National University Rail Center - NURail
US DOT OST-R Tier 1 University Transportation Center

NURail Project ID: NURail2013-MTU-R06

An automatic method for detecting sliding railway wheels and hot bearings using thermal imagery

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05-03-2016

Grant Number: DTRT12-G-UTC18

DISCLAIMER

Funding for this research was provided by the NURail Center, University of Illinois at Urbana - Champaign under Grant No. DTRT12-G-UTC18 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research & Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

TECHNICAL SUMMARY

Title

An automatic method for detecting sliding railway wheels and hot bearings using thermal imagery

Introduction

One of the most important safety-related tasks in the rail industry is early detection of defective rolling stock components. Railway wheels and wheel bearings are two components prone to damage due to their interactions with brakes and railway track, which makes them a high priority when the rail industry investigates improvements to current detection processes. One of the specific wheel defects is a flat wheel, which is often caused by sliding during a heavy braking application. The main contribution of this research work is development of a computer vision method for automatically detecting the sliding wheels from images taken by wayside thermal cameras. As a byproduct, the process will also include a method for detecting hot bearings from the same images. We trained our algorithm with a set of simulated data and tested it on several thermal images collected in in North American revenue service by the Union Pacific Railroad (UPRR).

Description of Activities

The process of the railway wheel sliding on the rail heats up the steel wheel, which can be observed and potentially detected in thermal images. UPRR has been investigating the potential of using a thermal camera for sliding wheel detection during revenue service. A set of thermal images were provided by the UPRR to Michigan Tech with an objective to develop an automatic algorithm for identification purposes. We first developed an automatic detection and segmentation method, which identifies the wheel and bearing portion of the image. Then, we found a method, using "Histogram of Oriented Gradients" to extract features of these regions. These feature descriptors are later employed by "Support Vector Machine" to build a fast classifier with a good detection rate, to detect abnormalities in the wheel.

We found that the heat pattern generated from a sliding wheel can be automatically detected in the thermal imagery, making it a noteworthy technology for such applications. In this research we identified the heat pattern (hot spots) produced by sliding wheels and also found we could detect the hot bearings, another common defect of wheel assemblies. The basic procedure for our proposed automatic wheel defect detection method includes the following steps:

- Acquisition of a labeled data set with thermal images of defective and normal train wheels (preferably collected in revenue service).

- Partitioning of the available data set into a training set for the proposed algorithm, and a test set to evaluate its operation.
- Segmenting the wheel part of all the images in both training and test set.
- Extracting the wheel features of both training and test set.
- Training the wheel classifier using feature descriptors extracted from the training set.
- Evaluating resulting classifier on the test data set.

The procedure for automatic hot bearing detection method adds the following:

- Segmenting the bearing part of the thermal images.
- Calculating the mean intensity/temperature of the bearings.
- Detecting hot bearings based on a temperature threshold.

Outcomes

To evaluate the accuracy of our sliding wheel detection method, a sufficient sample size of images with and without defects was required. Due to small sample size of actual wheel images with defects obtained from the UPRR, we found it necessary to develop additional set of simulated wheel images for algorithm training purposes and using the UPRR data set for evaluating the algorithm. The results showed that our method was able to detect 98% of the total number of simulated and real world defective wheels in addition to identifying all the normal wheels without any false alarms.

In addition to sliding wheel detection, thermal imagery could be used for hot bearing detection with little additional effort. Since the majority of our hot bearing detection algorithm takes place in conjunction with the sliding wheel detection procedure, the only additional effort to identify hot bearings in this approach includes comparison of the calculated mean intensity/temperature with a set threshold.

Conclusions/Recommendations

The objective of wayside detection systems for rolling stock is to identify potential defects and inform the operators about the need to remove or repair the parts before they cause damage or an accident. To achieve this goal, fast and reliable defect detection methods are necessary. This project used data obtained through thermal imagery and introduced a novel automatic method for detection of sliding wheels and hot bearings from the data. Our proposed algorithm offers an alternative and reliable method for detecting sliding wheels based on uneven temperature distributions long the wheel rim and defective bearings based on the heat stamp in the bearing region.

The goal of this work was to find the optimum algorithm, which is both accurate for detecting patterns indicative of a sliding wheel and at the same time reasonable in terms of time and memory needed for computational purposes. This was successfully done in the research. Since the current project concentrated on sliding wheels, no emphasis was placed on identifying defects outside the wheel/rail interface. However, our algorithm can detect the flat spots at any other point of the wheel, as long as it is visible in the thermal image. The next research step will apply the same method for detecting hot spots located throughout the rim. To remove the potential occlusion by the car bogie components, two cameras need to be installed in series to ensure that a full wheel rotation is visible.

An important and difficult part of our algorithm is to identify the wheel and bearing parts in the thermal imagery. Future process improvements for this part include additional steps of image pre-processing with focus on noise cancellation and deblurring to obtain better wheel and bearing segmentation accuracy. In addition, we are investigating the potential to fuse thermal imagery with visible-spectrum imagery, which would provide both additional benefits to detection and also the ability to specify the location (car, axle) of the defective wheel or bearing. Furthermore, a train wheel history/profile can be fused with the result of the wheel inspection algorithm for more accurate conclusions and possible wheel damage prediction.

Publications

- Deilamsalehy H, Havens T C, Lautala P, Medici E and Davis J. (2016). "An automatic method for detecting sliding railway wheels and hot bearings using thermal imagery". Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit.
- Deilamsalehy H, Havens T C and Lautala P. (2016). "Detection of Sliding Wheels and Hot Bearings Using Wayside Thermal Cameras". Joint Rail Conference. American Society of Mechanical Engineers.
- Deilamsalehy H, Havens T C and Lautala P. (2015, March). "Automatic Method for Detecting and Categorizing Train Car Wheel and Bearing Defects". Joint Rail Conference (pp. V001T02A007-V001T02A007). American Society of Mechanical Engineers.

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Original Article

Institution of MECHANICAL ENGINEERS

Journal of RAIL AND RAPID TRANSIT

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Proc IMechE Part F: J Rail and Rapid Transit
0(0) 1–11

DOI: 10.1177/0954409716638703
pif.sagepub.com
SAGE

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Abstract

One of the most important safety-related tasks in the rail industry is an early detection of defective rolling stock components. Railway wheels and wheel bearings are the two components prone to damages due to their interactions with brakes and railway track, which makes them a high priority when the rail industry investigates improvements in the current detection processes. One of the specific wheel defects is a flat wheel, which is often caused by a sliding wheel during a heavy braking application. The main contribution of this paper is the development of a computer vision method for automatically detecting the sliding wheels from images taken by wayside thermal cameras. As a byproduct, the process will also include a method for detecting hot bearings from the same images. We first discuss our automatic detection and segmentation method, which identifies the wheel and bearing portion of the image. Then, we develop a method, using *histogram of oriented gradients* to extract the features of these regions. These feature descriptors are later employed by *support vector machine* to build a fast classifier with a good detection rate, which can detect abnormalities in the wheel. At the end, we train our algorithm using simulated images of sliding wheels and test it on several thermal images collected in a revenue service by the Union Pacific Railroad in North America.

Keywords

Railway wheel, flat spot, hot spot, sliding wheel, hot bearing, defect, automated inspection, thermal imagery, histogram of oriented gradients, support vector machine, finite element method

Date received: 6 November 2015; accepted: 12 February 2016

Introduction

As the demand for the rail transportation capacity and speed grows, there is an increasing trend toward higher productivity and efficiency in the rail industry. Both railroad track and rolling stock have rigorous inspection requirements to maintain the safety of the network. Even then, 84% of all the rolling-stock-related accidents in 23 countries are confirmed to be caused by the wheel set or bogie defects.[1] According to Liu et al.,[2] bearing failure and broken wheels are respectively the third and fourth major cause of freight train derailments on main tracks in North America. The authors also note that these derailment causes are most prevalent at speeds above 40 km/h (25 mile/h), exposing the rail industry to extensive damages from each occurrence.

Current inspection methods of the rolling stock components include both automated and visual systems, but the industry is increasingly moving toward detector and performance-based rolling stock maintenance to improve the efficiency and to reduce costs and reliance on human interpretation. Wayside monitoring systems are most commonly used for automated rolling stock inspection processes.[3] Inspection equipments are installed at fixed locations in or next to the track, where the train passes over the section. As the train rolls through the inspection station, different inspection sensors collect the information on possible defects like hot bearings, hot wheels, dragging equipment, and high, wide, or shifted loads. After inspecting a train, modern wayside detectors will automatically report their findings by radio or wireless connections.[4]

Many defects such as flat spots worsen gradually. Therefore, a fast and early detection of these defects can prevent further and more serious damage. Flat spots occur mainly as a result of violent braking,

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causing the wheel to lock up and slide on the rail while the train is still moving, making detection process during such braking event ideal. There are also other less common reasons for a flat spot to occur, such as poorly adjusted, frozen, or defective brakes and also contaminations on the rail such as grease, leaves, snow, and ice.[5] A flat spot induces great forces on both the rolling stock and the track and can lead to fatigue damage and failure of various vehicle and track components such as wheel sets, bearings, and rail ties.[1] In some cases, the damage can even cause later derailment which is a serious concern for the rail industry. The wheel–track interaction has been studied in several papers,[6–9] which describe the importance of the effect of a defective wheel on the track. In addition to the safety considerations, this type of defect causes an unpleasant noise, reducing passenger comfort and disturbing people in adjacent properties. Thus, an online automatic wheel defect detection system, which monitors the wheel condition and detects sliding wheels at an early stage, can help the maintenance to be scheduled more proactively, improving safety and reducing operational disruptions. We will discuss some of the existing methods to detect these types of defects and then move on to our proposed method.

Hypothesis and research methodology

The process of the railway wheel sliding on the rail heats up the steel wheel, which can be observed and potentially detected in the thermal images. We hypothesize that the heat pattern generated from a sliding wheel can be automatically detected in the thermal imagery, making it a noteworthy technology for sliding wheel detection. In this paper, we will identify the heat pattern to detect hot spots/sliding wheels and also to detect the hot bearing, another common defect of the wheel assembly. The basic procedure for our proposed automatic wheel defect monitoring method is as follows:

i. Acquire a labeled data set with the thermal images of defective and normal train wheels.
ii. Partition the available data set into a training set to train the proposed algorithm, and a test set to evaluate its operation.
iii. Segment the wheel part of all the images in both the training and test set.
iv. Extract the wheel features of both the training and test set.
v. Train the wheel classifier using feature descriptors extracted from the training set.
vi. Evaluate resulting classifier on the test data set.

Furthermore, the procedure for automatic hot bearing detection method is as follows:

i. Segment the bearing part of the thermal images.
ii. Calculate the mean intensity/temperature of the bearings.
iii. Detect hot bearings based on a temperature threshold.

The rest of this paper is organized as follows. We first briefly review the previous work in this field and then will go through our proposed algorithm steps in details (Figure 1). Each phase will be described in the following sections. We then complete the paper by demonstrating our proposed automated monitoring method on a collection of simulated images and real thermal imagery taken on several trains on a Union Pacific Railroad (UPPR) (a North American class 1 freight railroad).

Previous work

Previous work that focuses on the automatic wheel defect detection includes different techniques, such as acoustic, optical, thermal, and laser-based detection technologies.[10]

One way to detect flat spots and hot bearings is using the sound-based (acoustic) detection. This method is based on the fact that defective wheels and bearings produce vibration.[10,11] The work of Papaelias et al.[3] is an example of this method, in which the authors implement an integration of the acoustic emission and vibration analysis for onboard

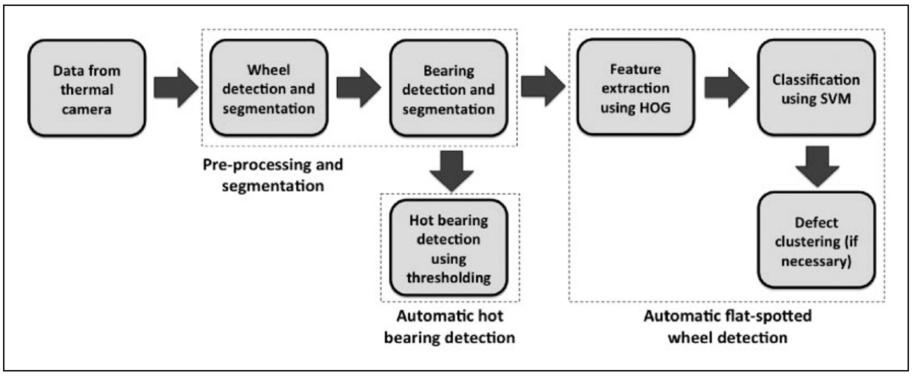

Figure 1. Automatic wheel and bearing defect detection block diagram.

evaluation of the bearings and wheels. The challenge with this method is that the measured acoustic signal might contain the surrounding noise, limiting the method accuracy or increasing implementation cost to remove the noise.

Another approach uses vision cameras that are installed as a wayside monitoring system, but wheel failures are not always visually detectible. This makes visual images by themselves insufficient for detecting certain wheel defects. According to Asplund et al.,[12] only half of all wheels with a force peak over 400 kN are visually seen as damaged wheels; while American Association of Railroads (AAR) recommends that a wheel with peak impact force of 222.41–226.89 kN due to a single flat, should be replaced.[1] Visual cameras can be useful for detecting other type of defects which are visible in the images. Li et al.[13] employed vision cameras for the automatic wheel bearing bolt defect detection. In contrast to the wheel surface which is our study in this paper, bolts are visible in the vision camera image and thus the necessary information can be acquired using the camera.

Measurement of the wheel profile can also be helpful for detecting abnormalities. Wheel profile detectors employ digital images to determine the profile of the tread while in service and then compare it to the standard profile.[10] Examples of a wheel profile case study using laser scanning are presented by Asplund et al.[12,14] In these papers, the authors study the wheel profile monitoring system (WPMS) on a track section in Sweden in order to detect failures related to the wheel.

An alternative well-studied procedure to detect a wheel flat is to measure the dynamic force or acceleration of the track under the wheel.[15] This method is known as wild impact load detector (WILD) and can be used as a predictive and proactive maintenance system.[16,17] In a related work,[1] UI Alam Uzzal et al. have gone even one step further, studying the impact of multiple wheel flats by measuring the acceleration of the wheel set.

One of the most common methods to detect hot bearings is employing hot box detectors.[10] The hot box detectors work based on the principle that an axle bearing will emit a large amount of heat when it is close to failing.

While there is no question that the currently available methods have been successful in identifying sliding wheel/flat spot and bearing defects, the continuing interest by the industry toward alternative technologies reveals that there are still opportunities for development. For example, one of the challenges with the acoustic and hot box detectors in identifying sliding wheels is their incapability to reliably detect uneven temperature distributions within the wheel. This has created an interest among industry to investigate the use of thermal cameras as an alternative solution for detection.[18] Hence, in this paper we explore how the generated heat pattern from a sliding wheel can be automatically detected using a thermal camera. We also demonstrate how the same camera can be used simultaneously to identify the hot bearings. Our results show that this method has much promise for effective detection of these types of defects.

Thermal image segmentation (pre-processing)

A few samples of the thermal images we are working with are shown in Figure 2(a). Furthermore, several examples of the sliding wheels are demonstrated in Figure 2(b). Comparing the images of the normal wheels with the defective ones shows that sliding wheels possess a distinctive heat pattern at the wheel–track contact point. In the following sections, we will explain our proposed algorithm for detecting this heat pattern in the damaged wheels.

Automatic wheel detection and segmentation

The first step of algorithm is to segment the wheel portion of the image from the suspension hardware in the thermal image. As can be seen in Figure 2, in addition to the wheel, the image may contain hardware components of the train as well as the track, which play no role in our investigation process and might interfere with the sliding wheel detection algorithm. As shown in these images, the wheel can be partially to almost fully occluded by suspension hardware. Hence, our algorithm must be flexible and effective at detecting the wheel portion of the image automatically. If the thermal image has been captured while the wheel was sliding, it signifies that the hot spot is located at the contact point of the wheel and the track and this part is always visible in the images. It is also possible that the wheel has rotated after sliding, and the hot spot is somewhere else along the wheel. It might even be occluded by the suspension hardware in the thermal image. Nevertheless, as long as the hot spot is visible in the image, it can potentially be detected. In order to locate this hot area in the image, first we need to recognize the wheel in the thermal image.

The train wheel is originally in the shape of a circle, but because of the combined effect of the motion of the train and the rolling shutter of the imager, there is skewness in the shape of the wheel and the wheel appears as an ellipse in the image. To automatically detect the elliptical portion of the image associated with the wheel, we employ the Hough transform (HT).[19] The HT is a feature extraction method that is widely used in image processing. Originally, this method was used to extract lines in an image, but it can be extended to extract more complicated and arbitrary shapes, e.g. circles or ellipses. In this paper, we will use the extended version of the transform to detect the elliptical wheel in the

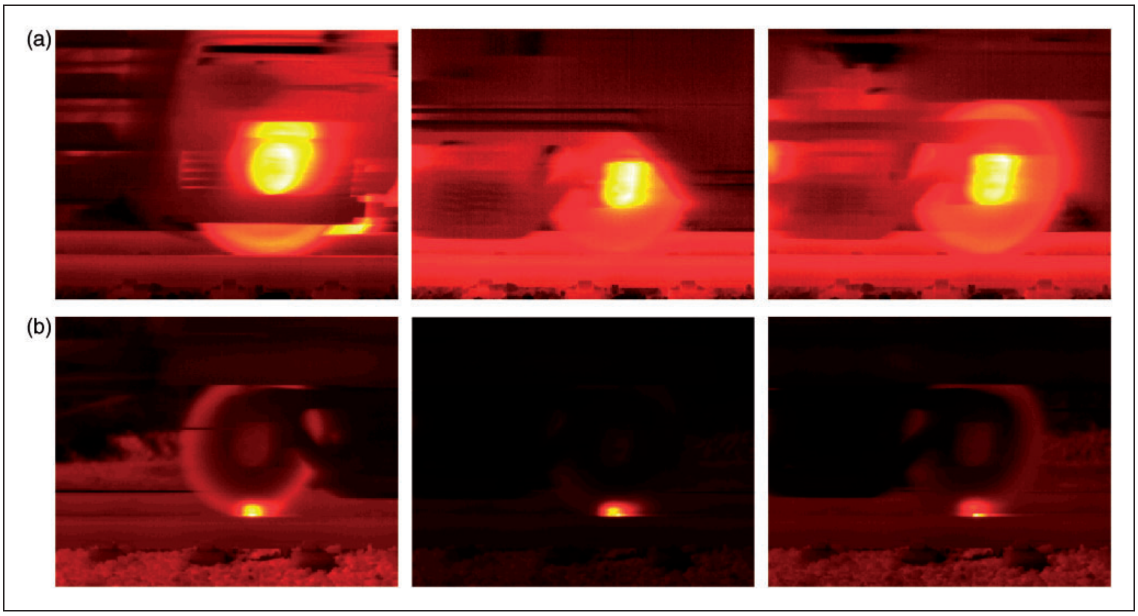

Figure 2. Examples of the train wheel thermal images taken by wayside thermal imaging system.

thermal imagery. The parametric equation of an ellipse is

$$x^2 + p_1xy + p_2y^2 + p_3x + p_4y + p_5 = 0 \tag{1}$$

where p_1, p_2, p_3, p_4, and p_5 determine the shape and the location of the ellipse. Since the ellipse is defined by five parameters according to equation (1), by identifying five independent points on the ellipse, we can calculate the parameters. Following the HT method, first five independent points in the image are selected, and the ellipse consisting of these points is found. This process is done for all the points/pixels in the thermal image. Then, every ellipse receives votes from all the points located on its perimeter. The summation of the acquired votes for each ellipse determines how strong this ellipse is. In other word, the ellipse in the image that have the most points located on its perimeter will be chosen. In this approach, we are actually mapping the xy coordinates to a five-dimensional space, using a five-dimensional accumulator for the HT. If we choose to do an exhaustive search, the order of complexity employing this method will be $O(n^5)$. Therefore, finding an ellipse using the HT will be expensive in terms of memory usage and computation time. To overcome the complexity problem, we use a Canny edge detector[20] to reduce the number of pixels investigated, thus reducing the processing cost. We first apply the Canny edge detector to the wheel thermal image to obtain a binary image consisting of only edges; then, we use the HT to detect the train wheel in the image. To speed up the process even more, we use randomized Hough transform (RHT)[21] rather than the original HT. In the RHT, the HT is applied to a random subsample of all the image pixels, instead of all possible pixels. Assuming that there are enough wheel edge pixels in the binary image, the HT still should be able to detect the wheel part.

There are several ways to mathematically define an ellipse. As mentioned before, five independent parameters should be determined. In this paper, we define the ellipse by the following parameters:

- Center of ellipse (x and y coordinates),
- Orientation of ellipse which is defined as its angle with x-axis,
- Length of major axis of ellipse,
- Length of minor axis of ellipse.

We follow the method introduced by Xie et al.[22] to detect the wheel. For each pair of image pixels (x_1, y_1) and (x_2, y_2), we assume that these points are two vertices on the major axis of an ellipse, then we can calculate the following parameters for the ellipse

$$x_0 = (x_i + x_j)/2 \tag{2a}$$

$$y_0 = (y_i + y_j)/2 \tag{2b}$$

$$a = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}/2 \tag{2c}$$

$$\alpha = \text{atan}[(y_j - y_i)/(x_j - x_i)] \tag{2d}$$

In the above equations, (x_0, y_0) is the center of the ellipse, a is the half length of the major axis, and α is the orientation. As illustrated in Figure 3, the minor axis can be calculated as

$$b = \sqrt{(a^2d^2(\sin(\phi))^2)/(a^2 - d^2(\cos(\phi))^2)} \tag{3}$$

where b is the half length of the minor axis, $\cos(\phi) = (a^2 + d^2 - f^2)/(2ad)$ and d is the distance between the point (x, y) on the ellipse and the center of ellipse. Accordingly, if we have (x_1, y_1) and (x_2, y_2), we can calculate all the ellipse parameters except for the minor axis. Therefore, we use the HT to vote on the half length of the minor axis. This way, a one-dimensional accumulator is enough to detect the ellipse and we output the parameters for the best ellipse found in the thermal image,[21] i.e. the ellipse with the maximum votes. This procedure of finding the elliptical wheel and subsequent bearing (which will be explained in the following section) detection and extraction is illustrated in Figure 4.

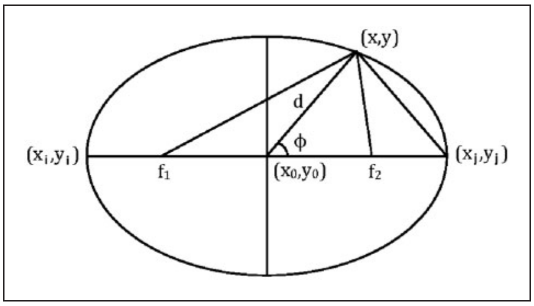

Figure 3. Ellipse geometry.

Automatic bearing detection and segmentation

In addition to abnormal heat pattern generated by the sliding wheel, a hot bearing may also cause elevated heat pattern in the images. To differentiate between these two causes, it is necessary to separate the bearing portion from the overall image, enabling the remainder of the image to be used for the sliding wheel identification. Once the bearing portion has been identified and separated, its heat pattern can also be used at an indication of potential faulty (hot) bearing.

Similar to a wheel, because of the motion effect in the image, the bearing is also seen as an ellipse in the image. Therefore, to find the bearing, we apply the HT to the extracted wheel part and detect the bearing

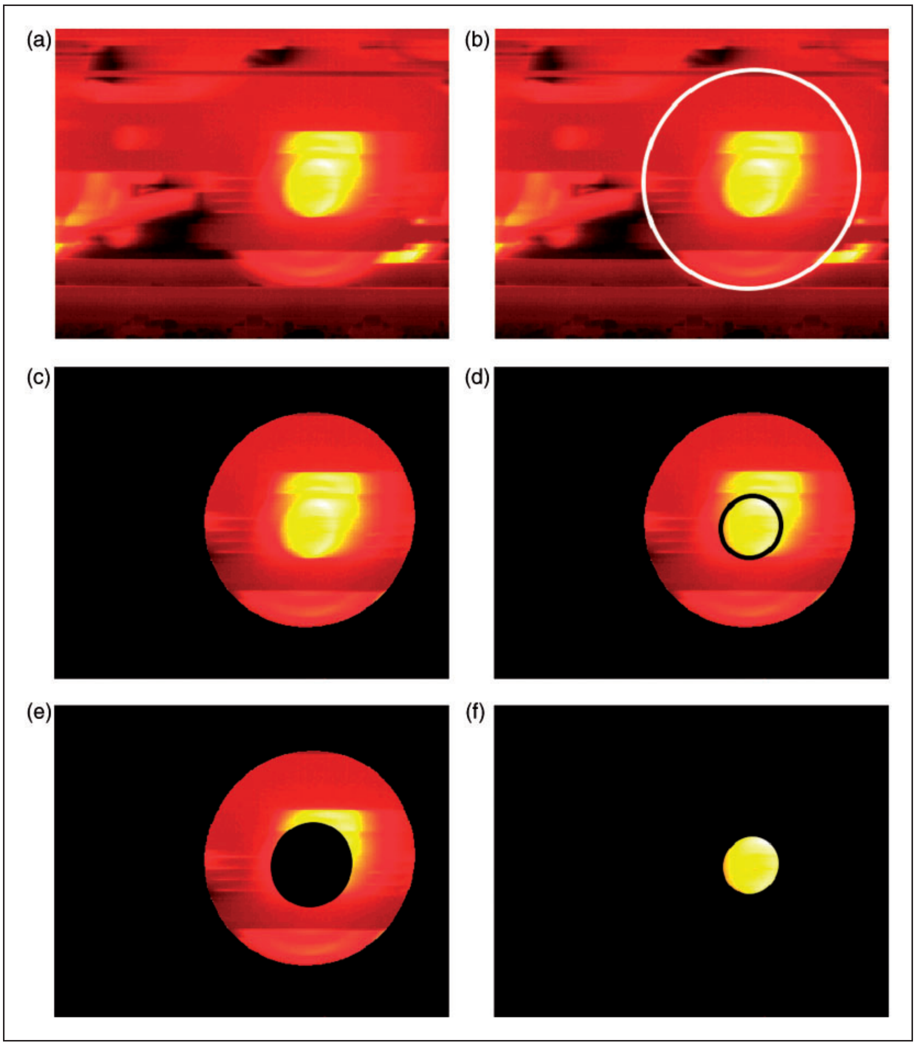

Figure 4. Image segmentation of the wheel and bearing regions.

as a separate part. The procedure is analogous to wheel detection, explained in the previous section. As a consequence of train movement, there is a motion blur effect which can be observed primarily at the edges. Because of this blurriness, for the purpose of wheel heat pattern analysis, the bearing should be removed from the wheel image with a safety margin, which is bigger than the detected bearing (see Figure 4). On the other hand, for the hot bearing detection algorithm, this safety margin is unnecessary and in fact the bearing should not include any wheel part. Therefore, in order to detect hot bearing, we have to segment the detected bearing without any margin.

Automatic sliding wheel detection

Feature extraction using histogram of oriented gradients

After the wheel and bearing extraction, the corresponding segmented parts of the thermal image are ready for further analysis. The first step after preprocessing is to extract image features with which we can train our algorithm. Image features must be chosen in a way that a defective wheel can be distinguished from a normal wheel. Our image set is a collection of the thermal camera imagery, which does not contain any distinguishable texture. This means the only information that can be obtained from the images is pixels temperature. In the thermal imagery, the temperature is represented as pixel intensities. Hence, we need to identify local heat pattern of the sliding wheels, which in our data set can be observed at the wheel–track contact point. Figure 2(b) illustrates this pattern on the sliding wheel.

We have to employ feature descriptors that can capture the hot spot pattern. In order to do this task, we use the histogram of oriented gradients (HOG) feature. The HOG is a feature descriptor which is widely used in the computer vision and image processing to detect object in imagery. HOG decomposes an image into square cells of a given size; then it counts occurrences of intensity gradient orientation in localized portions of the image.[23] It has been widely accepted as one of the best features to capture local shape information about objects in the imagery.

The essential thought behind the HOG descriptors is that local pattern within an image can be described by the distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within each cell. The HOG descriptor operates on localized cells; therefore it has the advantage that upholds invariance to geometric and photometric transformations, except for object orientation which is not an issue in our work. To obtain the HOG feature descriptor, there are four main steps which should be taken:

i. Gradient computation: Calculate the gradient values.
ii. Orientation binning: Create the cell histograms.
iii. Descriptor blocks: Group the cells together into larger blocks.
iv. Block normalization: Normalize the gradient strengths.

The implementation of the HOG is illustrated in Figure 5. As it can be seen in the figure, by applying the HOG to an image, we will obtain a histogram of its intensity gradient orientations.

In this paper, first we segment a window in the thermal image, which includes the wheel. Since we detected the wheel portion in pre-processing stage, we know all the parameters needed to locate the wheel in the image. Thus, the position of the window can be chosen in a way that contains the wheel. The original image size is 240×320 pixels and the area of interest is divided into 8×8 pixels regions subsequently. Each of these pixel regions is called a cell. The smaller the cell size is, the more details it captures. We examined different cell sizes and for the purpose of this research work, 8×8 pixels is the appropriate cell size to capture the desired features. Next, for each cell we calculate a one-dimensional histogram of gradient orientations over pixels in the cell. These histograms capture the local heat pattern properties. The gradient at each pixel is

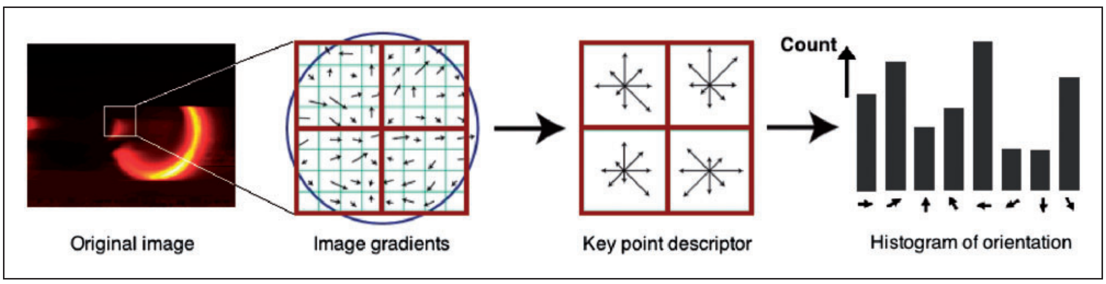

Figure 5. Histogram of oriented gradients (HOG) algorithm.

discretized, and then each pixel votes for the orientation with a weight which depends on the magnitude of its gradient. Finally, the histogram of each cell is normalized with respect to the gradient energy in a neighborhood around it. The HOG features for three normal and three sliding wheels are illustrated in Figure 6(a) and (b) accordingly. The features are shown on the thermal image and without the image at the background. It can be visually seen that the orientation pattern of the HOG descriptors around the hot spot, which is shown with a circle, is different from the same part in a normal wheel.

Classification and sliding wheel detection with support vector machine

The HOG descriptors extracted from the thermal images provide a feature set by which we can potentially distinguish defective wheels from normal wheels. After acquiring the feature descriptors, we train a support vector machine (SVM) classifier to detect the sliding wheel. The SVM is a supervised learning method, which can find a decision boundary between two classes based on their feature data. Assume that we have a training set D which is defined as

$$D = \{(\mathbf{x}_i, y_i) | \mathbf{x}_i \in R^p, y_i \in \{-1, 1\}\}_{i=1}^{N} \qquad (4)$$

where y_i is the label of feature vector $\mathbf{x}_i$ (e.g. $y_i = +1$ indicates a normal wheel and $y_i = -1$ indicates a defective wheel), p is the number of features in the vector $\mathbf{x}_i$, and n is the number of data points in the training set. We want to find the optimal hyper plane which separates the data labeled as $y_i = +1$ from the ones labeled as $y_i = -1$. The SVM is a method by which an optimal decision function can be learned from training data D. This is illustrated in Figure 7.

In our paper, the two classes are normal and sliding wheels and our data set consists of a set of simulated thermal images and a set of real images taken by a wayside thermal camera on the UPRR. The inputs to the SVM are the HOG feature descriptors. The SVM uses the feature descriptors in the training data to learn a detection algorithm that can be applied to classify incoming wheels as defective or not.

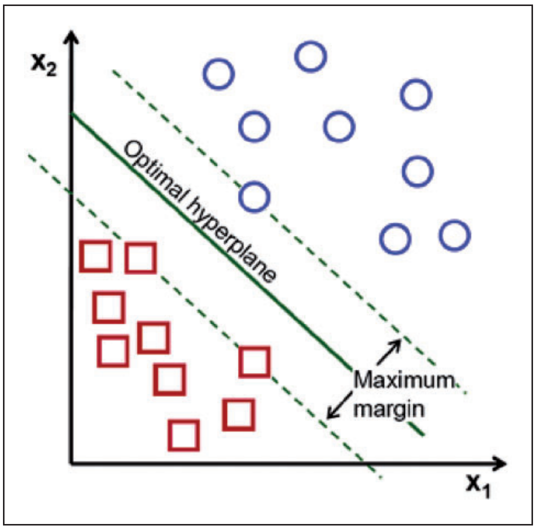

Figure 7. Support vector machine (SVM) for linearly separable data points.

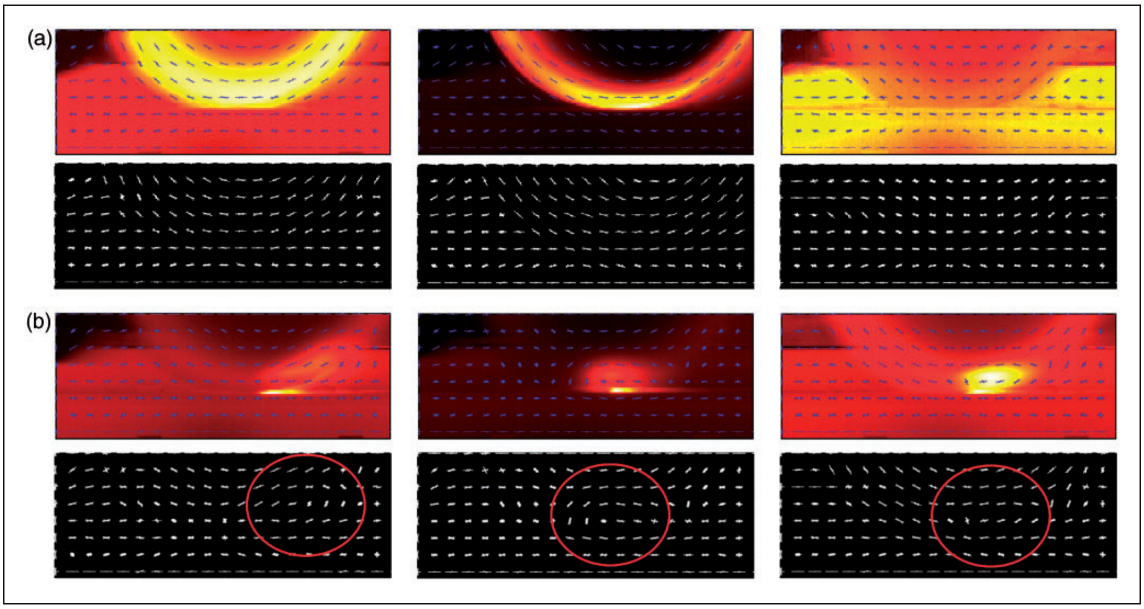

Figure 6. Visualization of the HOG feature descriptors of the train wheels. The top rows in (a) and (b) visualize the HOG features on the wheel thermal images and the bottom rows are the HOG visualizations of the same thermal images without the wheel on the background. In the bottom row of (b) the areas inside the red circles demonstrate the feature descriptors of the contact point of the sliding wheels.

Depending on the wheel damage level, different approaches should be taken after detecting a sliding wheel. Hence, it can be helpful if the damage level is also determined. After detecting the defective wheel, it can be further categorized into different classes, which determine the level and severity of the damage. We call this procedure *defect clustering* and it is done based on the size and number of flat spots. In our previous work,[24] we developed and introduced such algorithm that can be applied to the detected damaged wheel images to estimate the damage level.

Automatic hot bearing detection

As mentioned before, the bearing region of the image is automatically detected by applying the HT to the detected wheel. To calculate the bearing temperature, we do not use any safety margin while segmenting the bearing. Instead, we use exactly the bearing pixels (see Figure 4). Next, we calculate the mean intensity of the bearing, which has a direct relation with the bearing mean temperature. By having the mean intensity of the bearing, its mean temperature can be easily calculated. A threshold, based on the maximum normal bearing temperature/intensity should be set and those bearings that have a mean temperature/intensity above this threshold are labeled as *hot bearings*. The intensity distribution of the bearings of the UPRR data set and a hypothetical threshold for hot bearing are illustrated in Figure 8. As the actual temperatures were not provided by the UPRR and the primary objective of the research was on sliding wheel identification, we did not test the accuracy of bearing detection procedure, but rather the intensity values of the image data set to demonstrate the idea.

Implementation and results

To evaluate our proposed algorithm, we applied it to a set of simulated and real thermal images. Creation of the simulated images was necessary as our defective wheel sample data set was not large enough by itself to train the model. To simulate train wheel thermal images we used ANSYS,[25] which employs finite element method (FEM) to generate the model. Our model simulates the wheel and bearing temperatures and identifies the temperature gradient at the wheel–track contact point. The simulation parameters are explained in detail in the next section.

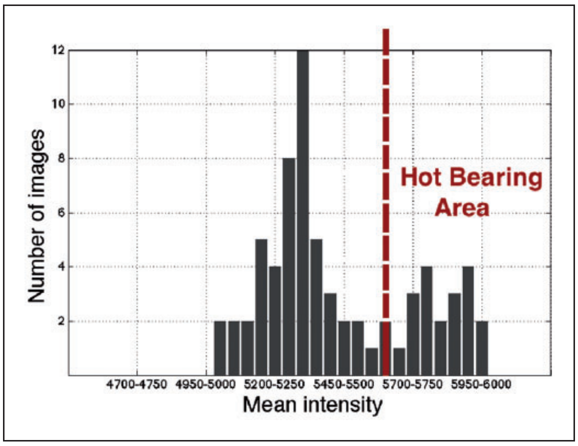

Figure 8. Bearing intensity distribution for the UPRR data set.

Simulating the wheel temperature profile using a finite element method

Temperature distribution on the railway wheel can be obtained through the FEM simulations.[26] The advantage of using a numerical model to generate the wheel temperature profile is the possibility to test the versatility of our proposed technique under different heat flux scenarios.[27] A two-dimensional, static, steady-state FEM model of the wheel and rail was developed using ANSYS FEM software, where a set of heat sources and sinks are set to mimic the heat fluxes of the wheel while in motion. For instance, the convection heat transfer coefficient around a wheel moving at 80 km/h (50 mile/h) is approximately $h = 56\,\mathrm{W/m^2K}$.[28] Using this heat transfer coefficient, the resulting Biot number becomes $Bi = 1.14$. A Biot number larger than one indicates that the temperature gradient inside the wheel is larger than between the wheel and the air. This is also indicative of a very small thermal boundary layer.[28] To mimic this condition, the wheel surface is modeled as a constant temperature source term with no convection to the air. The outside temperature of the wheel is then set at 300 °C. This temperature is based on experimental measurements of a train wheel overheating due to the contact friction between the rotating wheel and the rail under normal wheel–rail interaction.[29] The axle bearing is also set at the same temperature. Once the wheel experiences an abnormal behavior, inducing the wheel sliding on the rail instead of rotating, an extra localized heat source will appear between the wheel and the rail. This overheating due to sliding is modeled as an area on the wheel with a higher temperature. The temperature of the hot spot is varied from 550 °C to 800 °C in our study and its size is between 15 and 40 pixels. Additionally, ambient air temperature is modeled at 25 °C and the rail temperature is modeled at 80 °C (Figure 9). The wheel and the rail are modeled with the material properties of steel. The temperature profiles obtained from the FEM simulations are then imported into Matlab for post-processing. The post-processing consists of uploading the FEM simulations files and converting the temperature profiles into an image with similar image size and properties as those obtained from the thermal camera. Furthermore, the motion blur effect is simulated using Matlab build in Wiener filter. In order to have more realistic images, Gaussian noise is added to them. This noise resembles the overall noise of the thermal camera and environment. An example of the simulated thermal camera images is shown in Figure 10.

Training and testing the algorithm

We applied our proposed algorithm to a set of simulated data as well as a real data set from the UPRR. The image size for both data sets is 240×320 pixels. We divided the available simulated images into two sets of training and test and used the real data set for the evaluation purpose only. The training data set consists of 200 simulated images in which 100 of the images are the normal train wheels and 100 of them are the sliding wheels. The test data sets include a set of simulated images with 50 normal wheels and 50 defective wheels and a set of real images with 400 and 8 normal and sliding wheels, respectively. We first train our algorithm on the training set. After the training phase, we apply the trained algorithm to the simulated test data set to evaluate its performance on the simulated images. Then we apply it to the test set consisting of real camera images, in order to evaluate the accuracy of the algorithm for real world data. Table 1 outlines the application results of our proposed algorithm to each of the test data sets separately, as well as the overall performance. As the results show, the accuracy of our proposed algorithm for the simulated data set was 100% which means our algorithm was able to detect all the sliding wheels without any false alarms. For the real data set, the algorithm was able to detect 88% of all the defective wheels and it identified all the normal wheels correctly. The major algorithm failure reason was wheel segmentation inaccuracy that can be mitigated in the future through improvements in the wheel detection process. Despite the fact that our algorithm was trained on a simple simulated model (which was built based on only two parameters: size and temperature of the hot spot), it still resulted in good accuracy for the real world data.

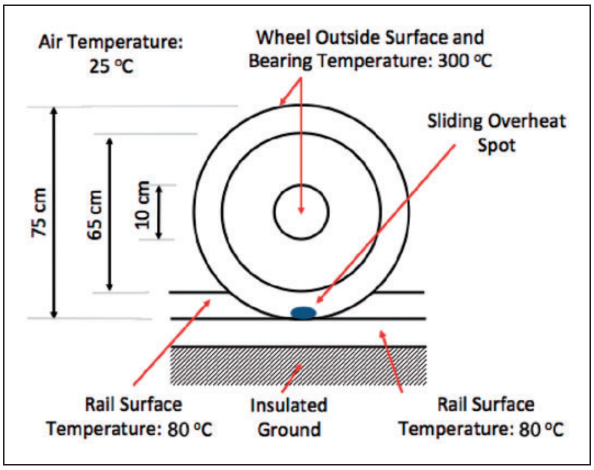

Figure 9. Schematic diagram of the thermal FEM wheel–rail system.

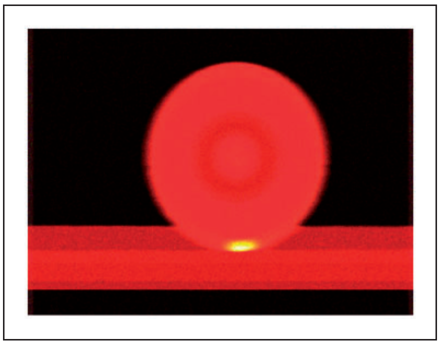

Figure 10. Simulated thermal wheel image using the FEM.

Conclusion and future work

The objective of wayside detection systems for rolling stock is to identify failures and inform the operators about the need to remove or repair the parts before they cause more damage or an accident. To achieve this goal, fast and reliable defect detection methods are necessary. This paper introduced a novel automatic method for detection of the sliding wheels and hot bearings from the thermal imagery. Our proposed algorithm offers an alternative method for detecting the sliding wheels and hot bearings, one that can reliably identify uneven temperature distributions and defective bearings.

To evaluate the accuracy of our sliding wheel detection method, we applied the algorithm to a set of simulated wheel images as well as the real data obtained from the UPRR. The results showed that

Table 1. Wheel defect results on simulated and Union Pacific data set.

Dataset	Number of normal wheels in the data set	Number of defective wheels in the data set	Algorithm precision for normal wheels (%)	Algorithm precision for defective wheels (%)
Training set	100	100	–	–
Simulated test set	50	50	100	100
Real test set	400	8	100	88
Total test set	450	58	100	98

it was able to detect 98% of the total number of the simulated and real world defective wheels in addition to identifying all the normal wheels without any false alarm.

In addition to the sliding wheel detection, it was realized that the thermal imagery can be used for hot bearing detection with little additional effort. Since the majority of our hot bearing detection algorithm takes place in conjunction with the sliding wheel detection procedure, the only additional effort to identify hot bearings in this approach includes comparison of the calculated mean intensity/temperature with a set threshold.

The objective was to find the optimum algorithm which is accurate for detecting patterns indicative of a sliding wheel and at the same time, reasonable in terms of time and memory needed for computational purposes. This was successfully done in the research. Since the current project concentrated on the sliding wheels, no emphasis was placed on identifying defects outside the wheel–rail interface. However, our algorithm can detect the flat spots at any other point of the wheel, as long as it is visible in the thermal image. The next research step will apply the same method toward detecting hot spots located throughout the rim and to remove the potential occlusion by the car bogie components, two cameras will be installed in series to secure that a full wheel rotation is visible. An important and difficult part of our algorithm is to identify the wheel and bearing parts in the thermal imagery. Future process improvements for this part include additional steps of image pre-processing with focus on noise cancellation and deblurring to obtain better wheel and bearing segmentation accuracy. In addition, we are investigating the potential to fuse the thermal imagery with visible-spectrum imagery, which will provide both additional benefit to detection and also the ability to specify the location (car, axle) of the defective wheel or bearing. Furthermore, a train wheel former history/profile can be fused with the result of the wheel inspection algorithm for more accurate conclusions and possible wheel damage prediction.

Acknowledgements

We would like to thank Tom Bartlett and William GeMeiner at Union Pacific for providing us with data and guidance in this project.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by a National University Rail (NURail) center, a US DOT-OST tier and University Transportation center [grant number DTRT12-G-UTC18, 2012].

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