

# Algorithms for Detection of Rail Wheel Squeal

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## ABSTRACT

Trackside systems for automatic monitoring of noise from train passbys are becoming more common. Typically these will record an audio file for each passby, and download this file for spectral and other analysis. Automatic detection of the presence and level of wheel squeal from these files provides significant additional information for both operators and environmental authorities. Recently in NSW, two groups have independently developed algorithms for detecting and quantifying wheel squeal. Both are based on a spectral analysis, but details of the procedures differ. Outputs include the maximum level, SEL, duration and spectrum of squeal, and in one case also of flanging noise. This paper compares the procedures and outputs of the two algorithms, using a set of recorded audio files from train passbys. Results indicate the potential of detection based on pattern-recognition techniques in this and similar applications, and also point to some issues associated with their implementation.

## INTRODUCTION

Noise generated at the wheel-rail interface of a rail system can be broadly classified into four types [1]:

- rolling noise;
- wheel squeal;
- flanging; and
- impact noise.

Wheel squeal and flanging are both associated with wheel-rail interaction on curves, and the distinction between them, as well as the mechanism for their production, is subject to some dispute [2]. However, it is clear that this interaction sometimes generates a distinctive ringing noise that is strongly tonal, while for other passbys a broad-band high-frequency sound is generated. For some passbys both sounds may be produced. In this paper the former sound will be described as “wheel squeal”, and the latter “flanging”. Following [2], the term “curve squeal” will be used to describe either or both effects.

Wheel squeal is a particularly important source of noise impact because it is tonal in nature. Tonal noise is known to cause more annoyance than non-tonal noise at the same level, either because of reduced masking by background sound [3], because tonal noise may be inherently more annoying due psychologically-based factors [4] or, most likely, both. Many standards incorporate a positive “correction” when assessing the impact of noise when it is tonal in nature (e.g. [5]).

Squeal and flanging both generally occur on curves, but as described below they do not occur reliably, and when they do occur their level can vary by over 10 dB between passbys at the same point. Mitigation is possible, generally through the use of friction modifying agents – top-of-rail friction modifiers in the case of squeal, and gauge face lubricators in the case of flanging. However, despite advances in deploying and monitoring friction modifier applicators, they cannot be

used on every curve where curve squeal may occur. Hence some form of prioritisation is required to identify sites where tonal noise is most prevalent and causes most disturbance.

Trackside systems for automatically monitoring noise from train passbys have been deployed in a number of locations recently. These are typically designed to record the maximum and/or SEL noise level from each passby, with the object of:

- recording and tracking the overall train-related  $L_{Aeq}$  at the monitoring position; and
- identifying individual noisy vehicles (or bogies), so they can be treated.

The latter represents a particularly effective form of noise control, because it is often the case that overall exposure is dominated by the noisiest few vehicles.

The object of the work reported here is to provide these trackside monitoring systems with the additional ability to detect the level of curve squeal in each passby, and preferably also to separate this into wheel squeal and flanging. This allows for:

- long-term logging of the range of curve squeal levels experienced, giving a reliable form of prioritisation for deploying friction-modifying devices;
- verifying and tracking the effect of those devices to ensure that curve squeal is reduced and remains so; and
- identification of vehicles that are particularly susceptible to curve squeal, for individual treatment.

## SOURCES OF CURVE SQUEAL

### Wheel Squeal

In the generally-accepted mechanism, wheel squeal results from lateral movement of the rail head over the track. Under certain conditions this can result in a “slip-stick” interaction, which couples strongly to lateral vibrational modes of the wheel. A model proposed by Huang et al [6] predicts, for a typical wheel geometry, maximum excitation of the 3<sup>rd</sup> and 4<sup>th</sup> lateral modes, at frequencies of 1102 Hz and 1976 Hz respectively. (A similar conclusion is reached by Brunel et al [7].) This is consistent with typical results. Huang et al’s model predicts approximately equal contribution from the high and low rails, which is contrary to previous experience [2], although some recent analysis indicates that in some cases squeal can arise from the high rail..

Models such as that in [6] predict a very narrow peak in the emission spectrum – in [6] the quoted damping ratio for the relevant modes is .0001, giving a bandwidth of less than 1 Hz at the relevant frequencies. Vincent et al [8] quote a similar damping ratio of .0004. Moreover, in these models the wheel (and rail) dynamics are separated from the contact dynamics, and hence there appears to be no mechanism for the squeal frequency to alter depending on rolling velocity, friction or any other gross parameters, except by differential excitation of different modes.

### Flanging

The mechanism for flanging has been much less studied than that for wheel squeal. It is generally considered to result from direct flange contact with the rail, although the exact mechanism for sound radiation is unclear. Figure 1 shows a spectrogram of a passby exhibiting clear squeal with minimal flanging, while Figure 2 shows a passby with significant flanging but little squeal. (Some short sections of squeal can be identified.) In this case the flanging noise is seen to consist of a series of “chirps” - short signals with multiple broad resonances extending to very high frequencies and generally falling quickly in frequency before disappearing. This sound would be very difficult to generate by the mechanism generally proposed for wheel squeal.

Figure 3 shows a case where both flanging and squeal appear together. It is notable that in this case the spectral “line” representing the squeal is somewhat broader than in the “squeal only” case, and is not as constant in frequency. Apparent broadening of the line is likely to be due to amplitude modulation effects associated with the presence of flanging. Frequency change (apart from the obvious apparent change due to Doppler shift) could potentially be caused by deformation of the wheel under stress due to flange contact with the rail. This would imply that the outer wheel was squealing. Alternatively, wheel vibration could be influenced by vibrational modes of the bogie as a whole.

## DETECTION OF CURVE SQUEAL

The focus of this paper is on the detection and potential classification of curve squeal from a passby event. The algorithms described can be used in real time (with a small time delay in the case of the SoundScience algorithms). However, we will focus on their implementation in permanent, low-power trackside noise monitoring systems. Such systems can:

- automatically detect passby events using a magnetic wheel detector or similar device;

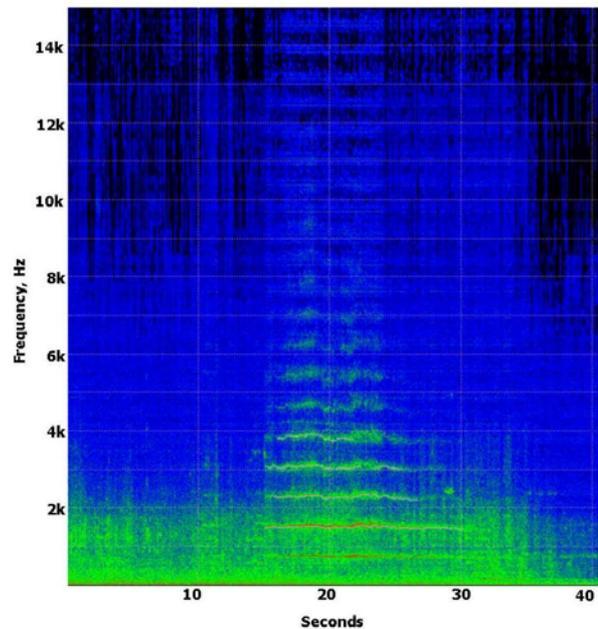


Figure 1. Example of passby with squeal

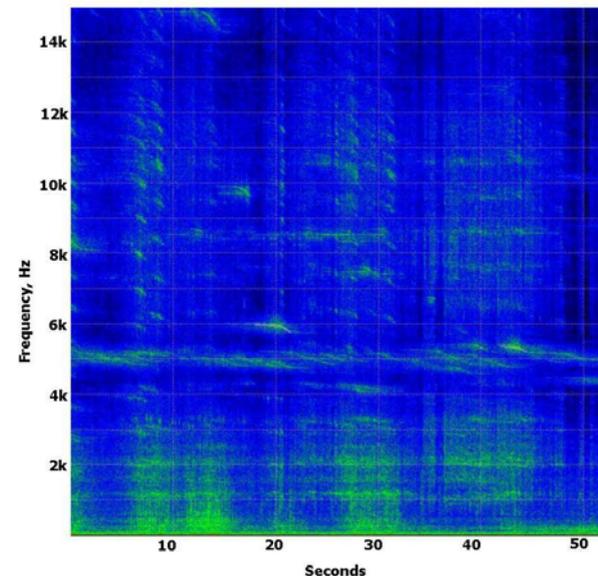


Figure 2. Example of passby with flanging

- save a digital recording of the audio waveform – generally as 16 bit WAV format, sampled at 44,100 Hz;
- automatically upload the file to a remote server after completion of the event;
- analyse the file to detect curve squeal and other features of interest; and
- save the results of the analysis in a database that can be interrogated on-line.

Over the last 2 – 3 years the University of Wollongong and SoundScience P/L have both independently developed, or assisted in developing, systems to perform this task. Monitoring systems of both types are currently in permanent operation in NSW and elsewhere in Australia. The two algorithms developed for squeal detection are similar, but differ in significant ways. The two methodologies are compared and contrasted in the discussion below.

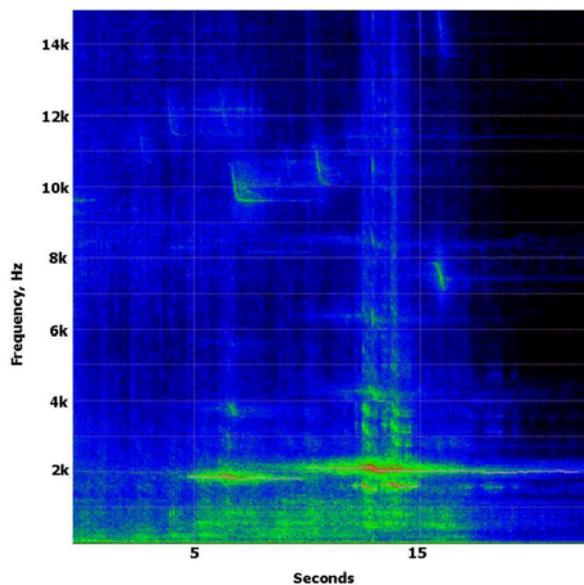


Figure 3. Example of passby with both squeal and flanging

### University of Wollongong (UW) Algorithm

The University of Wollongong set out with the intention of separately estimating sound levels due to wheel squeal and flanging. In both cases, detection is performed on the basis of a 1/24-octave spectrum, representing the current rms spectrum with “Fast” weighting. This is updated continuously through the passby.

Squeal is considered to be detected when one band between 1 KHz and 10 KHz:

- has the highest level of any band in the spectrum; AND
- has a level exceeding both the neighbouring bands by at least a threshold value (typically set at 10 dB).

The level of the squeal, for this spectrum, is simply the level in the selected band.

Note this assumes that the width of the peak is significantly less than 1/24-octave, and that if squeal is present it will be the dominant feature of the spectrum. The total squeal energy for a passby is simply the energy sum of squeal levels at any times when squeal was detected.

Flanging is detected separately on the basis of the ratio of energy between 2 KHz and 10 KHz (excluding any squeal) to the total energy in the spectrum. Where this exceeds a threshold (typically 0.8), the energy in this range is considered as flanging noise. Once again the total flanging level for a passby is the sum of the flanging levels at any times when flanging was detected.

### SoundScience (SS) Algorithm

The algorithm developed by SoundScience is designed to detect any significant tonal noise, on the assumption that this is the most significant component for human reaction. Flanging is not currently detected. However, some of the energy found as “flanging” in the UW algorithm is detected as squeal in the SS algorithm.

The SS algorithm is designed to detect lower-level and less obvious tones than the dominant squeal considered by the UW algorithm, and to potentially detect multiple simultaneous tones. Hence it is somewhat more complex than the UW algorithm. It is based on standard pattern recognition proce-

dures used in image processing, in particular the Canny edge detection algorithm [9], applied to a spectrogram such as Figures 1-3. The edge detection procedures are modified to:

- detect a line rather than an edge;
- privilege the detection of lines that change slowly in the vertical direction; and
- remove a preliminary smoothing stage designed to correct for focal blur and shading in photographs.

The algorithm proceeds as follows.

1. Form a spectrogram from the recorded audio data, using a short-term Fourier transform. In general an FFT of length 4096 with 50% overlap and using a Hamming window gives an appropriate trade-off between time- and frequency-resolution. Frequency bins then have a width of 10.8 Hz.
2. For each bin in the spectrogram, calculate a contrast value based on the schema in Figure 4. The contrast for the target bin will be the difference, in dB, between the mean-square FFT magnitude in the line bins and that in the contrast bins. Adjusting the width of the line, null and contrast bins allows for detection of narrower or broader lines. Adjusting the number of bins included on the time axis gives more or less preference for horizontal lines. The current implementation is designed to detect lines that may be 50 – 100 Hz wide, and uses 7 line bins, with 4 null bins and 8 contrast bins on each side. Averaging is over 8 time frames (371 ms).

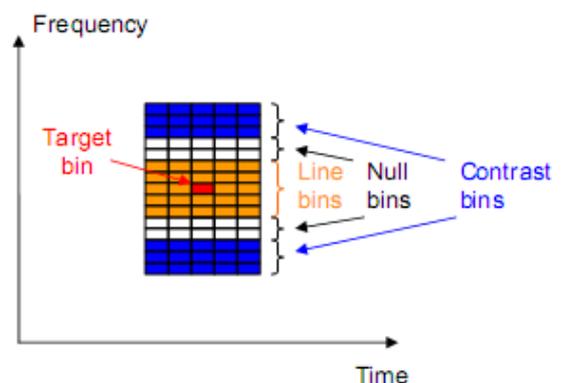


Figure 4. Calculation of contrast value for each bin in a spectrogram

3. Now join bins with high contrast values into lines. Two threshold contrast values are defined – a Select Threshold (ST) that determines whether a new line is started, and a Connect Threshold (CT) that defines whether an existing line will be continued. The current implementation has ST = 15dB and CT = 8 dB.

Starting with the bin with the highest contrast (assuming this is greater than ST), join bins vertically above and below until their contrast falls below CT. This defines the width of the line at that point, and the level associated with the line is the energy-sum of the FFT magnitudes in these bins.

Now move forward and backward from the central bin, potentially moving up or down by one bin per frame, and define a line width and level for the adjacent frames.

Continue until no adjacent bin has a contrast greater than CT.

- Finally, select lines whose frequency is between 1 KHz and 10 KHz at some point, whose length exceeds 1 second and whose total level exceeds a site-dependent threshold.

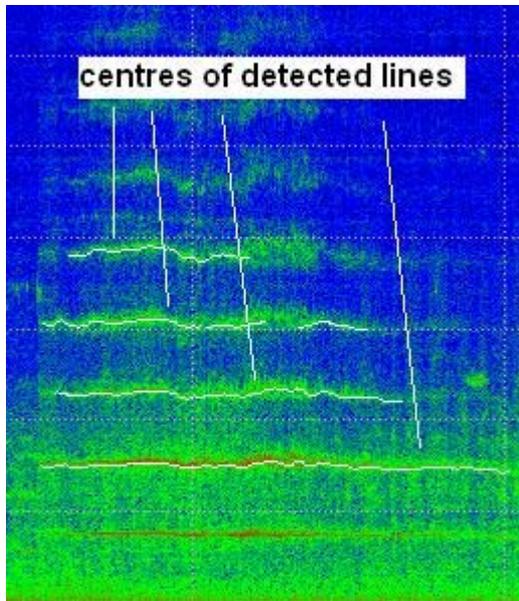


Figure 5. Lines detected by the SS algorithm

Figure 5 shows lines detected by the SS algorithm from the spectrogram shown in Figure 1. Unlike the UW algorithm, the SS algorithm detects harmonics of the fundamental squeal frequency.

**COMPARISON OF RESULTS**

To compare the two algorithms, ten recorded passbys were selected for analysis. They were recorded near a curve at Beecroft, NSW, using a monitor at 1.5m above ground and 2m from the nearside rail. Each recording was analysed using the UW and SS algorithms to determine whether squeal occurred (and/or flanging for the UW algorithm), and if so the  $L_{Amax}$  and SEL levels arising from the squeal (and/or flanging).

Figure 6 shows the results in terms of the maximum noise level (Fast speed) during the passby.

First, the algorithms agree that passbys 1, 2, 5, 8 and 10 contain squeal and passbys 4, 7 and 9 do not (although the UW algorithm finds flanging in passby 4). The SS algorithm finds squeal in passby 3, whereas the UW algorithm does not. This is in fact a mis-classification – from the audio, the sound detected appears to be a short section of aerodynamic noise from the pantograph. This emphasises that the use of more sensitive algorithms raises the chance of false positive identifications.

Where squeal is identified, the SS algorithm generally produces a higher level, due to the fact that it is more sensitive and can include multiple tones within the “squeal” component. The largest difference is in passby 10. Figure 8 shows the “squeal” section of this spectrogram, indicating a very broad peak with significant frequency change. As noted above, this appears to be characteristic of squeal that occurs

in the presence of other processes. Broadening of the peak is likely to be due to amplitude modulation.

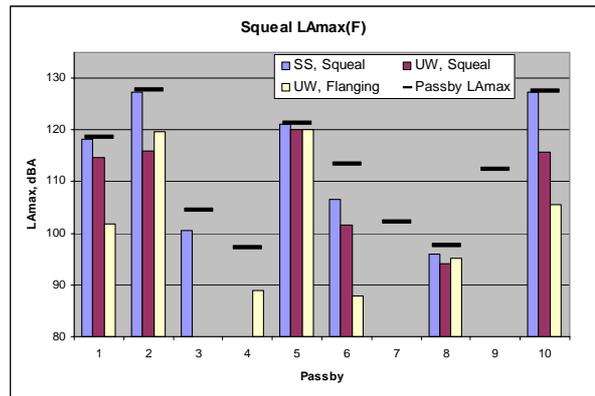


Figure 6. Maximum sound levels detected by the SS and UW algorithms

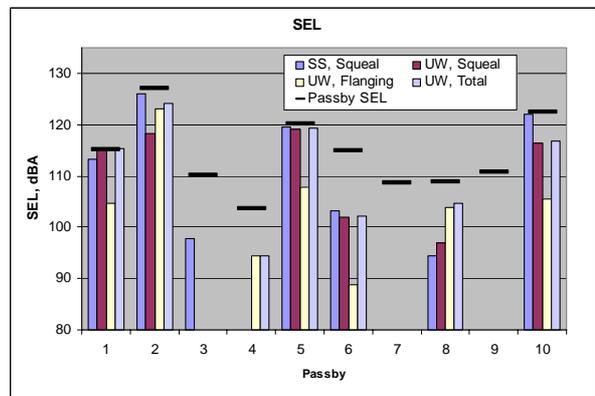


Figure 7. SEL sound levels detected by the SS and UW algorithms

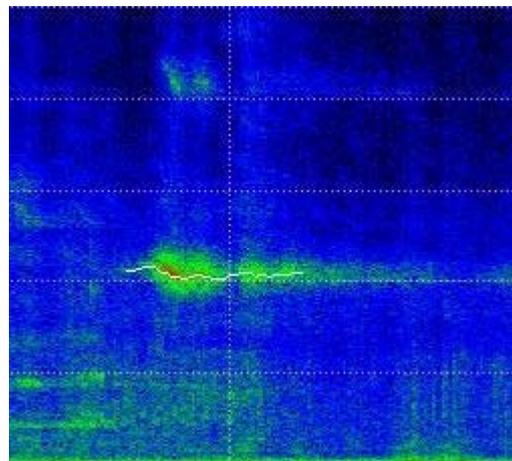


Figure 8. Detail from spectrogram, passby 10

The sound in this section of passby 10 is definitely identified audibly as squeal. However this form of squeal is difficult to detect with the UW algorithm, and some sections of the “squeal line” shown are classified as flanging, or not classified at all. Hence, although the SS algorithm indicates the maximum passby level is entirely due to squeal, the UW algorithm shows the maximum squeal level at about 10 dB below the overall maximum.

Similar comments apply to passby 2, which is the passby shown in Figure 3.

In terms of SEL, the agreement between the two algorithms is better (Figure 7), particularly if the squeal detected by the SS algorithm is compared with the total of “squeal” and “flanging” from the UW algorithm. For passbys 1, 2, 5 and 10, curve squeal is seen to represent the major part of the acoustic energy in the passby.

Passby 8 is the passby shown in Figure 2. In this case, detection of wheel squeal alone, even with the SS algorithm, clearly underestimates the total curve squeal noise.

## CONCLUSIONS

Automatic detection of curve squeal during remote monitoring of rail noise can provide extremely useful information. It allows prioritisation of sites for squeal mitigation measures; verification of the efficacy of those measures; and identification of noisy vehicles.

The algorithm used for detection and quantification of curve squeal should be considered when designing a monitoring system, as different algorithms may produce different outcomes.

If the focus is on detection of whether curve squeal occurs at all, and if the occurrence of false positives is a significant issue, then a spectrally-based algorithm such as UW gives a more robust and reliable evaluation than alternatives.

However, if detection of the **level** of tonal noise, and its contribution to the total noise in the passby, is important, consideration should be given to a more complex pattern-recognition-based algorithm such as SS. Otherwise, noise levels from some passbys, particularly  $L_{Amax}$  levels, may be underestimated by up to 10 dBA.

Again, if detection of flanging noise, in the absence of squeal, is important, this cannot currently be offered by pattern-recognition-based algorithms. Providing a detailed spectrogram-based method of detecting flanging noise will almost certainly require a more solid understanding of the mechanism of flanging.

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