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ESTIMATION OF THE PAVEMENT CONDITION INDEX VIA TYRE CAVITY NOISE MEASUREMENTS AND AI SIGNAL PROCESSING

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ABSTRACT

Regular monitoring of the pavement condition is an essential feature to ensure both traffic safety and passenger comfort. In fact, pavement distresses directly influence traffic safety and passenger comfort and could produce negative effects on air and noise pollution of the vehicles. In this field local agencies commonly use the Pavement Condition Index (PCI), which is based on pavement distress types and their spatial extension, as a reference indicator of the pavement condition. Unfortunately, traditional methods to evaluate PCI can require an on-site "walk and look" approach that are time-consuming, expensive and may request the closure of the road to traffic. To overcome such difficulties, in the last years different measurement methods have been developed and tested. In this paper an innovative methodology to estimate the PCI in urban context, permitted a dynamic and continuous acoustic measurement of tyre cavity noise (TCN) by means of a microphone inside the tyre. This innovative way involved the definition of new pavements classifying parameters. The new indicators seem to show a good agreement with the PCI values evaluated with the previous methodology. A possible improvement of the method will be tested by applying an AI signal processing to infer the PCI value from the TCN.

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1. INTRODUCTION

Road maintenance plays a fundamental role in travel safety, comfort, pavement lifetime and in the reduction of air and noise pollution [1]. In this field, dynamic urban pavement condition monitoring could play a crucial role against the traditional methods that require an on-site "walk and look" approach. Traditional methods are time-consuming, expensive, and usually demand the closure of the road to traffic [2].

Different pavement performance indicators have been developed to decide the best maintenance time for the pavement. Given the large variety of general conditions of the pavement's location, global pavement condition indicators are based on distinct aspects of the pavement surface and ride quality. The most well-known performance indicators are Pavement Condition Index (PCI), International Roughness Index (IRI), Present Serviceability Index (PSI), and Surface Distress Index (SDI) [3-5].

In this context, the SURFace Analysis for Classification and Evaluation (SURFACE) project developed by iPOOL s.r.l. in collaboration with the University of Pisa, iDNA, and InTouch, focused on the development of a real-time monitoring system to classify and describe the pavement surface condition. The system is based on the Tyre Cavity Noise (TCN) measurement, which strongly correlates with the pavement texture [6]. Tyre Cavity Microphones (TCM) have found their place in road monitoring systems and the

evaluation of different road surface parameters characterization [7-8].
This paper aims to find a way to describe and correlate PCI values measured by AVR S.p.A. (agency specialized in management and maintenance of roads for infrastructure concessionaires and public procurers), with the measured TCN signals based on the SURFACE project results and classification. All measurements were taken in normal traffic conditions.

2. EXPERIMENTAL METHOD AND PAVEMENT EVALUATING PARAMETERS

This sections firstly presents the parameters defined in the SURFace project to classify pavement segments and the ones used to search for relations with the PCI of the investigated pavements. Description of the experimental setup and case study are reported in the second subsection.

2.1 PCI definition

PCI value is an extended pavement surface evaluation parameter that depends on the pavement distress types and extensions. Its value ranges from 0 to 100 corresponding to pavement condition from "failed" to "excellent". Distresses are classified by means of their spatial extension or ride quality in low severity (L), medium-severity (M), and high-severity (H). Pavements are divided with respect to their location and use. Each pavement section is divided into a defined number of survey samples. PCI sample estimation depends on the deduct value of the pavement distress. Deduct value is obtained by the pavement distress surface density on the sample surface weighted by a specific curve in accordance with the severity case. Eq.1 reports the PCI surveyed sample and Eq.2 the PCI value of the section.

$$\mathrm{PCI} = 100 - \mathrm{CDV} \tag{1}$$

$$\mathrm{PCI_s} = \frac{\sum_{i=1}^{n}(\mathrm{PCI_i} \cdot \mathrm{A_i})}{\sum_{i=1}^{n} A_i} \tag{2}$$

In Eq.1 CDV is the corrected deducted value obtained from the sum of the different deducted values. In Eq.2 $\mathrm{PCI_s}$ is equal to the section PCI value, $\mathrm{PCI_i}$ the sample's PCI, and $\mathrm{A_i}$ the sample's surface extension. Examples of PCI calculation, pavement distress severity case weighting curves, and classified pavement distress types are reported in [9].

2.2 Definition of TCN classification parameters

Pavement classification segments were classified in the SURFACE project using the maximum absolute value of the normalized signal inside the tyre. Classes defined in the project were: silence, good-quality, bad-quality, and pothole. The silence case corresponds to a classification segment in which TCN values are too low to be evaluated. The three threshold values were found by video visual inspection of different pavements at a reference speed of 40 km/h. The pothole class corresponds to pressure values in which the signal was higher than 0.95.
In this paper, spatial parameters are defined based on linear density pavement classes. Surveyed pavement elements are divided into classification segments classified via the SURFACE procedure. Eq. 3 reports the general formula to estimate the linear density class of a selected road piece.

$$\rho_c = \frac{L_c}{L_m} \tag{3}$$

In Eq.3 L_c is the total length of classification elements with the same class, L_m is the length of the surveyed road, and ρ_c is the linear class density.

2.3 Experimental setup and site test

This work is based on an acquisition system developed by iPOOL s.r.l. in the SURFACE project. Measurement devices used in this work were:

- A Standard Reference Test Tyre (SRTT) with an electret microphone inside, adapted to measure high-pressure values;
- A pressure internal measuring system (Pint) composed of a preamplifier, an ADC converter, and a microprocessor with implemented software to transmit data via Wi-Fi;
- A GPS system to georeferenced the memorized signals and to correlate the signal with other spatial observations;
- A rotatory encoder, positioned on the rear-left tyre, to measure the travelling speed and distance of the mobile laboratory;
- A piezoelectric-monoaxial accelerometer mounted on the back of the measuring vehicle.

Accelerometer and rotatory encoder signals were acquired by the same acquisition module. Synchronization between the encoder and the TCN signals was obtained with the aid of an external known impulsive signal applied to the TCN measuring tyre. TCN measuring system was implemented on the rear-right tyre of a Mercedes-Benz-VITO. Fig.1 shows the mounted pint measuring system.

TCN pressure signals were measured in normal traffic conditions. Evaluation of the pavement surface was done by measuring the absolute maximum TCN pressure in a chosen time interval window. The corresponding pavement element is called the classification element in this paper. A speed threshold equal to 27 km/h was chosen to select regions with neglectable engine noise. The first and final classification elements with speed above the speed threshold were excluded to consider acceleration and deceleration phases. Only speed-filtered measured pavement length with at least three classification segments were considered in this paper and are called evaluation segments.

PCI values, measured by AVR S.p.A., were given for road elements with different surface areas. Fig.2 is the scatter plot between the surveyed segments and the corresponding PCI measured by AVR S.p.A.. PCI values were grouped in 10 wide bins from 0 to 100 to improve visualization of data. Fig.3 shows the different roads of Florence measured and classified in the SURFACE project. Measurements were done in two different days. Fig. 4 illustrates the steps followed to create a dataset of different road pavement segments that were used to find a relation between the TCN signal and the PCI values.

Figure 1: pint system developed by iPOOLs.r.l.

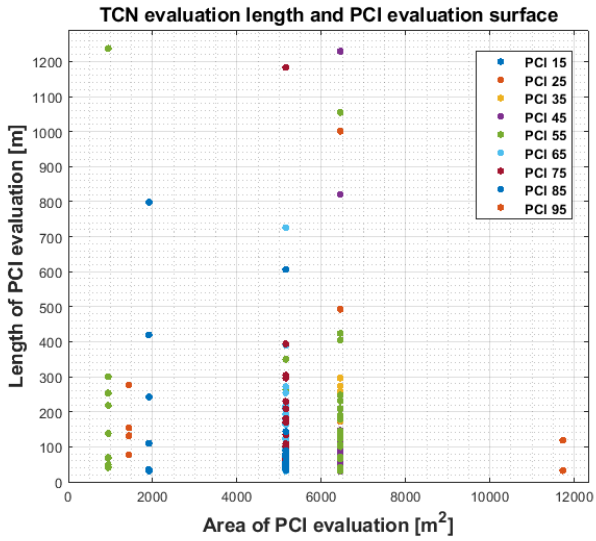

Figure 2: Intersection TCN track and PCI surface.

Figure 3: Roads tests in Florence. Some tracks are overlapped.

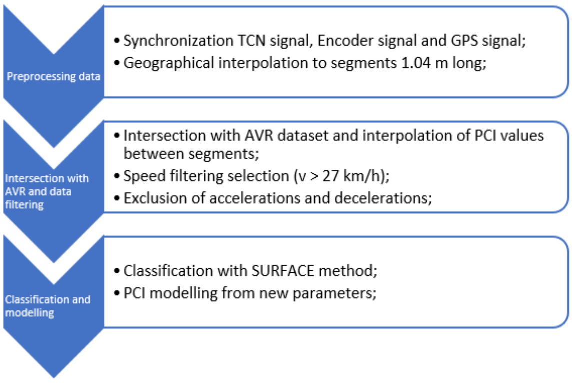

Figure 4: Flowchart of signal classification

Initially, the correlation was searched by taking the whole intersection length, and measurement speed range between 27 and 50 km/h with a mean value of 40 km/h. TCN pressure signals were normalized with respect to the maximum observable value of the pint system.

3. RESULTS

In this section, the results of the correlation between the new parameters and the PCI values measured by AVR S.p.A is reported. An attempt at classification with IA signal processing is presented in Subsection 3.2.

3.1 Analytic results

In the classification, the segment length is variable due to the travelling speed during data acquisition. An overall classification is taken with a segment classification equal to 1 s time interval, as in the SURFACE project, and ρ_c values are calculated considering the evaluation segment length equals to the intersection between the evaluation segments and the PCI measured area. Evaluation segments were taken inside pavement surface with homogenous PCI values and no interpolation. This analysis did not take evaluation segments which intersected different PCI areas. Influence of the measurement speed on the classification segment is included in the different classification segment length due to the speed. Fig.4 reports the Pearson correlation coefficient between the density classes and the PCI values. Fig.5 represents the p-value of the non-correlation null hypothesis. All p-values, except the correlation between PCI and $\rho_{bad-quality}$, of the non-correlation null hypothesis are lower than 1%. The corresponding p-value for the $(\rho_{bad-quality}, \text{PCI})$ is equal to 6%.

To consider the road characteristic variability, values were binned with respect to the PCI intervals whose width is equal to 10. This procedure allows defining of 9 PCI broad classes.

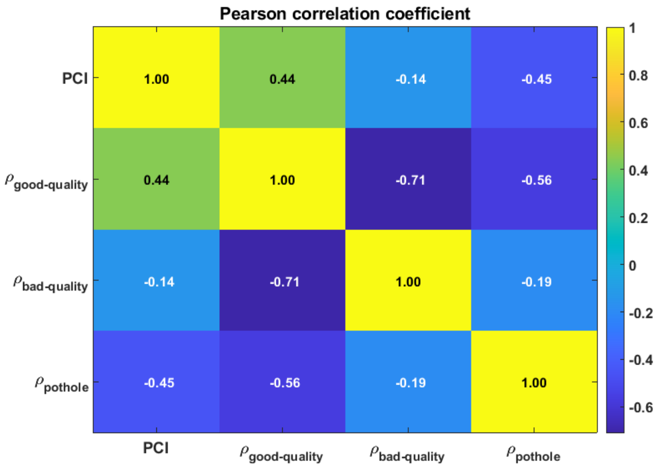

Figure 4: Pearson correlation coefficients

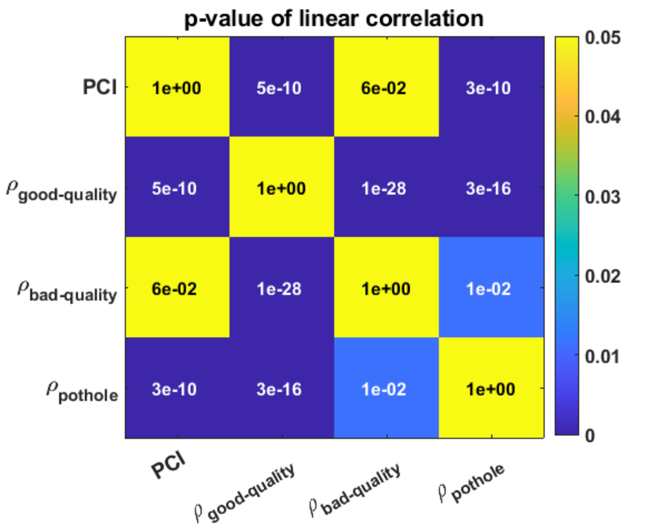

Figure 5: p-values of linear correlation test

Two different models to describe the PCI-$\rho_{pothole}$ and PCI-$\rho_{good-quality}$ relation was proposed in accordance with data and expected behavior. An exponential decay curve was proposed to fit the $\rho_{pothole}$ in function of the PCI value and a linear relation to describe the $\rho_{good-quality}$.

Fig. 6 and Fig. 7 reports the relation between the $\rho_{pothole}$ and $\rho_{good-quality}$ with respect to the binned PCI values. Fig. 8 shows the measured $\rho_{bad-quality}$ measured and predicted results. Uncertainties of prediction are not shown in the graphic.

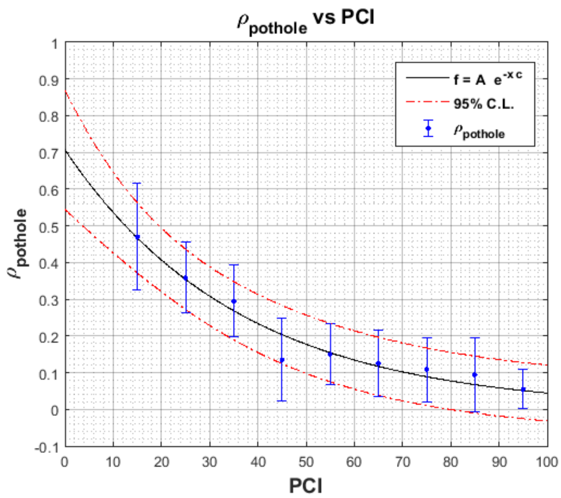

Figure 6:relationship between PCI and $\rho_{pothole}$ ($R^2_{adj} = 0.96$).

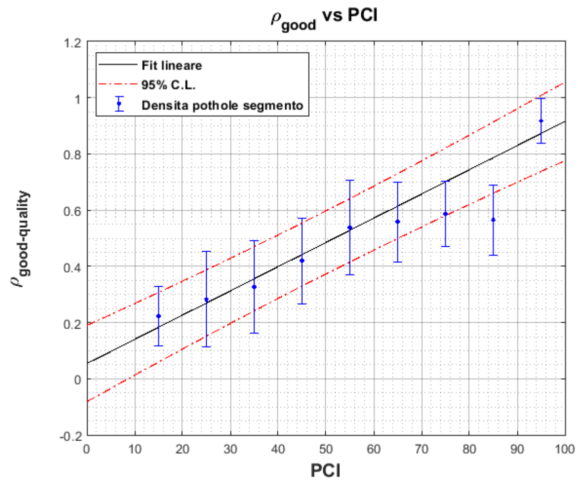

Figure 7: $\rho_{good-quality}$ and PCI values scatter plot ($R^2_{adj} = 0.97$).

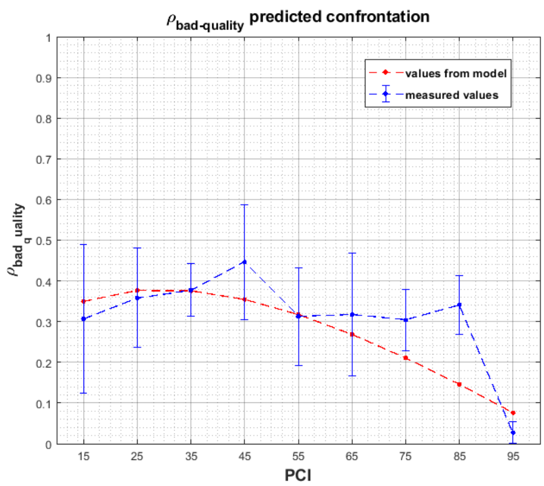

Figure 8:$\rho_{bad-quality}$ extracted from the $\rho_{good-quality}$ and $\rho_{pothole}$ modelling.

3.2 Machine Learning classification test

Data were augmented by measuring the density of subsegment pavements of time length 1s with overall evaluation length varying from 40 to 120 m equally spaced with 10 m interval. PCI binning values were grouped as in [10] in three classes.

- Poor: [0,55] PCI;
- Fair: [55,70] PCI;
- Good: [70,100] PCI.

A Deep Neural Network (DNN) was developed to classify the pavement condition with length from 40 to 120 m. Input arguments were the density classes and the output the three cases. The DNN structure was built with one fully connected hidden layer with 100 neurons, Adam optimization algorithm and cross-entropy loss function were trained on two-dimensional reduced feature space determined by the principal component analysis. The new extracted features explained all data variation. Tab. 1 reports the total number of samples per class.

Table 1: Dataset division

Dataset	#Poor	#Fair	#Good
Train	1095	871	492
Test	273	217	122

The results of the trained neural network over 50 epochs are:

- training accuracy = 61 %;
- training loss = 1.0;
- test accuracy = 40 %.

4. DISCUSSION

Fig. 5 does not show a strong correlation value between linear density classes and the measured PCI value. Fig. 6 and Fig. 7 show a density class trend as expected from a general discussion. In fact, $\rho_{pothole}$ values are higher to lower values of PCI and $\rho_{good-quality}$ grows with higher values of PCI. Combining both fitted models, it was possible to predict the $\rho_{bad-quality}$ results in a concave curve, depicted in Fig. 8, as it was expected from general argumentations. The models seem not to be in accordance with the result for high PCI values, especially at 75 and 85 PCI bin centres The same behaviour can be seen in Fig. 7 for the $\rho_{good-case}$. The high uncertainty of the measured densities shows how the relation between the wheel track and the whole pavement is not direct and needs further studies.

The simple DNN, trained on the augmented data, shows how variables defined by the principal component analysis are not sufficient to classify the overall pavement into the three categories. It also could show the influence of the measurement classification length in the PCI and density class relation.

5. CONCLUSIONS

The analytic results show satisfactory results with the expected behaviour. Especially, $\rho_{pothole}$ and $\rho_{good-quality}$ fits are in accordance with the proposed models in this paper and PCI influence on the TCN maximum amplitude is visible. Also, the results show how SURFACE classification procedure gave a right weighting to the classification segments with respect to the speed.

Even if PCI values were measured on the entire pavement surface, this measurement method supplies a good description of the distresses' effects on the vibrational part of the tyre-pavement interaction. High uncertainties in the measurement probably arise from the low number of samples and the physical nature of the problem. In fact, the pavements under analysis were composed of different numbers of lanes and therefore a relation between linear and PCI area characteristics is not always direct. Urban travelling condition probably influences the classification procedure and speed correction are probably required. Machine learning classification test results show the necessity to define a higher number of health pavement classes that can be related to the three class examples defined in Subsection 3.2. In addition, the results highlight the problem of selecting measurement outliers and evaluation segment length.

In conclusion, it must be remarked that the proposed classification only depends on the absolute maximum pressure within a time interval and on the travelled length and therefore maps different distresses as a single distress with a certain degree of severity. Nevertheless, a good relation between the expected behavior of the different classes is clear and PCI of the pavement seem to show a strong correlation with the TCN pressure signals. Better spatial estimation of distresses could be achieved by following [7].

Possible further studies will be focused on the relationship between the distress effects on the non-measuring wheels, and evaluation of PCI along the measuring wheel track. This could help to improve the Pint system to extend its evaluation surface and to evaluate the ability to describe overall pavement health state from lane track evaluations.

6. ACKNOWLEDGEMENTS

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