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# ROAD SURFACE STATE MONITORING AND POTHOLE LOCALIZATION BY OPPORTUNISTIC, IN-VEHICLE MONITORING

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## ABSTRACT

Degradation of roads affects not only rolling noise emissions but also indicates the need for maintenance in order to avoid even stronger damage. Our opportunistic in-vehicle noise and vibration monitoring system is applied to detect this degradation. To this end, noise, vibration and location data for a fleet of vehicles was collected during 2 years. GPS readings and lateral acceleration values are fed into a map-matching and lateral lane detection algorithm to locate the vehicles on 20m road segments. This paper focuses on which road features are captured and how these measurements complement existing, but expensive techniques to monitor road infrastructure. Potholes, bridge joints and misaligned concrete slabs are object of this study, focusing on interpretability of the AI system over complexity. A model using sound level spectra peaks is proposed to localize potholes, bridge joints and concrete slab joints. Road features on a location remain constant in short time frames (months), but lane detection and map matching errors spread out the observations. In addition, very localised road features are only sporadically sampled while driving over the same road section (such as potholes). This causes complications in the predictions system. Hence a strategy is proposed to combine multiple noisy road feature observations into single predictions on a location using distribution statistics. Thus, pinpointing the location of these potholes on a scale of 20m.

## 1. INTRODUCTION

As Internet-of-Things sensors (IoT) are a mature technology, creative uses for collected data have been conceived. One such application is monitoring road surface. In this case-study, disruptions in the road surface are studied, such as potholes, bridge joints and concrete slab joints. Several studies already show the capabilities of detecting such road features using machine learning. Research includes detector mechanisms for potholes ([1]), speed bumps ([2], [1]), manhole covers ([3]), alligator cracks and ravelling ([4]) and finally road profile estimation ([5]). Amongst the sensor being used are: accelerometers ([2], [1], [5]), camera's ([6]), thermal imaging ([7]), sound ([4]) and LIDAR ([3]). However, to the author's knowledge in-vehicle sound has not been previously applied to detect potholes.

Feature collection is often looked at the reference point of the driver. In particular, studies focus on trying to assign a label to time-frames of features (e.g. statistics of vertical acceleration, sampled at every second). In addition, the data is mostly carefully prepared by manually labelling the time series, allowing a supervised approach. Finally, the vehicles drive around at constant conditions (e.g. same speed, acceleration and weather conditions). Road features are however spatial data. Multiple vehicle passages sample the same underlying road. In particular road features could be missed if vehicles do not drive over it. Looking at both the temporal and spatial domain should therefore give more realistic results.

In section 2 (materials and methods) the following topics are covered: a broadband filter (2.1), a single and double peak detector (2.2) and a method for aggregating multiple passages (2.3). Finally, in section 3 (validation) a supervised model is constructed predicting ground truth pothole labels using a neural network. Two methods have been compared: the single peak and the double peak detector (3.2).

## 2. MATERIALS AND METHODS

In this study the vehicles are driven in everyday driving conditions, only limited by restrictions of transport legislation. Opportunistic monitoring refers to taking the opportunity of vehicles that are on the roads for other purposes to collect spatial data - on road surface quality in our case. A sensor box has been installed in the trunk of the cars. A GPS, 3D accelerometer and a microphone are included in the sensor boxes. Vehicles are geo-located on 20m road segments on an OpenStreetMap road network of August 2019 using map matching [8]. Lateral accelerometer readings are used to estimate the driving lane [8]. Features are based on 1/3 octave band sound spectra sampled each 20ms [9]. In section 2.1 a broadband filter is proposed to detect peaks in the audio signal, then section 2.2 introduces an idea of single peaks and double peaks. Finally, section 2.3 explains how multiple passages are aggregated for a road segment.

## 2.1 Broadband filter

A vehicle driving over road surface causes noise excitation originating from the front wheels and the back wheels. In particular, disruptions perpendicular to driving direction such as misaligned bridge joints cause the greatest signature. Algoji et al. in 2018 [10] has proposed a method to identify the axle distribution of vehicles (passenger cars, trucks, buses...). Sound levels were recorded at a static location along a bridge joint. Then, passages of vehicles are analysed for axle distribution. With some slight modifications, the problem has been translated to the mobile sensor box.

A bandpass filter between  $500Hz$  and  $1000Hz$  was applied to the sound pressure signal  $p(t)$ . Then, energy  $p^2(t)$  was collected at a sampling interval of  $20ms$ . This sampling frequency is chosen as a compromise between being able to capture fast transient and fulfilling the bandwidth-time (BT product) constant conditions.

A Gaussian filter  $g$  of 250 samples (corresponding to 5s) was applied to  $p^2(t)$  and subtracted from  $p^2(t)$ . Doing so eliminates the background noise due to tyre-road interaction (the continuous hum) and engine noise. The final signal  $L(t)$  sampled each  $20ms$  is given by:

$$L_p(t) = 20 \log_{10} (1.0 + \max(\alpha(p^2(t) - (g * p^2)(t)), 0)) \quad (1)$$

The calibration constant  $\alpha = 10^2$ , is dependant on the band filter choice, but should reflect the maximum value of  $(p^2(t) - (g * p^2)(t))/8$ .

## 2.2 Single and double peak detector

When the tire hits a pothole tire vibrations will be triggered and a sound peak is expected in the trunk of the car. Two peaks occur closely to each other: the peak due to front wheel and the peak due to the back wheel hitting the pothole. Since the microphone is located close to the rear tyre, the back peak should be higher than the front peak. A single peak detector can select possible potholes from noise by applying a threshold on the back wheel peak  $\theta_b$ . However, problems might occur due to random sound events happening in the car (music, talking people). Therefore a double peak detector mechanism is proposed. A possible pothole is registered in case two peaks are found, separated by a time difference of  $dt = l/v$ , where  $v$  indicates vehicles speed in  $m/s$  and  $l$  the car length. The passenger vehicles are assumed to have a length of  $l = 2.5m$  from front wheel to back wheel. In the dataset however, the actual lengths may vary slightly due to the distribution of cars. A wider car length range of  $[l - dl, l + dl]$  is taken to find the front peak given the back peak.  $dl$  is chosen to be:  $0.25m$ . The following thresholds were used:  $\theta_b = 3$ ,  $\theta_f = 1.5$  for double peak detection.

The chosen algorithm for peak detection is the function `scipy.signal.find_peaks` provided by the Python library SciPy [11]. A list of detected peaks is given at time instances  $t_k$  with  $k$  the sequential index of the peak. In addition the peak width  $w(t_k)$ , amplitude  $L_p(t_k)$  are collected.  $w(t_k)$  is measured as the width of the peak where

$L_p(t_k + dt) \geq \frac{3}{4} L_p(t_k)$  for  $dt$  close to 0. This peak finding procedure is used as a low-threshold detector. In the following step, the selected (double) peaks are filtered further.

## 2.3 Aggregating multiple passages

Multiple passages through a 20m segment are combined, based on an analysis of the distribution of  $L_p(t_k)$  over multiple passages and peaks detected. Following statistics of  $L_p$  (back peak) are included: minimum, maximum, standard deviation, percentiles 15%, 30%, 50%, 70%, 85% and distance between 70% and 30% percentile (dynamic range). The lower percentiles reflect the sound level when a pothole is not driven over. For the double peak detector, the same statistics of the front peak are added. In case no passages of a segment have got relevant peaks, the peak statistics are set to 0. For  $w(t_k)$  the following were chosen: minimum, maximum, standard deviation, percentiles 15%, 30%, 50%, 70%, 85%. Statistics of speed  $v$  are included as well: minimum, 15%, 50%, 85% and maximum. This should help making distinctions between low speed roads and high speed roads and avoid errors due to traffic jams. Finally  $\log_2 N$  with  $N$  the amount of passages of a segment and  $|\{L_p(t_k) \geq \theta\}|/N$  are added (fraction of amount of relevant peaks).

The procedures results in a number of features per segment: 21 for the single peak case and 29 for the double peak case. These features can then be further fed into a supervised machine learning model to predict if there are potholes on a segment.

## 3. RESULTS: VALIDATION WITH GROUND TRUTH LABELS

Agentschap Wegen & Verkeer (AWV) has provided the research project with a pothole ground truth dataset around the city of Ghent. AWV drives on main roads with the ARAN vehicle at right-most driving lane. The ARAN vehicle profiles the road and marks potholes using laser scanning and image recognition. In addition, bridge joints are also included in the dataset. The goal is to expand the dataset to include local roads, highways, all the driving lanes and driving directions.

For the ground truth, information is provided in 5 m segments. To translate this information to the 20m segments used in this study. Each 5m segment is mapped to the nearest 20m segment. The dataset was reduced for model training and validation purposes: segments should have a ground truth label and should have been driven over at least once. A random sample was taken of non-pothole segments. This was done to rebalance the dataset to contain the same amount of non-pothole segments compared to pothole segments. The test set is constructed by taking a 20% consecutive section from each trajectory in the dataset to make sure test set is independent from train set. The performance of the double peak approach was compared to the single peak approach.

For two cases (single peak and double peak) a neural

network with a single hidden layer (128 nodes and tanh activations) and output layer (1 node with softmax activation) was then trained with ADAM optimizer on the labelled train set. The observations have been reweighted, since only 6% of the observations are potholes. The model output is the detection probability  $p$ . Then, the model was validated using precision - recall curves. The purpose of this is to measure the effect of varying the threshold of the detection probability  $p$ . Lowering the threshold results in a lower precision and a higher recall rate. As explained in [12], a low-threshold can be set to include all possible potholes (high recall), but with a large amount of false positives. Then, manual inspection can further distinguish the actual potholes (true positives) from the false potholes (false positives).

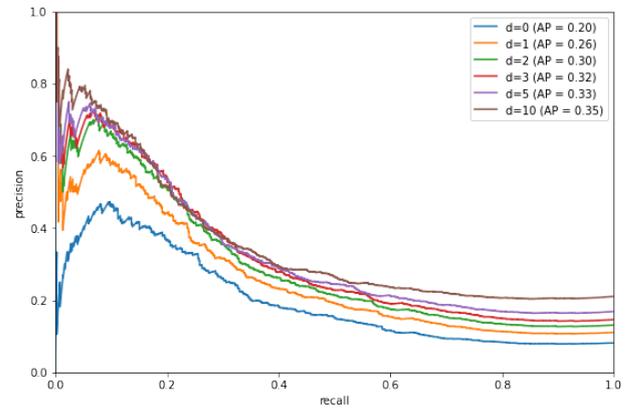
### 3.1 Assigning pothole labels to neighbouring segments

Due to GPS noise, detected potholes might appear at a neighbouring segment, therefore introducing false positives. The ground truth pothole labels are assigned to neighbouring segments as well after training, for different distances (see figure 1). At  $d = 2$  average precision (AP) is 10 percentage points higher than at  $d = 0$ , when using the single peak detector. It seems that  $d = 2$  is the optimal choice. This does not affect the predicted labels, but rather gives an indication that some of the mispredictions are due to GPS noise.

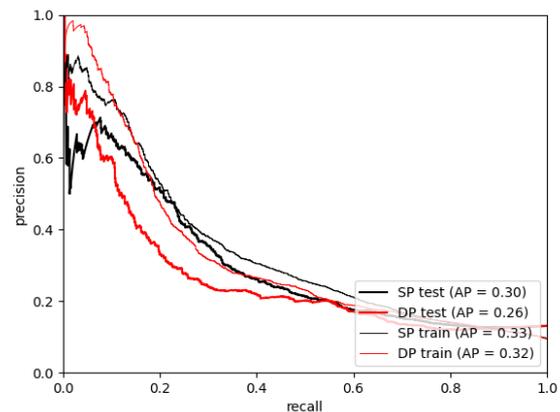
### 3.2 Single peak versus double peak

In figure 2, a comparison between single and double peak detector. Single peak detection obtains similar results compared to the double peak detector. There is however a slightly better average precision value for the single peak detector on the test set compared to double peak detection. The model therefore generalizes slightly better. For both single and double peak detector, the precision is not so high for higher recall rate. Several hypothesis can be formulated to explain this. To begin, the front and back peak threshold  $\theta_b$  and  $\theta_f$  might have been chosen to be too high, effectively eliminating relevant peaks at lower speeds and smaller disruptions of the road surface. Next, the ground truth data has been collected from January 2018 to December 2018. In February, approximately 50% has been collected, followed by May (20%), July (10%) and June (5%). The opportunistic dataset has been collected starting April 2018 until October 2019. 85% of the data has been collected after December 2018. Hence there is a mismatch in data collection periods: new potholes could have appeared or potholes could have been fixed by then. In addition, lane detection could attach a wrong lane to the ground truth data or to the opportunistic data. Finally, considering the ARAN vehicle, precision and recall curves are probably not perfect either for real-world potholes.

In addition, this single peak model has been plotted on a map for varying thresholds, see figure 3 and figure 4. To evaluate the model accuracy, the test set has been plotted on a map for a single detection probability threshold in figure 5.



**Figure 1.** Precision - recall curves of the single peak detector. Pothole labels are spread out over neighbouring segments ( $d$  segments). Average precision (AP) is also given.



**Figure 2.** Precision - recall curves for the cases single peak detector (SP) and double peak detector (DP) with pothole labels being spread out over a radius of 2 segments. Average precision (AP) is also given.

## 4. CONCLUSION

A model to detect potholes has been proposed using multiple passages of passenger cars. The basic building block is sound pressure in a frequency band from 500Hz to 1000Hz which measures the sound level (peaks) compared to background sound level (continuous hum of tyre-road noise). Sampling the broadband feature 50 times a second keeps the transient peaks. Then, a double peak detector has been tried out which measures the peak caused by the back wheel and front wheel of passenger cars. It was shown that a single peak detector is sufficient to detect potholes on a road. The single peak detector depends only on the back wheel excitation to the pothole. A non-linear, feed-forward neural network has been constructed which predicts ground truth pothole labels from Agentschap Wegen & Verkeer. Using maps and varying detection probability thresholds it was shown that the presence of potholes could be predicted. This information could be used by road administrators to localize locations which need to be

repaired or by route planners to avoid roads in bad shape when transporting sensitive cargo.

## 5. ACKNOWLEDGEMENT

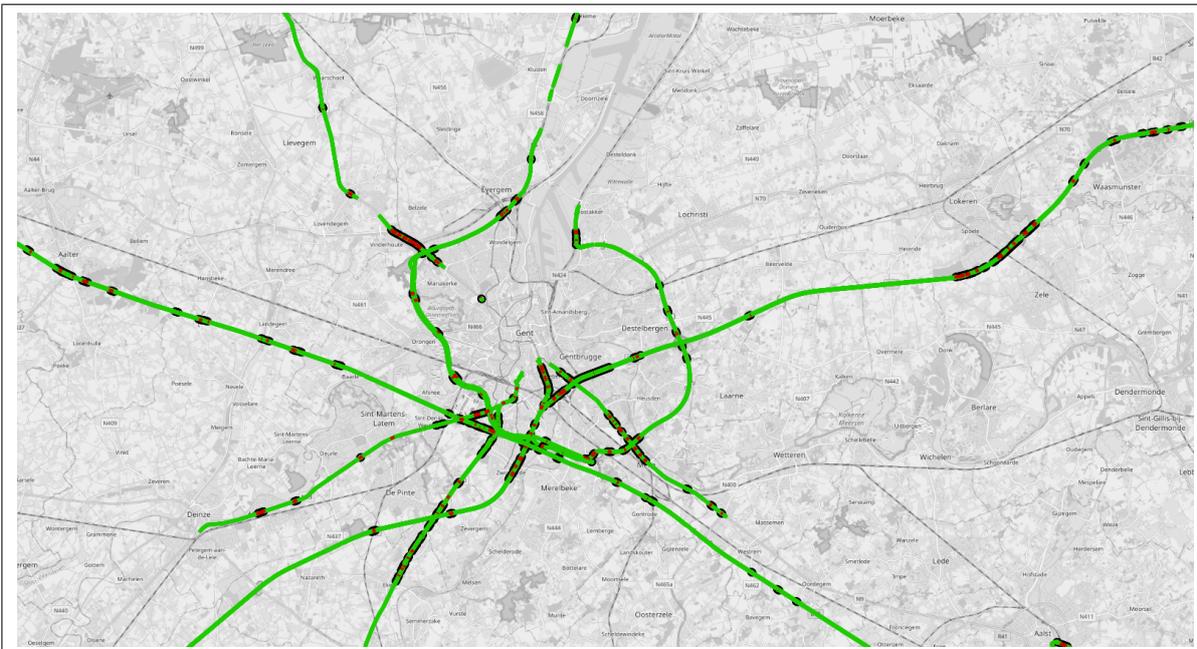
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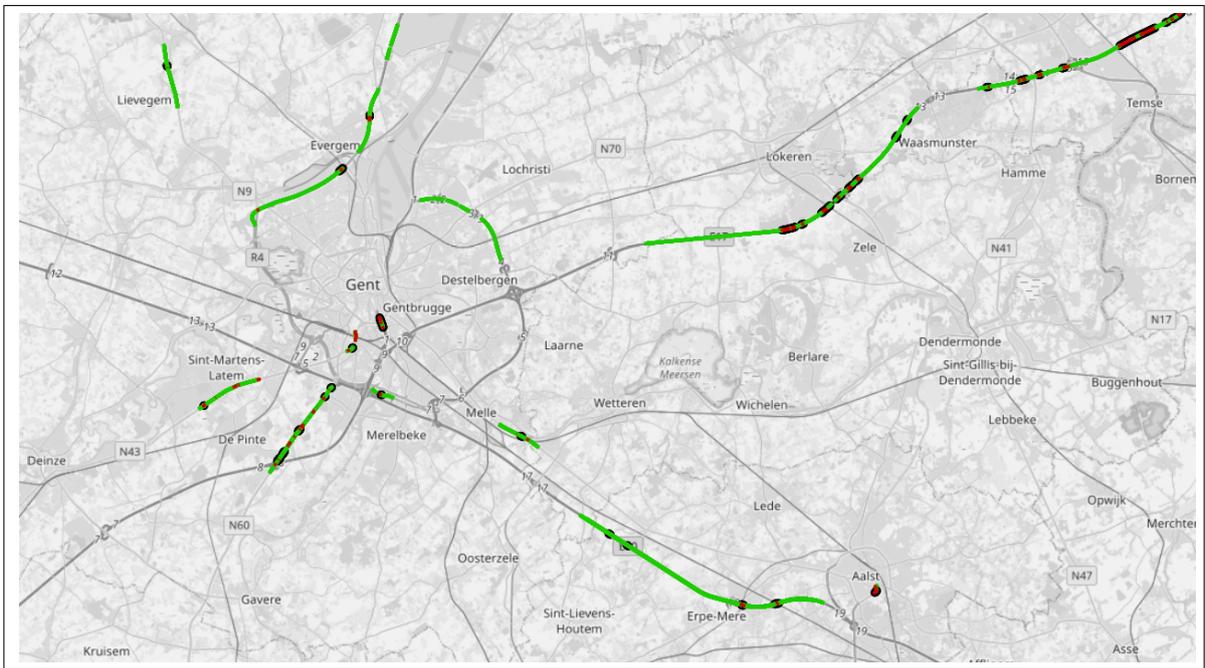
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**Figure 3.** Accuracy of single peak pothole detector for a detection threshold of  $p \geq 0.7$ . Location: Ghent, Belgium ( $51^{\circ}03' N 3^{\circ}43' E$ ). Pothole locations are indicated with black circles, as labelled by Agentschap Wegen & Verkeer (AWV). Green indicates an accurate prediction of the road state, red indicates a faulty prediction. E.g.: red center inside black circle indicates a false negative, green spot without black circle indicates a true negative. Road map: ©OpenStreetMap contributors.



**Figure 4.** Accuracy of single peak pothole detector for a detection threshold of  $p \geq 0.8$ . Location: Ghent, Belgium



**Figure 5.** Accuracy of single peak pothole detector for a detection threshold of  $p \geq 0.7$ . Dataset has been reduced to only test set - meaning how would the model react to new samples?