Detecting Patches on Road Pavement Images Acquired with 3D Laser Sensors using Object Detection and Deep Learning

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Introduction

- Transport and road infrastructure departments perform regular inspections on pavements to assess surface condition.
- These inspections are used to make decisions about pavement maintenance planning, including cost considerations (Koch and Brilakis, 2011).

- In this study, we are focused on patch detection using object detection methods to detect patches on images acquired using 3D laser profiling systems
- The contributions of this work are 1) an automatic pavement patch detection model for images acquired by 3D profiling sensors and 2) comparative analysis of RCNN, and SSD MobileNet-V2 models for automatic patch detection.

Dataset

- This research utilizes asphalt pavement images acquired using the LCMS (Laser Crack Measurement) system supplied by PMS Pavement Management Services Ltd.
- LCMS surveys at speeds around 80 km/h, allowing a transverse profile to be captured every 5 mm.
- Image a is a range image - a visual representation of the height data collected from the lasers. Image b is an intensity image – a visual representation of the intensity data collected from the lasers.

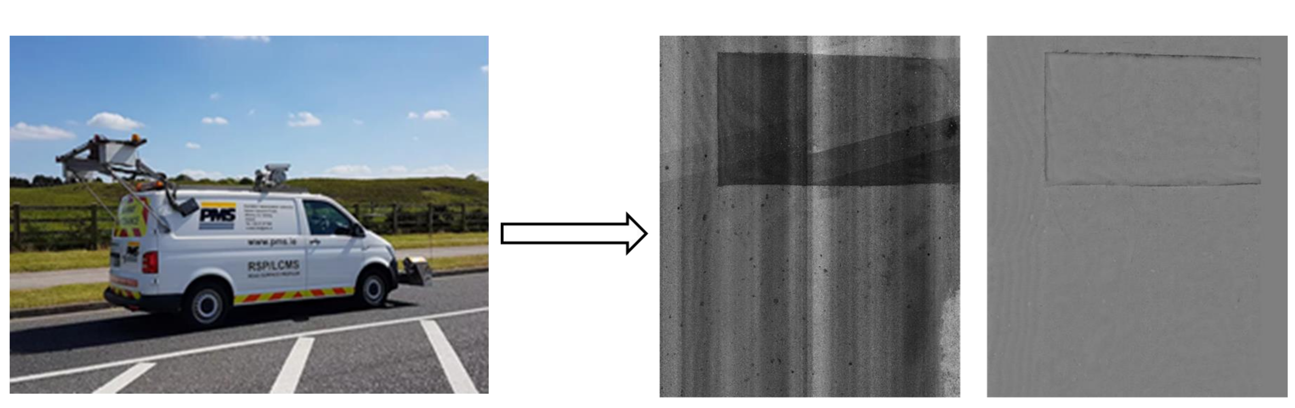

Figure 1: Left: Pavement data collection van with LCMS mounted on backside. **Right:** (a) Intensity image (b) Corresponding Gray-scale Range image.

Table 1: Details of entire training & testing set

Image Type	Total Images	Training Set	Testing Set
LCMS Range	2,242	1636	603
LCMS Intensity	2,242	1636	601

Table 2: Breakdown of testing set

Image Type	Total Images	# of patches in testing set
LCMS Range	603	856
LCMS Intensity	601	853

Methodology

- This work proposes a method for automatically detecting the presence and location of patches in images of pavements acquired using 3D laser profiling systems.
- Each patch must be detected and localized since road maintenance requires an estimate of the size and proportion of patched surface on a length of pavement.
- Therefore, we use object detection to draw bounding boxes and use box coordinates to determine the scaled area of an individual patch.

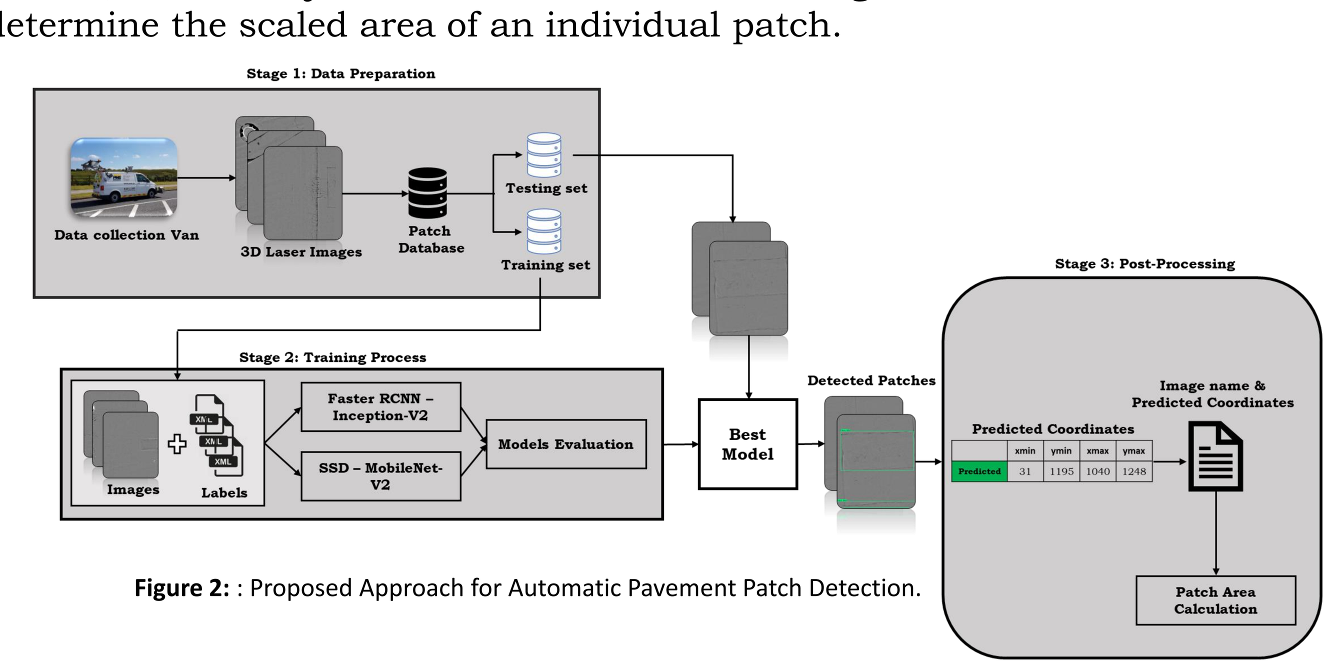

Figure 2: : Proposed Approach for Automatic Pavement Patch Detection.

Results

- We aim to address the following research question. How accurately can object detection methods detect patches on images acquired using LCMS?
- The metrics used to answer this question are Precision and Recall using IoU (Intersection over Union).

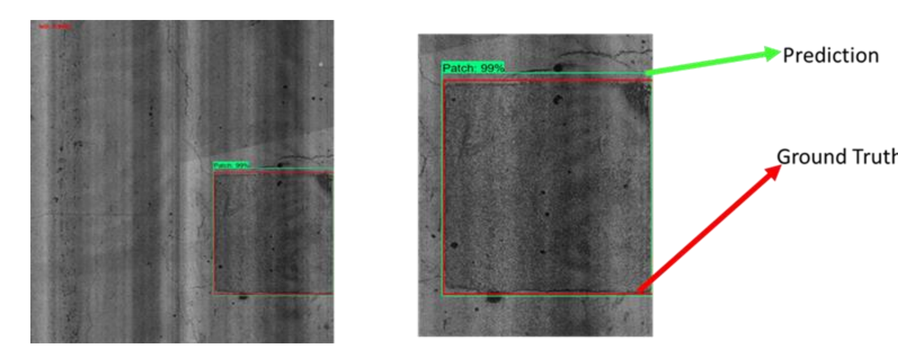

Figure 2: Example of Intersection over Union (IoU).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

Where TP+FP is the total number of ROI generated from the model.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Where FN is the number of ground truth boxes.

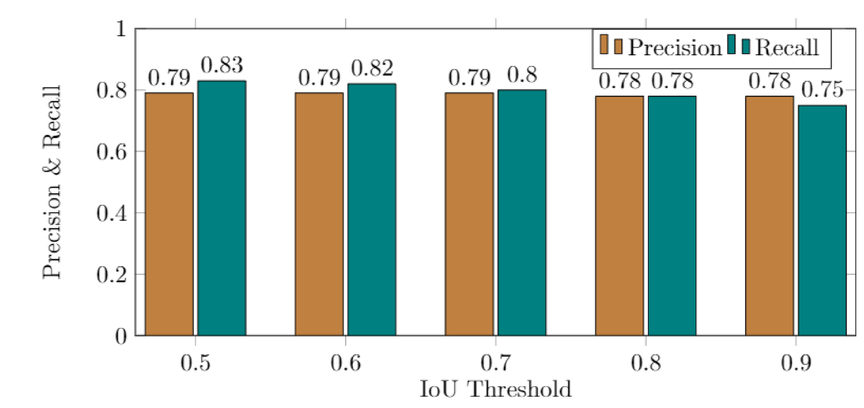

Figure 3: Comparison of Precision and Recall at different IoU threshold values using Range Images.

Experiment 1 & 2 (Patch Detection using Range & Intensity Images)

- Table 3 & 4 shows the detection performance of both models across range & intensity.

Table 3: Detection performance on Range images

Model	Backbone	Precision@0.5IoU	Recall@0.5IoU
Faster RCNN	Inception-V2	0.79	0.83
SSD	MobileNet-V2	0.87	0.7

Table 4: Detection performance on Intensity images

Model	Backbone	Precision@0.5IoU	Recall@0.5IoU
Faster RCNN	Inception-V2	0.67	0.74
SSD	MobileNet-V2	0.84	0.39

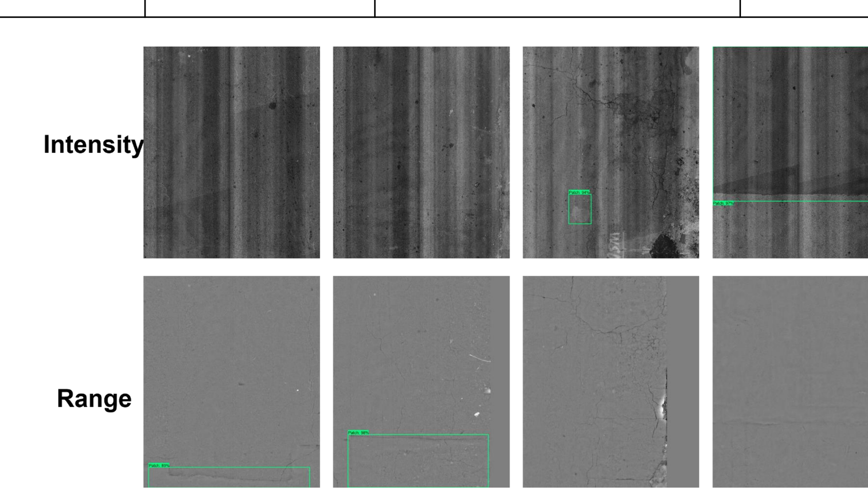

Figure 4: Visual analysis of Range and Intensity images.

Combined Model

- Using a combined model, we take the individual predictions from each of range and intensity models. If either or both models identify a patch, we count that patch as a detection.
- This leads to a higher true positive rate as more patches are found using results from both models, as indicated in Tables 5 & 6.

Table 5: Comparative analysis on Range & Intensity images

Model	# patches detected in Range images but not in equivalent Intensity images	# patches detected in Intensity images but not in equivalent Range images
Faster RCNN	142	46
SSD MobileNet-V2	292	31

Table 6: Detection performance on Combined Model

Model	Backbone	Precision@0.5IoU	Recall@0.5IoU
Faster RCNN	Inception-V2	0.6	0.88
SSD	MobileNet-V2	0.79	0.7

Conclusion

- Both Faster RCNN and SSD models provide better patch detection on range images. While Faster RCNN can detect more patches when compared to SSD, it has a higher false-positive rate on both image types.
- A combined model based on both image types identified the most patches, achieving 0.88 recall rate using Faster RCNN which is 5% higher than the best of the range-only and intensity only models.
- In future work we will investigate data pre-processing techniques such as identifying uncertain labelled images, further tuning of model hyperparameters, and testing other state of the art object detection networks such as Yolov5.

Acknowledgements

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