Machine Learning techniques applied to Road Health Status Recognition through Tyre Cavity Noise Analysis

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Abstract. This paper proposes a system based on Neural Networks (NN), designed for providing an efficient, non-invasive and automated method for monitoring the health status of road pavements by using features derived from Tyre Cavity Noise (TCN) analysis. Indeed, visual inspection remains to date the most common choice for evaluating the condition of road pavements; however, this method is both labor-intensive and time consuming. The system presented in this work uses a microphone placed inside the vehicle tyre that measures TCN while travelling normally, and an embedded data acquisition system based on a Raspberry Pi which feeds the NN tools to recognize and classify road deterioration. We also present a preliminary analysis of features based on temporal and spectral characteristics of TCN signals generated by tyre/road interaction and acquired on three different kind of road distresses. The results show good classification capability and, moreover, the sound pressure measured inside the tyre was correlated accelerometric data measured on-board.

1. Introduction

Regular maintenance of road pavements is of paramount importance to ensure both traffic safety and passenger comfort. Swift actions can be crucial not only to prevent further damages to road pavements, caused by the constant and intensive use of road infrastructures and other environmental factors, but also because with proper scheduling, road maintenance costs can be reduced up to three times [1]. Indeed, the main cause of pavement distresses is the repeated passage of heavy traffic loads, temperature variations, adverse weather conditions and frequent temperature oscillations. The quality of asphalt components and of the laying process is also fundamental to ensure the durability of the road surface [2, 3].

Traditional monitoring methods can be divided in destructive and non-destructive methods. Among the destructive ones, pavement coring is the most popular since it has the advantage to provide an in-depth analysis of the pavement status; however, it is expensive and requires closing the road to traffic. Non-destructive techniques rely mainly on visual inspection, which can require an on-site “walk and look” approach or measurements made with mechanical devices. This techniques can provide both an accurate estimation of the road health status and a proper identification of the distresses, but have the disadvantage of being time-consuming and lack repeatability, since they depend on the operator’s judgment [1]. On the other hand,
aside visual inspection, other mechanical devices are used, such as laser profilometry [4] or Ground Penetration Radar (GPR), which exploits the propagation and reflection of electromagnetic waves in underground media [1, 5]. However, both destructive and non-destructive traditional methods have the disadvantage of being expensive, due to the costs related to the operator and to the measurement equipment.

In the last decades, new sensors which rely on accelerometric [6, 7], photographic [8, 9] and acoustic [10] measurements combined to Artificial Intelligence (AI) technologies have been developed. In the context of the so-called Smart Roads [11] these new technologies and possibilities increase the efficiency of road infrastructure maintenance, not only for damage detection but also to improve viability, combining their efforts with other smart methods such as the intelligent traffic light systems [12].

This work presents a novel, non-invasive and automatic method to identify different kinds of road surface degradation, by studying the different acoustic features of three different kind of distress. The acoustic signal is measured thanks to an edge sensor mounted on the vehicle which is able to measure the pressure inside the tyre cavity. The method is particularly useful, since it recognises the state of degradation of road surfaces automatically using AI techniques. Moreover, the acquisition data system is cheaper compared to other systems [13]. The study also involved an in-depth analysis of the spectral features of the acoustic signal coming from different types of distresses, which was carried out in order to gain accurate information about the physical processes at the foundation of tyre/road acoustic interaction.

2. State of the art
Over the years, several acoustic methods have been developed to identify road surface wearing. These methods mostly rely on noise measurements outside or inside the vehicle. Therefore, the signal measured by the sensors is related to both the pavement status and to the type of road surface [14].

Measurements performed outside the vehicle rely on the evaluation of Tyre/Road Noise (TRN), caused by the tyre/road interaction during the motion of the vehicle. Initially, TRN was studied for its role on Road Traffic Noise (RTN), which has been linked to sleep disturbances, cardiovascular disease, hypertension, myocardial infarction [15, 16, 17, 18, 19]. TRN is widely studied in literature and many methods have been developed, such as Close-Proximity (CPX) method [20] or the various Pass-By methods (SPB [21], CB [22], CPB [23]).

Moreover, in the last decade, the interest in the use of AI algorithms to automate the process of road surface classification has increased more and more. In particular, several works were developed with the aim of identifying the pavement type and to classify its degradation [24, 25]. This task can be carried out by using microphones placed close to the contact patch of the tyre, in order to directly measure the TRN [26].

Beside internal/external vehicle noise measurements, another classification technique that was recently proposed relies on the measurement of TCN generated by tyre/road interaction. TCN studies were initially carried out by Bschorr [27] in the context of the study of passenger’s acoustic comfort.

Indeed, as the tyre rolls on the pavement, the moving tyre-contact patch compresses the air inside the cavity, thus providing a source for the acoustic pressure field. Due to the size of the tyre cavity, this field allows for the formation of standing waves. Moreover, natural frequencies of the tyre/wheel system include all deformation axes, the effect of the rim, and the suspension system, as studied by Mohamed [28]. For example, a typical Power Spectral Density (PSD) measured with a tyre cavity microphone is shown in figure 1. Standing modes can be easily identified in the low-frequency region, while at frequencies higher than 1 kHz modes are overlapped and no longer recognizable. Lastly, a preliminary model for the classification of road pavements using TCN measurements and machine learning techniques was presented by Krauss and Masino [10, 29].
In this scenario, this work focuses on the use of an edge computing platform that processes audio signals measured by a TCN microphone, in order to produce a classification of the status of the road surface. In particular, this work shows the results of the analysis performed so far.

Differently from other authors [29, 10], these analyses focus on highlighting specific acoustics features of road pavements related to their maintenance status, capable of classifying the different distresses present on the road surface, rather than on the correlation with CPX measurements or asphalt type. This was possible thanks to a preliminary analysis of the spectral components of the signal aimed at identifying the response of the cavity to the stresses induced by the different types of distress. The TCN signal was compared with accelerometric data measured by accelerometers placed on board. The features analysis carried out represents therefore the first step to develop a multi-layer neural network classifier of pavement distresses.

3. Experimental Methods

The sensor used for these analyses was developed by the Karlsruhe Institute of Technology (KIT) [13] and is composed by:

- A electret microphone CMA-4544pf-w, placed inside the tyre and connected through a SMA connector to an external Bluetooth device;
- A Bluetooth module, composed by a TL072 preamplifier and a BC127 Bluetooth module with a DAC converter;
- An LM540-054 Bluetooth device, placed on board and connected through USB port to a Raspberry Pi 2 Model B V1.1;
- The Raspberry Pi that receives data and saves it in 16 bits .wav format.

The accelerometer signal data acquisition system is instead composed of:
• A piezoelectric accelerometer B&K 4507B, placed inside the vehicle in proximity of the SRTT tyre;
• Apollo light version Apollo lt 8C data acquisition board.

The whole set up is placed on the mobile laboratory, i.e. the vehicle used for measurements. As the vehicle travels on the road, the system gathers data on-the-go and saves it in a local SD card. The vehicle used is a Mercedes-Benz Vito: this choice was performed since it can mount the Standard Reference Test Tyre (SRTT) used for CPX measurements [21] (see figure 2). Indeed, TCN measurements were seldom performed together with CPX noise measurements.

The acoustic signal measured was analyzed in post-processing. The measurement campaign was carried out near the city of Pisa, Italy, and all the pavement analyzed in this work were dense-graded pavements. Moreover, in order to minimize the effects of the vehicle speed on TCN signal, the speed was always been maintained approximately around \( v = 40 \) km/h. Acoustic data was used to analyze three different categories:

• Good condition: a signal of a pavement without distress;
• Type-1 distress: superficial and extended distresses which affect a wide part of the road;
• Type-2 distress: superficial distresses which have smaller size than Type-1 distresses, i.e. they have size of maximum 1 m; they are localized on the road.

Spectral analysis of noise signals measured while travelling on roads belonging to the three categories was used to derive a set of parameters that could be used to perform the classification task. Moreover, accelerometric data was used to gain a deeper insight on the origin of modes present in the noise signal very low frequency region, but was not used to perform the classification.

All post-processing tools were developed using MATLAB 2021b.
4. Results

4.1. Signal Analysis and comparison with accelerometric data

At first, the analysis of transient signals such as Type-2 distresses was performed using spectral analysis in one-third octave bands. One-third octave band levels were obtained through FFT calculation.

A qualitative analysis yields that the signal from Type-2 distresses shows typically an excitation of both tyre cavity eigenmodes and other low frequencies (i.e. $f < 100$Hz) and high-frequency bands (i.e. $f > 2$kHz), as shown in figure 3. Low-frequency modes cannot be explained by taking into account only the tyre [28] and, for this reason, other physical sources were investigated, such as the suspensions and wheel axle using the accelerometric data.

In order to provide a more in-depth analysis of the low-frequency modes, TCN signals were compared to the accelerometric data provided by the accelerometer. Using one-third-octave band analysis, the correlation between accelerometric data and TCN was calculated. In particular, as shown in figure 4, the correlation between low-frequency TCN and accelerometer bands results high, since it lies between 0.61 and 0.75.

![Spectrogram](image)

**Figure 3.** Example of one-third octave bands analysis for a Type-2 distress signal. Both low-frequency and high frequency modes are excited: low-frequency modes refer to long-lasting phenomena such as vertical oscillations of the vehicle, while the tyre interaction with the road surface distress excites high frequency modes.

4.2. Parameters for NN classification

Type-1 distresses provide a different excitation compared to Type-2 ones. Indeed, one-third octave bands analysis of the TCN signal on Type-1 distresses shows that the most excited modes are the tyre cavity eigenmodes, instead of the suspension modes which are relevant for Type-2. An example of the signal generated by this kind of distress is shown in figure 5. The differences that arise between the spectral analysis of the two distresses could be explained by taking into account the spatial characteristics of the distresses: Type-2 distresses are highly
localized, and provide an impulse-like excitation of the tyre, while, on the one hand, Type-1 distresses increase the sound energy inside the cavity.

Several features for distinguishing the different signal produced by each distress were identified, by using a mix of broadband and frequency-dependent features. Broadband parameters are:

- $L_{p,tot}$: signal Sound Pressure Level (SPL);
- $L_{p,(f_d-f_u)Hz}$: signal SPL within the frequency range $(f_d-f_u)$;

While frequency-dependent features used in this work are:

- $R_1 = \frac{L_{p,(200-240)Hz}}{L_{p,(270-400)Hz}}$: ratio between the $L_p$ evaluated in the tyre first resonance and the $L_p$ evaluated between the first and the second tyre resonance;
- $R_2 = \frac{L_{p,(400-460)Hz}}{L_{p,(480-600)Hz}}$: ratio between the $L_p$ evaluated in the tyre second resonance and the $L_p$ evaluated between the second and the third tyre resonance;
- $R_3 = \frac{L_{p,(630-660)Hz}}{L_{p,(700-830)Hz}}$: ratio between the $L_p$ evaluated in the tyre third resonance and the $L_p$ evaluated between the third and the fourth tyre resonance;
- $HF = \frac{L_{p,(2,5-8)kHz}}{L_{p,(1,5-2)kHz}}$: it indicates the $L_p$ evaluated at high frequencies, i.e. $2,5-8$ kHz;
- $LF = L_{p,(20-100)Hz}$: it indicates the $L_p$ evaluated at low frequencies, i.e. $f < 100$ Hz.

![Figure 4. Correlation between accelerometer and TCN signal, shown in one-third octave bands.](image)

A measurement campaign was carried out for the purpose of acquiring data to study the possibility of evaluating the feasibility of a NN classifier based on these features. TCN signals were divided into samples of long 0.4 s each. In this way, the total number of samples from the measurement campaign for the Good condition class is $N_{GC} = 1770$. The sample size of Type-1 class is $N_{CR} = 2136$ while $N_p = 41$ samples belonged to Type-2 class. In table 1, 2 and 3 the correlations between the parameter chosen for the three different classes are shown.

The low correlation found between the features used for Good Condition (table 1) and Type-1 distresses (table 2) shows that the features are indeed suitable for a NN classifier, while for the Type-2 distresses (table 3) $R_1$, $R_2$, $R_3$ and $HF$ are strongly correlated. For this reason, the parameters chosen to train the NN were only $L_{p,tot}$, $R_1$ and $LF$. 
Figure 5. Example of one-third octave bands analysis for a signal caused by a Type-1 distress: low-frequency modes are less excited compared to Type-2; for Type-1, the interaction excites mainly the tyre cavity resonance modes.

Table 1. Features correlation for the signal of Good condition class.

|          | $L_{p,tot}$ | $R_I$ | $R_{II}$ | $R_{III}$ | HF  | LF  |
|----------|-------------|-------|----------|-----------|-----|-----|
| $L_{p,tot}$ | 1           | 0.04  | -0.18    | -0.27     | 0.08| 0.72|
| $R_I$     | 0.04        | 1     | 0.26     | 0.41      | -0.01| -0.20|
| $R_{II}$  | -0.18       | 0.26  | 1        | 0.32      | -0.01| -0.19|
| $R_{III}$ | -0.27       | 0.41  | 0.32     | 1         | -0.18| -0.24|
| HF        | 0.08        | -0.01 | -0.01    | -0.18     | 1   | -0.03|
| LF        | 0.72        | -0.20 | -0.19    | -0.24     | -0.03| 1   |

4.3. NN development and performances

By using the aforementioned parameters, a multi-layer NN with 2 hidden layers and 100 neurons per layer was chosen. This choice was deemed suitable since the number of input parameters of the model is small and this type of net performs well on edge devices [30]. However, the small sample size for Type-2 class could affect the net’s recognition ability: for this reason, the sample size was increased to 205 samples by adding White Gaussian Noise to the original samples [31], with a signal-to-noise ratio SNR = 20. 70% of the sample size was used for the training phase, while for validation 15% of the samples was used and the remaining 15% was used for the testing phase.

The net performance was evaluated by testing it on a road classified previously by means of visual inspection. Table 4 shows the performances for training, validation and testing.
Table 2. Features correlation for the signal of Type-1 class.

|       | \(L_{p,\text{tot}}\) | \(R_I\) | \(R_{II}\) | \(R_{III}\) | \(HF\) | \(LF\) |
|-------|-----------------|--------|---------|-----------|-------|-------|
| \(L_{p,\text{tot}}\) | 1                | -0.36  | -0.39   | 0.26      | 0.78  |
| \(R_I\)   | -0.36           | 1      | 0.66    | 0.70      | -0.48 | -0.44 |
| \(R_{II}\) | -0.36           | 0.66   | 1       | 0.66      | -0.54 | -0.35 |
| \(R_{III}\)| -0.39           | 0.70   | 0.66    | 1         | -0.64 | -0.38 |
| \(HF\)   | 0.26            | -0.48  | -0.54   | -0.64     | 1     | 0.23  |
| \(LF\)   | 0.78            | -0.44  | -0.35   | -0.38     | 0.23  | 1     |

Table 3. Features correlation for the signal of Type-2 class.

|       | \(L_{p,\text{tot}}\) | \(R_I\) | \(R_{II}\) | \(R_{III}\) | \(HF\) | \(LF\) |
|-------|-----------------|--------|---------|-----------|-------|-------|
| \(L_{p,\text{tot}}\) | 1                | -0.75  | -0.86   | -0.88     | 0.90  | 0.44  |
| \(R_I\)   | -0.75           | 1      | 0.88    | 0.84      | -0.75 | -0.16 |
| \(R_{II}\) | -0.86           | -0.88  | 1       | 0.92      | -0.86 | -0.24 |
| \(R_{III}\)| -0.88           | 0.84   | 0.92    | 1         | -0.85 | -0.30 |
| \(HF\)   | 0.90            | -0.75  | -0.86   | -0.85     | 1     | 0.25  |
| \(LF\)   | 0.44            | -0.16  | -0.24   | -0.30     | 0.25  | 1     |

Table 4. NN classifier’s performances of success on training, validation and testing dataset.

| Class    | Training | Validation | Test  |
|----------|----------|------------|-------|
| Good condition | 93.9%   | 95.5%      | 94.0% |
| Type-1    | 96.7%   | 96.5%      | 93.1% |
| Type-2    | 78.9%   | 90.0%      | 75.8% |

The accuracy, i.e. the overall percentage of success, is shown in table 5. The values obtained are:

- 80.0% for Type-2;
- 94.1% for Type-1;
- 96.2% for Good condition;

In table 5 the metrics used to evaluate the NN performances are reported, i.e. accuracy, precision, recall and F1-score.

Table 5. NN classifier’s performances.

| Class    | Accuracy | Precision | Recall | F1-score |
|----------|----------|-----------|--------|----------|
| Good condition | 94.1%   | 94.9%     | 94.1%  | 94.5%    |
| Type-1    | 96.2%   | 93.8%     | 96.1%  | 95.0%    |
| Type-2    | 80.0%   | 98.8%     | 80.0%  | 88.5%    |
5. Discussion
The first part of the work consisted in analyzing the acoustic signal produced by different kind of distresses inside the tyre cavity, using also data from an on-board accelerometer. Comparing the signal measured by the microphone and the signal measured by the accelerometer, the presence of low-frequency modes inside the tyre finds a reasonable explanation. Indeed, since the modes are visible in accelerometric signals, they could be caused by the vehicle suspensions.

Then, the features of different distresses were analyzed by means of a spectral analysis performed in one-third-octave bands. While low frequencies take into account phenomena with a longer time scale, high-frequency modes are useful for locating short-time events, such as Type-2 distresses. Indeed, due to their nature, they act as an impulsive force on the system and are thus capable of exciting the whole spectrum, rather than providing energy only to the natural frequencies of the tyre.

On the other hand, analysis of the correlation between $L_{p,\text{tot}}$, $R_I$, $R_{II}$, $R_{III}$, HF and LF shows that $L_{p,\text{tot}}$, $R$ and LF are sufficient to train the net.

The classifier shows a good percentage of success in identifying Type-1 distresses; however the identification of Type-2 distresses is still non adequate. This is consistent with previous analyses [26] and might be due to the smaller amount of samples of Type-2 distresses compared to other features. The performance of our classifier and the choice of adopted features show nonetheless that different road pavement distresses can be recognized. However, a larger data-set with more distress classes and more samples per class could pave the way towards a more complete efficient classifier. The sample size remains however a critical issue for training NNs and, therefore, on-site measurements are fundamental when defining the dataset.

6. Conclusions
In this work, AI technologies were used to classify three different types of road pavement distresses. The goal was to design a system capable of classifying automatically the type of road pavement distress. This tool could improve the time efficiency of the damage recognition and could thus reduce the cost of of pavement maintenance [32] besides providing means to support decision-making for planning road maintenance.

In this stage, the main focus was to study how to classify good road conditions and two different kind of class of distress: distresses extended over the road and distresses localized in a short region, called respectively Type-1 and Type-2 distresses. A preliminary analysis of the spectral features of each kind of distress and the study of the correlation of the Type-2 distresses with the signal taken from accelerometers allowed to identify the proper features in order to train a NN classifier. Network performance, evaluated by using accuracy, precision, recall and F1-score, is appropriate for a valid classification of types of distress. Therefore, the system shows potential for the identification of features associated with pavement defects. Indeed, most of the problems found so far regard the Type-2 identification: this could be due to the smaller sample size in the data-set. This limitation should be overcome with more measurements. Another the major limit of this work is that the net classifies during post-processing analysis, so different classifying algorithms such as k-Nearest Neighbors (KNN) or Convolutional Neural Networks (CNN) could be tested in the future in order to build a net which gives a real-time classification during the vehicle motion. Moreover, adding more types of distress to the classifier could be useful for obtaining more detailed and precise information about its structural conditions. At the same time repeated measurements over time could lead to a study of the temporal evolution of distress, proving a time scale for each distress that can contribute to the decision-making for planning road maintenance. This may be possible by trying to build different neural network models such as Long-Short Term Memory (LSTM) networks, that take into account data from different time-scales.
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