Objective and Subjective Classification of Creep Groan Noise

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ABSTRACT: Stick-Slip effects occur at the contact surface between the brake pads and the brake disc. The Creep Groan phenomenon is associated with stick-slip effects in the frequency range up to 500 Hz. It induces vibrations on the entire brake system and influences the structural vibrations of the vehicle. Vibrations are transmitted to large surfaces which produce audible noise. Creep Groan Noise is unpleasant and can be considered as a defect, especially for drivers of luxury cars. Harshness and annoyance caused by Creep Groan noise depends on many factors. For this reason, vehicle tests often include a subjective analysis of the Creep Groan Noise. Unfortunately, subjective tests suffer from the inherent uncertainties of subjective evaluation. A model for the assessment of Creep Groan noise harshness is necessary to reduce these uncertainties and to improve the Creep Groan assessment. For this purpose, experimental tests with over 1000 measurements were carried out. Many different features from the measurement data were extracted and analyzed. Selected features (quasi acoustic emission, simulated sound pressure level and vibration level) were used to classify Creep Groan into eight annoyance classes using Kohonen's Self Organizing Maps and a K-Means algorithm. The results of both unsupervised classification algorithms were correlated with a subjective quantification ranging from 1 (very poor) to 10 (excellent). After the right interpretation of the unsupervised algorithmic classification, performed with the K-Means algorithm, the correlation between the algorithmic classification and the subjective quantification of the creep groan harshness is obtained. It is shown that Kohonen's self-organizing map, in combination with selected features of vibroacoustic signals, provides readily usable results without any need for subjective evaluations.

KEY WORDS: Kohonen Neural Network, Self Organizing Maps, K-Means, Unsupervised Classification, Breaks, Creep Groan, NVH, Noise Event Classification, Vibrations, Acoustic Emission

1. Introduction

1.1 Motivation

The annual costs associated with the brake noise and vibration problems are estimated to be up to $100 million. Well-researched brake squeal remains one of the main factors within this number; however, low-frequency problems such as creep groan gain attention due to current trends such as drive train electrification or automated driving functions, [28]. Hence, sophisticated creep groan rating procedures are necessary for simultaneous prediction as well as experimental validation. These rating procedures can consist of subjective or objective assessments. Subjective assessments of creep groan phenomena remain an important part of practical studies due to the extreme complexity of the problem. The automotive industry spends a lot of time and effort to evaluate and quantify the occurrence, intensity and harshness of creep groan noise. Subjective tests are time-consuming and many resources are needed to obtain useful results. In addition, subjective results tend to vary due to the different perception of noise by different test persons. Consequently, many test persons have to perform tests in order to achieve a well-averaged final rating.

Objective assessments are able to conquer many of the mentioned drawbacks such as result variation or high effort. Certainly, objective approaches need to be sophisticated enough to deal with the high complexity of creep groan phenomena. Therefore, an attempt was made to find an approach that eliminates the need for subjective testing and allows the evaluation of the creep groan harshness on the basis of measurable quantities. At the same time the proposed approach should be able to provide sufficient correlation with subjective quantification of the creep groan noise harshness.

1.2 Creep Groan Phenomena

Creep groan is described as a noise and vibration phenomenon related to a vehicle’s friction brakes with a rather low dominant frequency. Throughout literature, it is defined as a combination of vibration and sound below 300 Hz, [3], below 200 Hz, [5], or within a frequency range usually from 20 to 500 Hz, [6]. Typically, creep groan occurs at low speeds and positive to high brake pressures, [21]. It can occur in particular in a vehicle with automatic transmission when starting by simultaneously applying engine torque and releasing brake pressure.

Creep groan is typically excited by stick-slip transitions in the contact between disk and pads as stated within many publications, e.g. [8, 22, 23]. These stick-slip transitions separate stick-phase (suspension wind-up) and slip-phase (release, damped oscillation), [24]. Due to their abrupt nature, sticks-slip transitions excite...
vibrations in a wide frequency range. Vibrations are a result of contribution from many suspension components, see e.g. [24], ultimately introducing time-variant forces into the vehicle body and generating structure-borne noise. This structure-borne noise is further transferred to the interior of the vehicle and the driver’s ear via the chassis components, as proposed by Bettella et al. [8]. They found that both airborne and structure-borne paths are present, with the structure path being typically more important. An experimental investigation on a test vehicle using accelerometers and microphones showed that the front brake calipers are the main source of creep groan noise.

The phenomenon of creep groan in the vehicle cabin and outside the vehicle is usually assessed subjectively on full vehicle prototypes or on test rigs with a (reduced) physical setup. To tackle creep groan propensity already at an early stage, effort is put into simulative methods too. Coming from minimal models with two, three, four or five DOFs, even half-axle models are investigated for their creep groan behavior as e.g. within [6, 25].

1.3 Detection and Quantification of Creep Groan

Detection and quantification of creep groan is an important issue. A detection based on the measured sound pressure (Pa) may have problems with the so-called ‘transition’ groan, as defined within [27], which will most likely confuse a threshold based detection algorithm. Furthermore, a distinction between different brake NVH phenomena can be difficult.

In vehicle tests, the vibration signals from acceleration sensor data can be used for creep groan quantification in a variety of ways, e.g. by the length of the creep groan event, the peak-to-peak range or the root mean square (rms) value [7,13]. A rms value of the accelerometer signal is most often used to assess the creep groan harshness in the vehicle tests. Nevertheless, disturbances by e.g. engine/drive train noise and vibration need to be eliminated within such procedures.

Abdelhamid and Bray, [10], tried to identify creep groan from the audio signal by means of psychoacoustic features first. Tonality has been found to correlate well with the investigated creep groan noise. However, further analysis showed that tonality may not be the best metric for creep groan as it is not able to distinguish between closely related events, [10]. They concluded that dB(max) and loudness are better metrics for the creep groan quantification than tonality.

Creep groan’s characteristic non-linear behavior is utilized within frequency-based detection methods as explained within [7] or [11]. Multiple orders in frequency domain can be found by peak detection.

Another detection and quantification method is given by the kurtosis of the vibration signal. Investigations regarding creep groan signals can be found within [26]. Detection as well as creep groan harshness can be assessed with this parameter.

1.4 Scientific Approach

First, creep groan experiments on full-vehicle level were performed. To mitigate influences by engine noise and vibration, creep groan’s structure-borne nature was used: An adaptive FIR filter transfer function between measured caliper acceleration and the measured sound pressure at the driver’s ear was approached by a classical multi-channel LMS algorithm. Thereby resulting signals resemble the measured sound pressure signal without disturbing background noise.

Second aim of the study was to identify relevant features within these processed vibroacoustic signals. Various psychoacoustic features were tested for correlation with subjective quantification (Loudness, Sharpness, Roughness, Fluctuation strength, Tonality), including some synthetic parameters such as Noise Annoyance, AVL index and VACI. Other vibroacoustic signal features like dB(B), dB(C), dB(A), crest factor, kurtosis were also tested. Overall, more than 100 different features on signals from 8 different sensors were tested.

The third step comprised of ‘feeding’ unsupervised classification algorithms with different combinations of these relevant signal features. Unsupervised classification algorithms were applied to feature vectors consisting of 1) the vibration level, 2) Quasi Acoustic Emission, see [29], 3) the sound pressure level at the driver’s ears, simulated by vibrations using FIR and “B” filter, and 4) the pulse integration of the sound pressure in the cabin.

2. Experiment

Experimental plan was designed around well-defined driving conditions during which creep groan frequently appears. Three parameters have been included into the experimental plan; Direction of the driving (forward or backward), acceleration (acceleration from or to standstill), inclination of the road (Uphill and downhill). A car with an automatic transmission was selected. Each of the following scenarios has been tested at least five times, and the driver rated each experiment regarding creep groan noise with a mark between 1 (very poor) and 10 (excellent).

Two different brake pad materials were compared (marked ECE and NAO). Five measurement repetitions were performed for each driving condition. The subjective evaluation of the creep groan noise was carried out by 8 drivers. The subjective quantification of the creep groan noise harshness was carried out for the noise inside the cabin and for the noise outside the vehicle. Creep groan events were subjectively quantified with numbers between 1 and 10. Mark 10 indicates that creep groan could not be detected and mark 1 indicates that the creep groan noise harshness to be so unpleasant that it is totally unacceptable for the vehicle. More than 1000 measurements were carried out and all recorded signals were attributed with a subjective quantification of the creep groan noise harshness.

Triaxial accelerometers were mounted on all four brakes. Two microphones were mounted in the vehicle's cabin. The left side was at the position of the driver's ears and the right side at the position of the passenger's ears. Microphones were also placed outside the cabin, under the wheel arch, to the vicinity of the brakes. All channels were recorded with 51.2 kHz sampling rate and 24 bit resolution. A calibration of all microphones was performed and the AD conversion was performed with about 6.2% of full range at 93.8 dB. The analysis of the measurement data to identify the correlation with the subjective quantifications of creep groan noise harshness was carried out in 4 steps:
1. Extraction of signal features from: a) the microphone placed in the cabin at driver’s head, b) the microphone, placed under the wheel arc, c) accelerometers, placed on the brake calliper, d) from the simulated noise in the cabin, based on the identified transfer function using FIR filter.

2. Implementation of K-Means algorithm for unsupervised classification of the Creep Groan noise harshness, based on selected signal features.

3. Implementation of Self Organizing Maps for unsupervised classification of Creep Groan noise harshness based on selected signal features.

4. Analysis of unsupervised classification results and determination of matrix for their correlation with subjective quantification of creep groan harshness.

2.1. Extraction of signal features

Creep groan is not an easily predictable phenomenon, nor does it have a high repeatability or reproducibility of results – at least during full-vehicle tests. Recordings of vibroacoustic signals are therefore of different length and with creep groan phenomena occurring at different time intervals with different length and intensity. However, each recording was assigned a subjective quantification. During the subjective evaluation of the creep groan event, experts quantified the severity of the phenomena. They concentrated on the noise level of the creep groan noise and on its duration. Signal features, which are based on the integration, depend on the time resolution (length of the integration time window). The selection of the integration time for feature extraction proved to be extremely important. After a few tests with different integration times of 50, 125, 250, 500, 1000, 2000 and 5000 msec, it was found that the correlation between measured features and subjective quantification is highest when the 1000 msec integration time was applied. Signal features were therefore extracted for each second of the recorded vibroacoustic signal, and maximum values from each recording were set in the feature vector, describing individual recordings. During the study more than 100 features have been tested. In the final stages, the study focused on the four features given in Table 1.

Table 1: List of selected (used) features

<table>
<thead>
<tr>
<th>Ind.</th>
<th>Feature</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC-1</td>
<td>Acc. level</td>
<td>$10 \log(a_{\text{rms}}/a_0)$</td>
</tr>
<tr>
<td>ACC-2</td>
<td>Integral of peaks</td>
<td>DSP according to figure 2 and 3. Hp=500Hz and Lp=250 Hz. Max value of Quasi AE signal integration</td>
</tr>
<tr>
<td>MIC-3</td>
<td>dB(B) simulated sound</td>
<td>Lp[dB(B)] of Simulated sound in the cabin, based on FIR filter, presenting the transfer function between vibrations and noise</td>
</tr>
<tr>
<td>MIC-4</td>
<td>Integral of peaks</td>
<td>DSP according to figure 2 and 3. Hp=500Hz and Lp=250 Hz. Max value of Quasi AE signal integration on simulated sound in cabin</td>
</tr>
</tbody>
</table>

2. Simulations of the sound in the cabin were performed using an adaptive FIR filter with LMS algorithm. The extraction of the transfer function between vibrations at the brake callipers and noise in the cabin was performed with a multi-channel adaptive FIR filter and the implementation of the classical LMS algorithm. An averaged impulse response was calculated from a large number of measured impulse responses, as shown in Figure 3A. Due to the constantly present low-frequency background noise of the engine the impulse response did not converge to zero after the excitation event had decayed. To eliminate low frequency noise from the measured impulse response, we implemented a method for filtering the impulse response based on varying window length, which was proposed in our previous work [9].

Figure 2 Transformation of Creep Groan Vibration signal into Virtual Acoustic Emission signal for further feature extraction

If we assume that the high frequencies in the impulse response die out faster than the low frequencies, then the high-frequency part of the impulse response must ultimately be a consequence of the noise. Therefore we can introduce a moving average with a variable length of the averaging window to minimize noise. The length of the averaging interval changes as shown in Figure 3B. It is based on a low pass filter design. The length of the averaging...
window depends on the relative position of the averaging interval in the impulse response. Since the high frequency noise has more influence at the end of the impulse response, longer averaging windows were used at the end of the impulse response and very short ones at the beginning of the impulse response. The length of the averaging window was determined using the following two equations [9]:

\[ N_{avg}(n) = \text{round}(e^{r/n}) \]  
\[ h_{avg}(n) = \frac{1}{2N_{avg}} \sum_{i=1}^{N_{avg}} h(2n - N_{avg} + 2i) \]

where \( r \) is the coefficient whose value depends on the length of the impulse response and the desired filter rate. The impulse response was filtered with a moving average, using the equation for variable window length \( h_{avg}(n) \).

This approach is to eliminate possible human error from the learning process of the supervised algorithm.

K-Means is one of the basic unsupervised algorithms and can be thought of as a self-learning K-NN algorithm. The classification is random and depends on the initial conditions of the centroids, but similar measurement results are classified into the same class. The results of the K-Means algorithm are interpreted by the experts only afterwards. SOM is a slightly more advanced algorithm and, in the case of 1-dimensional classification, it already allows results to be classified according to the ordered difference between them, leading to results ranging from the class presenting one extreme to the class presenting the other opposing extreme.

3.1. Unsupervised classification algorithm K-Means

The K-means algorithm is one of the most frequently used algorithms for unsupervised classification. It is an iterative algorithm that attempts to classify the data set into K different, non-overlapping clusters, where each data point can only belong to one group. Data points are D-dimensional vectors, with each component representing a feature extracted from observations. The K-Means algorithm attempts to arrange N observations in K clusters in such a way that the data points between the clusters are as similar as possible, while retaining the clusters as much as possible. The assessment of similarity between the points is based on the Cartesian distance between the points. The distance between a centroid with the index cm and the observed point \( x_n \) is defined by an equation:

\[ d(x_n, y_{cm}) = \sum_{i}^{D} (x_{ni} - y_{ci})^2 \]

The K-means algorithm assigns each data point to the nearest cluster; defined with its centroid. The algorithm is based on minimizing the arithmetic mean of all data points belonging to the same cluster. The less variation we have within the clusters, the more homogeneous the data points within the same cluster are. K-means clustering therefore aims to classify the N observations into K (\( \leq N \)) clusters defined with the centroids \( C = \{c_1, c_2, ..., c_K\} \) to minimize the sum of the squares within the cluster. Formally, the goal is to find:

\[ \arg\min_{c} \sum_{i=1}^{N} \sum_{x \in c_i} (x - c_i)^2 = \arg\min_{c} \sum_{i=1}^{K} \sum_{x \in c} [y_{cm} - \epsilon_{mi}]^2 \]

where \( \epsilon_i \) is the average of points attributed to \( c_i \). This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

\[ \arg\min_{c} \sum_{c} \frac{1}{|c|} \sum_{x \in c} [y_{cm} - \epsilon_{mi}]^2 \]

The equivalence can be deduced from identity:

\[ \sum_{k \neq i} [x_i - c_i]^2 = \sum ([x_i - \epsilon_i], [\epsilon_i, -y_i]) \]

Since the total variance is constant, this corresponds to a maximization of the sum of the quadratic deviations between the points in different clusters, which is derived from the law of total variance. The K-means algorithm is normally initiated with a randomly filled matrix of centroids C. Then Cartesian distances are calculated for each pair of data points to each centroid.

Figure 3: Averaging of FIR filters for identification of transfer function from vibrations to sound sound (A), and filtering of averaged FIR filter in time domain for improving Signal to Noise Ratio (B).

3. Classification algorithm

Supervised learning is inherently exposed to subjective perception due to the correlations determined by the experts. In order to circumvent this influence of subjectivity in the supervised learning methods, such as K-NN and Neural Network, two algorithms for unsupervised classification were selected: the K-means and Kohonen's Self Organizing Maps - SOM. The advantage of unsupervised learning is that the algorithm can classify the measured data independently. Classification is based on clustering, and we can only correlate each class with a corresponding subjective quantification later. The advantage of
A self-organizing map (SOM) or Kohonen map [12] is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional, discretized representation of the input space. It differs from other artificial neural networks in that it applies competitive learning as opposed to error-correcting learning (such as backpropagation with gradient descent), in the sense that it uses a neighborhood function to preserve the topological properties of the input space. The SOM normally consists of a two-dimensional grid containing a number of neurons. These neurons are usually arranged rectangular or hexagonally. The position of the units in the grid, especially the distances between them and the neighborhood relations, are very important for the learning algorithm. Self-Organizing Map has been implemented in numerous fault diagnosis studies [13, 14, 15, 16, 17] and has proven to be a useful tool for classification when using vibration and sound signals. Kane and Andhare have shown that extracted psychoacoustic and statistical features are able to classify different gear faults, [18].

On an intuitive level, both k-means and SOM move the neurons to denser areas of the input space. With k-means, the nodes move freely and without direct relationship to each other. In SOM, as one neuron moves toward the data, it drags neighboring neurons on the 2D grid with it. This of course maintains a topology embedded in the data space, and the clusters are formed geometrically. Unlike k-means, a neuron in SOM can easily be responsible for zero data points. This indicates that such neurons are located in empty space and are pulled in all directions by their neighbors. It has been shown that self-organizing maps with a small number of neurons behave similar to k-means, while larger self-organizing maps rearrange data in a way that is fundamentally topological in nature character. The SOM algorithm shows better results when using small data sets. It is also less susceptible to noisy input space, [19, 20]. The conventional SOM algorithm consists from the following steps:

**Step 1:** Initialize the weight vectors $c_i$’s on the grid of $a \times b$ neurons, with arbitrary values.

**Step 2:** Randomly select an input vector $x_n$ and it is input to all the neurons at the same time in parallel.

**Step 3:** Find the winning neuron, i.e. BMU (best matching unit), using the same equation as with k-means algorithm, i.e. the Euclidean distance measure.

**Step 4:** The weight vector of the neurons is updated using the following equation:

$$c_{n}^{(n+1)} = c_{n}(n) + h_{r}(n)[x_{n} - c_{n}(n)]$$  \hspace{1cm} (7)

where $h_{r}(n)$ is a Gaussian neighborhood function:

$$h_{r}(n) = \alpha(n) \exp \left( \frac{r^{2}}{2\sigma^{2}(n)} \right)$$  \hspace{1cm} (8)

where $r$ is the coordinate position of the neuron on the map, $\alpha(n)$ is the learning rate and $\sigma(n)$ is the width of neighborhood radius. Both $\alpha(n)$ and $\sigma(n)$ decrease monotonically using the following equations:

$$\alpha(n) = \alpha(0) \left( \frac{\alpha(N)}{\alpha(0)} \right)^{N/n}$$  \hspace{1cm} (9)

$$\sigma(n) = \sigma(0) \left( \frac{\sigma(N)}{\sigma(0)} \right)^{N/n}$$  \hspace{1cm} (10)

For all the input data $N$, steps 1-4 are repeated. In our case we used a 1-D grid ($a = 7$, $b = 1$). The reason is that the output layer (subjective quantification) is quite straightforward and ranges linearly from 3 to 10. As we can see from the results, the topological layer (input layer) of SOM correlates to the order of the neurons, which must be done manually with the k-means algorithm. The neurons on each side of our 1-D grid automatically land on the opposite sides of the 5-D input space due to the neighborhood function. This is directly correlated to the values of subjective quantification.

**4. Results**

Four features were extracted from the measured signals during braking: maximal vibration level, maximal integrated value of the QAE, maximal simulated sound pressure level dB(B) in the cabin and maximal integrated QAE of the simulated sound in the cabin. 1018 feature vectors with 1018 subjective classifications were recorded. Two unsupervised classification algorithms (K-means and SOM) classified the results into 8 classes. The SOM algorithm classified results according to the interactions between the neurons; therefore 6 intermediate centroids are automatically ordered between the two extremely opposing centroids, as presented in Figure 4(A) with blue dots. The centroids obtained with the K-Means algorithm are obtained from the randomized initial conditions; therefore, all centroid converges to their result individually, each one representing one class. The results are shown in Figure 4(A) with red crosses.

![Figure 4: Correlation between algorithmically defined classes and averaged values of subjective evaluations](image)

The analysis of the centroids representing each class was carried out to understand the results of unsupervised classification. Each
algorithmically defined class was quantified with an averaged value of subjectively values from this class. Figure 4(A) shows how the averaged value of 5.713 from all subjective values within class 3 was assigned to this class, for example. The arrangement of algorithmically defined classes is necessary to ensure traceability with subjectively defined classes. Figure 4(B) shows a correlation between the subjective values and the K-Means classification after each class has been quantified with an averaged subjective value. Both types of brake pads are included in the results as well as different drivers and driving conditions. Overall correlation on 1018 samples is $R^2=0.77$.

It is interesting to note that the algorithmic classification is very good for the type of breaks prone to the creep groan occurrence, (ECE), where the correlation between the subjective classification and the classification based on unsupervised learning is $R^2=0.89$, as presented in Figure 7(A). Furthermore, the results in Figure 5 clearly show a significant discrepancy between subjective and objective classification at 97th and 98th measurement, which in our opinion indicates to an obvious human error. This error could occur due to a misinterpretation or incorrect reporting of the data. These two outliers were removed from further statistical analysis. The results in Figure 6 also show a good correlation between the unsupervised algorithmic classification of the Creep Groan noise and the subjective classification of creep groan noise harshness. The correlation is $R^2=0.62$, as shown in Figure 7(B), because the difference between the creep groan noise and the normal breaking noise is less pronounced. Smaller and less pronounced differences can be attributed to better types of the braking pads (NAO). These breaking pads are less susceptible to the creep groan. Consequently, the subjective evaluation was also more difficult for the drivers, what introduced additional uncertainty.

The results for only one type of breaking pads (ECE) are shown in Figure 5. The results for the other type of breaking pads (NAO) are presented in Figure 6. Black squares in both figures represent results of the subjective quantification. The values are not discrete, as the drivers attributed creep groan noise with marks between 0 and 10 and with resolution of 0.5. Mark 10 indicates that creep groan could not be detected and mark 1 indicates that the creep groan noise harshness was so unpleasant that it would be totally unacceptable for the vehicle. For each subjective value, two subjective marks were averaged. Subjective values are ranging from 3 to 10 with a resolution of 0.25. Red crosses represent biased classes to which the K-Means algorithm has assigned an individual result. Their value is between 4.7 and 9.8, as defined by the matrix shown in Figure 4(A). Figure 5 and Figure 6 clearly show that unsupervised classification is closely related to the subjective classification for both types of algorithms.

Figure 5: Correlation between the subjective classifications of Creep Groan severity and the weighted classification provided by the K-Means algorithm and SOM algorithm, for the ECE type of brake pads.

Figure 6: Correlation between the subjective classifications of Creep Groan severity and the ordered classification of K-Means algorithm and SOM algorithm, for the NAO type of breaks.

The results of unsupervised classifications performed with the two algorithms K-Means and SOM are shown in Figure 8. Both algorithms offer a similar classification of results into eight classes. The correlation between the classifications performed by two algorithms is 0.96, as shown in Figure 8(A). When the classification results of both algorithms are averaged and the averaged unsupervised classification is compared with the subjective classification, the correlation between unsupervised classification and subjective classification increases to $R^2=0.79$. Such a result confirms the possibility of using both unsupervised
classification algorithms to classify creep groan harshness based on four selected features. This means that after the identification of the transfer function between the vibrations on the brakes and the sound in the cabin, only vibrations on the front wheels are needed for unsupervised classification of creep groan noise harshness and no further need for subjective tests is needed.

5. Conclusions

The experiment to study creep groan phenomena was designed and completed. The subjective quantification of the creep groan noise was included in the experimental design. Subjective values of the creep groan harshness were attributed to the measurement data; sound and vibration signals. The integration time of the features extraction from sound and vibration signals, has a significant impact on the correlation between the unsupervised classification of the creep groan harshness and the subjective quantification of the creep groan harshness. The best results have been obtained with 1 sec long integration times.

The transfer function, which describes the generation of noise from the vibrations on the brakes, was identified in the time domain by means of an adaptive multichannel FIR filter and the least means square (LMS) algorithm. The implementation of the transfer function in the time domain enabled calculations of the creep groan sound in the cabin, without additional low-frequency background noise from the engine, the cooling fan and the air conditioning system.

The so-called Quasi Acoustic Emission signal feature was developed. Its integral value was included in the feature vector together with the vibration level and the sound pressure level of the simulated creep groan sound in the cabin. All features are based on a vibration signal, but a microphone signal at the driver’s ears was used to identify the FIR filter used to simulate the creep groan noise in the cabin.

Two unsupervised classification algorithms were tested: K-Means algorithm and Kohonen’s self-organizing map (SOM). The results of both unsupervised classifications algorithms were analyzed to understand the unsupervised classification process and to design a matrix to correlate the algorithmically defined classes with the subjectively quantified creep groan harshness.

The results clearly confirm that both algorithms for unsupervised classification can be used in the future to quantify creep groan harshness, without further need of a subjective reference. It is shown that Kohonen’s self-organizing map in combination with selected features of vibroacoustic signals provides readily usable results without any need for subjective evaluations whatsoever.

References

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