Machine Vision Using Multi-Spectral Imaging for Undercarriage Inspection of Railroad Equipment

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Undercarriage Inspection Background

- Undercarriage inspection today is a manual process
  - Labor intensive
  - Time intensive
  - Subjective
- Machine vision systems have the potential to automatically monitor, assess, record and transmit information on the condition of rolling stock
  - Trains can be inspected without stopping
  - Enhanced or specialized vantage points possible
  - Objective assessment that facilitates comparative analysis using templates and/or previous inspections of same or similar equipment
  - Multispectral system can analyze both physical and thermal condition
Project Objectives

- Investigate feasibility of multi-spectral machine vision inspection of railcar and locomotive undercarriages
  - Locate and identify key undercarriage components
- Incorporate and relate visible and thermal images
- Detect damaged or missing objects
- Detect problems or evidence of incipient failures
- Integrate into algorithms *a priori* knowledge of structure and appearance of rolling stock types and components
Modular Approach to Multi-Spectral Machine Vision Inspection

MODULE 1
- Video Acquisition
- Video Decomposition into Frames

MODULE 2
- Panorama Generation
- Creation of Car Panoramas
- Compare with car template
- Divide panorama into cars

MODULE 3
- Global Anomaly Identification
- Component-level Defect Classification
Module 1: Image Acquisition from Visible and Infrared Video Cameras
Portable Image Acquisition System

- Cameras and lighting located in inspection pit
- Below rail perspective to view undercarriage with minimal obstruction
- Determine best location and orientation of camera
- Wide-angle lens (~4 mm focal length) required to capture entire undercarriage
- Rails are the limiting factor in viewing entire undercarriage from this angle

Camera Lens Location

\[
127 + l = \frac{l}{320} = \frac{l}{143.5} = 103.25 \text{cm}
\]

Camera Focal Length

\[
f = k \frac{D}{w} = 6.4 \frac{1032.5}{1435} = 4.6 \text{mm}
\]
Camera and Lighting Setup

- Image acquisition of in-service trains at Amtrak S&I Facility, Chicago IL
  - Infrared and visible range cameras
  - Video Recording at 30 frames/sec
  - Even illumination of undercarriage a nontrivial task
Module 2: Panoramic Image Generation

MODULE 1
Video Acquisition
Video Decomposition into Frames

MODULE 2
Panorama Generation
Creation of Car Panoramas
Divide panorama into cars
Compare with car template
Panoramic Image Stitching

- Frames extracted from video
- Center strip of frame cropped
- Consecutive frames compared to determine train speed
- Center strip length adjusted based on train speed
- Strips ‘stitched’ together to create panoramic image of entire train

Video frames

Stitched image
Distinguishing Cars in Train

- Need to divide panoramic image of train into single-car panoramas

Axle detector

Determines range where couplers will be found

Coupler detector

Use couplers to divide panorama into single cars

Panoramic image of entire train

Panoramas of single cars
Example Panoramic Image
Dividing Infrared Panorama Into Cars

- Divide the infrared panoramic image into individual cars using the same algorithm
  - Axle detection followed by coupler detection
- Edges correspond between the infrared image and the visual image
  - Scale and shift the axle edge template used for visual matching
  - Scale and shift values also enable car alignment with the visual information

Partial infrared panorama
Module 3: Defect Detection and Classification

**MODULE 1**
- Video Acquisition
- Video Decomposition into Frames

**MODULE 2**
- Panorama Generation
- Creation of Car Panoramas
- Divide panormas into cars
- Compare with car template

**MODULE 3**
- Global Anomaly Identification
- Component-level Defect Classification
Module 3 Subparts

Module 3A
Global Anomaly Identification

Module 3B
Component-level Defect Classification

Module 3C
Balanced Component Verification
3A: Visible Car Template Matching

- Store unique template of each railcar
- Use block-wise correlation to identify global changes from previous inspection of railcar
  - Detects foreign and missing components
  - Detects large defects in parts
- Locate blocks of low correlation (appearing as dark blocks)

Stored template of railcar

Railcar image for comparison

Detection using blocks of correlation
3A: Infrared Car Template Matching

- Store unique template for each car
  - Adjust template for environmental temperature
- Use block-wise luminance difference to identify global thermal anomalies
  - Detects regions with differing temperatures
- Locate blocks of large temperature difference (appearing as dark blocks)
3B: Processing Components

- Motivation for component-level processing
  - Finer granularity than block-level correlation
  - Allows classification of component defects

- Process individual components
  - Identification of components
    - Identify components of interest
    - Align in one coordinate space

- Location of defects
  - Compare to stored component template
  - Locate areas of low correlation with respect to template

- Classification of defective regions
  - Create regions from the areas of low correlation
  - Classify the regions using semi-parametric techniques such as Gaussian mixture modeling
3B: Locating Components

A.C. Blower Unit

Traction Motor
3B: Semi-Parametric Defect Classification

- Create a feature vector for each region
  - Color
  - Shape
  - Location

- Approximate a semi-parametric distribution in feature space and classify each type of defect
  - Each class of region has its distribution in feature space described by a Gaussian mixture model (GMM)

- Regions are classified by the probability that they originated from one of the existing GMM distributions
  - Unseen defects have a small probability of being generated from any of the classes, and are therefore detectable
3B: Anomaly Detection and Defect Classification: Component Level

**Visible Spectrum**

- **Region 1**: No error (shine)
- **Region 2**: Missing faceplate
- **Region 3**: No error (shine)

**Component template matching**

* Same method used for infrared spectrum
3C: Balanced Component Verification

- Spring compression component and brake caliper are located using the Canny edge transform of the infrared panorama
  - Measurements of the amount of spring compression and the width of caliper opening are made

Visible Image

Edge Image Overlay

Component ID

Measurements
3C: Outlier Identification

- Locate the brake disk on the infrared panorama and record its temperature

- Create a multidimensional feature vector consisting of
  - Return spring compression (pixels)
  - Brake caliper opening (pixels)
  - Disk brake temperature

- Using Gaussian mixture modeling (as in Module 3B), locate outliers with respect to:
  - Other brakes in the car
  - Predefined levels of acceptable operating conditions
Conclusions

- This work demonstrates the feasibility of a multi-spectral machine vision system for undercarriage inspection of rolling stock and locomotive undercarriages, as the train passes over a repair pit.

- Multispectral machine vision algorithms provided the capability of identifying missing, damaged, and overheated components, while also detecting incipient failures and foreign objects.

- This process combined information from the infrared and visible spectra to identify certain defects that could otherwise be unnoticed with traditional visual inspections.
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