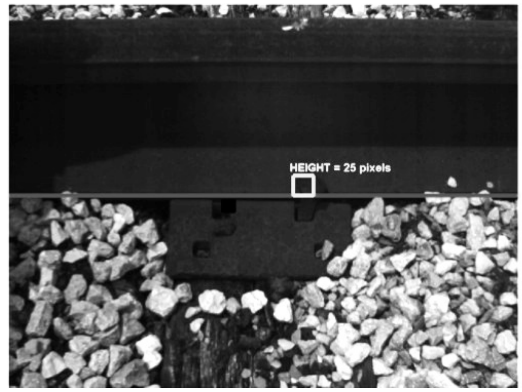


Figure 9. Video frame taken with LED light and processed by the machine vision algorithms showing successful detection of a spike head and its distance from the rail.

3.5 Current Additions to the VTC

The VTC currently requires an operator to propel it along the track to ensure a consistent speed. To keep the cart moving at a more consistent rate, a motor and position encoder is being added to the Video Track Cart, the speed will be maintained by a position-integral-differential (PID) controller. In addition, a Global Positioning System (GPS) device is also being interfaced to the laptop to mark the areas inspected and, combined with the encoder, the location of the defects found.

CHAPTER 4. ALGORITHM DEVELOPMENT AND DATA ANLYSIS SYSTEM

4.1 Track Inspection Algorithms

Early algorithm development focused on spike and anchor 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 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 the 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 material types or 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 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 (21). Image gradients (edges) should be consistent among differing ties and rails, but unanticipated track obstacles could create unanticipated edges, causing difficulty for the algorithms. For this reason, texture information from the ballast, tie, and steel was incorporated into the 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 (21).

4.2 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. Then, we differentiate ballast texture from non-ballast texture using Gabor filtering. Labeled examples of ballast, tie, and steel textures were created using previously stored images (Figure 10). When presented with a previously unseen image, texture patches are extracted and classified as either "ballast" or "non-ballast". This classification incurs some errors due to foreign objects and other image noise, and the patches do not necessarily occur on object boundaries. Though the boundaries are inexact and the classification imperfect, in all test images, the tie, rail, and ballast areas were reliably isolated for subsequent processing.

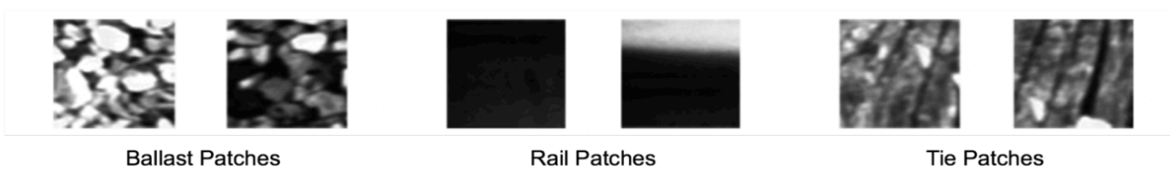


Figure 10. Template Images of Specific Ballast, Rail, and Tie Textures Used for Image Processing

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, when the tie plate is delineated, prior knowledge of the dimensions of the tie plate can be compared to the image to calibrate its scale for defect measurement estimations.

The major delineations are performed in the following sequence (Figure 11): (a) horizontal rail-to-tie plate, (b) horizontal tie-to-tie plate, (c) vertical tie-to-tie plate on left and right side, and (d) vertical tie-to-ballast on left and right side. Texture information is used to ensure that (a) the rail-to-tie plate edge separates two steel textures, and that (b) the tie-to-tie plate edge separates steel and tie textures. After delineation of the two horizontal edges (a) and (b), the vertical edges (c) and (d) 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 (c) tie-to-tie plate edges are the dominant gradients above the (b) horizontal tie-to-tie plate edge, and the vertical (d) tie-to-ballast edges are the dominant gradients below the (b) horizontal tie-to-tie plate edge. These edges delineate the tie plate area.

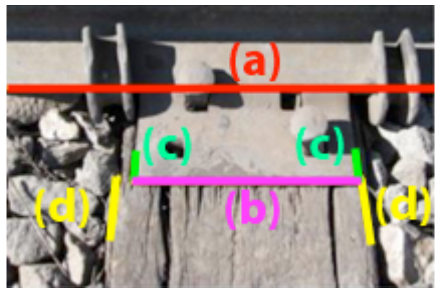


Figure 11. Major Delineations of Lateral View

4.3 Spike and Anchor Inspection

The spikes are located with spatial correlation using a previously developed template (1, 2). 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. Rail anchors, when installed correctly, have more distinctive visual characteristics when viewed from the gauge-side as compared to the field-side, therefore, our anchor inspection primarily uses this view (1, 2). The anchors are identified and the distances to both the tie and tie plate are measured. 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 (1, 2).

4.3.1 **Video Processing - Over-the-rail View**

The over-the-rail camera view can be used in conjunction with the lateral view to assist in the identification of spikes and tie plate holes and can aid in estimating the distance a spike is raised above the base of rail. For processing this view, we apply the same basic approach as is used for the lateral view. The algorithm first estimates the tie locations, then delineates the base of the rail, identifies the location of the ties and tie plates, and finds the spike heads and tie plate holes.

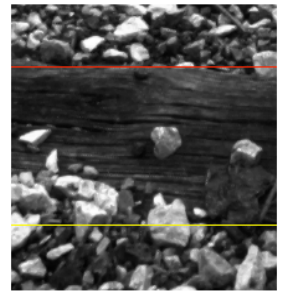
We inspect the individual video frames and process them independently. The items are inspected when they appear near the center of the images, thus minimizing the effect of lens distortion. The inspected items are not in the exact center of the image because the lower half of the image provides a more desirable viewpoint as compared to the exact center. However, the borders of the image remain unprocessed to avoid introducing distortion to the algorithm. With this approach, the results are compiled and superimposed onto the original video.

An evaluation will be made between the panoramic and video processing approaches to provide documented information on the advantages and disadvantages of each approach to help guide users and developers of a machine-vision track inspection system.

4.3.2 **Tie Location Estimation**

The estimation of tie location is performed using the texture procedures described earlier for discriminating ballast textures from non-ballast textures. This produces the images seen in Figure 12, showing the detection of texture patches of the respective types; white patches representing ballast and black patches representing all non-ballast areas. Next, a "tie filter", consisting of a rectangular strip of non-ballast patches, is used to isolate the tie in the black and white patched image, thus delineating the tie location. The frames containing a tie in the foreground produce the maximum response values to the “tie filter”, and this occurs periodically with respect to time as the video frames are processed.

A: Texture Classified Image in Which White Squares Represent Ballast and Black Squares Represent Non-ballast Areas

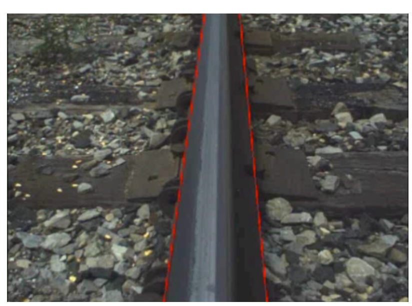


B: Tie Location Found Using Tie Template

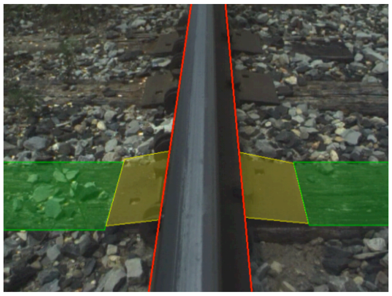
Figure 12. Texture Detection

4.3.3 **Location and Delineation of the Rail - Over-the-rail View**

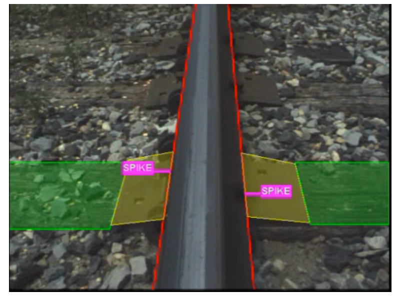
The rail is identified in the video by finding an area of low intensity difference between consecutive frames due to the consistency of the appearance of the rail compared to the changing ballast and ties. This step coarsely estimates the location of the rail in the center of the image. Using this estimation, each frame is further processed by finding the image gradients near the boundary of the identified area to refine the location of the edge at the base of the rail (Figure 13A).



A: Delineation of the Base of the Rail from the Over-the-rail View Using the Strong Gradient Produced by the Edges of the Rail in the Foreground Against the Sections Containing Ballast and Ties in the Background



B: Delineated Tie and Tie Plate Location Estimations



C: Component Identification Using Gradient Templates Inside the Restricted Search Area

Figure 13. Over-the-Rail Image Capture and Analysis

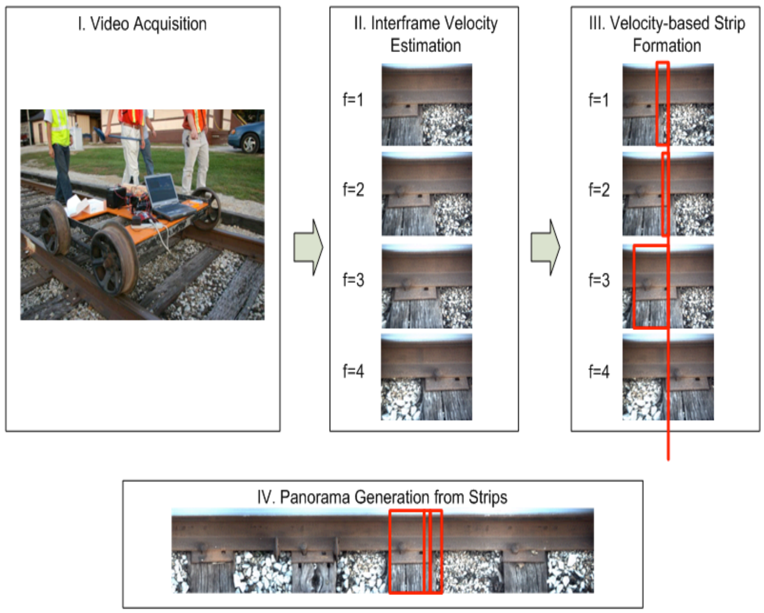
4.3.4 **Delineating the Ties**

After the location of the rail edge has been determined, lower level texture processing can be used to find the ties and tie plates. Using the methods described in the "Image Decomposition" section, the ballast and tie texture patches can be classified. Next, the ballast-to-tie edges are found using this texture information and the tie-to-tie plate edges are then found using their strong gradients (Figure 13B). With the area of the tie plate restricted by the previous steps, the spike head, tie plate holes, and potential defects can be found by using gradient templates in the search area (Figure 13C).

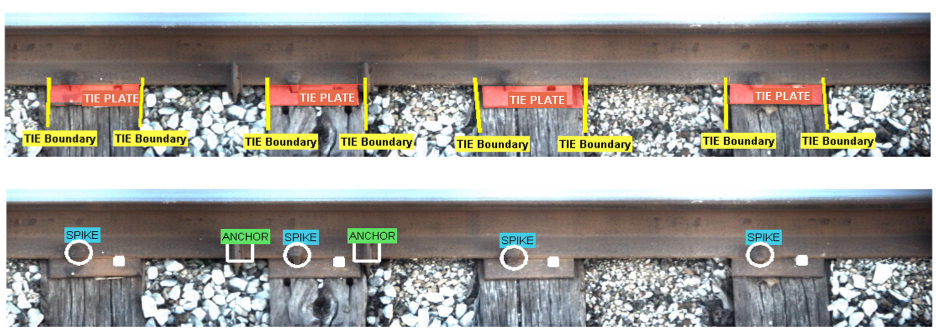
In the video processing method, knowledge about defects in the surrounding track can be traced by numbering ties as the algorithm isolates them, and storing their respective health information. In addition, tie health details can be superimposed on the video frames and the video reassembled so it can easily be viewed, interpreted, and confirmed by a human operator. As these two methods are refined, they will be integrated for verifying the defects and increasing the accuracy of measurement estimates.

4.4 Track Component Defect Detection and Panorama Generation

Panoramic images aid in visualizing defects and can be used in the future to provide a chronological record of track conditions (Figure 14).



A: Panorama Generation Using Velocity Estimation for Accurate Panoramas



B: Tie, Tie Plate, Anchor and Spike Delineation on Test Panorama

Figure 14. Panorama Generation for Track Component Detection

Algorithms generate panoramas from video data by selecting vertical strips from the center of the frames, thereby minimizing the effect of distortions and perspective differences, which become more severe as the distance between the component and the center of the image increases (Figure 14A). After the video is acquired, the first step performed by the algorithm is velocity estimation, which detects the distance the camera moved between consecutive frames. This velocity information is used to determine the size of the strip required from each frame to construct accurate panoramas at a variety of data collection speeds. These strips are then appended to each other to create the final panoramic image. Once the panorama is generated, the results of the component inspection can be superimposed onto it (Figure 14B). Alternately, the inspection can take place on the panorama itself by detecting the appropriate search areas, and subsequently recognizing the components and detecting defects.

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).

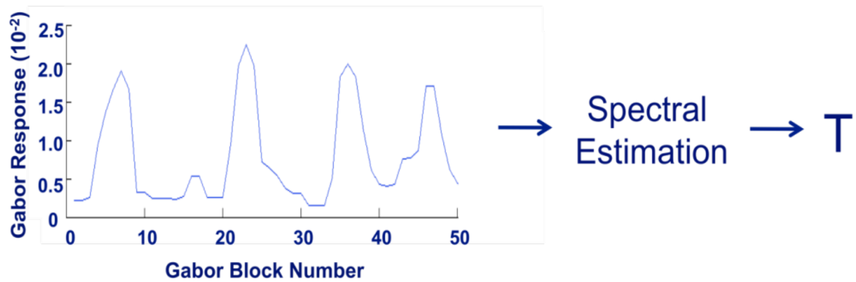
4.6 Approach for Turnout Inspection

Components in turnouts differ in both size and shape from those found in normal track. For that reason is important to know what section of the track the system is measuring – either within special track work or on tangent or curved track outside of turnouts. To accomplish this, the system looks for periodic components (T), such as frog bolts or joint bar bolts (Figures 16A).

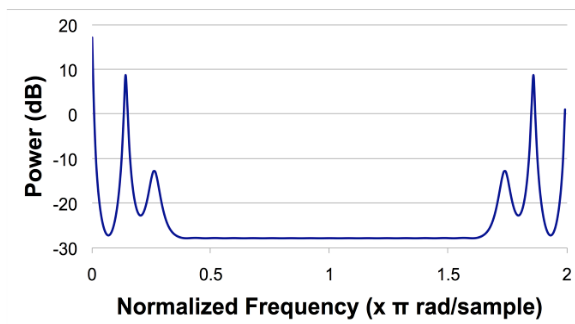
A: Original Image Switch Point Bolts

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 15. Turnout Component Recognition

The estimation of periodic component location on turnouts is carried out by converting the video of the mid-rail area into a panoramic mosaic (Figures 16B). The periodicity of the components in the panoramic mosaic must be 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. 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 (21).

The image is transformed in a block-wise manner into the Gabor frequency domain (Figures 16C). Each block's height is identical to the height of the mid-rail area of Figure 16B, and each block's response is computed using an overlapping width of one-half its height with its right neighboring block (Figure16C). This block-wise Gabor response is then processed as a one-dimensional signal (Figure 16D). Spectral analysis is subsequently performed to find periodic components (Figure 16E). Spectral analysis is a technique in which a received signal is analyzed for the frequency components that it contains. We used the Multiple Signal Classification (MUSIC) algorithm because of its ability to extract frequencies from a signal containing multiple superposed signals of different frequencies (22).

The MUSIC algorithm outputs a frequency analysis, where the input signal's frequency response is computed for each frequency (Figure 16E). Dominant frequencies are then detected. The output of Figure 16E 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 $\omega = 0.14\pi$, the component repeats every T=14.3 blocks (23). This is a satisfactory approximation since the distance between bolts is not always constant (Figure 16A), 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 16B).

Spectral estimation provides frequency detection, but not phase estimation. Because of that, 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 16C). The autocorrelation between a candidate block and all blocks that are nT blocks apart would be measured, where n is some positive integer. Blocks that yield a strong Gabor response and that are highly correlated to blocks nT away would be considered repeating components

Algorithms such as the one presented here, which identifies parts of the track, will become valuable as various inspection algorithms are honed for specific parts of the track, such as turnouts.

CHAPTER 5. CONCLUSIONS

This chapter summarizes the research, highlights its contributions, and proposes directions for future research.

5.1 Summary

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 needed for trend analysis. Moreover, they are subject to variability and subjectivity in different inspectors' abilities and interpretation of what they observe. Also, 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.

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 derailment statistics and input from subject-matter experts, we focused our initial research and development efforts on inspection of cut spikes, rail anchors, and turnout components.

A Virtual Track Model was designed to generate synthetic images for the initial development of the machine-vision inspection algorithms. This simulation also provided a test-bed for selecting specific camera views, which would capture the components of interest, using virtual cameras placed in the simulation at locations consistent with track regulations and vehicle mounting conditions. We were also able to easily simulate poor track conditions by raising spikes and shifting anchors for the system to identify.

A Video Track Cart provides a means for collecting continuous video data of low-density track from various local railroads. It also enables experimentation with camera views, adjustment of camera parameters, and lighting under various environmental conditions in a manner analogous to what will be required when attaching the system to track inspection vehicles. Future methods for synchronizing the camera views to identify the same component within the two videos will be investigated and incorporated on the vehicle.

An image acquisition system was designed to capture video recordings of track components from a moving vehicle. This system uses a CCD video camera and ruggedized computer to obtain and store video on the track. The system will be augmented by adding lighting for adverse daylight conditions (e.g. shadows and low contrast areas) that inhibit the machine vision algorithm performance.

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 allows the algorithms to determine the presence of spikes and rail anchors even when there are variations in the appearance of the components.

5.2 Future research directions

Future work involves refinement of the algorithms to improve the reliability of spike and anchor detection. 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 component detection in the presence of anomalies.

The machine-vision algorithms require previously stored models of the textures and components. We will experiment with dynamically updating the existing models. Dynamic updates are needed for the situations where the part of the track that is being investigated changes (e.g. closure area followed by a switch area) and also other situations where the components are changing appearance based on environmental or manufacturing differences. Central to this update method is the ability to detect and localize the periodically repeating parts. This will be accomplished in a manner similar to what is demonstrated in the "Turnout Component Recognition" section. We will detect periodicity, and then implement the additional component localization step that was proposed where autocorrelation is applied to the Gabor frequency domain. The models will be updated using the results of this, which are inherently robust, since the detected periodicity relies on some consistent component being repeated.

Work is continuing on processing the over-the rail view and merging results from this view with the lateral view to increase the accuracy of the identified defects and the estimated measurements. Once the algorithms and lighting for inspection of spikes and anchors have been refined using the video track cart, the next step is to adapt the system for testing on a high-rail vehicle.

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