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IMAGE-BASED PREDICTION OF NOISE: A TWO-STEP CONCEPTUAL MODEL

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ABSTRACT

Noise importance in pavement performance evaluation is often overlooked. However, noise directly impacts environmental quality and human health. There is a lack of methods to approximately derive the noise contribution of a pavement based on its surface texture and/or other easy-to-measure factors.
Based on the above, the objectives of this study were confined to the following: 1) Setting up a conceptual model to derive the acoustic contribution of a pavement based on its surface texture, this latter assessed through images. 2) Investigating the surface texture prediction based on the pavement surface analysis.
After setting up the model, this study developed image-based indicators to analyse macrotexture characteristics of bituminous mixtures. These indicators were validated through experimental results, highlighting their potential in predicting surface texture and noise contributions.
In order to pursue the goals above, the following tasks were carried out:
1)Study of the literature.
2)Set up a two-step model in order to derive the texture based on image analysis and the noise based on texture.
3)Design of the experiments.
4)Production of a set of bituminous mixtures and measurements.
5)Derivation of the relationship between an image-based indicator and macrotexture
6)Discussion of results and future work.

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1. INTRODUCTION

Road traffic noise is the most ubiquitous outdoor environmental pollutant, and tyre-road interaction has been revealed as a dominant source, especially for speeds above 50 km/h. As engine noise decreases owing to ever more quiet contemporary vehicles, especially with the increasing popularity of electric vehicles, the relative importance of tyre-road noise remains even more apparent. Characterization and prediction of tyre-road noise in terms of pavement surface texture has emerged as a highly sought research area in recent years [1].
Even if rolling noise depends on many factors [2], pavement texture has a pivotal role. Categorized into microtexture, macrotexture, and megatexture, surface texture directly influences the acoustic response of the tyre-pavement system. Various models have been developed to predict tyre-road noise based on these textural properties using empirical, analytical, and machine learning methods. Of those, Linear Regression models relate noise to straightforward indicators like Mean Profile Depth (MPD) [3]:

$$L_{noise} = \alpha \times MPD + \beta \quad (1)$$

Where: L_{noise} is noise level in dB(A); MPD = Mean Profile Depth (mm); α, β = regression coefficients.

Spectral models based on ISO 13473-4[4] perform frequency decomposition of texture profiles using Fast Fourier Transform (FFT). (Praticò et al. [5]) modelled the curve of texture levels as follows:

$$L_{tx}(\lambda_j) = m_j \,.abs \left[log_{10}\frac{\lambda_j}{\lambda^*}\right] + E\left[L_{tx,max}\right] \qquad (2)$$

Where: L_{tx} = texture level, m_j is the slope corresponding to the j^{th} wavelength; abs stands for absolute value; λ^* is the estimate of the point of maximum of the texture spectrum; and $E[L_{tx,max}]$ (the estimate of the maximum of the texture spectrum) includes coefficients to calibrate and gradation-related factors or constants. More advances in tyre-pavement interaction modelling have led to the development of sophisticated techniques, such as the Indentor Algorithm, to model tyre deformation over surface texture [5]. The method provides a more realistic description of how a tyre engulfs pavement texture, a significant factor in the prediction of rolling resistance and tyre/road noise.

Recent developments also include machine learning algorithms such as Random Forests and Principal Component Regression using 3D texture parameters (e.g., RMS height, skewness) to predict CPX noise levels [6]. In addition, Multivariate Nonlinear Regression models incorporate mix design parameters like aggregate particle size, the voids filled with asphalt and air voids [7]:

$$L_{TX}(\lambda_i) = C_1 + C_2\left(\frac{VV}{VFA}\right) + C_2\left(\frac{D_{90}}{D_F \,.\sum sin\theta.\sum \emptyset}\right) + C_4\left(\frac{1}{\sum CLAP}\right) \qquad (3)$$

where, L_{TX} (λi): the surface texture level at the central texture wavelength (λi) in octave band, mm; VV: the volume of air voids, %; VFA: the voids filled with asphalt, %; D_{90}: the aggregate particle size in 90% passing ratio, mm; D_f. : the fractal dimension of aggregate gradation; $\sum sin\theta$: the summation of aggregate direction angle sine per100 cm^2 area size of mixture section; $\sum\Phi$: the summation of regulation degree of aggregate per 100 cm^2 area size of mixture section; $\sum$ CLAP: the total contact length amongst aggregate particles per 100 cm^2 area size of mixture section, mm; c1, c2, c3 and c4: model coefficients.

Several other algorithms have been developed to analyse the relationship between pavement texture and noise generation, including what follows[24]: 1) The Expected pass-by noise level difference from texture level variation of road surface (ENDT, cf. ISO 10844:2014[8]). 2) The Estimated Road Noise Level (ERNL, Goubert et al. [9]. 3) Von Meier's Algorithm: This method limits the second-order derivative of the profile signal to assess tire deformation on pavement surfaces. It has been found to have a limited correlation with high-frequency noise [5]. 4) Indenter Method by Sandberg and Goubert[29]: This novel approach enhances correlation with low-frequency noise while preserving information at higher frequencies, providing a more comprehensive analysis of tire-road interaction openaccessrepository.it [5]. 5) Three-Dimensional (3D) Texture Parameters: Utilising photometric stereo techniques, this method characterises concrete pavement surface textures in three dimensions. It has been shown that the direction and distribution of pavement texture significantly impact noise and friction [10]. 6) Predictive Rolling Noise Model Based on Texture and Mix Volumetrics: This statistical model predicts the Close-Proximity (CPX) noise level at 80 km/h for porous and semi-porous mixes by considering porosity and texture band levels. It has demonstrated adequate accuracy, particularly when applied to average values along test sections of 200 meters [11]. 7) Bailey Method Indicators: This approach models pavement surface characteristics for noise prediction by analysing aggregate gradation and packing characteristics. The texture level has been found to correlate well with asphalt mixture composition, aiding in the design of mixtures that comply with specific requirements (cf. [12]). Huschek texture index-based prediction of sound pressure level [13]. 9) Prediction of the sound pressure level at different speeds based on the so-called Tino Index, which is based on the maximum texture level (TINO project, cf. Domenichini et al. [14]).

Despite these advancements, most models for noise prediction depend on texture-related parameters to be assessed through specialised equipment or lab analysis. To address this, the present study introduces a two-step conceptual model. The first step derives texture indicators using image-based techniques such as Wavelet Transforms. The second step relates this indicator to tyre-road noise using acoustic prediction models, enabling a practical, scalable approach to pavement noise evaluation. Based on the above, it may be observed that there are many models to derive noise-related indicators based on surface texture. On the other hand, the assessment of surface texture through traditional methods (e.g., laser-based methods, cf. ISO 13473-1, -2, -3,[15,17] and ASTM E1845 [18]) and the sand patch method (EN 13036-1[19]) is quite complex and time-consuming, and this calls for high-speed methods.

2. OBJECTIVES

Based on the above, the objectives of this study were confined to the following: 1) setting up a conceptual model linking texture and noise to use in mix design and performance prediction. 2) Investigating the surface texture prediction based on pavement surface analysis.

After setting up the model, this study developed image-based indicators to analyse macrotexture characteristics of bituminous mixtures. These indicators were validated through experimental results, highlighting their potential in predicting surface texture and noise contributions.

To achieve the goals above, the following tasks were undertaken: 1) A literature review. 2) Set up a two-step model in order to derive the texture based on image analysis and the noise based on texture. 3) Design of the experiments. 4) Production of a set of bituminous mixtures and measurements. 5) Derive the relationship between an image-based indicator and macrotexture. 6) Discussion of results and future work.

3. MODELLING

Based on the above, the following conceptual model is herein set up, where the first step refers to surface texture assessment and the second to noise derivation through the algorithms mentioned above.

Figure 1. Conceptual model.

4. MATERIALS AND METHODS

This section discusses the sample preparation of asphalt and the measurement of surface macrotexture. It also discusses how image-derived measures correlated with measured texture values. Three asphalt mixtures were designed and produced in the laboratory in the perspective of assessing several consequences deriving from the use of crumb rubber [20-22]. Mixture A consisted of 2% crumb rubber with a nominal maximum aggregate size (NMAS) of 8 mm. Mixture B consisted of 1% crumb rubber with an NMAS of 8 mm. Mixture C consisted of no crumb rubber but had an NMAS of 10 mm. Following compaction, samples were subjected to different tests. Macrotexture was measured using the sand patch test according to EN 13036-1 to determine the Mean Texture Depth (MTD). Image processing techniques, such as the Fuzzy Logic Edge Detection technique (Zuniga-Garcia & Prozzi, [23]; Ghaderi & Abedini, [24]) were used to obtain the indicators, such as the Fuzzy Count Number (FCN), for predicting MTD. In addition to image testing, physical tests were performed, including specific gravity [25], binder extraction [26], aggregate grading [27], and air void content [28]. The Fuzzy Logic Edge Detection Method used to derive FCN is described as follows.

4.1 Fuzzy Logic Edge Detection Method

The Fuzzy Count Number (FCN) quantifies surface voids, defined as visible gaps and valleys between exposed aggregates, using an edge detection algorithm in Python. As illustrated in Figure 2, OpenCV was used to convert RGB images to grayscale and then apply histogram equalisation to correct contrast and Gaussian blur to remove noise and small surface undulations (Figures 2a to 2c). Sobel filters were employed to find image gradients in horizontal and vertical directions to detect strong variations in pixel intensity. The gradients were combined and thresholded to detect strong edges. Edge maps were overlaid in green on the grayscale image for visualisation (Figure 2d). The edge pixel number was determined to compute the FCN value, which is the macro-texture of the surface. This methodology adheres to fuzzy logic conventions, where the magnitude of the gradient defines classification. To validate the algorithm, nine photos of aggregate quantities with a known number ranging from 0 to 300 were studied. Various shapes and sizes of aggregates were cast onto a black pavement binder background simulating a roadway and were captured under controlled light (Figure 3a). The algorithm detected edge features (Figure 3b), computed FCN values (Figure 3c), and compared them with actual aggregate counts. A strong linear correlation (R^2 = 0.99) confirmed the accuracy and sensitivity of the algorithm to surface texture variations (Figure 2d).

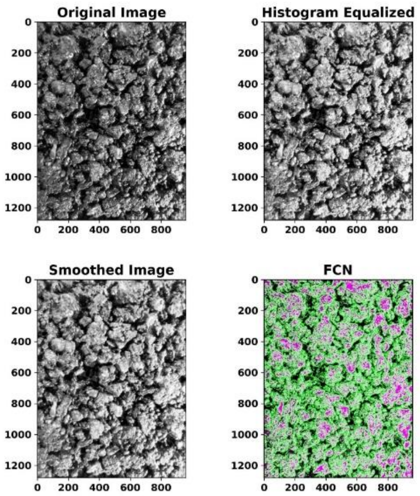

Figure 2. Preprocessing Stages for fuzzy logic edge detection method: Original, Histogram Equalized, Smoothed, and FCN.

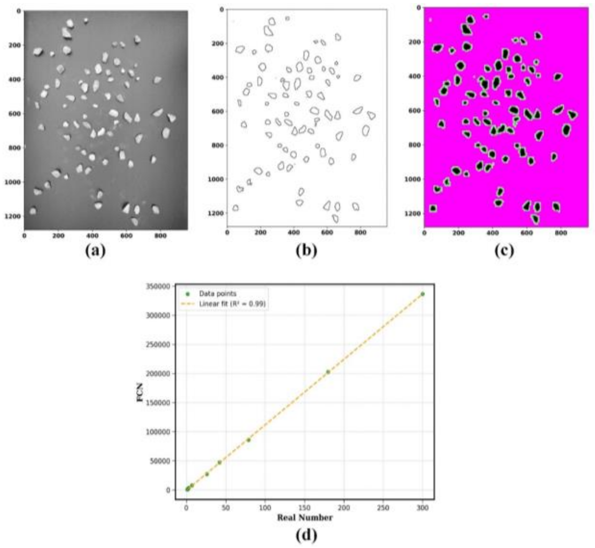

Figure 3. Validation of counting algorithm: (a) input image with 79 aggregates, (b) detected edges by code, (c) applying counter code (FCN = 86212), (d) correlation between counted number and real number (for nine images with different numbers of aggregates).

4.2 Results

As revealed in Table 1 and illustrated in Figure 4, the relationship between Mean Texture Depth (MTD) and the reciprocal of the Fuzzy Count Number (FCN) was investigated by using different curve fitting models. Among them, the quadratic model possessed the maximum coefficient of determination (R^2 = 0.85), indicating that FCN was most strongly correlated with MTD. The exponential and linear models came in a close second and third, respectively, with R^2 values of 0.82 and 0.81. Logarithmic regression yielded a slightly lower correlation, with R^2 = 0.79. The results above demonstrate that the quadratic model provides the best explanation for the non-linear relationship between FCN and macrotexture depth.

The FCN is a reflection of the edges' and voids' density in the pavement surface. A High value of FCN indicates that fine aggregates are high per unit area, and there would be a more dense surface with small and fewer voids, and thus an MTD value would be low. Low FCN indicates greater voids, and thus, there would be greater texture depth. This inverse relationship between FCN and MTD is nonlinear.

Indeed, in order to better model this relationship, the inverse of FCN (1/FCN) was used as the independent variable for curve fitting. This transformation reversed the inverse relationship and enabled a direct positive relationship with MTD, which is illustrated in Figure 4. The quadratic fit of 1/FCN provided not only the best statistical correlation but also the physical model of aggregate packing and surface roughness. Parallel attempts at modelling macrotexture from image-based predictors have also been reported in the literature, which reflect the utility of inverse transforms in predicting texture-depth [23,24]. Lastly, the research confirms that 1/FCN is an effective predictor of MTD, and the effect of aggregate arrangement on macrotexture is best explained by a non-linear, quadratic function.

Table 1. Summary of curve estimation analysis for MTD.

Method	Type of fit	Equations	R^2
FCN	linear	$y = 3000000x - 2.52$	0.81
	Logarithmic	$y = 3.27\ln(x) + 45.49$	0.79
	Exponential	$y = 0.013e^{3000000x}$	0.84
	Quadratic	$y = (7E+12)x^2 - 1000000x + 6.73$	0.85

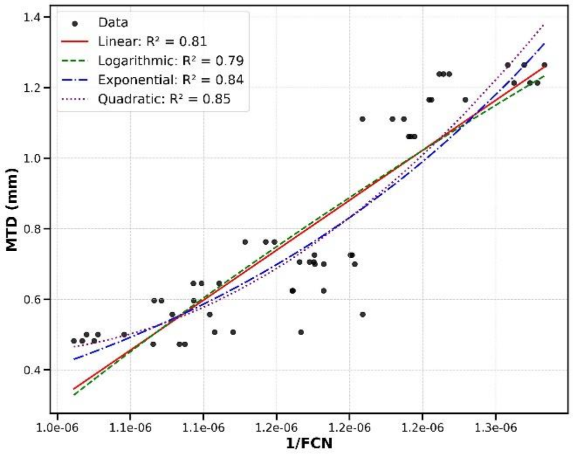

Figure 4. Relationship between MTD and 1/FCN.

5. CONCLUSIONS

Based on the analysis of the results, the correlation of MTD and FCN is used to determine the most accurate model of pavement macrotexture. The overall conclusions are as follows: 1) Quadratic regression demonstrated maximum accuracy (R^2 = 0.85), exhibiting non-linear correlations between FCN and MTD. 2) Transforming FCN to its reciprocal (1/FCN) converted the inverse relationship to a positive direct correlation, which improved statistical and physical interpretability. 3) The results confirm that fine aggregates (high FCN) reduce surface voids, lowering MTD, and that coarse aggregates (low FCN) increase texture depth. 4) The findings validate earlier studies on image-based texture prediction, reiterating the success of inverse transformations for modelling macrotexture.

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