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A multiple regression model for predicting rattle noise subjective rating from in-car microphones measurements

Benoît Gauduin^a, Christophe Noel^a, Jean-Louis Meillier^b and Patrick Bousard^a

^aGenesis S.A., Bâtiment Gérard Mégie, Domaine du Petit Arbois - BP 69, 13545 Aix-en-Provence Cedex 4, France

^bRenault, Centre Technique d'Aubevoye, Parc de Gaillon, 27940 Aubevoye, France
benoit.gauduin@genesis.fr

In some situations when the road is deformed, the suspension system of vehicles may produce a specific sound, called rattle noise. It may be perceived by the driver and wrongly considered as a malfunction of the vehicle. This sound is part of the global acoustic comfort of the vehicle and hence is studied by RENAULT.

The approach presented here aims at predicting the rattle noise subjective rating given by a RENAULT expert on a scale from 0 to 10, by developing a model based on in-car binaural microphones measurements in the ears if the driver.

First, a set of 11 metrics has been built, related to temporal aspects, spectral components and time-frequency information of the rattle noise recorded. The corpus is made of 19 different configurations of suspension systems of a given car.

The method used to select the most relevant metrics for the multiple regression model is presented. This selection is based on a statistical robustness estimation of the model. Hence, it appears that only 6 metrics are sufficient to build the model.

Finally, the performance of the model is evaluated on 5 new configurations of suspension systems.

1 Introduction

In some situations when the road is deformed, the suspension system of cars is highly solicited and may produce a rattle noise. It may be perceived by the driver and wrongly considered as a malfunction of the vehicle. This sound is part of the global acoustic comfort of the vehicle and hence is studied by RENAULT.

The present paper describes the method used to objectify this phenomenon: the aim is to link physical measurement (metrics) to a subjective evaluation of performance of the rattle noise.

First, the problematic of objectivization of suspension rattle noise is exposed. Then, the metrics to characterize the phenomena, based on signal processing of binaural recordings, are exposed. Three types of metrics are proposed: spectral, temporal and time-frequency metrics. Next, the method used to build a multiple regression model between the metrics and the subjective ratings is presented. Lastly, the model is validated on a new set of suspension systems.

2 Problematic of the objectivization of the rattle noise

2.1 Description of the rattle noise

The rattle noise occurs when the suspension system is highly solicited, for example when the road is deformed. It induces a tapping noise in the cab interior. This noise is generated by the suspension system: hydraulic chocks and the resulting vibrations are first attenuated by filtration of the suspension and then transmitted to the body of the vehicle. The noise is propagated via the structure and diffused inside the car.

Regarding frequency aspects, the rattle noise of suspension is localized in the [100 – 400] Hz frequency band. In time domain, the phenomenon happens with a succession of chocks resulting in a tapping noise. The figure 1 shows a time-frequency representation of pressure signal recorded inside the vehicle at the driver position. The signal has been first filtered with an A-weighting filter. This representation

shows clearly the succession of chocks that are a characteristic of the rattle noise.

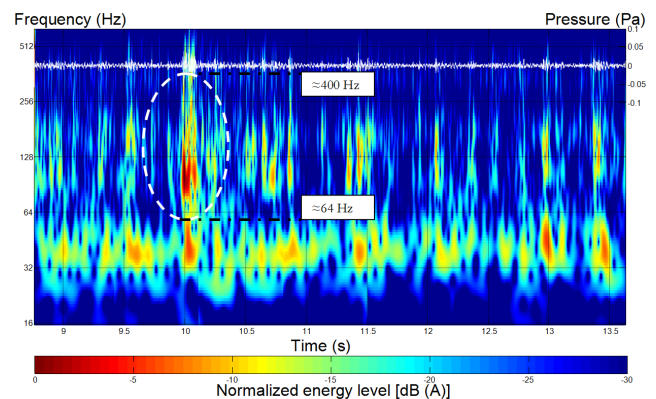


Fig. 1 Time-frequency representation with MORLET wavelet of rattle noise

2.2 Data set

The data set for the suspension systems tested is composed of 25 elements build from different combinations and tunings of shock absorbers and filter elements. All the suspensions systems are tested on the same RENAULT car model. From this set, 19 suspension systems are selected to build the regression model and 6 suspensions systems are used to validate the estimation.

The subjective rating of each of the 25 suspensions systems is given by a RENAULT expert on a scale from 0 to 10 with a 0.5 step. At a rating of 3, the contribution is already considered very bad. At a rating of 9, the contribution is judged excellent. The rating is done by driving the car on tracks with different sollicitations of the suspension system.

Pressure recordings have been done at the ears of the drivers with a binaural headset BHS I from HEAD ACOUSTICS with a SQUADRIGA recorder. The recordings are made with the car placed on a test bench in order to control precisely speed and road profiles. Thus the same excitation is applied to the different suspension systems.

2.3 Difficulties

Considering the elements described previously, some difficulties have been identified.

First, the subjective rating is given with a 0.5 step precision, thus the model has to reach an estimation error less than 0.5. The estimation error is the difference between the subjective rating done by the RENAULT expert and the prediction given by the model.

Secondly, the rattle noise is non stationary and composed of short time shocks. Their analysis, from a signal point of view, is non trivial.

Lastly, for time computation limitations, the signal analysis is done on a short segment of time of the binaural recordings (around 20s). Some phenomena judged by the expert may not be present in the selected segment of the recordings.

3 Characterization of rattle noise with signal processing metrics

The metrics proposed here aims at characterizing the rattle noise, both on spectral, time and time-frequency domain. They are done on a short portion of signal (20s), filtered with a low-pass filter at 630 Hz from the binaural recordings.

3.1 Spectral metrics

In order to observe more precisely the frequency bands related to the rattle noise, a high resolution time-frequency analysis has been performed. The figure 2 shows the Reassigned Pseudo MARGENAU-HILL representation of a pressure signal of a rattle noise.

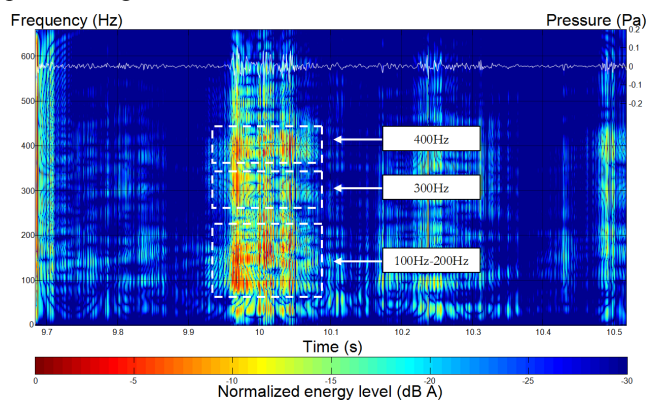


Fig. 2 Reassigned Pseudo MARGENAU-HILL representation of the rattle noise

This representation shows clearly that the phenomenon is localized in the frequency band [100 – 200] Hz, around 300 Hz and around 400 Hz.

Hence, the spectral metrics proposed are the following:

- M1 : A-weighted level in the 3 Barks band covering 200 to 510 Hz
- M2 : spectral center of gravity expressed for specific loudness estimation
- M3 : Sum of specific loudness for the first 6 Bark bands (from 0 to 630 Hz)

The specific loudness calculation is done with the ISO 532 B model [1, 2, 3].

M1 focuses on the loudness of the rattle noise. M2 represents the tonality of the noise in regard of the

bass/medium/high content of the noise. M3 is a more global loudness measurement.

3.2 Temporal metrics

Regarding temporal metrics, we try to focus on the localization of the chocks corresponding to peaks in the temporal signal. The figure 3 represents the envelope of the pressure signal with a time integration of 20 ms.

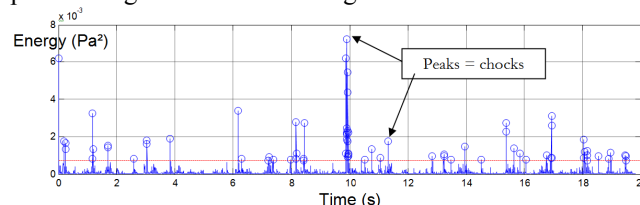


Fig. 3 Temporal envelop with 20 ms of time integration

The temporal metrics proposed are the following:

- M4 : A-weighted level of the most energetic chocks
- M5 : inverse of the mean period of chocks occurrence
- M6 : variance of chocks occurrence
- M7 : skewness of chocks occurrence
- M8 : kurtosis of chocks occurrence

3.3 Time-frequency metrics

Time-frequency metrics are intended to keep the time and frequency information together. We focus on the MORLET wavelet decomposition, as shown on figure 1. More precisely, we analyze the level distribution of the MORLET coefficients for the A-weighted signal of the rattle noise. The figure 4 shows a histogram of the level distribution of the coefficients corresponding to 3 suspension systems.

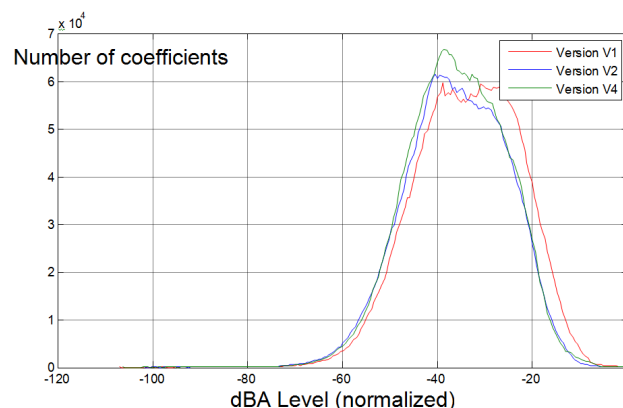


Fig. 4 Distribution of the coefficients of MORLET wavelet decomposition

The time-frequency metrics proposed are the following:

- M9 : mean of the distribution
- M10 : variance of the distribution
- M11 : Kurtosis of the distribution

4 Objectivization model

4.1 Introduction to multiple linear regression

p is the number of metrics (predictors) and n is the number of suspension system tested (observations). Observation vector y is composed of n subjective ratings of the expert for the different suspension systems. The matrix X is composed of the values of each metrics for each suspension system. The size of the matrix X is $n \times p$. We try to find the function that links y and X :

$$y = f(X) \quad (1)$$

In the multiple linear regression model we suppose that y and X are related with the following equation (2):

$$y = Xb + a \quad (2)$$

In order to find the p coefficients of vector b and the constant value a , a least square algorithm is used [4]. To reduce the influence of outlier observations which could perturb the regression, a weighted least square algorithm is used [5, 6].

The linear regression resolution is seldom exact. Hence the resulting vector y^* is an estimation of vector y and called the estimate vector. It is close to y in the least square sense:

$$y^* = Xb + a \quad (3)$$

4.2 Quality estimation of the regression

To determine the global quality and the precision of the regression obtained, some indicators are calculated. The first indicator is the correlation coefficient R^2 between y^* and y . The more R^2 is high, the more y^* and y are subject to be close. If $R^2 = 1$, y^* equals y and the model is perfectly adjusted.

The second indicator is the statistical root mean square error defined by:

$$\sigma = \frac{\|y - y^*\|}{\sqrt{n - p - 1}} \quad (4)$$

The operator " $\| \cdot \|$ " stands for the norm of a vector, n the number of observations and p the number of explicative variables. This indicator measures the spreading of the error of the estimation.

The third indicator used to quantify the predictability of the model is called goodness of prediction and noted Q_2 . Q_2 is a function of the Predicted residual sum of squares (Press) and defined as:

$$Press = \sum_{i=1}^{i=n} (y_i - y_{(-i)}^*)^2 \quad (5)$$

With $y_{(-i)}^*$ the estimate obtained with $(n-1)$ observations that exclude the i^{th} observation. This indicator measures the stability of the model when removing a single observation: if the quality of the estimation does not change when the model is rebuild with one observation removed, the predictability is very high.

Hence a multiple linear regression model can be qualified by 3 indicators: R^2 , σ and Q_2 .

Finally, an interesting statistical indicator for each estimate value is the confidence interval (CI). The CI is used to indicate the reliability of the estimate value by providing an interval likely to include the estimate with a specified probability. We use the confidence interval at the 95% level, i.e. we have a 95% chance that the estimate is indeed inside the interval. For example, the rattle noise estimation for a suspension system can be estimated at 7.4 with 95% confidence interval [7.0; 7.8]. Lower and upper bounds for confidence intervals are computed from the sample estimate of the parameter and the assumed sampling distribution of the estimator. A large confidence interval corresponds to a poor estimation. With a quantization of 0.5 for the subjective rating, we would like to keep the confidence interval lower than [-0.5; 0.5], i.e. a width lower than 1.0.

4.3 Selection of the best metrics

If all 11 metrics are used, a model with a very good correlation coefficient ($R^2 \approx 98\%$) is obtained, but the goodness of prediction is very low $Q_2 \approx 60\%$ while the 95% confidence interval is large (3 units). These results can be explained because of the high number of predictors (11 metrics) regarding to the number of observation (19). It is more judicious to select the most pertinent metrics in order to increase the predictability and to decrease the confidence interval at 95%.

To identify the best metrics, the following exhaustive method is used:

1. Selection of all the possible combination of metrics : 1 from 11, 2 from 11, 3 from 11, etc...
2. For each combination (one from $2^{11}-1$), a multiple linear regression is computed
3. Computation of R^2 and Q_2
4. Selection of models with the highest Q_2
5. Verification that R^2 is high ($> 90\%$)

Figure 5 shows the results for the correlation coefficient and goodness of prediction function of the number of explicative variables

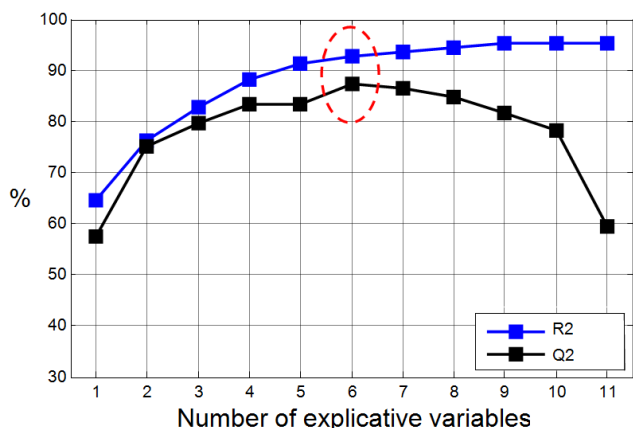


Fig. 5 Correlation coefficient and goodness of prediction function of the number of explicative variables

Figure 5 shows that the correlation coefficient increases with the number of explicative variables while the goodness of prediction increases and then decreases. Thus the model offering the highest predictability is built by selecting 6 explicative variables. The corresponding metrics are detailed in the Table 1.

<i>Spectral metrics</i>	M1 : A-weighted level in the 3 Barks band covering 200 to 510 Hz M2 : spectral center of gravity expressed for specific loudness estimation M3 : Sum of specific loudness for the first 6 Bark bands (from 0 to 630 Hz)
<i>Temporal metrics</i>	M4 : A-weighted level of the most energetic chocks M8 : Kurtosis of chocks occurrence
<i>Time-frequency metrics</i>	M9 : mean of the distribution

Table 1 : Selected metrics

In order to validate the choice of the metrics, we first verify that the selection of best metrics is coherent when increasing the number of explicative variables. It is preferable to observe that the previous chosen metrics are kept when increasing the number of metrics. Figure 6 shows the evolution of selected variables for the models offering the highest predictability with the number of explicative variables. We observe that, except for 2 selected variables, the progression is stable and for each step, the previous chosen metrics are kept.

Finally, we verify that the correlation between each of 6 metrics is held low. The highest correlation is found between M1 and M3 at 75%. The correlations between other metrics are lower than 60%.

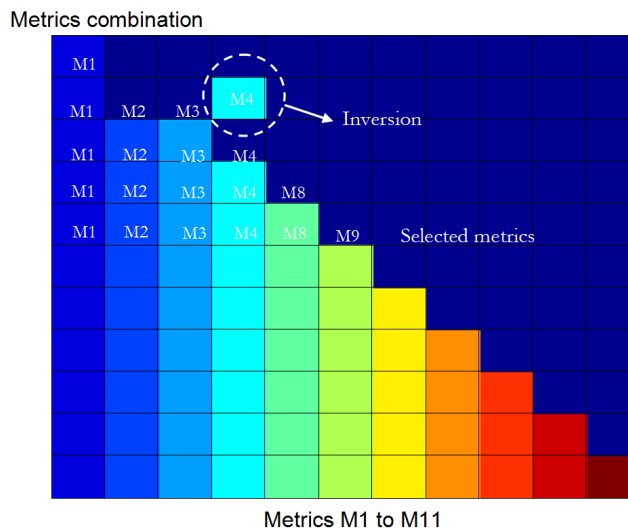


Fig. 6 validation of choice of metrics

5 Analysis of the linear model

5.1 Results

A multiple linear regression model has been applied between an observation vector containing the 19 ratings of rattle noise of suspension system from RENAULT and 6 explicative variables previously selected. The performance indicators of the model are summarized in the table 2.

Statistical indicator	Value
Correlation coefficient R^2	94%
Goodness of prediction Q_2	87%
Statistical root mean square error σ	0.39
Mean width of confidence interval at 95%	1.01

Table 2 : Statistical indicators of the model

The statistical indicators are in concordance with the objectives fixed: correlation coefficient and goodness of prediction are high and the spread of the error is in the range [-0.5; 0.5].

Figure 7 represents the model estimation versus the subjective rating. If the model was perfect, the dots should be on the diagonal of the plots. We observe the good performance of the model. Only 3 suspensions system (V1, V13 and V18) are slightly outside the +/-0.5 range from the subjective rating.

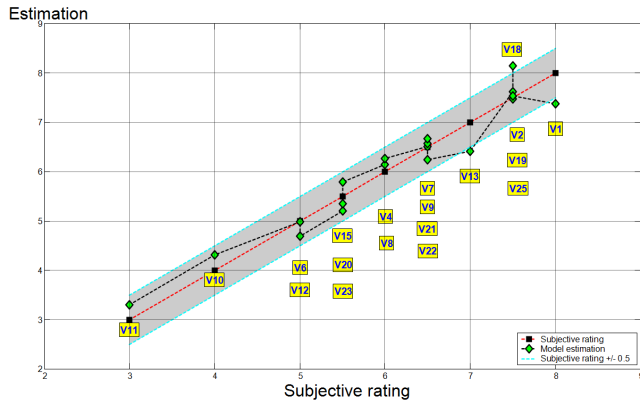


Fig. 7 Model estimation vs. Subjective rating

5.2 Validation on 6 new suspension systems

In order to validate the model, the prediction is computed for 6 new suspensions systems which do not belong to the ones used to build the model. The validation on the new corpus shows good results. The statistical indicators show 95% for the correlation coefficient and 0.45 for the root mean square error, while the mean width of confidence interval at 95% is 1.17. Figure 8 shows the estimation versus the subjective rating. The estimation error versus the subjective rating is below 0.5 except for V24 where the error is 0.7. Hence, it can be observed that the model achieves quite good results.

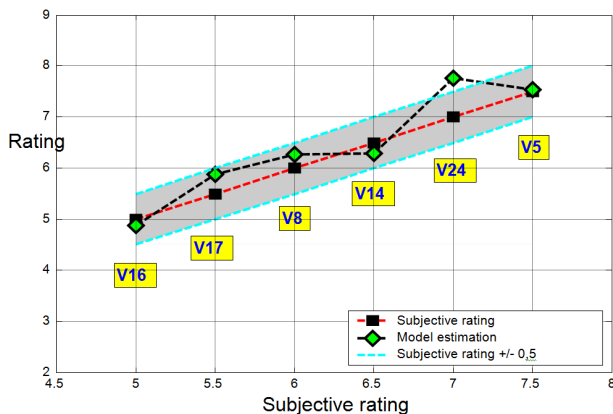


Fig. 8 Model estimation vs. Subjective rating for 6 new suspension systems

5.3 Further understanding of the rattle noise

In order to further understand the rattle noise, a principal component analysis for the 6 metrics used by the model has been performed. This kind of analysis allows better understanding of the rattle noise perception. This analysis is out of scope of this paper but is mentioned to offer an exhaustive analysis method.

Finally a tool has been developed in order to provide direct analysis and estimation of the rattle noise from a recorded signal. This tool allows RENAULT experts to analyze sounds and experiment with the model.

5 Conclusion

The rattle noise of suspension systems is impacting the acoustic comfort of car vehicles. The work presented here shows a method deployed in order to build an objectivization of this phenomenon. This approach is divided in four parts:

1. Construction of signal processing metrics from binaural recorded signals
2. Selection of the best metrics to describe the phenomenon with the help of statistical indicators
3. Computation of multiple linear regression model from the selected metrics
4. Validation of the model on a new set of rattle noise recording from different suspension systems

For each step, a particular care has been provided to use advanced techniques. The metrics use together spectral, time and time-frequency analysis. The selection of the best metrics is based on statistical indicators. This study led to an accurate model given the data provided (19 rattle noises from 19 suspension systems for the same car). Nevertheless, rattle noise objectivization needs still further investigations. Particularly, the model has to be tested and extended for different cars.

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References

- [1] AFNOR. *Acoustique – Méthode de calcul du niveau d'isophonie*. Norme Internationale ISO 532, réf. n° ISO 532-1975 (F),
- [2] ZWICKER E. FASTL H. *Psycho-acoustics – Facts and Models*. Berlin : Springer-Verlag, 1999, 416 p.
- [3] MOORE B. *An Introduction to the Psychology of Hearing*. London : Academic Press Inc., 1982, 293 p.
- [4] SAPORTA G. *Probabilité – analyse des données et statistique*. Paris : Editions Technip, 1990, 493 p.
- [5] WEISBERG S. *Applied Linear Regression*. New Jersey : JohnWiley & Sons, 3ème édition 2005, 330 p.
- [6] MONTGOMERY D. et RUNGER G. *Applied Statistics and Probability for Engineers*. New Jersey : JohnWiley & Sons, 3ème édition 2003, 822 p.