Shifts detection in the road surface condition through tyre/road noise analysis and pattern recognition approach.

Carlos Ramos-Romero[1], **Juan Manuel Cermeño**[1], **César Asensio** [1]

[1]Instrumentation and Applied Acoustics Research Group i2a2, Universidad Politécnica de Madrid, Madrid, Spain.

c.ramosr@alumnos.upm.es, jm.cermeno@upm.es, casensio@i2a2.upm.es

Abstract
A car moving on the road is an element of tyre/road noise generation in itself. The rolling noise levels and spectral components change by the effect of the road aging, speed, and the surface characteristics of both the tyre and the asphalt. The processing of this sound signal by acoustic featuring tasks can provide valuable information on the characteristics and status of the road surface. Pattern recognition techniques are applied to detect areas with similar asphalt conditions. The features in the frequency domain have proven to be suitable as a source of information for automatic asphalt quality detection for a test route where there are two kinds of asphalt conditions.
In this study, some results of both acoustic featuring comparison and automatic learning algorithms for road condition identification are presented. The capabilities of the new methodology for asphalt condition identification are shown as an alternative to improve maintenance activities and road safety. Additionally, the basic sensors setup provides the advantage of any passenger car, even a fleet, to easily become an asphalt condition inspector collaboratively.

Keywords: tyre/road noise, pattern recognition, road condition.

1 Introduction

The continuous exposure of roads to mechanical loads from vehicles and environmental factors are the main causes of pavement deterioration. This gradual degradation influences both road safety and traffic noise emissions, making it important to perform periodic inspections of the asphalt surface [1]. Several road infrastructure inspection methods have emerged to assist in road and street maintenance and rehabilitation plans. In this regard, new inspection methods based on indirect acoustic analysis have presented some advantages over traditional methods [2]. Accordingly, the results of automated detection of changes in the road surface condition from the characterization of the sound recorded in the tyre-road interaction zone are presented. Classification and analysis of surface homogeneity using pattern recognition algorithms have shown good performance in identifying the defectology of the tread layer.

2 Material and methods

The workflow for the automatic road distress identification, depicted in Figure 1, starts with the acquisition of the tyre pavement interaction noise (TPIN), driving conditions (speed and acceleration), and georeference throughout the driving over a testing route.
The test route has an approximate length of 2.4 km, and clearly shows two conditions of superficial status based on ageing and deterioration. The newest street zone is one year old, while the oldest one is more than three years old. See the Figure 2.

The materiality of the asphalt mixture is considered the same over the road circuit although the macrotexture would change due to the deterioration status. The tests were performed with a unique tyres set.

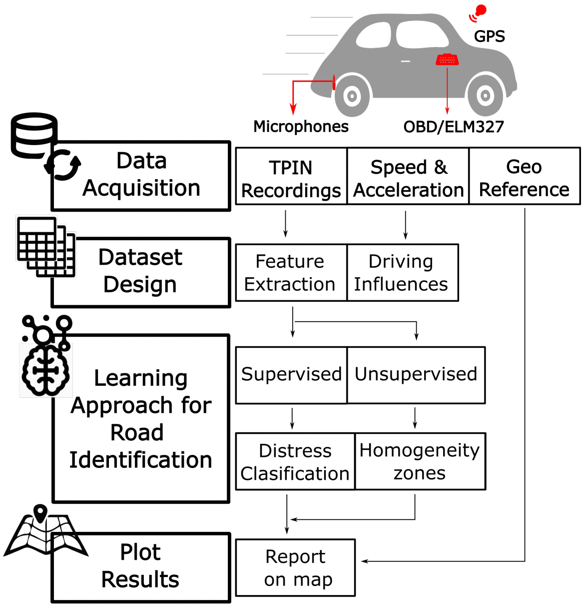

Figure 1: Block diagram for the automatic shifts detection in the road surface condition

Figure 2: Actual road status on experimental route.

Then, the databases are constructed by digital signal processing of the TPIN. Next, the processing by pattern recognition algorithms will detect the shifts on superficial road status. Finally, the classification results will be presented by road map reports.

2.1. Data acquisition

For the data acquisition, a portable set of sensors was employed to the simultaneous register of the TPIN signal, the GPS trip information and the driving parameters, during a normal trip of a light diesel vehicle. For the sound signal register, one microphone was located on each rear wheel arch, pointed to the tyre/road interaction zone. The acquisition device was connected to a laptop computer, and the audio files were recorded at 51,2 kHz sample rate.

The georeference and driving parameters were registered by the OBD adapter mounted on the car and linked to the smartphone via Bluetooth. Both the phone and laptop were linked to the same Wi-Fi network obtaining the same date-time information.

2.2. Dataset design

The feature extraction process of N (1-second) sound signal frames was executed in the time, frequency, and cepstral domain. Only audio frames that have been captured while the car was travelling faster than and including $30km/h$ will be processed.
The first dataset was made only considers the features of TPIN on time, such as equivalent noise: L_{rms}, crest factor CF , and the zero-crossing ratio ZCR.
The second data set consists of the spectral representation of the signal using a 1/3 octave filter bank [3].
The third dataset includes as features a set of t=31 triangular filters. The central frequencies of the triangular filter bank are logarithmic spaced based on mel-scale, where the initial central band starts in $fc_{t=1} = 392.8Hz$. Then the low cut-off frequency: $fl_t = fc_t/1.0718$ and the upper cut-off frequency $fu_t = fc_t * 1.078$. In addition, it follows that $fc_{(t+1)} = fu_t$ [4].
The influence of the car speed and acceleration on each triangular frequency band was considered and subsequently corrected by the linear relation of the Eq. 1 .

$$L_f^{'} = L_f - \alpha_f \cdot \log_{10}\left(\frac{v}{v_{ref}}\right) - \beta_f \cdot ac \tag{1}$$

Where, L_f is the tyre/road noise level on each frequency band, v is the car speed, ac is the car acceleration, $v_{ref} = 70km/h$ is the reference speed, α and β are coefficients of the linear regression by each frequency band.
The last dataset includes the 14 MFCC coefficients of each audio frame. Table 1 presents the amount of data for each dataset extension. Consequently, three datasets on different domains could be examined for the detection of road deterioration status.

Domain	Features	Number of features	Observations-Frames [N]
Time	Overall noise levels	3	744
Frequency	Triangular filter banks	31	744
	1/3 octave filter bank	31	744
Cepstral	MFCC	14	744

Table 1: Datasets for automatic detection.

The Figure 3 shows the tyre/road noise amplitude of the signal obtained by 1 microphone during a lap of the test road. It shows that the zones corresponding to the label “1-deteriorated” are the ones with the highest amplitude; and the zones corresponding to label “0-new” have the lowest amplitude of the extracted features.

2.3. Results of the automatic learning approaches

Road condition identification was analyzed using two strategies. First, supervised classification will assign a road state according to two possible state classes known a priori. Subsequently, the unlabeled dataset will be processed by unsupervised learning to detect clusters that can be associated with the road state.

Supervised classification

The supervised classification models trained were: Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN). These showed strong results for the classification of sound events based on rolling noise [3, 5, 6].
The models were trained and evaluated with the datasets separately, see Table 1. The training and evaluation

process was developed through cross-validation (k-fold=5) and the “F1-score” metric was used and reported in the Table 2.

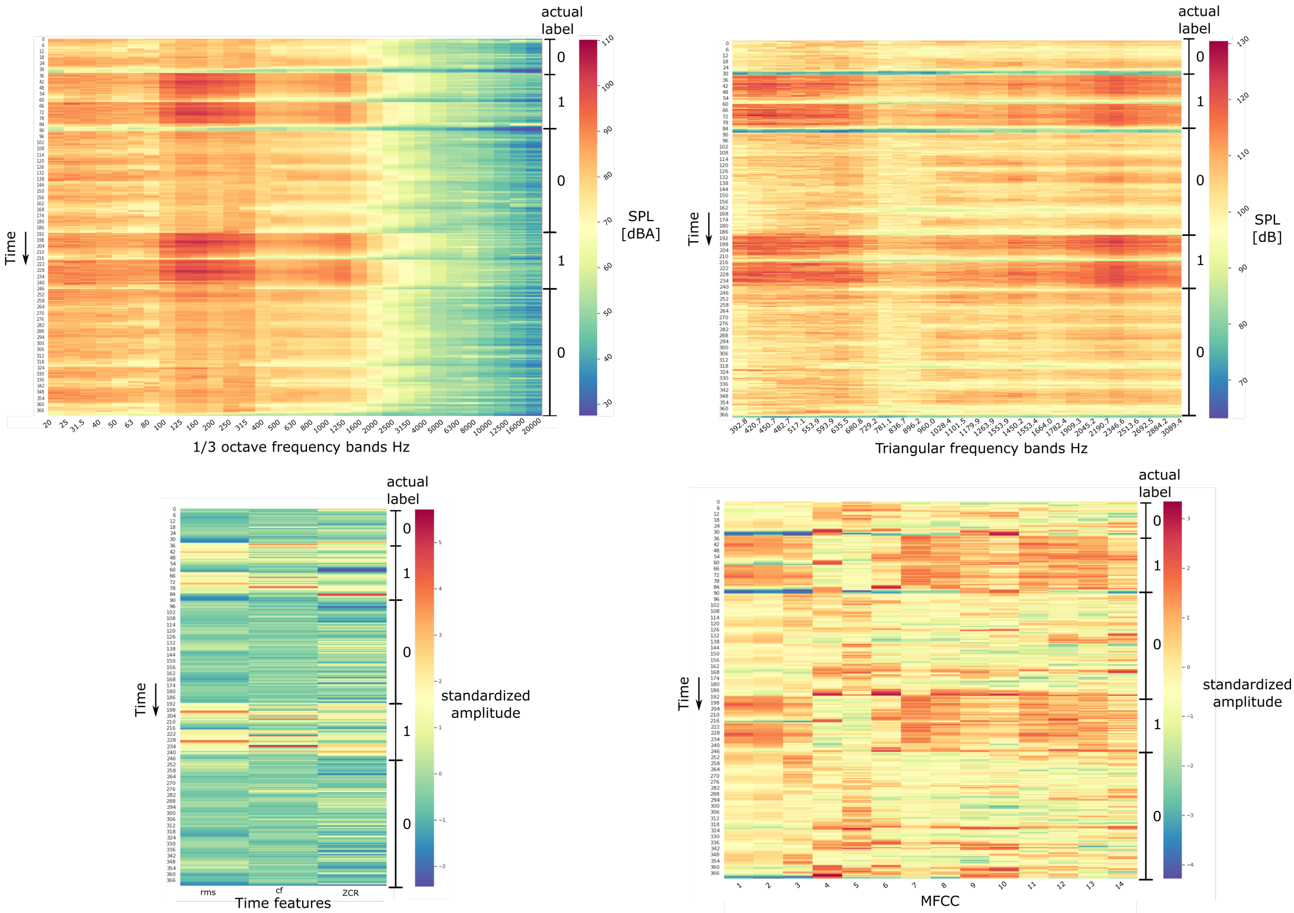

Figure 3: Feature space domains. Actual labels: 0-new pavement, 1-deteriorated pavement.

	F1-score	
	Model	
Features	**k-NN (k=5)**	**SVM**
Time	0.88 (0.03)	0.88 (0.04)
Freq 1/3 oct.	0.93 (0.02)	0.97 (0.02)
Freq Triangular	0.93 (0.03)	0.95 (0.03)
MFCC	0.97 (0.01)	0.96 (0.01)

Table 2: F1-score metric for the classification supervised model

Unsupervised classification

Unsupervised learning aims to train a clustering model that can identify groups into feature space data corresponding to different road surface conditions, from the distribution of the unlabeled data. A new dataset was formed by both features: in the time and the triangular filters obtained in the frequency domain. The features were standardized. Subsequently, the t-SNE algorithm was run for feature reduction; see Figure 4.

The elbow method assists in the selection of the optimal number of clusters K by Sum of Squared Errors or Inertia (SSE) function minimization; see Figure 5.

Finally, the clustering analysis was performed using the probabilistic Gaussian Mixture Model (GMM) technique, which forms ellipsoidal clusters [7].

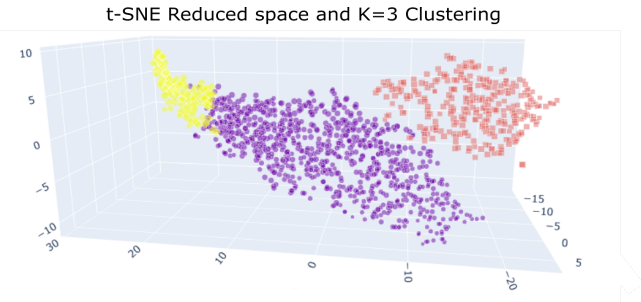

Figure 4: Visual representation of vectors distribution from test data using t-SNE [8]

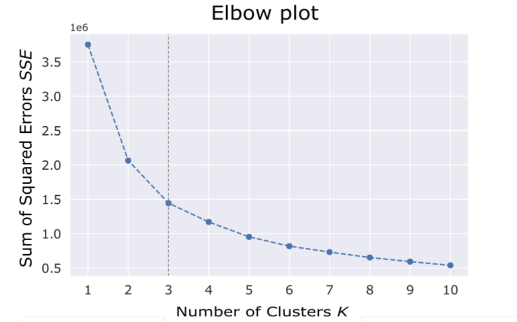

Figure 5: Selection of clusters number K by elbow method [7]

3 Results on map

The comparison of the results of the above approaches for the identification of changes in road condition is presented in maps; see Figure 6. The observations from the predicted dataset predicted dataset are presented georeferenced and were coded by the color assigned to each class of road surface deterioration. Also for the unsupervised clustering results, each cluster was assigned a different color code.

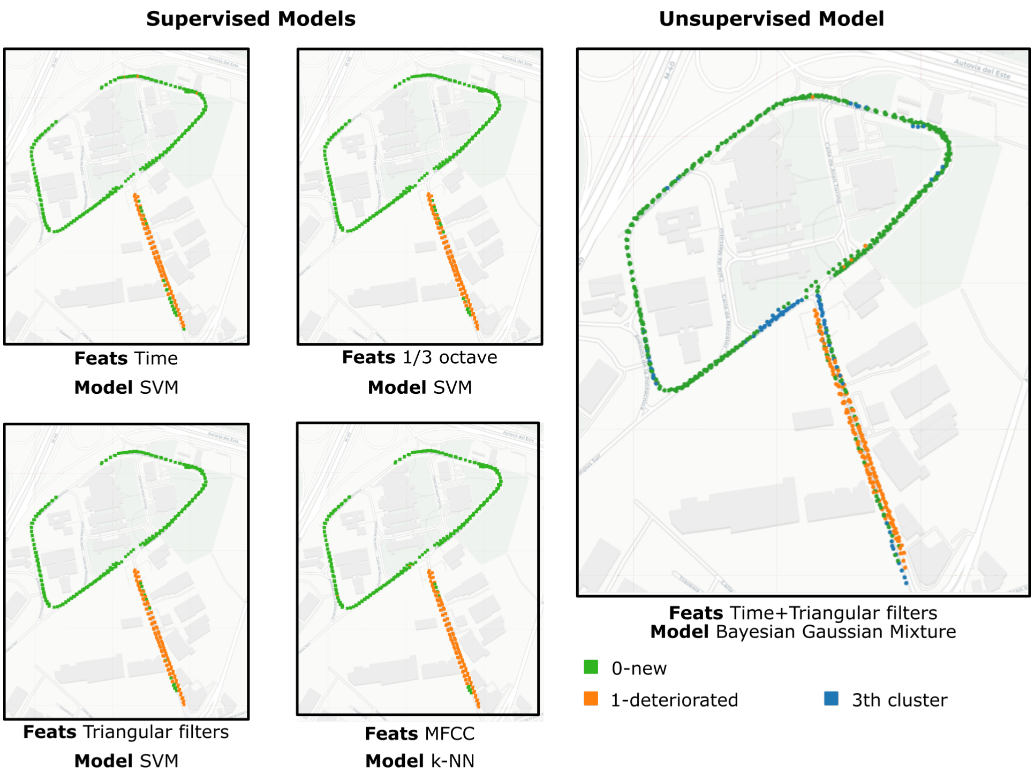

Figure 6: Georeferenced road surface detections

4 Conclusions

This paper reports the results of a straightforward experiment for the automatic identification of road surface condition based on its deterioration, by processing the rolling noise signal and with the application of pattern recognition algorithms.

We first evaluated the performance of two supervised classification algorithms for detecting deteriorated areas of the road surface. The SVM and k-NN models show satisfactory performance in the identification of areas with "new" or "deteriorated" asphalt, based on the features obtained from the acoustic footprint of the rolling noise. However, when running the unsupervised learning or clustering algorithm, it is observed that the algorithm can identify the existence of a third group of data. The extra group of data appears concentrated in the transition zones between the a-priori known asphalt status classes, it lets us to identify the road status shifting zones. The unsupervised learning approach has made it possible to detect homogeneous areas of the asphalt surface. The results were compared with supervised detections and with visual evidence of the road surface condition.

Some methodological details colud be improved for future works, such as driving an electric vehicle to record a more purely rolling signal, exploiting the detection task using frequency features and deep learning algorithms; finally, the unsupervised learning could include unattended feature generation in latent spaces using autoencoders and subsequent clustering of these features.

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References

[1] Elisabete Freitas, Hélder Torres, Cedric Vuye, and Paulo Pereira. Effect of road pavement defects on tyre-road noise. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings*, volume 259, pages 5534–5544. Institute of Noise Control Engineering, 2019.

[2] Mohammad Reza Ganji, Ali Ghelmani, Amir Golroo, and Hamid Sheikhzadeh. A brief review on the application of sound in pavement monitoring and comparison of tire/road noise processing methods for pavement macrotexture assessment. *Archives of Computational Methods in Engineering*, 28(4):2977–3000, 2021.

[3] C Ramos-Romero, P León-Ríos, BM Al-Hadithi, L Sigcha, G De Arcas, and C Asensio. Identification and mapping of asphalt surface deterioration by tyre-pavement interaction noise measurement. *Measurement*, 146:718–727, 2019.

[4] Malcolm Slaney. Auditory toolbox: A matlab toolbox for auditory modeling work. *Interval Research Corporation, Tech. Rep*, 1998.

[5] J Alonso, JM López, I Pavón, M Recuero, C Asensio, G Arcas, and A Bravo. On-board wet road surface identification using tyre/road noise and support vector machines. *Applied acoustics*, 76:407–415, 2014.

[6] M Kalliris, Stratis Kanarachos, Rigas Kotsakis, Olivier Haas, and Mike Blundell. Machine learning algorithms for wet road surface detection using acoustic measurements. In *2019 IEEE International Conference on Mechatronics (ICM)*, volume 1, pages 265–270. IEEE, 2019.

[7] Eva Patel and Dharmender Singh Kushwaha. Clustering cloud workloads: k-means vs gaussian mixture model. *Procedia Computer Science*, 171:158–167, 2020.

[8] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008.