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

NURail Project ID: NURail2020-MTU-R19

Computer Learning and AI-Based Investigation of Outward Facing Locomotive Videos for Trespassing Events and Behavior

By

Timothy C. Havens
Director, Institute of Computing and Cybersystems,
Associate Dean for Research, College of Computing,
William and Gloria Jackson Associate Professor,
Department of Computer Science
Michigan Technological University,
1400 Townsend Drive, Houghton, MI 49931
phone: (906) 487-3115
thavens@mtu.edu

and

Pasi Lautala
Associate Professor
Director, Rail Transportation Program,
Department of Civil and Environmental Engineering,
Michigan Technological University,
1400 Townsend Drive, Houghton, MI 49931
phone: (906) 487-3547
ptlautal@mtu.edu

09-30-2020

Grant Number: DTRT13-G-UTC52

DISCLAIMER

Funding for this research was provided by the NURail Center, University of Illinois at Urbana - Champaign under Grant No. DTRT13-G-UTC52 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.

USDOT Tier 1 University Transportation Center Final Report

TECHNICAL SUMMARY

NURail Project ID: NURail2020-MTU-R19 Final Report September 30, 2020

Title
Computer Learning and AI-Based Investigation of Outward Facing Locomotive Videos for Trespassing Events and Behavior

1. Introduction
This project explored using the analysis of big data through AI and CL to better understand the leading causes for trespassing incidents. Our main data set for the analysis is the images from outward facing cameras located in locomotives. Such data are regularly used for analyzing the events in the case of trespasser fatality or serious accident, but we are looking to expand their use to systematically identify/analyze all trespasser events. Our approach is to first develop an automatic "trigger" algorithm when human movement is identified in the outward facing locomotive camera and then, in the long-term, use the video data before and after the trigger event to 1) locate every trespasser event visible from the video (within approved limits) and 2) investigate behavioral trends and potential causal factors through application of artificial intelligence, computer learning, and human models on trespasser events. It is unknown how many risky events take place for each incident/casualty. The outward facing video data, combined with proper analytics and technology, offer an opportunity to identify all trespassing events, not only those reported or those leading to casualties, and then use that enlarged understanding toward more systematic analysis of trespasser events, both from spatial and behavioral perspectives. This exploratory portion of the project concentrated on the suitability and quality analysis of the video footage for such analysis.

2. Methodology

We used the high-quality Metra front camera video streams available on the Youtube channel: https://www.youtube.com/user/MetraCommuterRail for the initial development of the algorithm. This channel has six one hour like trips. At the high-level the algorithm development involved three components: Rail detection, Person detection, and Distance estimation of the person from rails. We used the existing algorithms that detect lines and structures in the image based on sharp changes in contrast, and developed a rail detection algorithm. Person detection was performed using the Yolo person detection algorithm. To estimate the distance of the detected person to the rails, we first perform a perspective transformation of the video frame as measured the distance between the bounding box of the detected person and the rails. Section III describes these three components of the algorithm in a greater detail. We later tested the algorithm on the video streams provided by the Metra team, and results and recommendations are discussed in sections 4 and 5.

3. Results

3.1. Rail detection:

To identify someone as a trespasser, the algorithm needs to be able to identify the location of the rails in the frame. We developed a rail detection algorithm that marks the rails in the frame. This algorithm uses the sharp changes in the contrast of the image to identify the edges, and as a result, also marks the edges identified on the physical structures in the proximity. We applied several rules based on the slopes of the detected edges and the lengths of the lines to identify only the rails and avoid most of the false positive detection. Fig. 1 is a sample screenshot of the rails detected in the video frame.

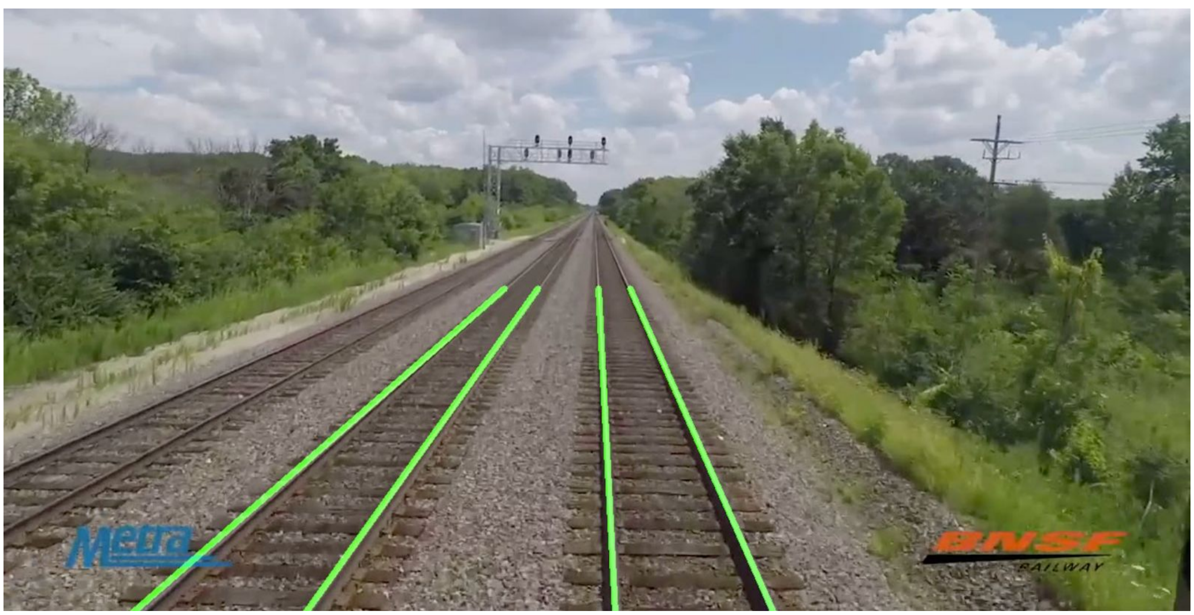

Fig. 1: Rail detection

3.2. Person detection:

We used the Yolo person detection module to identify people in each frame. The algorithm marks a bounding rectangle around each person detected in the frame. We applied the algorithm on several publicly available locomotive video streams. Fig. 2 is a sample screenshot of people detected in the video frame.

Fig. 2: Person detection

3.4 Distance to the identified person:

To measure the distance of the identified person from the rails, we first transform the skewed view of the camera frame into a bird's-eye perspective. This approach uses the line equations of the identified rails to produce an adjusted bird's-eye view. Please see the sample demonstration in Figures 3 and 4.

Fig. 3: Video frame prior to perspective transformation

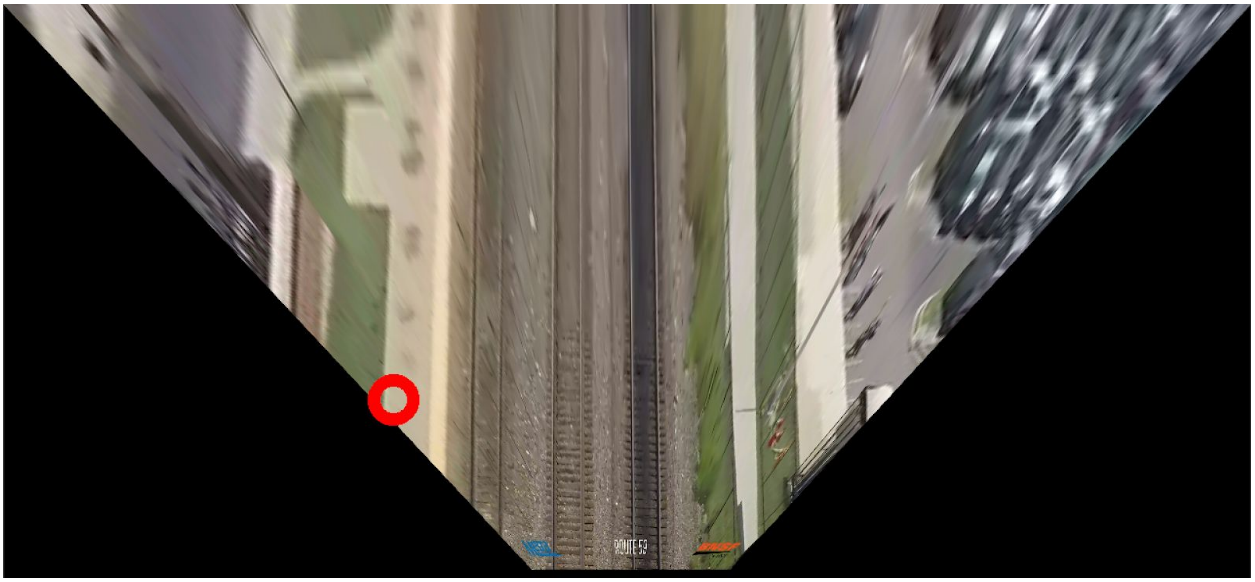

Fig. 4: Video frame after perspective transformation

In the transformed perspective, all the rails will be parallel lines. This makes the measurement of distance to the identified person a straight forward calculation. When a person is identified in the frame, we measure the distance of the bounding box to the closest rail and display the distance on the top of the bounding box. Please see the sample demonstration video using the Youtube link below. In this video, we have a trespasser at 1:10. The distance to this person from the leftmost rail is presented on the top bounding box. The distance is currently displayed as the number of pixels from the closest rail. This value can be transformed into feet using an appropriate multiplier.

https://www.youtube.com/watch?v=2hhF689HEGs

4. Summary of Data Analyzed

We ran our model on all the 7 trips of data provided by Metra. A summary of these tests is presented in Table 1. Each file has four video streams, of which we focused only on one stream: Forward_Signal_L/H.

Table 1: Metra video stream data

Video Name	Quality and Time	Sample links	Comments
METX86_0608_PM	Evening, Low res	https://youtu.be/NCc-oQ3R8jE	Rail detection worked fine for the most part. There were some false positives near the train station and at the railway crossings.
METX86_0609_LATEPM	LatePM, Low res	https://youtu.be/1CoSX	Rail detection was poor

		uv5a4g	on this late night video stream.
METX86_0609_PM	Evening, Low res	https://youtu.be/eGwvYTOIP7U	Rail detection worked fine for the most part. People Detected at 0:30, 1:00, and at 1:30.
METX8533_0609_PM	Evening, rain, Low res	https://youtu.be/VPVGB83X2Fo	Performance on both the rail detection and person detection was poor on this dark, low-resolution stream.
METX8533_0610_AM	Low light, low res	https://youtu.be/gVTwESo0hq8	Several false rail detections at the train station and at railway crossing. Person detection worked fine.
METX8533_0610_PM	Evening, low res	https://youtu.be/FE6M9a-FVdk	Rail detection had some trouble at the turn, but the person detection at the station was good.
METX8533_0611_AM	Morning, high res	https://youtu.be/dkBx66No9VY	Rail detection had several false positives, possibly due to the shadows at the sunset.

While the rail and person detection worked fine on several of the Metra low resolution videos, the performance however, did not match the high-definition Metra video streams we found on Youtube.

5. Recommendations

While we achieved a good performance on both lane detection as well as person detection on high-quality Metra public video streams, the performance on lower resolution videos that are more commonly used in front facing locomotive cameras was not very satisfactory. We identified the video resolution to be a key contributor factor--specifically, future work that addresses person detection and motivation of trespasser presence, would greatly benefit from the availability of higher-resolution video streams. The lane detection model needs improvement in terms of false detection rate, specifically at the train stations and in urban environments, where we find a significant amount of structured lines that resemble rails. Based on our preliminary tests on the low resolution video data, the results on person detection are encouraging--while the performance did not match that of High-resolution Youtube videos, the person detection module was able to detect people even in the low resolution video streams. Using the location of identified person, and some additional metadata, it is possible to model and score the potential risk associated with the identified person. However, at the available resolution, it is quite challenging to assess the body language, gestures, or any distress signals in the identified person. Future work can make use of High-resolution videos, and leverage from the existing scientific literature on surveillance of suspicious behavior at public places, to build on this work. Also, our model was developed primarily using the video streams from day time with good weather conditions. Future work needs to extend the applicability of the algorithm to a diverse set of weather conditions and to night time.

Contacts

Principal Investigator
Timothy C. Havens, Ph.D.
Director, Institute of Computing and Cybersystems,
Associate Dean for Research, College of Computing,
William and Gloria Jackson Associate Professor,
Department of Computer Science
Michigan Technological University,
1400 Townsend Drive, Houghton, MI 49931
phone: (906) 487-3115
thavens@mtu.edu

Co-Principal Investigator
Pasi Lautala, Ph.D., P.E
Associate Professor
Director, Rail Transportation Program,
Department of Civil and Environmental Engineering,
Michigan Technological University,
1400 Townsend Drive, Houghton, MI 49931
phone: (906) 487-3547
ptlautal@mtu.edu

Graduate Research Assistant
Siva Krishna Kakula
Department of Computer Science
Michigan Technological University,
1400 Townsend Drive, Houghton, MI 49931