TECHNOLOGY DIGEST
TD-09-032
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# Machine Vision Inspection of Railroad Track

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**Summary**

In a project to develop machine vision technology, researchers at the University of Illinois at Urbana-Champaign (UIUC) have developed algorithms to detect the rail, tie plates, ties, cut spikes, rail anchors, and ballast using a global-to-local algorithmic approach. This approach uses low-level features such as image gradients and textures to provide robust detection of more consistent features, such as the rail; then it uses these features to resolve a restricted search area to find components with greater visual variation, such as cut spikes and anchors. The spikes and anchors are then found in these restricted search areas using spatial template matching. UIUC researchers use the detection algorithms on panoramic images generated from videos to further increase their accuracy. Panoramas also allow interim approaches to inspection using digital images and human inspectors before full machine vision algorithm development and implementation.

The algorithms developed to detect basic track components are capable of accomplishing the following track inspection functions:

- Missing components, such as tie plates, rail fasteners (e.g., cut spikes, rail anchors): The location and number of missing components can be determined.
- Components out of place, such as raised spikes or shifted rail anchors: The relative distance of each component from its nominal location can be determined.
- Amount of ballast in the cribs between ties: A relative measure of ballast level below the top of tie can be determined.
- Tie count and tie spacing: Counts of components per length of track and spacing and dimensions of components may be determined with the appropriate number of cameras and angles.

The machine vision based inspection system will be adaptable to meet FRA track safety regulations and railroad-specific track standards that may involve additional parameters of interest. Because data will be stored digitally, recall capabilities will enable quantitative comparisons and trend analyses. These will facilitate long-term predictive assessment of the health of the track system and its components and will lead to more informed preventative maintenance strategies and a greater understanding of track structure degradation and failure modes.

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## INTRODUCTION

Railroads conduct regular inspections of their track in order to maintain safe and efficient operations. In addition to internal railroad inspection procedures, periodic track inspections are required under FRA regulations. Although essential, track inspection requires both financial and human resources and consumes track time. The objective of the research underway at UIUC is to investigate the feasibility of using machine vision technology to make track inspection more efficient and effective. 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.[1,2,3,4,5]

## INSPECTION PRIORITIZATION

This project focuses on inspection of Class I railroad mainline and siding tracks, which generally experience the highest traffic densities. The cost associated with removing track from service due to inspections or 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.

In order to prioritize the specific tasks that are most conducive to machine vision inspection, the FRA Accident Database was analyzed to identify the most frequent causes of track related accidents from 2001-2005.[1,2,6] Also, researchers considered the limitations of current technology, the severity of the defects, and their potential contributions to accident prevention. The following inspection tasks were selected as a result of the investigative process: cut spikes, rail anchors, turnout components, and crib ballast.[1,2]

## DATA AQUISITION

Initially, a track simulation model was developed to evaluate camera views and to provide images for preliminary machine vision algorithm development. This enabled virtual experimentation by varying the camera location used to view and record images of track components of interest. The simulation model was developed based on American Railway Engineering and Maintenance of Way Association recommended practices[7] and representative Class I railroad track standards. 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. The virtual cameras were then adjusted to view the relevant track components and allow the assessment of their conditions for algorithm development. This process led to the selection of three camera views currently being used to record images of the track structure and its components: (1) a gage side lateral view, (2) a field side lateral view, and (3) an over-the-rail view.

A track cart was designed to support the image acquisition equipment used in the field data collection efforts. Ultimately, the system will be adapted for vehicles suitable for use on mainline track such as rail flaw detection cars, geometry cars, revenue service locomotives or cars in revenue trains, and high-rail equipment.

## ALGORITHM DEVELOPMENT

Algorithms developed by researchers at the UIUC Computer Vision and Robotics Laboratory can be described as a coarse-to-fine approach for detecting objects. First, the track components with little variability in appearance and predictable locations (e.g., the rail) were located. Then, objects subject to high appearance variability (e.g., spike heads and anchors) were located in subsequent stages. This increased robustness of component detection by restricting the search space for the smaller components that vary in appearance.

To further increase the algorithm's robustness to changes in environmental conditions and object appearance from corrosion or occlusion from objects, such as leaves, features were selected that do not rely on a specific spatial description, but rather a configuration of simple, local classification features. The spatial templates used were restricted to the final stages, and because the location of the objects was isolated by then, it was not necessary that the objects have a strong response to the template in order to be detected.

The simple, local features used included edges and Gabor features. Edges are frequently used to detect objects in machine vision because object boundaries often generate sharp changes in brightness. Image gradients (edges) should be consistent among differing ties and rails, but unanticipated track objects or debris could create unwanted edges, causing challenges 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 relies on texture classification using Gabor filters, which produce low-level texture features.

Using a coarse-to-fine approach, the image was decomposed 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 due to their varying appearance, so texture classification is used to detect the tie closest to the camera.

Next, Gabor filtering reliably differentiated ballast texture from nonballast texture. Labeled examples of ballast, tie, and steel textures were created using previously stored images. When presented with a previously unseen image, texture patches were extracted and classified as either ballast or nonballast. Although a nonballast 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. Using this method, the rail was isolated, as were parts of the tie visible on both sides of the rail (Figure 1). Though the boundaries were inexact, in all test images the area was reliably isolated for subsequent processing.

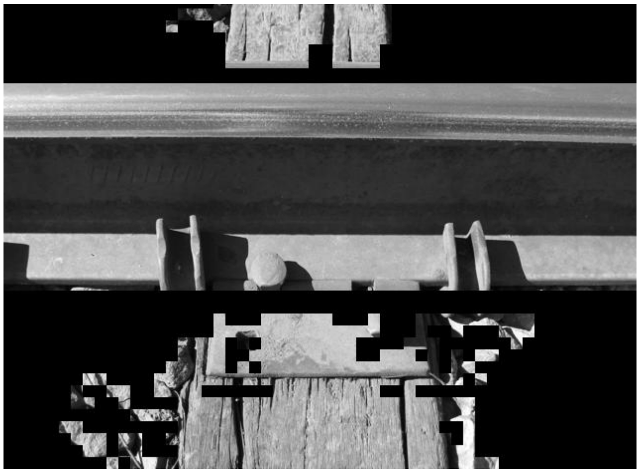

**Figure 1. Isolated Nonballast Objects**

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.

The spikes are located with spatial correlation using a previously developed template (Figure 2). Spikes will be found only in certain locations, which decreases the size of the search area after the tie plate and rail are both detected. These locations include a row of line spikes next to the base of the rail and another row of hold-down spikes further from the rail. Because the search space is restricted, a low threshold can be set for the template response. Therefore, the appearance of a spike altered by conditions has a higher probability of being detected, because the threshold for a template match is lowered. Missing spikes are detected by a 2-D 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. The current detection of spike heads is not yet robust due to environmental variability and differential wear patterns, but when the search area is limited, the accuracy improves.

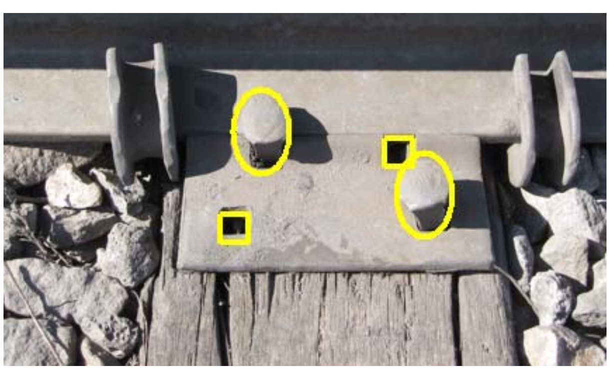

**Figure 2. Spike Detection Results**

**Figure 3. Rail Anchor Detection Result**

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, and the distances to both the tie and tie plate are measured. Color intensity information is also included to ensure that parallel edges have similar intensity distributions. This scheme is robust to shadows, because shadows will result in similar intensity distributions for parallel edges in the same anchor. It is also robust to anchor rotation and skewing, because the parallel edges detected need not be vertical.

The accuracy of the detection algorithms increases when detection is performed on panoramic images generated from video data collection rather than on single frames (Figure 4). The generation of panoramas uses only the vertical strips from the center of frames, thus minimizing distortions and perspective differences that increase toward the edges of the images.

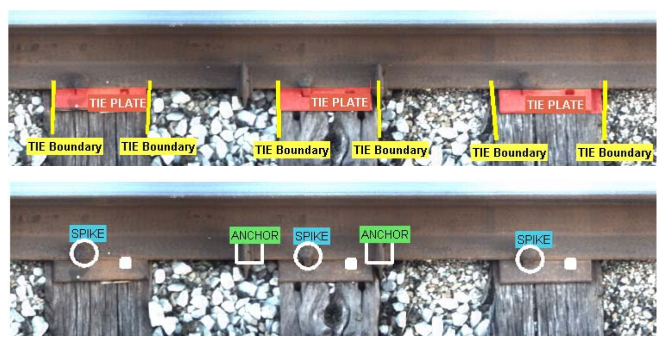


**Figure 4. Tie Plate and Component Detection on Panorama**

A previously developed algorithm to convert raw video data into panoramic images was modified for this application.[3,4,5] Many defects detected by this system cannot be classified as serious defects without knowing the state of the surrounding track. The panoramas provide a method to easily view the longitudinal condition of track, allowing a human operator to confirm the severity of defects detected by the system as a form of interim technology assisted manual inspection before full system development and implementation.

## CONCLUSIONS

Currently, the inspection of most railroad track components is conducted using manual, visual inspections, which are labor-intensive and lack the ability to easily record and compare data needed for trend analyses. The goal of this machine vision system for track inspection is to be part of a strategy to allow consistent and objective inspection of track components. NOTE: It is important to realize that machine vision systems are not intended to be overlay systems, but ultimately, a new inspection system.

## FUTURE WORK

Future work planned for 2009 and 2010 involves refinement of the algorithms to improve the reliability of spike and anchor detection and development of algorithms to detect turnout components and crib ballast. Beyond the current scope of work, track components and inspection tasks that have been identified for future machine vision research are 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. After preliminary algorithm development on cut spikes, anchors, and turnout components is complete, the system will be adapted for testing on a high-rail track inspection vehicle.

## ACKNOWLEDGEMENTS

This project was funded by AAR's Technology Scanning Program and the NEXTRANS Center. The authors thank the AAR Technology Scanning committee for their assistance and technical guidance. Additional support was provided by the FRA, BNSF Railway, CN, Norfolk Southern Corporation (NS), and Union Pacific Railroad. J. Riley Edwards has been supported in part by grants to the UIUC Railroad Engineering Program from CN, CSX, Hanson Professional Services, NS, and the George Krambles Transportation Scholarship Fund.

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