FIFTH INTERNATIONAL CONGRESS ON SOUND AND VIBRATION
DECEMBER 15-18, 1997
ADELAIDE, SOUTH AUSTRALIA

TOWARDS MORE EFFECTIVE PREDICTION OF ON-ROAD WIND NOISE CHARACTERISTICS FROM WIND-TUNNEL TESTS

Peter O'Shea, Simon Watkins, Christian Peric and Bruce Sloss

Royal Melbourne Institute of Technology (RMIT) , Australia

ABSTRACT. The airflow around a moving car results in wind noise which is partially transmitted into the cabin. With the trend towards quieter cars, this wind-generated noise can dominate other noise sources. Standard methods of developing car geometries (often with the aim of minimising wind noise) are based on tests in smooth-flow wind tunnels, rather than by road trials. However, it has been noted that wind noise sounds different in the two test environments. This paper sets out to characterise these acoustical differences. Higher-order spectral statistics and wavelet analysis have been utilised and significant variations were found. Ultimately, it is hoped that such analyses can be used to compare wind noise predicted from smooth flow wind-tunnel data (utilising a knowledge of the turbulent velocity fluctuations in the atmosphere) with data measured under turbulent on-road conditions.

1. INTRODUCTION The reduction of car cabin noise forms a significant part of modern car development and mechanical noises (engine, transmission and tyre) are now low. The reduction of wind noise is thus receiving considerable attention, with some automotive manufacturers building aeroacoustic tunnels dedicated to the measurement of wind noise (such tunnels are characterised by quiet, low turbulence flow and hemi-anechoic test sections). However, on-road the wind conditions vary continuously in time and space due mainly to fluctuations in the atmospheric wind [1] and hence the wind noise varies with time. This is not the case in wind tunnels [2]. Since the velocity fluctuations in atmospheric turbulence are well known, it is attractive to attempt to predict the wind noise that would occur under "real" on-road conditions utilising data obtained in wind tunnels.

2. TEST PROCEDURES In order to document wind noise and wind conditions, a modern passenger car was fitted with an Aachen artificial head system in the front passenger seat and hot-wire anemometers located upstream of the "A" pillar (to measure velocity fluctuations in the oncoming flow). All data were recorded on a instrumentation quality digital audio tape (DAT) and were sampled at 35,000 Hz. Initial data analysis, performed at various sampling frequencies, showed no significant levels of sound were present above about 17,000 Hz. A high pass filter with a cut-off frequency of 22.4 Hz, which was built into the Aachen Head System, was utilised.

The test vehicle was used to acquire noise and velocity data on a road that was characterised by negligible roadside structures (vegetation, buildings etc) and during times of no traffic. Thus the velocities relative to the moving vehicle were the vector sum of the atmospheric wind and the vehicle's road speed. Data presented here were recorded at a road speed of 120 km/h with a direct headwind of approximately 20 km/h. Thus the relative velocity was close to 140 km/h with negligible yaw angle.

Data were also recorded in the Monash/RMIT Vehicle Aeroacoustic Wind Tunnel. This tunnel has a background noise level that is 10 dB or more below the wind noise level of the test vehicle for the frequencies of interest. This is considered adequate for wind noise testing without corrections being needed [3]. Tests were performed at a wind-tunnel speed of 140 km/h and with the vehicle unyawed, thus replicating the relative air velocity experienced by the test vehicle on the road test. The wind tunnel had a longitudinal turbulence intensity of 1% and is a closed circuit, 3/4 open jet, wind tunnel with a maximum velocity of 160 km/h. Acoustic wedges, to replicate a free acoustic field, are planned to be installed, but were not present for these tests. Details of the tunnel can be found in [4].

3. PROCESSING OF THE ACOUSTIC SIGNALS The acoustic spectra of both on-road and wind-tunnel tests were compared, with a typical result being shown in Figure 1. It can be seen that the averaged sound spectra were only marginally different in the region above 400 Hz, where wind noise dominates [5]. However, amplitude fluctuations of very low frequency (approximately 1 Hz) could clearly be heard in the on-road wind noise. As engine speed, load and road characteristics were constant, it was concluded that these must be due to wind gusts. These fluctuations were not apparent in the averaged acoustic spectra, because of the short time scales over which the averaging was performed. That is, the averaging procedure masks them out. Thus the low frequency fluctuations which are highly perceptible to the human ear, are not perceptible in conventional averaged spectral representations.

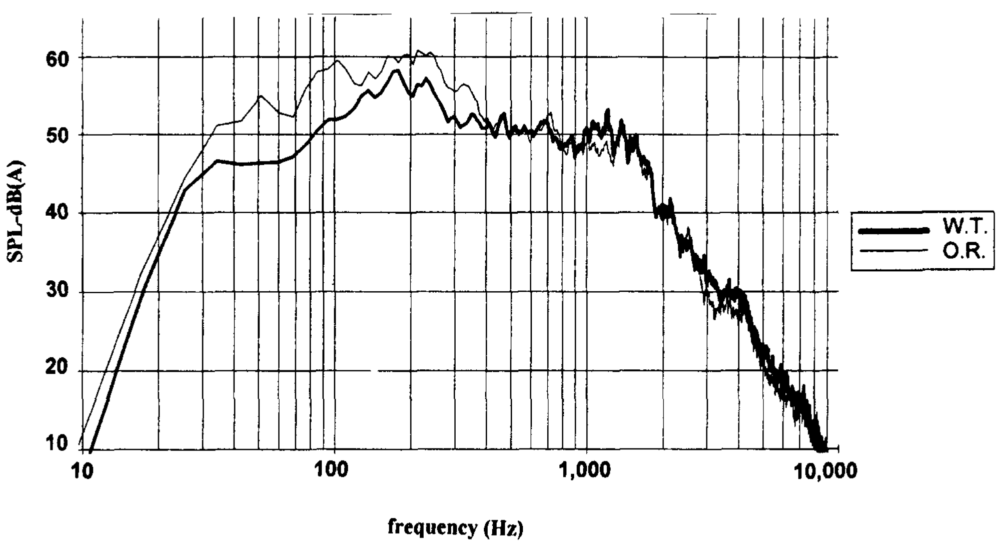


Figure 1: Comparing On-Road vs. Wind-Tunnel Noise

Two possible causes are suggested for these perceptual differences. The first possibility is that the processes have different levels of non-stationarity, and the second is that the processes have different higher-order moments. In order to investigate the type of non-stationarity in the data, "wavelet" analysis has been used. To test the possibility of dissimilar moments, skewness and kurtosis measures have been taken on 1/3 octave band decompositions of the acoustic signals.

3.1. Short-Time Wavelet Transforms (STWT) Short-Time-Fourier-Transforms (STFT) Conventional Fourier analysis decomposes a signal into an aggregate of sinusoids of different frequency. These sinusoidal "basis functions" are infinite in extent, and are consequently not well matched to short duration transient phenomena. In an attempt to overcome this mis-match, the signal is broken up into a number of segments and the Fourier transform is calculated for each segment. It is generally assumed that the signal is stationary over the duration of the window, and an evolution of the spectrum with time is thus obtained; this is the short-time Fourier transform (STFT).

There are resolution trade-offs with the STFT, however. For events which are highly localised in time, the interval of stationarity is short, and a short window must be used. Short windows, however, give poor frequency resolution, and hence present interpretation difficulties. The short-time wavelet transform (STWT) is an analysis technique which partly resolves the "time-frequency resolution" trade-off. In this approach, resolution is proportional to frequency. The STWT transform adapts its window length with frequency. That is, a sliding window is used to analyse the data, but the window is long for low frequencies, and short for high frequencies. The short windows at high frequencies allow transient data (which are typically rich in high frequency energy) to be captured effectively, while the long windows at low frequency allow good resolution for the near-stationary components of the data. This approach mirrors the behaviour of the human ear, and is thus gaining popularity as a tool for spectral analysis of acoustic signals.

The STWT is essentially a "proportional bandwidth" decomposition of a signal. The wavelet transform (and the STWT) is computed by decomposing the signal into basis functions which are obtained by stretching or compressing a time-localised elementary "wavelet", w(t). The STWT is defined by:

$$W(t_0,a)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}s(t)w\left(\frac{t-t_0}{a}\right)dt$$

where a is the "scaling" parameter, t_0 is the time at which the wavelet "window" is applied, and s(t) is the signal. With wavelets, the notion of frequency is replaced by that of scale, with high frequencies corresponding to short scales.

Figures 2 and 3 show respectively the STWT and the STFT of a portion of on-road wind noise. A Daubeshies 2 wavelet was used for the STWT, while a rectangular window was used for the STFT (with respective lengths of 32 and 128 samples in Figs. 3(a), and (b)). Around time sample 400 there is a short but strong transient burst of energy. The time localisation of this energy at high frequencies is captured much more effectively in the STWT (note the thin white lines) than in either of the STFT plots. The STFT, however, is useful in identifying truly sinusoidal components. See for example, the clear frequency line at normalised frequency, 0.3, in Figure 3(b)).

3.2. Wavelet Packets And Best-Basis Analysis The STWT offers an improvement over short-time Fourier analysis for many applications, but there are still a number of limitations.

The signal may be highly non-stationary and the window lengths are not varied over time to take account of this. (The window lengths are actually different for each frequency, but for a given frequency they are constant over time). Wavelet packets are a relatively new technique which elegantly allows the window lengths to be adapted in time and frequency to match the non-stationarity in the signal [6]. The new technique is described in the following paragraphs.

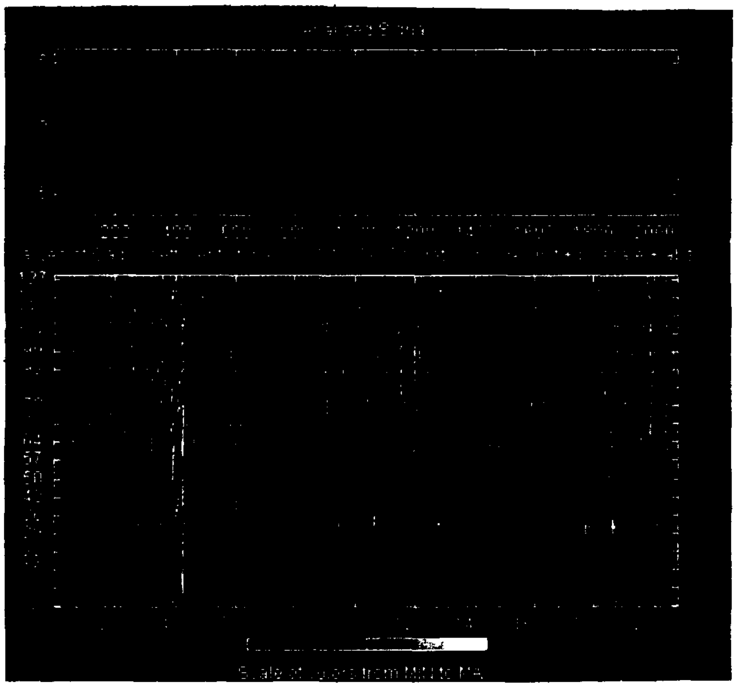
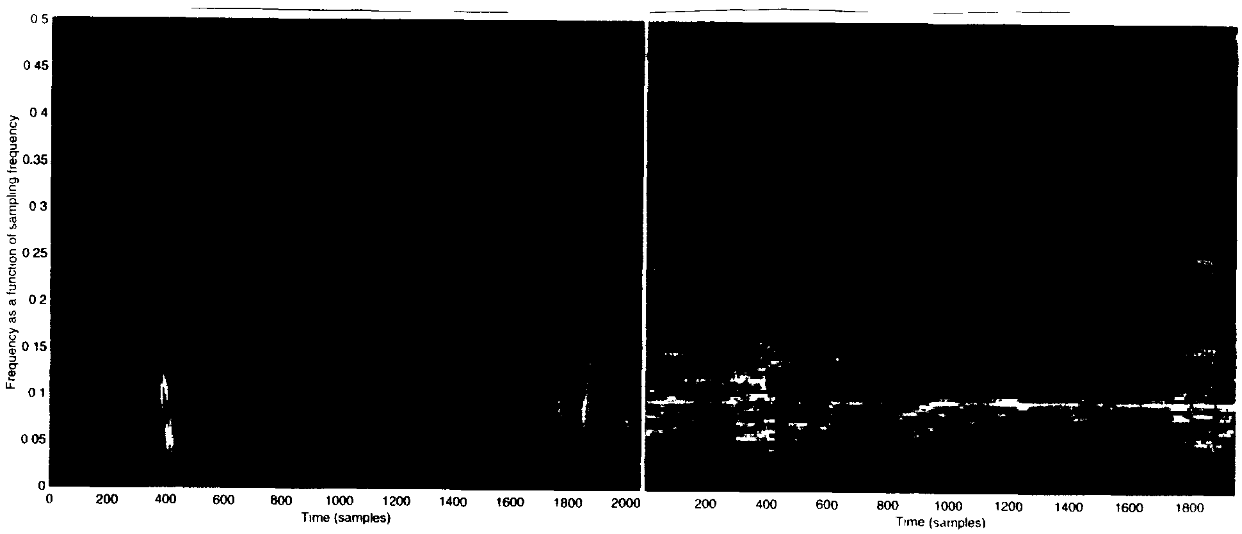


Figure 2. The STWT Of A Segment Of On-Road Data.



(a) (b)

Figure 3. The STFT Of The Same Segment Of On-Road Data As In Figure 2
With (A) A 32 Sample Window, And (B) A 128 Sample Window.

The idea behind spectral analysis is that the information in the spectrum is generally more compact, and therefore more easy to interpret than the time domain data. For a sinusoidal signal, for example, only the amplitude and phase of the sinusoid are required as frequency domain descriptors. The information content, or entropy, is much lower in the Fourier transform of a sinusoid than it is for the original signal. For the purposes of this paper, the entropy of a discrete set of data with samples, s_i, is defined as:

$$E = -\sum |s_i|^2 \log(|s_i|^2).$$

In practical signals, the Fourier transform (or the STFT) will often compact the signal information, but it will not compact it optimally. The best-basis wavelet packet method attempts to achieve such an optimal information compaction. The best basis analysis begins by decomposing a given signal segment into a low frequency component and a high frequency component, with these components then being decimated by a factor of 2. The decimation (sampling rate reduction) does not destroy information because the bandwidths of both components have been reduced by 2, and so the Nyquist rate will have changed. Then the process is repeated on each of the new signals. This separation is repeated until a user specified limit is reached. At this point the entropy is computed for both low and high frequency components at each "level" of the decomposition. The optimally compacted signal representation is taken as that combination of signal components which 1) covers the full bandwidth of the signal (and therefore contains all the information in the signal), and 2) has the lowest entropy.

Frequently, the particular decomposition used is represented in a "tree diagram", as shown in Figure 4. The top node of the tree corresponds to the original time domain signal representation. The next two branches downwards correspond to the initial low-pass and high-pass decomposition of the signal. Each subsequent splitting of the branches corresponds to further low-pass and high-pass separations. The branches which are drawn with thick lines in Figure 4 correspond to one particular decomposition which covers the entire bandwidth of the signal. Another breakdown of the signal which includes the entire bandwidth is depicted in Figure 5. The particular decomposition chosen in practice will be the one which has optimal compaction (minimum entropy).

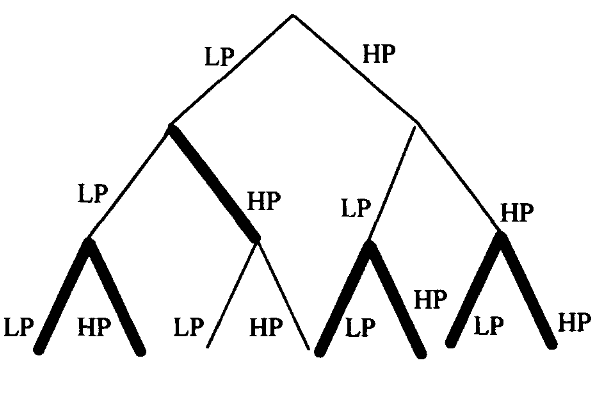


Fig. 4. A Typical Best-Basis Tree Diagram

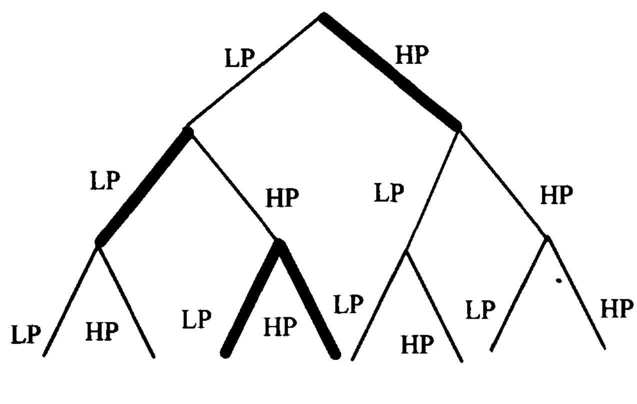


Fig. 5. An Alternate Best-Basis Tree Diagram

The best-basis method is very efficient; computation is of the order of Nlog(N) operations. Since the decomposition is automatically tailored to the data, the method is more versatile than either a constant bandwidth decomposition (Fourier transform) or a proportional bandwidth decomposition (Wavelet transform). Other advantages are that; 1) the availability of an optimal entropy measure means that there is a simple procedure for the segmentation of the signal into stationary intervals, and 2) there is an objective basis for determining what are the significant components in the data (the "signal") and what are the nuisance components (the "noise"). Very effective "de-noising" is then possible. This procedure, unlike Fourier based noise removal (i.e. conventional filtering), does not unduly distort transient information, which may be significant. See for example, Figure 6, which shows a denoised on-road acoustic wind sound. The sharp transient around time sample 400, is clearly retained, while the lower energy events were rejected. This is not the case for a Fourier based filtering, shown in Figure 7, which betrays the strong bias of Fourier techniques towards retaining sinusoidal components. The wavelet based de-noising was achieved by performing a best-basis analysis, thresholding the coefficients generated, and then inverting the signal. The Fourier de-noising was achieved by Fourier transforming, thresholding and then inverse Fourier transforming.

3.3. Statistical Variations In Spectra In order to characterise differences between on-road and wind-tunnel data of fluctuations of the (non-averaged) spectra, some standard statistical measures were applied to an ensemble of spectra. The spectra were presented in 1/3 octave band format, as these correspond approximately equivalent to the critical bandwidths of the ear. Since the means (or first order moments) of the spectra in Fig.1 did not reveal any significant differences between on-road and wind-tunnel data it was decided to investigate the possibility of differences in higher-order statistics. In particular, the 3rd order moment (skewness) and the 4th order statistical measure (kurtosis) were calculated for each 1/3 octave spectral band. The skewness (a measure of data symmetry about the mean), is defined as:

$$E(x-\mu)^3/\sigma^3,$$

while the kurtosis (a measure of the data distribution's peakedness), is defined as:

$$K=E(x-\mu)^4/\sigma^4.$$

where E is the expected value, x is the data, μ the mean and σ is the standard deviation). For Gaussian data, kurtosis is 3, and skewness is 0. Kurtosis values higher than 3 are "peaky" distributions.

The variation of skewness and kurtosis in each 1/3 octave band for the on-road noise is shown in Figure 8. The kurtosis values increase rapidly from a normal distribution of around 3 to very high values of 40 and greater at high frequency. By contrast, wind-tunnel data (see [5]) showed much lower kurtosis values at these high frequencies.

4. CONCLUSIONS AND FUTURE DIRECTIONS Wavelet and higher order statistical analysis have been found to be useful in characterising (and possibly predicting) differences between on-road and wind-tunnel noise. The higher order statistical measures have shown that the on-road data is much more "skewed" and "peaky" than the wind-tunnel data. Preliminary analysis with wavelets has also shown substantial non-stationarities in the on-road data, which would not be properly detected in conventional Fourier spectra, much less in *averaged* Fourier spectra. Wavelets and higher-order statistics, then, are a useful means for documenting the differences between on-road data and wind-tunnel data, and appear promising in predicting on-road wind noise from wind data obtained in smooth flow.

In future work it is intended to investigate the differences in the 7th, 8th and 9th order cumulants. (The cumulants are "moment like" statistical measures, but unlike moments, have the desirable property of obeying superposition for independent random variables [7]). The 7th to 9th order cumulants are of interest because these are known to strongly reveal 6-8th order non-linearities [7], the latter being thought to be present due to the power law transformation between velocity and acoustic fluctuations [3]. Such statistic measures, then, may provide a valuable source of information. It is also proposed to further investigate and characterise the differences in stationarity between the wind-tunnel and on-road data.

5. ACKNOWLEDGMENTS The authors acknowledge Monash University and RMIT's Mechanical Engineering Departments and FORD Australia for provision of facilities and vehicles. The work was supported by the Australian Research Council.

6. REFERENCES

[1] Watkins S. and Saunders J. W., "Turbulence Experienced by Road Vehicles Under Normal Driving Conditions", Society of Automotive Engineers (SAE) America Technical Paper Series SAE 950997, also in "Investigations into Vehicle Aerodynamics", Special Publication SP-1078, published by the SAE, USA, 1995.

[2] C. Peric, S. Watkins, E. Lindquist and J. Saunders, "Effects of On-Road Turbulence on automotive Wind Noise: Comparing Wind-Tunnel and On-Road Tests", SAE 970406, also in "Topics in Vehicle Aerodynamics", SP-1232, published by the SAE, USA, 1997.

[3] George A. R. (ed), "Automobile Wind Noise and Its Measurement", SP-1184, published by the SAE, USA, 1996.

[4] Lin C., Saunders J. W. and Watkins S., "Effect of Cross-Winds on Motor Car Engine Cooling", SAE 970138, also in "Topics in Vehicle Aerodynamics", SP-1232, SAE, USA, 1997.

[5] Peric C, Watkins S. and Lindqvist E., "Turbulence Effects on Aerodynamic Noise with Relevance to Road Vehicle Aerodynamic Noise" 3rd International Colloquium on Bluff Body Aerodynamics and Applications III, Virginia State University, Blacksburg, Virginia, USA, July 28-Aug 1 1996.

[6] R. Coiffman and M. Wickerhausen, "Entropy based algorithms for best basis selection", IEEE Transactions on Information Theory, 1992.

[7] C. Nikias and A. Petropolou, "Higher-Order Spectra Analysis", Prentice-Hall, 1993.

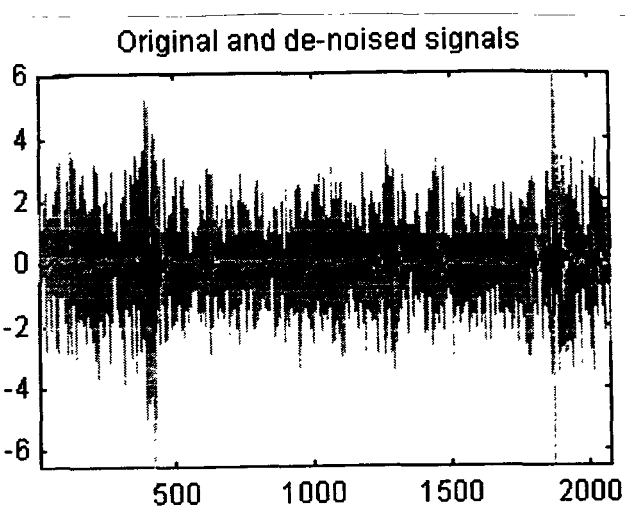


Fig. 6. A Portion Of On-Road Signal After "Noise" Removal By Best-Basis Wavelet Analysis

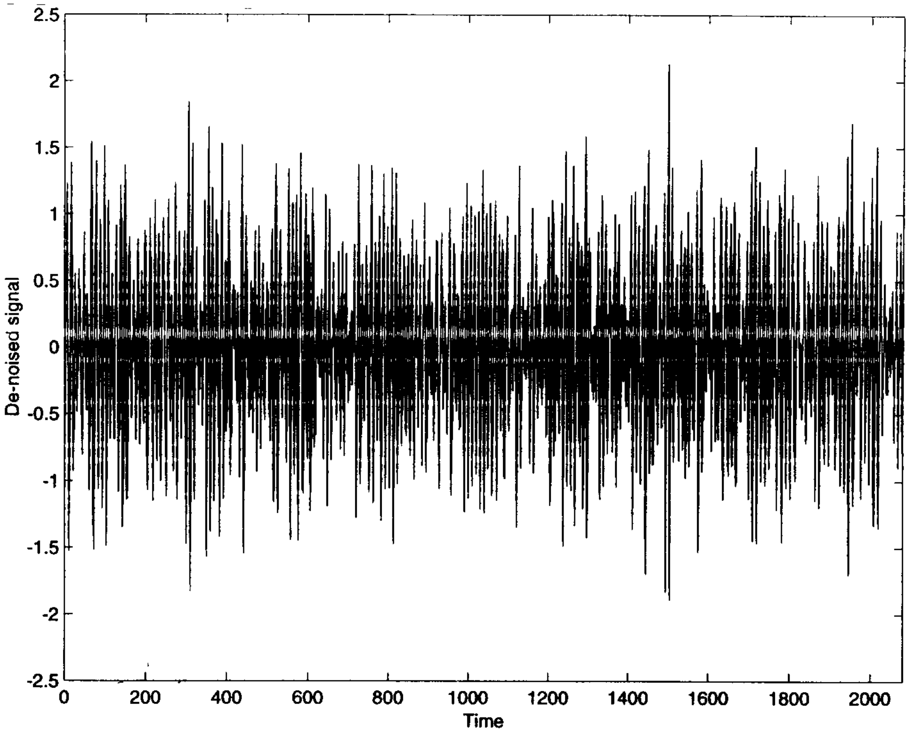


Fig 7. A Portion Of The Same Signal As Fig.6, After "Noise" Removal By Fourier Techniques

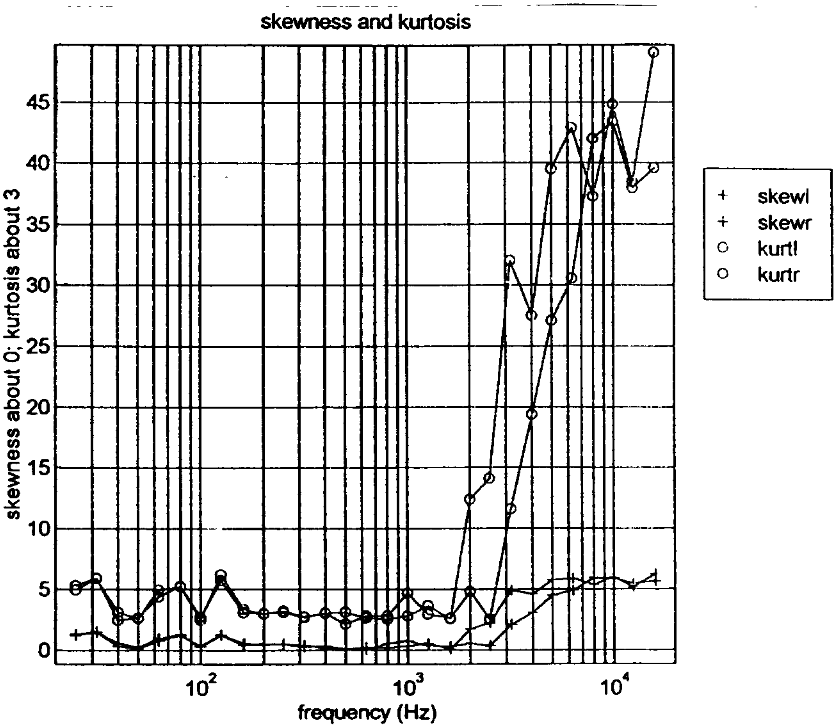


Figure 8: Skewness/Kurtosis, On-Road Data; Left/Right Ear