Journal of Sound and Vibration 329 (2010) 4567–4577

Contents lists available at ScienceDirect

Journal of Sound and Vibration

journal homepage: www.elsevier.com/locate/jsvi

Development of an algorithm for automatic detection and rating of squeak and rattle events

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ARTICLE INFO

Article history:
Received 28 October 2009
Received in revised form
3 May 2010
Accepted 7 May 2010
Handling Editor: K. Shin
Available online 3 June 2010

ABSTRACT

A new algorithm for automatic detection and rating of squeak and rattle (S&R) events was developed. The algorithm utilizes the perceived transient loudness (PTL) that approximates the human perception of a transient noise. At first, instantaneous specific loudness time histories are calculated over 1–24 bark range by applying the analytic wavelet transform and Zwicker loudness transform to the recorded noise. Transient specific loudness time histories are then obtained by removing estimated contributions of the background noise from instantaneous specific loudness time histories. These transient specific loudness time histories are summed to obtain the transient loudness time history. Finally, the PTL time history is obtained by applying Glasberg and Moore temporal integration to the transient loudness time history. *Detection* of S&R events utilizes the PTL time history obtained by summing only 18–24 barks components to take advantage of high signal-to-noise ratio in the high frequency range. A S&R event is identified when the value of the PTL time history exceeds the detection threshold pre-determined by a jury test. The maximum value of the PTL time history is used for rating of S&R events. Another jury test showed that the method performs much better if the PTL time history obtained by summing all frequency components is used. Therefore, *rating* of S&R events utilizes this modified PTL time history. Two additional jury tests were conducted to validate the developed detection and rating methods. The algorithm developed in this work will enable automatic detection and rating of S&R events with good accuracy and minimum possibility of false alarm.

1. Introduction

Recent technological advances in noise, vibration and harshness (NVH) engineering have brought about substantial reduction in noises reaching the passenger cabin. Hence the noises generated inside the passenger cabin due to squeak and rattle (S&R) events stand out, often resulting in highly detrimental perception of the quality of vehicles. Market surveys conducted as early as in 1983 reported S&R as the third most important customer concern in passenger cars after 3 months of ownership [1].

Historically, squeaks and rattles were detected and analyzed using purely subjective methods which are inconsistent and often time consuming. There have been numerous efforts to develop an automated method to detect and quantify S&Rs [2–7]; however, no method seems to be widely accepted for detection and quantification of S&R events. The present

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0022-460X/$ - see front matter
doi:10.1016/j.jsv.2010.05.003

Nomenclature

N_{inst}	instantaneous loudness of transient events
N_{PTL}	PTL used for automatic detection of S&R events
N'_{PTL}	PTL used for objective rating of S&R events
N_s	specific loudness of cabin noise
N'_s	approximate specific loudness of background noise
N_t	detection threshold
PTL	perceived transient loudness

study aims at developing a reliable method for automatic detection and quantification of S&R events occurring in actual operating conditions of the vehicle.

S&R are unexpected noises occurring in short time durations perceived by a listener to stand out from the background (expected) noise [4]. Squeaks are friction induced noises arising from stick–slip motion of surfaces in contact. Amplitude and frequency content of squeak depend on various factors such as material constituents, coefficient of friction, normal load, sliding velocity, inertia and thermal effects, wear characteristics, temperature and humidity conditions, etc. Rattles are impact-induced phenomenon generally caused by loose or overly flexible elements under forced excitation. The stick–slip motions and impacts produce audible sounds when the participating or adjacent surfaces are capable of effective radiation of sound energy. Instrument panels, seats and doors are main culprits in S&R generation [8].

S&R events cannot be detected reliably by using only basic physical quantities like sound pressure level (SPL) because of highly nonlinear and subjective nature of human hearing perception involved in detection of the events. Use of conventional subjective metrics like stationary loudness values also will not be sufficient because S&Rs are transient events with low signal to noise ratio (SNR) occurring in presence of background noise. Even a clearly audible S&R event under normal operating conditions can have a very low SNR. Such events become audible due to the remarkable spectral and temporal resolution of human auditory system that works like a bank of overlapping filters operating simultaneously on sound signals. The overlapping nature of the auditory filter will also result in spectral masking. Masking occurs when the perception of a sound is affected by the presence of another sound [9]. A S&R event becomes discernable when it has a favorable SNR ratio in at least one of those auditory filters.

Tran et al. [3] presented a technique for detecting and separating impulsive signals from a time domain signal. Their algorithm uses wavelet techniques and kurtosis, a statistical metric, to identify impulsive events, but their model does not incorporate the characteristics of human perception. Cerrato-Jay et al. used percentile levels and Kurtosis of loudness for detection of rattles in buzz, squeak, rattle (BSR) testing using road simulators [10]. Simulated test signals and Jury evaluations were used to arrive at detectability and acceptance thresholds. Percentile characteristics of loudness were suggested as a metric for evaluation of S&R events by Brines et al. [11]. However, the method is not suitable for S&R detection in presence of the background noise due to the low SNR. In most cases, loudness fluctuations in background

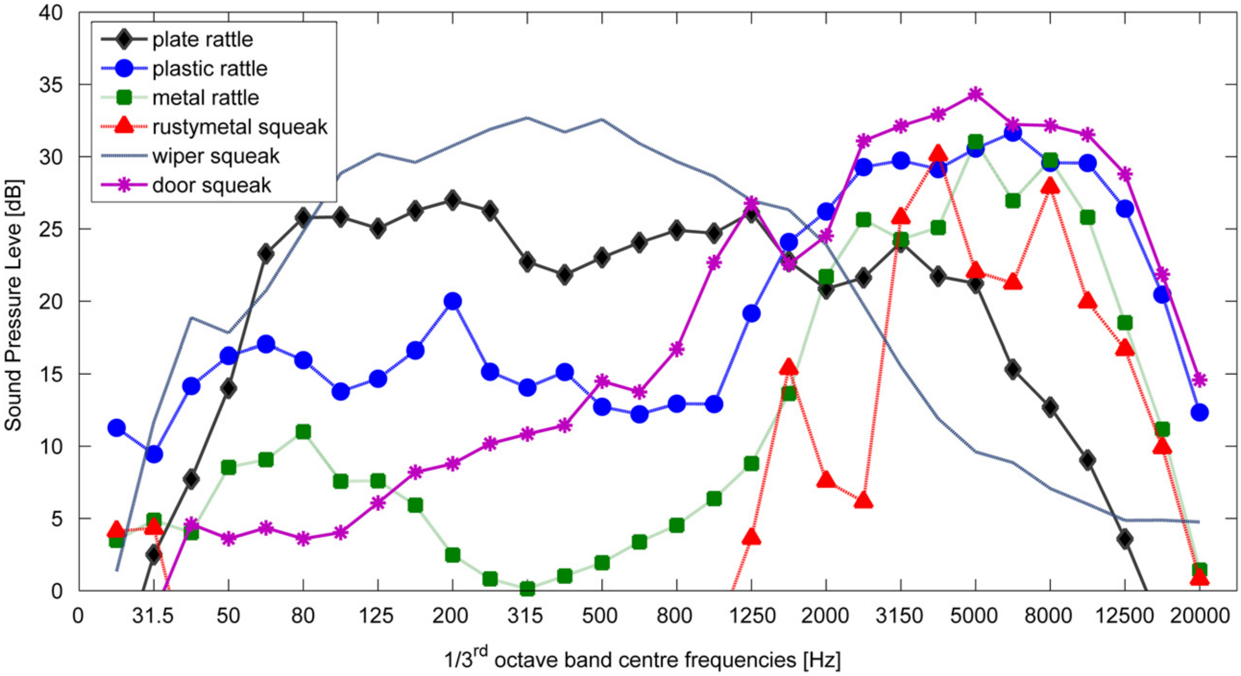

Fig. 1. One third octave spectra of selected S&R events generated using sound files downloaded from a website www.soundsnap.com [21].

noises resemble that of the S&R event. Feng and Hobelsberger [2] proposed to use the loudness values estimated from high-pass filtered sound. High pass filtering achieves higher SNR by removing the background noise, whose energy is distributed primarily in the low frequency bands. However, the removal of low frequency background noise will also result in removal of spectral masking effect of the components that are filtered out. This could lead to false detections. To prevent this problem, it is necessary to incorporate the characteristics of human perception and an advanced signal processing technique that can effectively handle the time-varying background noises.

A new S&R detection algorithm is proposed in this work to overcome the above-mentioned shortcomings of existing techniques to enable detection of S&R events occurring under normal operating conditions. A non-stationary loudness model based on Zwicker loudness [12–16] is used in this work to include the effect of the nonlinear spectral processing characteristics of the human auditory system. A procedure proposed by Glasberg and Moore [17] for modeling temporal integration of loudness is adopted to consider the time-domain masking effect. In addition, the proposed algorithm employs new techniques and concepts such as the analytic wavelet transform (AWT) [18–20] for time–frequency (*T*–*F*) characterization of the S&R event, the leaky integration to compensate for the background noise without causing the unwanted elimination of spectral masking, and the detection threshold defined as a function of statistics of the noise. Jury tests conducted as a part of this study showed noticeable improvements in detecting S&R events in the presence of background noises, indicating the improved performance of the proposed algorithm.

2. New algorithm for squeak and rattle detection

Fig. 1 shows 1/3-octave band spectrums of various S&R events scaled to have the same overall SPL of 40 dB. Human gets annoyed by an event of such widely different spectral characteristics even when it is embedded in the background noise of much higher overall SPL. This clearly suggests that an algorithm for automatic detection of S&R events should be developed by reflecting characteristics of the human hearing system.

Perceived transient loudness (PTL) is a time series developed to represent the human perception of transient events *above* the quasi-steady background noise in this work. A noise event is detected when the PTL value of a S&R event exceeds the detection threshold of the PTL value pre-determined by jury tests. Fig. 2 shows the five-step procedure to obtain the PTL time history of a given sound signal.

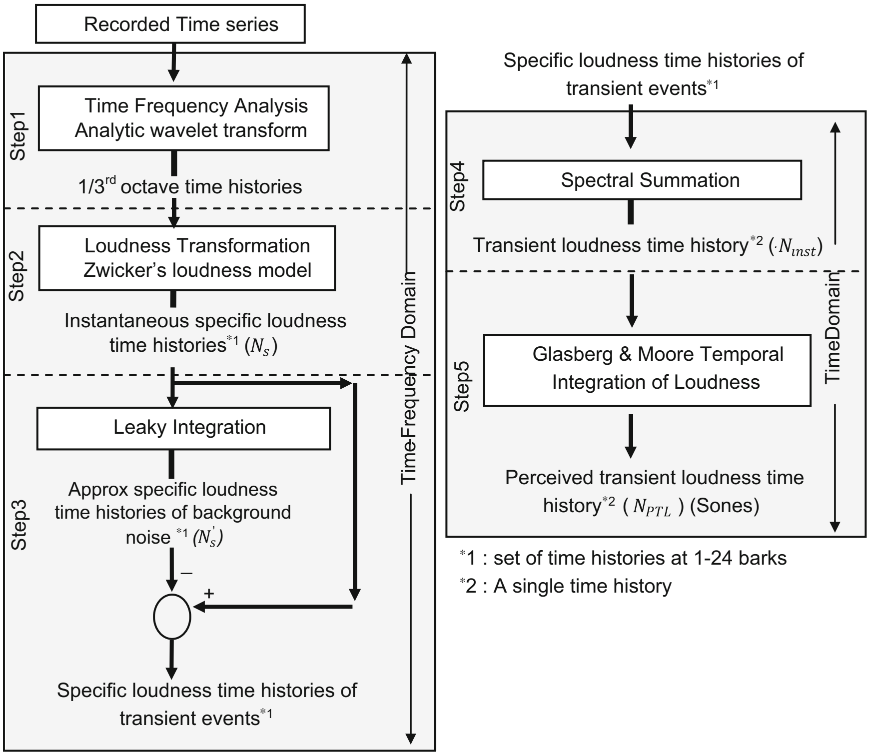

Fig. 2. Procedure to calculate the perceived loudness time history (N_{PTL}) shown in a block diagram.

2.1. Step1: T–F analysis

Because a S&R event is a highly time-localized event, a time–frequency (*T–F*) analysis is used for its initial characterization. Previous studies [2,15,22] have shown that the wavelet transform is ideal to characterize highly transient events. In this work, the analytic wavelet transform (AWT) developed by Zhu and Kim [18,20] is employed, which characterizes the noise as a set of instantaneous 1/3-octave SPL time histories. By applying the AWT, 28 1/3-octave SPL time histories are obtained at center frequencies in the range of 1–24 barks.

2.2. Step 2: loudness transformation

The 1/3rd octave time histories obtained in the previous step is converted to the 24 *specific loudness time histories* using the Zwicker's loudness model [12–15] that accounts for the transmission characteristics of the outer and middle ear and the spectral processing of human auditory system.

2.3. Step 3: calculation of transient specific loudness time histories

Humans recognize a signal in presence of background noise when the auditory sensation caused by the signal exceeds the masking effect of the background noise. *Transient specific loudness time history* is defined to represent this auditory sensation exceeding the masking effect. It is obtained by subtracting the contribution of the background noise from the specific loudness time history obtained in step 2. A technique called the leaky integration [23,24] is employed to estimate the contribution from the background noise. The leaky integration effectively filters the signal with an infinite impulse response (IIR) filter of low pass characteristics, which is shown in Fig. 3. The leaky integration retains gradual changes in specific loudness time histories by averaging out sudden changes caused by S&R events. The output of the leaky integrator approximates the specific loudness time history due to the background noise. The leaky integration of the specific loudness time histories is conducted as

$$N'_s(i) = (1-\alpha_t)N'_s(i-1) + \alpha_t N_s(i) \tag{1}$$

where, N_s is the instantaneous specific loudness, i stands for the ith time step, N'_s is the approximate specific loudness of the background noise and α_t is an integration constant. Numerous tests conducted by the authors proved 0.05 is an ideal value for α_t.

The transient specific loudness time history is obtained by removing the approximate specific loudness of the background noise from the specific loudness time history of the cabin noise. Transient specific loudness time histories obtained as such approximate the loudness of the S&R events above the background noise.

2.4. Step 4: spectral summation to obtain the transient loudness time history

The specific loudness time histories obtained in step 3 are summed over the selected frequency range, 4 kHz or higher, which results in a single time history called the transient loudness time history. The critical bands for the summation are selected based on the spectral distribution of energy in common S&R events and background noise. Fig. 4 compares the spectrums of a typical S&R event; squeaking sound of an automobile wiper in presence of cabin noise. It can be observed that the S&R event has favorable signal to noise ratios in high frequency bands which is seen in most S&R events. As the algorithm employs leaky integration to compensate for the background noise rather than filtering out the low frequency energy, even the frequency ranges with moderate SNRs can be used in estimating the loudness of S&R events above the background noise. Hence, the transient specific time histories of 4 kHz (critical band rates greater than 17.5) or higher are summed to obtain the transient specific loudness time history to utilize the favorable signal to noise ratio in the frequency

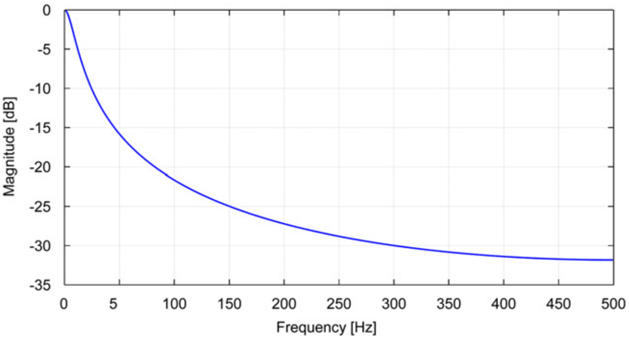

Fig. 3. Frequency response characteristics of the leaky integration process.

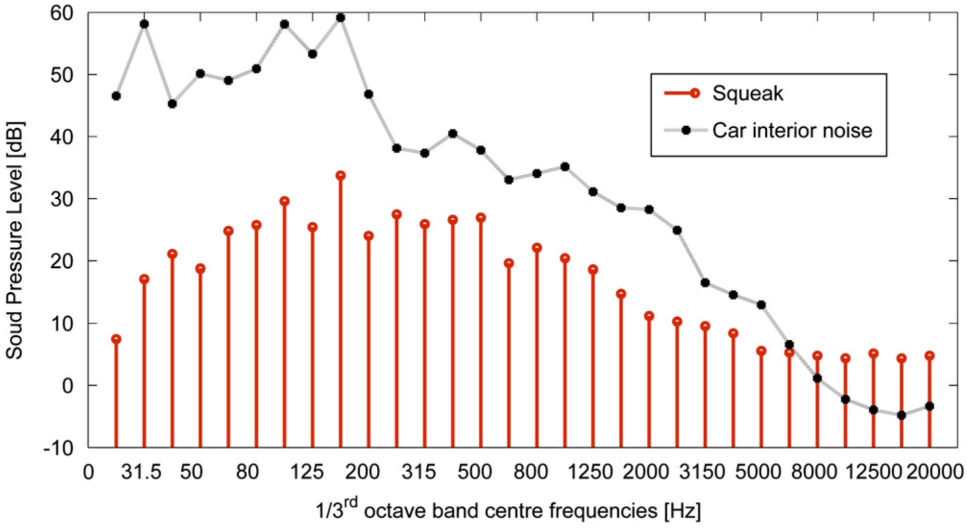

Fig. 4. Comparison between spectra of cabin noise and wiper squeak noise.

range. At each time instant, the *transient loudness* is calculated as the area under the specific loudness-bark graph over the range of 18–24 barks. The resulting single time history is called the *transient loudness time history*.

The background noise can also fluctuate, for example due to variations in riding conditions, which makes the transient specific time history fluctuate. These fluctuations in the low frequency range can trigger false detections of S&R events. Excluding low frequency components in calculating the transient loudness time history eliminates this problem, providing an additional advantage.

2.5. Step 5: temporal integration to obtain perceived transient loudness time history

The transient loudness time history obtained in step 4 does not yet reflect the temporal masking effect of the neural activity of the human ear. A temporal integration scheme suggested by Glasberg and Moore [17] is used to convert the transient loudness time history into the *perceived transient loudness* (*PTL*) time history as follows:

$$\begin{gathered}\text{if } N_{inst}(i) \geq N_{inst}(i-1) \\ \text{then } N_{PTL}(i) = (1-\alpha_a)N_{PTL}(i-1) + \alpha_a N_{inst}(i) \\ \text{else } N_{PTL}(i) = (1-\alpha_r)N_{PTL}(i-1) + \alpha_r N_{inst}(i)\end{gathered} \tag{2}$$

where, N_{PTL} is the PTL time history and N_{inst} is the transient loudness time history obtained in Step 4, α_a and α_r are attack and release time constants of integration. The lower value of α_r indicates a slower decay of loudness perception that models the persistence of neural activity corresponding to forward masking. In their model, Glasberg et al. used integration constants values of 0.045 and 0.02 for α_a and α_r, respectively, to achieve satisfactory prediction of variations in loudness perception of short duration sounds with variations in the duration of the sounds.

The PTL (N_{PTL}) obtained by the procedure explained above approximates the human sensory perception of S&R events above the masking effect of the background noise. A S&R event is detected when the level of N_{PTL} exceeds the detection threshold identified by a jury test.

3. Identification of the detection threshold

The detection threshold was identified in terms of N_{PTL} from a jury test. Test noises were constructed by mixing S&R events with independently recorded cabin noises to the extent to make the events barely detectable. Ten healthy subjects in the age group of 23–28 participated in the testing.

3.1. Construction of test signals

Three types of S&R events (wiper squeak, plate rattle, and rusty-metal squeak) and cabin noises measured from two different brands were used to generate the test signals. All these sound files were downloaded from Ref. [21]. The S&R sound signals were mixed with the cabin noises scaled to 55, 65 and 75 dB to generate test cases. Sharp transient events already present in cabin noise, if any, were removed before mixing it with the S&R event to minimize interference with subjective tests. The jury test was carried out using a calibrated headphone playback system in a quiet listening room.

The test noises were constructed by the following procedure.

1. Cabin and S&R noises are normalized to avoid clipping, then mixed by the following rule
$$P = P_{\text{cabin}} + \alpha P_{S\&R}, \quad \alpha < 1 \tag{3}$$
Initially 0.5 was chosen for α, a sufficiently high value that makes all jury members easily detect the S&R event present in the signal.
2. Scale the mixed noise so that it has the overall SPL of 55 dB.
3. Conduct the jury test. Reduce the α value if the S&R event is detected; increase α value if the S&R event is not detected.
4. Repeat steps 1 through 3 until the value of α is converged. The noise constructed with the converged α value is used as the 55 dB noise with a barely detectable S&R signal.
5. Steps 1–4 are repeated to construct 65 and 75 dB noises with barely detectable S&R signals.

There was a small variability in α among different subjects; therefore the average value of α was used to generate the test signals. Three types of the cabin noise and S&R noise combinations were used; therefore a total of nine barely detectable S&R events were constructed.

3.2. *Identification of detection metric*

PTL (N_{PTL}) time histories of the barely detectable S&R signals were calculated according to the procedure explained in the Section 2 for each of the nine test signals. Fig. 4 shows three PTL time histories calculated from the test signals obtained by mixing the cabin noise and metal squeak noise scaled at 55, 65, 75 dB. The highest peaks at around 1.6 s represent barely detectable S&R events; therefore, the PTL values of the peaks can be considered as the detection thresholds for those noises.

Obviously the detection threshold depends on the overall SPL of the signal, that is, a sound of higher SPL requires a higher PTL value to be detected. For the three cases shown in Fig. 5, the detection thresholds are 0.0052 sone (55 dB noise), 0.015 sone (65 dB noise) and 0.027 sone (75 dB noise). The detection threshold varies with the type of the background noise as well as the SPL of the background noise. Therefore, it is necessary to define the detection threshold of the PTL as a function of a given property of the noise. A percentile value of the PTL distribution was adopted for that property to determine the detection threshold in this work. A correlation study between the identified thresholds and percentile values of the PTL indicated that the 75th percentile value (n_{75}) of PTL curve showed the best correlation with detection threshold.

Fig. 6 shows the relationship between the 75th percentile value of the PTL and the detection threshold. By applying a linear regression to these 9 points in Fig. 5, the relationship between the threshold and the 75th percentile of the PTL was derived as Eq. (4)

$$N_t = 1.77 \times n_{75}(N_{\text{PTL}}) + 0.0022. \tag{4}$$

A very high correlation value of 0.96 is obtained for Eq. (4), which indicates that the detection threshold value can be defined in terms of N_{PTL}.

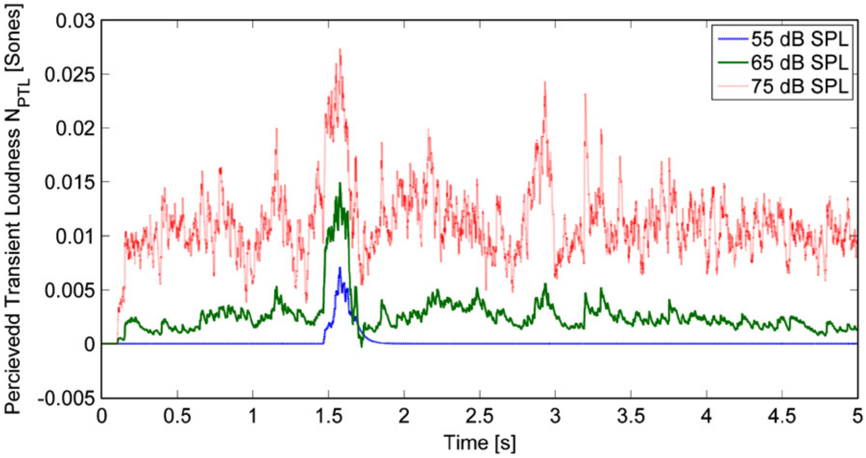

Fig. 5. Time histories of the perceived transient loudness of three test signals with barely detectable metal squeak.

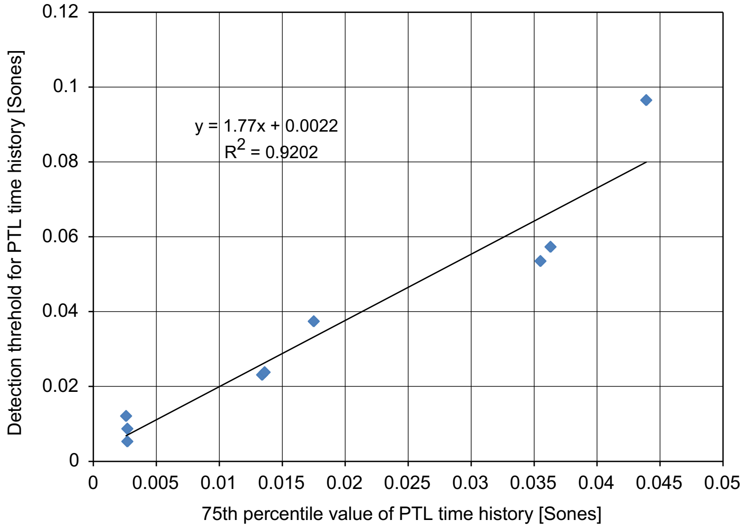

Fig. 6. The relationship between 75th percentile of PTL value and S&R at detection threshold with the regression line.

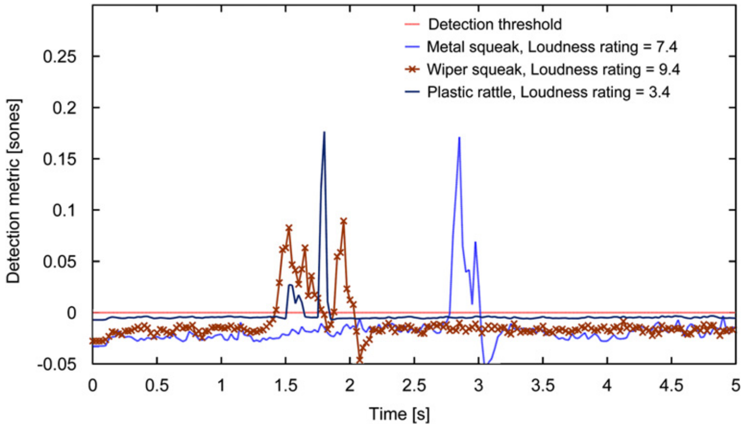

Fig. 7. Application of detection metric to simulated test signals.

The detection threshold (N_t) of the PTL of a given noise is calculated using Eq. (4), as follows:

1. Calculate N_{PTL} of the noise according to the procedure explained in the previous section.
2. Find n_{75} from the distribution of N_{PTL} values.
3. Find N_t from Eq. (4).

The S&R event is detected when N_{PTL} of the noise exceeds N_t, the threshold level. Therefore, the presence of S&R events is detected when the detection metric N_{PTL}–N_t becomes positive Fig. 7 shows examples of N_{PTL}–N_t plots of the events that have clearly audible S&R events.

4. Validation of the detection algorithm

Additional subjective testing was carried out using new test signals and new test subjects to validate the developed S&R detection algorithm. Five new subjects in the age group 23–24 participated in the test. Two sound files were generated by mixing two different cabin noises with two S&R noises, namely glove box rattle and door squeak. Six test signals were generated by scaling each sound file to 55, 65 and 75 dB SPLs. Each test file is composed of one background noise and one S&R event.

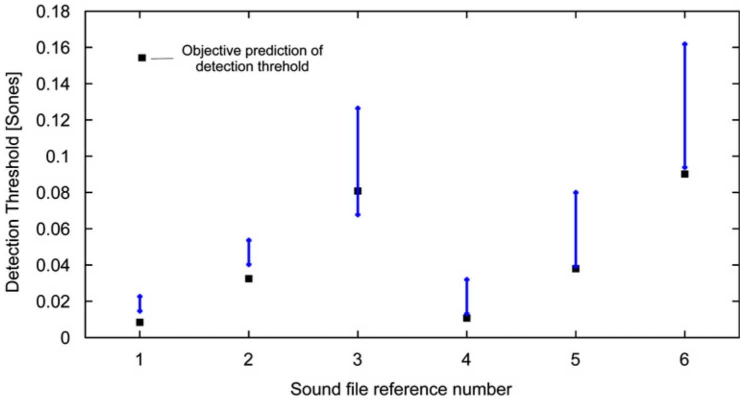

Fig. 8. Comparison of the predicted detection threshold with the range of detection threshold obtained by jury tests.

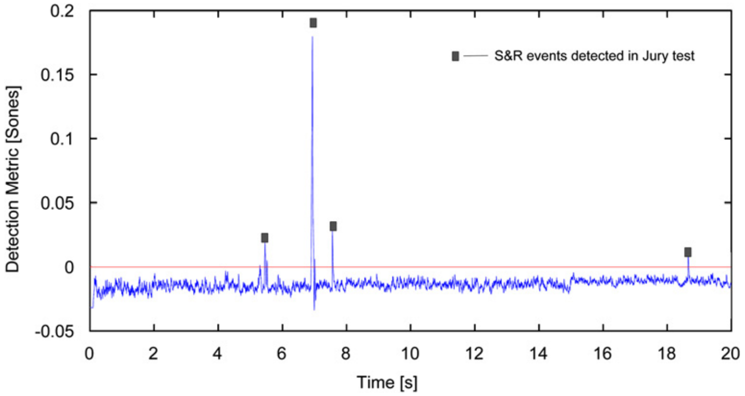

Fig. 9. Application of automatic detection algorithm to a cabin noise mixed with multiple S&R events.

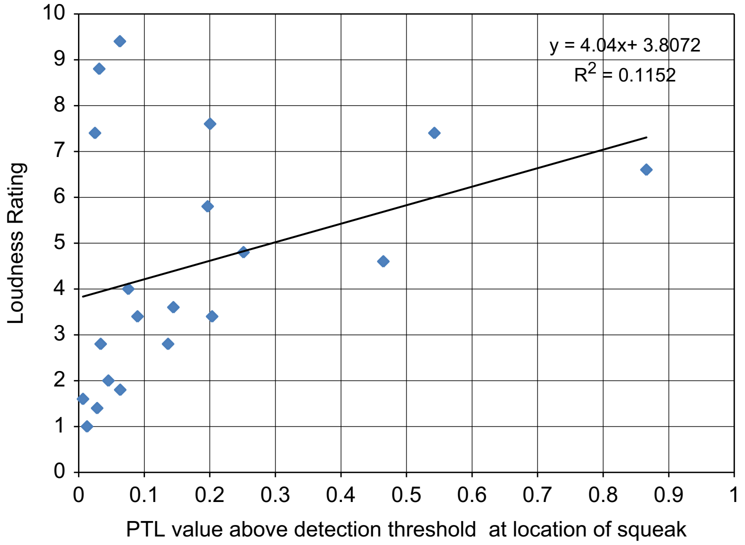

Fig. 10. Correlation of subjective loudness rating with the detection metric N_{PTL}.

Fig. 8 shows the comparison of detection threshold predicted by Eq. (4) with the range of detection threshold values the subjects actually identified. It is seen that the calculated detection threshold matches well with the lower bound of the detection threshold obtained from the jury test.

Fig. 9 plots N_{PTL}–N_t curve of an actual cabin noise that have multiple S&R events embedded. The S&R events identified by the test subjects are also marked in Fig. 9. A S&R event is identified each time when the curve crosses the zero line; therefore it is seen that the detection algorithm identifies all audible S&R events without any false detection in this example.

5. Development of a metric for quantitative rating of S&R events

The algorithm is now extended to a method to rate perceived loudness of S&R events. Subjective rating of S&R loudness was carried out using 20 different simulated test signals. The test signals were generated by mixing sound files from six S&R events and two background noises. The mixing ratios and loudness scaling were thoughtfully selected to obtain sound files in which the loudness of S&R events varied from just audible to very loud. Test signals were then played back in random order through a calibrated headphone in a quiet listening room. Subjects were asked to rate these signals on a 1–10 scale based on their perceived loudness of the events.

Fig. 10 shows the relationship between the metric N_{PTL}–N_t (PTL value above the detection threshold) estimated at the instant when the squeak occurs and subjective loudness rated by juries. One possible reason for the poor correlation seen in Fig. 10 was deduced to be due to omitting the frequency components below 4 kHz when the perceived transient loudness was calculated. We defined a modified perceived transient loudness N'_{PTL}, the perceived loudness calculated by summing all the frequency components greater than 200 Hz.

Fig. 11 shows the relationship between average value of subjective rating and the maximum value of the modified metric N'_{PTL}, which shows much better correlation than that in Fig. 10. It is concluded that using the transient loudness calculated over range 18–24 barks works better in detecting S&R event, and using the transient loudness calculated using all frequency components higher than 200 Hz works better in estimating the subjective loudness of the S&R event. From the regression analysis the objective rating of S&R loudness can be described as follows:

$$N_{\mathrm{obj}} = 2.9N'_{\mathrm{PTL}} + 1.33 \tag{5}$$

The modified metric N'_{PTL} has a correlation value of 0.85 with subjective loudness rating, a big improvement from 0.34, the correlation value of the original metric N_{PTL}.

For validation of automatic rating of the S&R events based on N'_{PTL}, eight new sound files were created by mixing sound files from two new cabin noises and three new S&R events. Fig. 12 compares the objective ratings N_{obj} calculated by Eq. (5) with the subjective test results. The spread of subjective rating value among the subjects is represented by error bars. It can be seen that the objective rating from Eq. (5) is within the range of the subjective rating except for two cases. This comparison shows that the developed method is a promising means for detection and rating of S&R events.

6. Conclusion

A new algorithm was developed in this work to automate detection and rating of squeak and rattle (S&R) events. The method enables detection of S&R events with a minimum possibility of false alarm and good correlations with human perception. The algorithm transforms the measured noise time history to the *T*–*F* domain, i.e., into a set of time series of frequency components. The instantaneous specific loudness time histories are obtained by applying the Zwicker model to these time histories. The specific loudness time histories of the S&R noise are then calculated by subtracting the

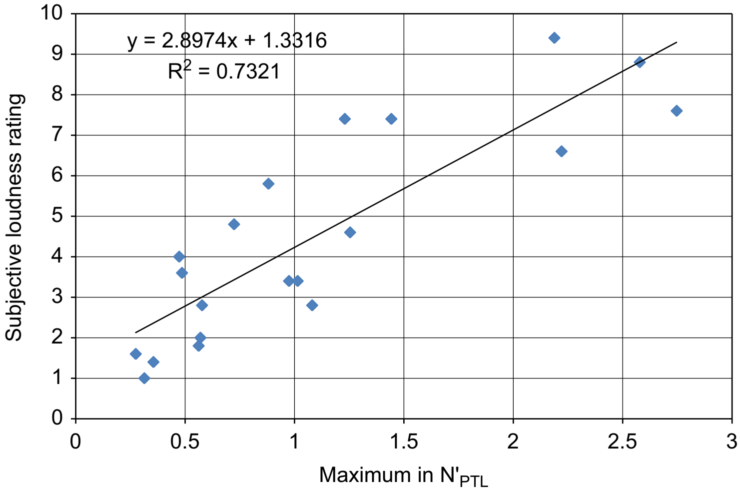

Fig. 11. Regression between the subjective rating of loudness and the modified metric N'_{PTL}.

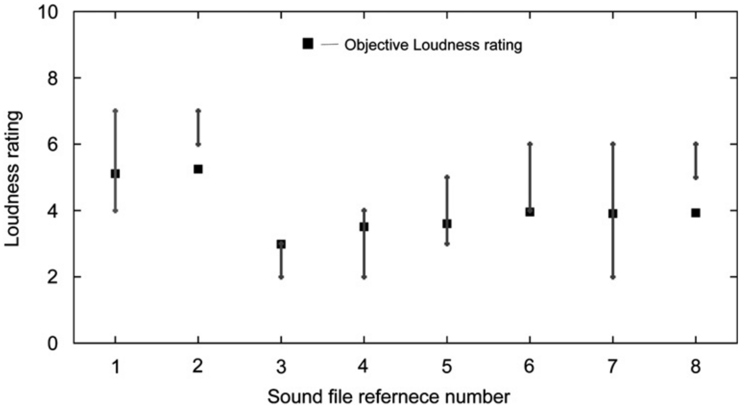

Fig. 12. Comparison between objective prediction and range of loudness rating obtained by jury tests.

contributions of the ambient noise in the cabin from the instantaneous specific loudness time histories. The contributions of the ambient noise are obtained by applying the leaky integration to the instantaneous specific loudness time histories. Applying Glasberg–Moore temporal integration to the spectral summation of the specific loudness time histories gives the perceived transient loudness (PTL) time history, a single time history that approximates the human perception of S&R events over the background noise.

The PTL time history is used for detection and rating of S&R events. It was observed that most S&R events had much better signal to noise ratio in the frequency range higher than 4 kHz. Therefore, the PTL time history obtained by summing only the components in 18–24 barks range is used for the detection. A jury test was conducted to identify the detection threshold of the PTL time history. When the PTL time history exceeds the detection threshold, the event is identified as a S&R. Performance of the detection method was demonstrated by a new jury test that used different sets of noises and test subjects. A rating method to quantify the seriousness of S&R events was developed using the PTL time history and another set of jury testing. The maximum value of the PTL time history of the event is used for rating of the S&R event. The jury test conducted for various S&R events showed that the maximum value of the PTL time history calculated by summing all frequency components was correlated with subjective ratings much better than the PTL time history calculated by summing only high frequency components. Therefore, the method developed in this work uses the PTL time history obtained by summing only high frequency components for detection and the PTL time history obtained by adding all frequency components for rating of S&R events.

Acknowledgements

The authors would like to thank all the people who participated and painstakingly completed the long subjective evaluation of squeak and rattle events.

References

[1] S.A. Nolan, J.P. Sammut, Automotive squeak and rattle prevention, *Proceedings of the Eighth International Conference on Vehicle Structural Mechanics and CAE*, Traverse City, MI, USA, April 1992, pp. 355–363.
[2] J. Feng, J. Hobelsberger, Detection and scaling of squeak and rattle sounds, *SAE Transactions* 108 (1999) 2685–2694.
[3] V. Tran, S.F. Lei, K. Hsueh, Application of adaptive impulsive noise separation to automotive squeak and rattle detection/quantification, *The Journal of the Acoustical Society of America* 106 (1999) 2249.
[4] D.E. Soine, H.A. Evensen, C.D. Van Karsen, A design assessment tool for squeak and rattle performance, *Proceedings of IMAC XVII*, Kissimmee, FL, USA, February 1999, pp. 1428–1432.
[5] R. Nolan, B. Rediers, H. Loftus, T. Leist, Vehicle squeak and rattle benchmarking, *Proceedings of the IMAC-XIV*, Detroit, MI, USA, February 1996, pp. 483–489.
[6] G. Weisch, W. Stucklschwaiger, A.A. Mendonca, N.T.S. Monteiro, The creation of a car interior noise quality index for the evaluation of rattle phenomena, *Proceedings of the SAE Noise and Vibration Conference*, Traverse City, MI, USA, May 1997, pp. 1177–1182.
[7] W.M. Rusen, E.L. Peterson, R. McCormick, R. Byrd, Next generation means for detecting squeaks and rattles in instrument panel, *Proceedings of the SAE Noise and Vibration Conference*, Traverse City, MI, USA, May 1997, pp. 1527–1532.
[8] F. Kavarana, B. Rediers, Squeak and rattle—state of the art and beyond, *Journal of Sound and Vibration* 35 (2001) 56–64.
[9] S. Gelfand, in: *An Introduction to Psychological and Physiological Acoustics*, Marcel Dekker, Inc., New York, 1998.
[10] G. Cerrato-Jay, J. Gabiniewicz, J. Gatt, D.J. Pickering, Automatic detection of buzz, squeak and rattle events, *SAE Transactions* 110 (2001) 1763–1770.
[11] R.S. Brines, L.G. Weiss, E.L. Peterson, The application of direct body excitation toward developing a full vehicle objective squeak and rattle metric, *SAE Transactions* 110 (2001) 1944–1948.
[12] E. Zwicker, Procedure for calculating loudness of temporally variable sounds, *The Journal of the Acoustical Society of America* 62 (1977) 675–682.
[13] E. Zwicker, H. Fastl, in: *Psychoacoustics: Facts and Models*, Springer-Verlag, New York Inc., 2007.
[14] E. Zwicker, H. Fastl, U. Widnmann, K. Kurakata, S. Kuwano, S. Namba, Program for calculating loudness according to DIN 45631 (ISO 532B), *Journal of the Acoustical Society of Japan (E)* 12 (1991) 39–42.

[15] R.J. Fridrich, Investigating impulsive sounds—beyond "Zwicker-Loudness", *SAE Paper Proceedings of the SAE Noise and Vibration Conference*, Traverse City, MI, USA, May 1993, SAE paper 931329.

[16] DIN 45631/A1, Calculation of loudness level and loudness from the sound spectrum – Zwicker method – Amendment 1: Calculation of the loudness of time-variant sound, 2008.

[17] B.R. Glasberg, B.C.J. Moore, A model of loudness applicable to time-varying sounds, *Audio Engineering Society Journal* 50 (2002) 331–342.

[18] J. Kim, D.E. Welcome, R.G. Dong, W. Joon Song, C. Hayden, Time–frequency characterization of hand-transmitted, impulsive vibrations using analytic wavelet transform, *Journal of Sound and Vibration* 308 (2007) 98–111.

[19] Y.S. Wang, C. Lee, D. Kim, Y. Xu, Sound-quality prediction for nonstationary vehicle interior noise based on wavelet pre-processing neural network model, *Journal of Sound and Vibration* 299 (2007) 933–947.

[20] X. Zhu, J. Kim, Application of analytic wavelet transform to analysis of highly impulsive noises, *Journal of Sound and Vibration* 294 (2006) 841–855.

[21] ⟨http://www.soundsnap.com⟩ (accessed 27th January 2007).

[22] M. Blommer, N. Otto, G. Wakefield, B.J. Feng, C. Jones, Calculating the loudness of impulsive sounds, *SAE Transactions* 104 (1995) 2302–2308.

[23] H. Scharstein, Input–output relationship of the leaky-integrator neuron model, *Journal of Mathematical Biology* 8 (1979) 403–420.

[24] ⟨http://sepwww.stanford.edu/sep/prof/pvi/zp/paper_html/node2.html⟩ (accessed 27 January 2010).