Development of Risk Assessment Method for Complex Noise

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List of Terms and Abbreviations

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ATE: Auditory evoked potential after exposure

AWT: Analytic wavelet transform

dB: Decibel

dBA: A-weighted decibel

EEH: Equal energy hypothesis

%IHC: Internal haircell loss

NIHL: Noise induced hearing loss

%OHC: Outer haircell loss

PRE: Auditory evoked potential pre-exposure

PST: Auditory evoked potential after 30 days post exposure

PTS: Permanent threshold shift

SPL: Sound pressure level

STFT: Short time Foureir transform

T-F: Time-frequency

TTS: temporary threshold shift

List of Symbols:

$g(t)$: Gaussian time window

s: Scale of the wavelet transform, related to the frequency by $\omega = \frac{\eta}{s}$

$W_s(u)$: The wavelet transform value at time u

P_{ref}: Reference pressure

L_{eq}: Equivalent SPL

L_{Aeq}: A-weighted equivalent SPL

P_{eq}: Equivalent pressure

L_{em}: Modified equivalent SPL

$\bar{T}_w(\omega)$: Weighted time

$\beta(\omega)$: Frequency by frequency kertosis

η: Frequency parameter of the AWT transform, related to the frequency by $\omega = \frac{\eta}{s}$

ρ_{mp}: Linear correlation defined between data sets m and p

σ_m, σ_p : Standard deviations of sets m and p

$\psi(t)$: Mother wavelet of the AWT

ω : Circular frequency (rad/s)

Abstract

Many workplaces are subject to complex noise environments where impulsive noises are embedded in the continuous background noise. Current noise guidelines recommend an exposure limit based on the equal energy hypothesis (EEH), thus overlooking the effect of temporal and spectral variations of the noise. This practice is widely believed inaccurate to assess the risk of complex or impulsive noises. An improved noise risk assessment method is necessary for more effective protection of workers from the noise-induced hearing loss (NIHL), the most common occupational disease. This research is a part of the long-term effort to develop a general noise risk assessment procedure. In this research, an advanced signal processing method and a general noise metric, two basic components of the noise risk assessment, were developed utilizing an existing set of chinchilla noise exposure data.

One of the main difficulties in assessing exposure risk to impulsive or complex noise environments is the quantitative characterization of the noise. A highly transient event such as impulsive noise should be characterized in the joint time-frequency (T-F) domain because its time and frequency characteristics are inter-related. An advanced T-F noise characterization method was developed by refining and extending the analytic wavelet transform (AWT) method developed in the PI's previous research. The method obtains T-F characteristics of the noise in a set of 1/3 octave time histories, from which the noise metric is calculated.

Most noise guidelines currently assess the noise risk based on a single-valued metric, typically the A-weighted overall SPL. A more general noise metric that reflects the T-F characteristics of the noise is necessary to accurately predict hazard of a noise of general type. In this research, 14 new noise metrics that reflect T-F characteristics of the noise in distinctively different ways were designed. The best metric was identified by based on the statistical correlations of these metrics with hearing losses measured in chinchillas.

Highlights and Significant Findings

Development of an advanced signal analysis method: An advanced signal processing method, a modified version of the analytic wavelet transform (AWT) was developed to characterize noises in the time-frequency (T-F) domain. The wavelet transform technique is inherently an ideal tool to characterize highly transient signals because of its superior T-F resolution. The AWT is a special version of the wavelet transform that works like a transient Fourier transform. The version of the AWT developed in this work characterizes the noise as a set of 1/3 octave time histories of given center frequencies.

The biggest advantage of the AWT developed in this work is that it characterizes the signal in familiar terms, sound pressure level (SPL) and frequency. The AWT is used in this project to re-dissect existing animal exposure study data to uncover relations between the noise and the hearing impairments that could not have been found in the past. The AWT enables defining noise metrics as functions of T-F characteristics of the noise, thus enables the correlation study between the hearing loss and the noise.

Identification of a general noise metric: Most noise guidelines currently assess the noise risk based on a single-valued metric, typically the A-weighted overall SPL. The practice is known to be accurate for relatively steady-state, broadband noises, however not for highly transient noises such as an impulsive noise. A more elaborate noise metric is necessary to predict hazard of transient noises accurately. In this research, 14 new noise metrics were designed, each of which to reflect T-F characteristics of the noise in a distinctively different way. The best metric was identified by studying statistical correlations between the metrics and hearing losses measured in chinchillas. The chinchilla exposure data was obtained by exposing groups of chinchillas to noises of widely different characteristics. A modified form of the equivalent sound pressure level L_{eq} showed the best overall correlation with measured hearing losses; therefore was identified as the best metric, which. The metric will be used to assess the risk of noises of various different types.

Development of the future research plan: The underlying long-term goal that motivated this study was the development of a NIHL risk assessment procedure for human. The task requires multiple projects involving a wide range of scientific disciplines; therefore, a long-term plan is necessary to steer the effort. A long-range strategy is (1) develop a general noise metric for chinchillas (this research); (2) develop a general NIHL risk assessment procedure for the chinchilla; (3) develop the human version of the procedure by converting the chinchilla version developed. The detailed plan for the stage (2) was developed in this research.

Translation of Findings

Two major outcomes of this research are the analytic wavelet transform (AWT) specialized for signal processing of transient noises and a general noise metric identified by the correlation study. The two outcomes will be used as the core components of an improved noise risk assessment method that the PI plans to develop in the future. The new method will consider the effect of spectral and temporal variations of the noise; therefore will enable more accurate assessment of the risk of impulsive and complex noises than current noise guidelines. The new method will also enable frequency by frequency prediction of the hazard of the noise.

Outcomes/Relevance/Impact

It is a near consensus that current guidelines are relatively accurate in assessing the risk of broadband Gaussian noises but not the risk of complex or impulsive noises; however continue to be employed because a better alternative is not available. The risk of exposure to industrial noises may have been severely underestimated, which contributed to making NIHL the most common occupational disease – affecting more than 11 million workers in the U.S. alone. The new risk assessment method that will be developed based on the outcomes from this research will improve workers safety and health by better protecting them from noise-induced hearing losses.

Scientific Report

Background of the Project

Noise-induced hearing loss (NIHL) is the most common job-related illness in the United States today, affecting more than 11 million workers (NIOSH, 1996). Hence, the National Occupational Research Agenda (NORA) identifies NIHL as one of its top-priority research areas. Current noise guidelines, such as ISO 1999 (ISO, 1999) and ANSI S3.28-1986 (ANSI S3.28-1986) recommend a noise exposure limit based on the equal energy hypothesis (EEH), thus ignoring temporal variations of spectral characteristics of the noise. It is believed by many researchers that this practice can lead to a severe underestimation of the risk when the exposure contains *impulsive* noises (Ahroon et al., 1993). For exposures to occupational noises, European Union Directive, ISO 1999 and NIOSH recommend integrating both impulsive and continuous type noises using EEH. This practice, applying EEH to impulsive noises, is highly controversial. Numerous animal and demographic studies strongly suggest the need for a more elaborate model (Hamernik et al., 1987, 1991, 1993, 2002). Developing an improved noise guideline is clearly an urgent task to ensure safe and healthy working conditions for workers in the United States.

A typical workplace has a complex noise environment that contains multiple reflected impulsive noises mixed with broadband Gaussian noises. A number of animal exposure studies showed that the interaction effect between impulsive and broadband noises may exacerbate the NIHL (Hamernik et al., 1987). For example, it was observed that the exposure to a complex noise resulted in much greater permanent threshold shift (PTS) and more extensive hair-cell losses than exposure to only an energy-equivalent continuous or impulsive noise alone would have caused. The interaction effect was dependent upon the frequency contents of the two classes of noise (Hamernik et al., 1993), indicating the need to consider *spectral* characteristics in assessing the risk of complex noises. Due to the time-averaging effect of the Fourier transform, a more elaborate T-F signal analysis technique is necessary to capture the characteristics of impulsive noises accurately. The PI developed an advanced T-F signal analysis technique called the analytic wavelet transform (AWT) (Zhu & Kim, 2005, 2006) and applied it to various noise and vibration signals.

Various human population studies and animal exposure studies have indicated that impulsive and continuous noises pose different hazards to the auditory system. Passchier-Vermeer (Passcheir-Vermeer, 1983) showed that an impulse noise below 100-dBA caused hearing loss of approximately 10-dB more than a continuous noise of equivalent level. Hearing losses induced by impulsive and continuous noises were compared to show the additional hazard of impulsive noises in various animal noise exposure studies. Nilsson et al. (Nilsson et al., 1983), using the guinea pig, reported that the impulse noise inflicted more cochlear hair-cell damage and accompanying hearing loss than the pure-tone noise of equivalent overall energy. Dunn et al. (Dunn et al., 1991) conducted a comparison test using two groups of chinchillas, each exposed to a broadband noise and an impulsive noise of approximately equal energy and frequency spectrum, respectively.

Variability in individual susceptibility has confounded investigators in interpreting results from noise exposure studies. Several large-scale demographic studies (Taylor et al., 1984) showed a wide range of individual susceptibility to NIHL. Considerable research has been conducted to understand possible causes for this variability focused on biological and environmental factors (Davis et al., 1989, Boetter et al., 1992) and chemical exposures (Humes, 1984, 1991). A significant degree of variability was also observed in controlled laboratory animal studies. The nature and possible cause of variability in animal study data are discussed in (Cody & Robertson, 1983).

A number of animal exposure studies showed that the interaction effect between the impulsive and broadband noises may exacerbate the NIHL (Blakeslee et al., 1977, Hamernik et al., 1974). The effect was dependent upon the spectra of the two classes of noise, indicating that spectral as well as temporal characteristics of the noise should be considered in assessing the NIHL risk. The time and frequency of a transient event are not independent but interwoven concepts (Zhu & Kim, 2005); therefore, they must be considered simultaneously. The effect of the T-F characteristics of noise could not be considered properly in past studies because of the lack of an effective signal analysis tool. Wavelet analysis is an ideal tool for transient signal analysis because it uses a variable T-F atom to characterize signals, unlike the Fourier transform which uses a fixed T-F atom. The special version of the AWT that the PI developed is ideal for analysis of transient noises because it can represent the signal in traditional terms, such as SPL and frequency. The AWT is used as the main signal analysis tool in this proposed research.

Specific Aims

The three specific aims of this project are as follows.

(Aim 1) **Develop a tool for time-frequency domain noise characterization:** An advanced T-F noise characterization software tool will be developed by refining and extending the modified AWT method proposed by the PI. The characterization software will be applied to the complex noises used in chinchilla based NIHL studies conducted by the consultants of this research to study correlations between the noise characteristics and observed hearing losses.

(Aim2) **Develop a quantitative procedure for NIHL risk assessment:** Several new noise metrics will be proposed as functions of T-F characteristics of noise. Statistical correlations of these metrics with hearing losses observed in chinchillas will be studied to identify the metric that best represents the hazard of complex noise environment. Employing this metric, a prototype for a general noise hazard assessment procedure will be developed. The procedure will consist of measurement, signal analysis and risk evaluation phases.

(Aim 3) **Design future NIHL study and test protocol:** Based on the experience of developing the new noise hazard assessment method, studies that become necessary or possible because of the capability of the new T-F noise characterization tool will be identified. These studies will then be combined to develop a protocol for future research.

Procedures

Currently nearly all noise guidelines use a single-valued metric, typically the A-weighted overall SPL, to assess the exposure risk of a noise. Risks of noises of widely different characteristics are predicted to be the same while numerous animal and demographic studies indicate that they are significantly different. To overcome this problem, the noise metric should be designed to reflect T-F characteristics of the noise. Additionally, for widely different types of noise, the value of the metric calculated from a noise should be well correlated with the hearing loss that the exposure to the noise will induce. The major goal of this research was to identify such a noise metric. The procedure adopted to develop the noise metric is described as follows.

(1) Develop a new signal processing method to identify T-F characteristics of the noise in a form that is easy to incorporate in the calculation of the noise metric.

(2) Design noise metrics as functions of T-F characteristics of the noise in various forms.

(3) Identify a set of chinchilla noise exposure study data that has been obtained for widely different types of noise for the correlation study.

(4) Compare correlations between the noise metrics and the NIHL observed in chinchillas to identify the best noise metric.

Methodology

I. Development of the Analytic Wavelet Transform Method

1.1 Wavelet Transform

A unique noise characterization method was developed by using the modified analytic wavelet transform (AWT), an advanced time-frequency (T-F) signal analysis method developed by the PI specifically for transient sound analysis (Zhu & Kim, 2005). The method calculates the time history of a 1/3 octave component of the given center frequency of the noise. The method is applied to characterize the noises used in the chinchilla exposure study. The identified characteristics are used as the basic data to calculate the noise metrics designed as function of the time and frequency. This approach, dissecting existing data with a new tool to uncover information that could not have been observed in the past, will prove very effective to increase the value of existing clinical laboratory data.

The wavelet transform, a relatively new signal analysis method introduced in 1970s (Daubechies, 1992; Grossmann & Morlet, 1984), decomposes signals using wavelets of variable scales, which are obtained by dilating and scaling the mother wavelet. The main advantage of the wavelet transform stems from the fact that it uses variable scales, therefore variable T-F resolutions. The transform with a small scale wavelet uses a T-F atom short in time and wide in frequency, thus picks up fast changing components efficiently, while the transform with a large scale wavelet uses a T-F atom long in time and narrow in frequency, thus picks up slowly changing components efficiently.

The analytic wavelet transform (AWT) provides a perfect solution for this situation. At first, the information obtained from the AWT can be represented and interpreted in exactly the same way as in the STFT. Secondly, the AWT process can be made numerically nearly as efficient as the STFT if it is programmed properly. With the AWT setup in the way used in this paper, end-users will not even notice the difference in using the AWT from using the STFT; the AWT just provides much clearer information on T-F characteristics of the signal. It seems there simply is no reason not to use the AWT over the STFT for transient signal analysis.

1.2 Design of the Analytic Wavelet Transform

The mother wavelet of the AWT is defined as follows:

$$\psi(t) = g(t)e^{j\eta t} \tag{1}$$

where, $j = \sqrt{-1}$, η is a parameter that will be related to the frequency and a Gaussian function is adopted for $g(t)$:

$$g(t) = \frac{1}{(\sigma^2\pi)^{1/4}} e^{-\frac{t^2}{2\sigma^2}} \tag{2}$$

In equation (2), parameter σ determines the shape of the function. The AWT is defined as follows.

$$W_s(u) = \int_{-\infty}^{\infty} f(t)\psi^*{}_{u,s} dt \tag{3}$$

The family of wavelets $\psi_{u,s}$ is obtained by dilating and translating the mother wavelet ψ :

$$\psi_{u,s}(t) = \frac{1}{s}\psi(\frac{t-u}{s}) \tag{4}$$

where, s is the scale and u is the translation amount.

The wavelet transform in Eq. (3) effectively performs as a real-time frequency filter. The value for η can be determined from the following center frequency equation:

$$\omega_c = \frac{\eta}{s} \tag{5}$$

The parameter σ can be determined from the bandwidth equation:

$$\Delta dB_l = -20\sigma^2\eta^2(1-2^{-1/6})/2\log_{10} e \tag{6}$$

For example to make 3 dB drop at the upper and lower limit frequencies as in typical band filters, η and σ have to be chosen so that $\sigma^2\eta^2 = 58$. Therefore in this work, $\sigma = 1.05$ and $\eta = 7.252$ are used. With this parameter set, performing the AWT returns the amplitude of the signal components contained in the frequency range of the 1/3 octave band centered at $\omega_c = \frac{\eta}{s}$.

If the sound pressure signal is in Pa, the result from AWT can be represented in the sound pressure level (SPL) as follows;

$$SPL(u)_s = 10\log_{10}\left(\frac{W_s(u)W_s(u)^*}{2P_{ref}^2}\right) \tag{7}$$

where, W_s is the complex amplitude obtained with AWT, W_s^* is its complex conjugate. $P_{ref} = 20\times10^{-6}$ Pa. This way, noise analysis with AWT can be done in terms of the SPL, which can be easily applied to noise signal analysis.

Fig. 1 shows the time history of the sound generated by an impact power wrench, which was measured at the operator's ear position for duration of 0.1 second (Kulkarni et al., 2004). The sampling rate of 40,000 Hz was used, which corresponds to the Nyquist frequency of 20,000 Hz. Operation of the tool involves very rapid metal-to-metal impacts, which create a train of highly impulsive sounds occurring nearly 50 times per one second, each time reaching to instantaneous SPL of nearly 120dB.

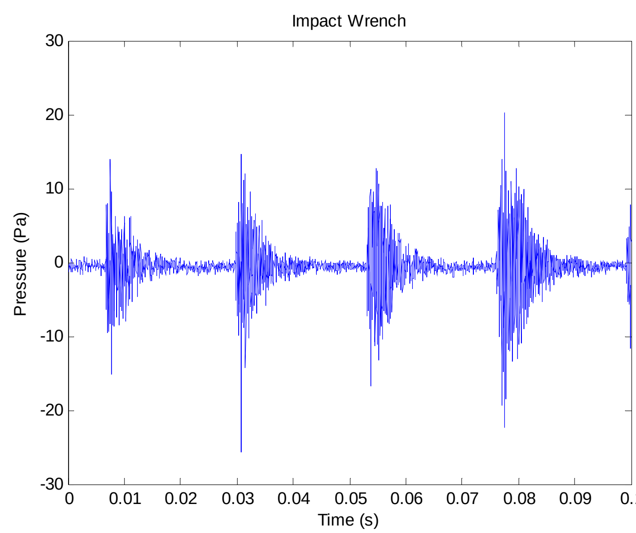

Figure 1. Time history of the sound from an impact power wrench

Fig. 2 shows the T-F plot obtained from the STFT of the signal shown in Fig. 1. A time window of 0.02s is used for each Fourier transform, which results in the frequency resolution of 50 Hz. 50 % overlapping is used; therefore the window is moved by 0.01 s for each FFT. A-weighting is applied to each spectrum $P(\omega)$ to convert the SPL to dBA.

The T-F plot in Fig. 2 was obtained by interlacing the frequency plots, which can be done by estimating the AWT at every 1/12 octave points. This provides 4 intermediate frequency points to each 1/3 octave frequency interval to make the surface smoother.

As illustrated in Fig. 2, the frequency axis of the AWT may be related to the positions of the basilar membrane because 1/3 octave frequencies match with critical bands in a wide range of frequency. Therefore, the curve obtained by cutting the T-F characteristic surface to the time axis direction at a given frequency may be considered as the time history of the stimulus felt by the basilar membrane at the corresponding position. Also, the curve obtained by cutting the surface to the frequency direction at a given time may be interpreted as a snap shot of the basilar membrane displacement. Employing the 1/3 octave band makes use of the effective averaging time of the auditory system as the time constant, thus makes a good sense for hearing research purpose. Used this way, the AWT can be very useful for correlation study of the hearing loss and noise characteristics.

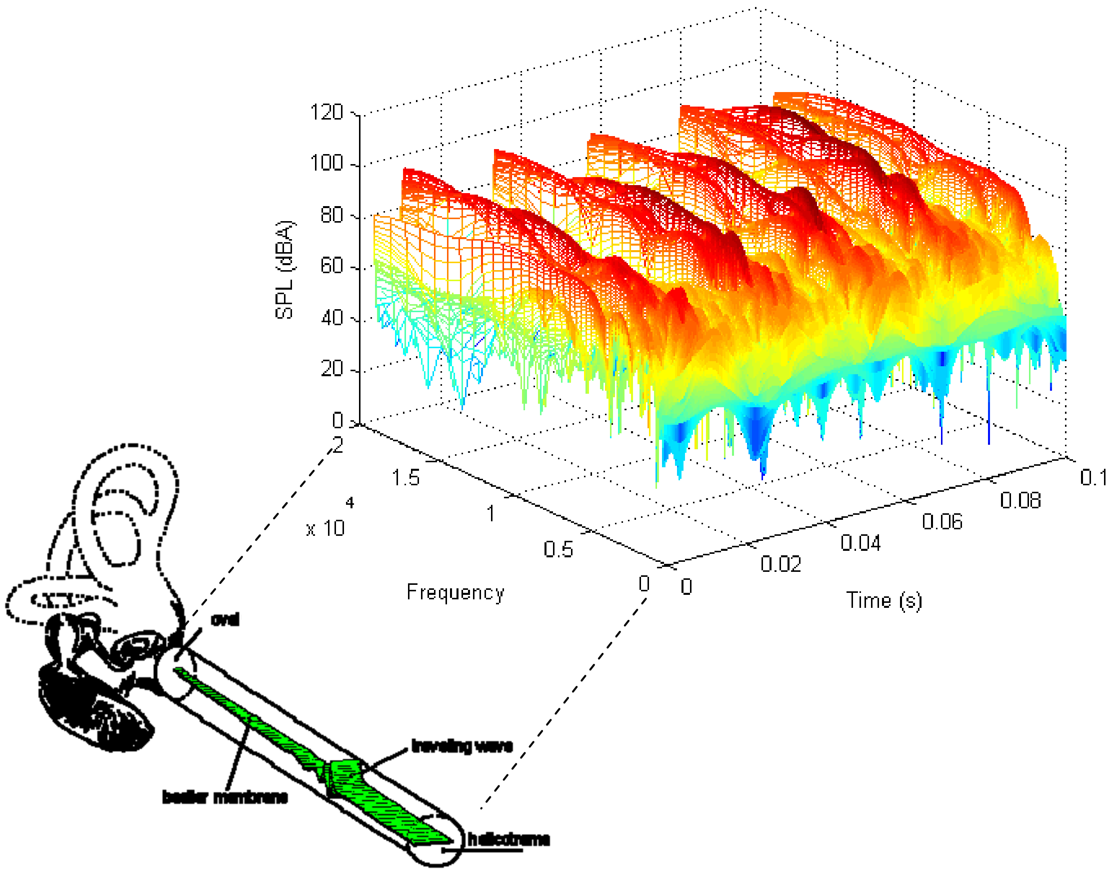

Figure 2. Time-frequency plot of the SPL of the impact power wrench obtained by AWT using more frequency points

1.3 Time Histories of 1/3 Octave Components of the Noise

The AWT obtained by equation (3) is actually the time history of the sound power contained in the 1/3 octave band of center frequency η / s. Fig. 3 shows six 1/3 octave time histories at 0.5, 1, 2, 4, 8 and 16 KHz. It is seen that the time history changes faster at higher frequencies as time atom becomes smaller. These transient 1/3 octave band time histories are new concepts that may have various applications.

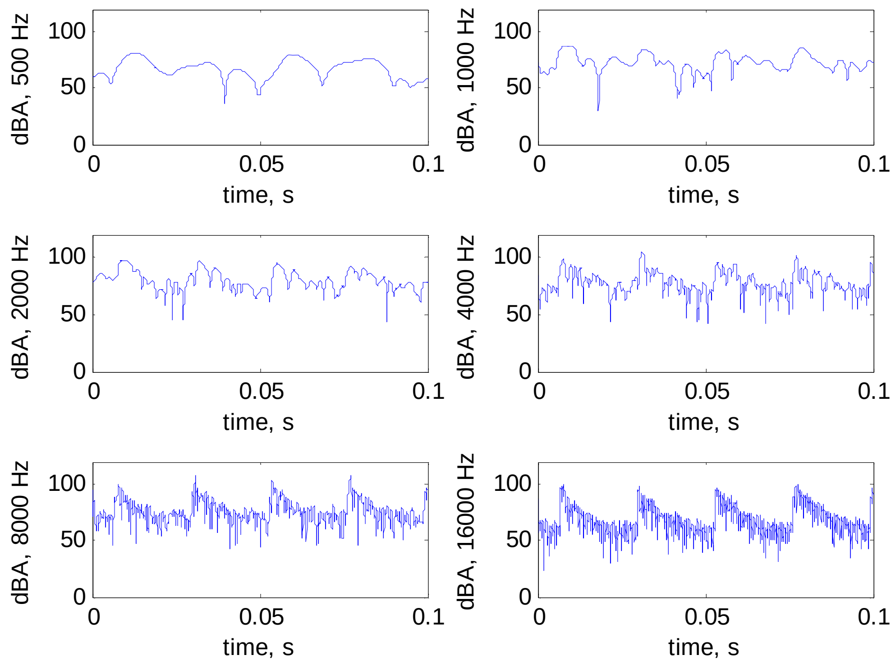

Figure 3. 1/3 octave time histories of the impact power wrench noise obtained by AWT; 6 time histories of 0.5, 1, 2, 4, 8, 16 KHz center frequency

II. Design of Metrics

2.1 The Need for an Improved Noise Metric

Noise guidelines currently being in use such as ISO 1999 (ISO-1999, 1990) and ANSI S3.28-1986 (ANSI S3.38-1986,) recommend the noise exposure based on a single-valued metric such as the A-weighted SPL, L_{eqA}, and the equal energy hypothesis (EEH). This assumes that noises of equal amount of energy cause equal NIHL. For example, ISO 1999 and NIOSH guideline (ISO-1999, 1990; NIOSH, 1998) recommend the exposure limit using the 85 dBA equivalent sound pressure level (L_{Aeq}) as the threshold and the 3-dB exchange rule. That is, 8 hours daily exposure is allowed for a noise of 85 dBA or lower; then every 3 dB increase from the threshold level halves the allowed exposure. It is generally considered that this EEH based approach is accurate for steady-state noises but not for impulsive noises as the time averaging effect can significantly underestimate the exposure risk (Ahroon et al., 1993, Hamernik & Qiu, 2001).

Typical workplaces are often subjected to a complex noise environment in which impulsive noises are embedded to a steady-state background noise. A number of animal exposure studies showed that the interaction effect between impulsive and broadband noises may actually exacerbate the NIHL (Blakeslee et al., 1977; Hamernik et al., 1987; Hamernik et al., 1974). For example, it was observed that the exposure to a complex noise resulted in much greater permanent threshold shift (PTS) and more extensive haircell losses than exposure to only an energy-equivalent continuous or impulsive noise alone would have caused (Blakeslee et al., 1977; Hamernik et al., 1974). Animal exposure studies strongly suggest the need for a more elaborate noise metric than L_{eq} for complex or impulsive noises (Ahroon et al., 1993; Dunn et al., 1991; Hamernik & Hsueh, 1991; Hamernik et al., 1991; Hamernik & Qiu, 2001; Hamernik et al., 2003; Hunt et al., 1976; Martin, 1975; Nilsson et al., 1983; Patterson, 1991; Roberto et al., 1985; Starck & Pekkarinen, 1987; Starck et al., 2003; Thiery & Meyer-Bisch, 1988; Voigt et al., 1980).

A new noise metric is designed as a function of T-F characteristics of the noise for more accurate assessment of the risk of impulsive or complex noises. By definition, a good noise metric should relate the noise with the resulting hearing loss with good correlations. To identify such a metric, six basic forms of noise metrics are designed by reflecting T-F characteristics of the noise in uniquely different ways. Fourteen metrics obtained by varying the basic six forms are compared by utilizing an existing data obtained from an animal exposure study (Hamernik et al., 2003; Hamernik et al., 1987; Hamernik et al., 1994; Hamernik & Ahroon, 1999; Hamernik & Qiu, 2000; Hamernik et al., 2002). In the exposure study, 18 groups of chinchillas were exposed to noises of different T-F characteristics, which included a steady-state noise and 17 impulsive and complex noises. The NIHL induced in the 18 groups of chinchillas were measured and the 18 noises used to expose them were digitally recorded.

2.2 Chinchilla Noise Exposure Test Data

Hamernik et al. (Blakeslee et al., 1977; Hamernik et al., 1987; Hamernik et al., 1974; Hamernik & Hsueh, 1991; Hamernik et al., 1993; R. P. Hamernik & Qiu, 2001) have long proposed that a time-averaged metric such as the equivalent sound pressure level (L_{eq}) is not sufficient to quantify the exposure hazard to complex noises.

Initially the correlation study of the noise metrics were conducted by using the noise exposure data that Hamernik and his collaborators obtained by using 18 different noises shown in Table 1. The complex noises were generated by combining high-level noise impulses of the Friedlander type with a Gaussian continuous noise (Hamernik et al., 1974). The total SPL was controlled at 100 dBA for all types of noise to give a standard platform for comparison.

In the experiment, 18 groups of chinchillas were exposed to a respectively different type of noises for 5 days 24 hours per day, and then allowed to recover for 30days. A total number of 214 chinchillas were divided into 18 groups, with 9 ~ 16 animals in each group, and exposed to the noise. Auditory evoked potential pre-exposure (PRE), auditory evoked potential after 30 days post exposure (PST), and auditory evoked potential after exposure (ATE) were measured. From these, the permanent threshold shift (PTS=PST-PRE) and temporary threshold shift (TTS=ATE-PRE) were calculated. Percentage of outer hair cell loss (%OHC) and percentage of inner hair cell loss (%IHC) were also carefully measured. The measurements were conducted at 6 frequency points, 0.5, 1, 2, 4, 8 and 16KHz.

The 18 noises used in the study consisted of a Gaussian noise and 17 complex noises composed with variant levels of Gaussian background noise and impulses or bursts at different peak values, occurrence frequencies and occurrence rates. A description of the 18 noise types and their characteristics is listed in Table 1. More details on the design of the noises can be found in (Hamernik & Qiu, 2001; Hamernik et al., 2003; Lei, Ahroon, & Hamernik, 1994).

Noise index	Noise name	Band type	Band width (Hz)	Time kurtosis	Peak SPL (dB)	Probability of Impulse in 750 ms	No. of animals
1	G-261	Gaussian	N/A	3	N/A	N/A	15
2	G-264	Three bands	400	12	116~126	0.6	12
3	G-266	Very broadband	100~10,000	15	113~127	0.6	12
4	G-250	Narrow band	1800~2200	21	114~128	0.6	11
5	G-244	Three bands	400	25	115~128	0.6	12
6	G-254	Three bands	400	25	15~128	Impact/1.5s	11
7	G-255	Very broadband	100~10,000	25	115~129	0.6	12
8	G-270	Burst broadband	710~5680	27	104~115	0.6	12
9	G-259	Two bands	400	30	115~129	0.6	12
10	G-249	Broadband	710~5680	33	115~129	0.6	12
11	G-260	Three bands	400	39	115~129	0.6	16
12	G-252	Three bands	400	53	123~127	0.6	11
13	G-253	Three bands	400	61	117~130	0.2	12
14	G-268	Very broadband	100~10,000	65	128~133	0.1	11
15	G-251	Three bands	400	75	118~130	0.6	11
16	G-269	Narrow band	1800~2200	75	114~129	0.6	9
17	G-263	Three bands	400	85~110	116~128	0.6	11
18	G-265	Very broadband	100~10,000	105	127~132	0.1	12

TABLE 1: Description of the noises used in the exposure study used for the initial correlation study

2.3 Characterization of the Noise by the AWT

The AWT is applied to G263 and G264, two of the noises used in the exposure study, for demonstration. G263 is a nearly pure impulsive noise while G264 is a complex noise consisted of impulsive noise and background Gaussian noise. Time histories of the noises are shown in Figs. 4 and 5 for randomly selected 3 second periods.

The T-F characteristics of the noises obtained by applying the AWT technique are shown in Figs. 6 and 7 that were obtained by overlaying 1/3 octave time series of the noise obtained for center frequencies with 1/12 octave interval. Differences of the noises are clearly seen in the figures.

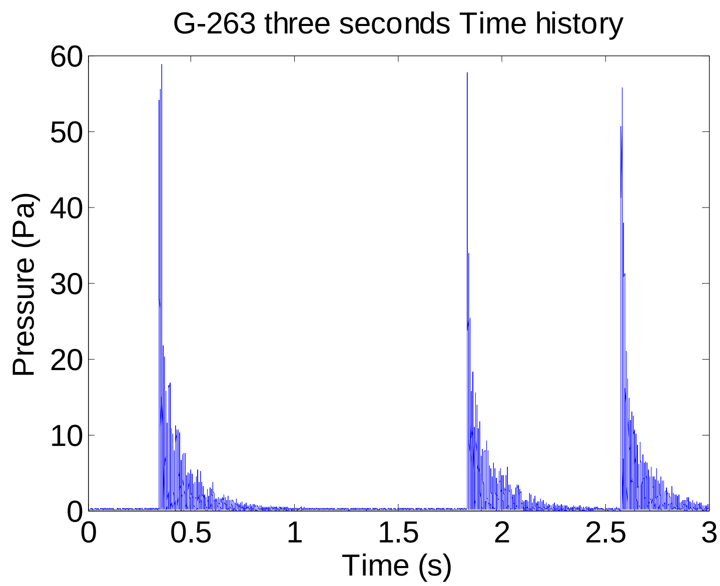

Figure 4. Time history of noise G253 for 3 seconds.

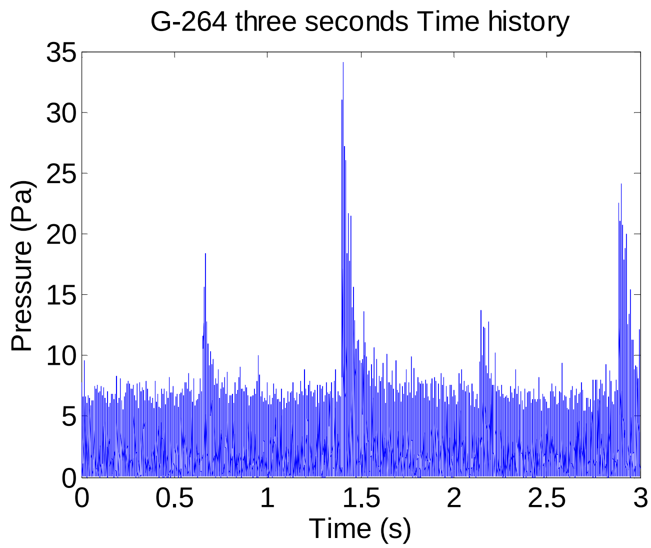

Figure 5. Time history of noise G264 for 3 seconds.

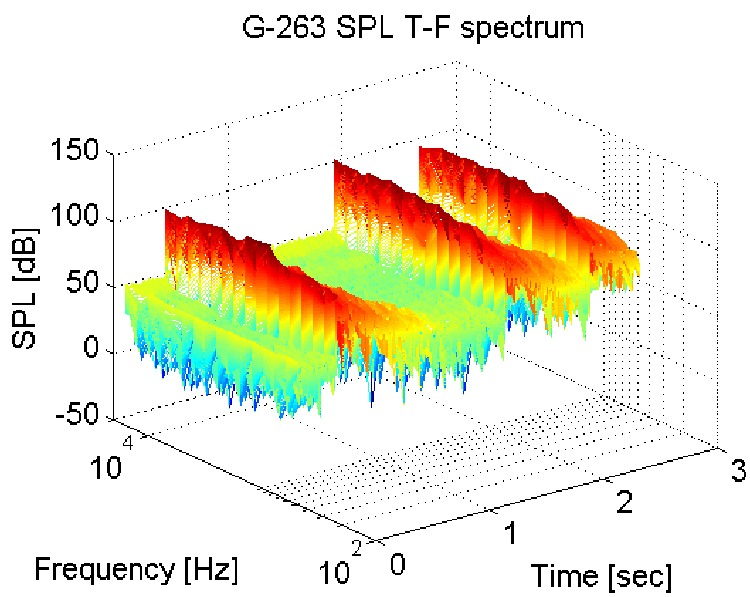

Figure 6. T-F representation of noise G263 obtained from AWT.

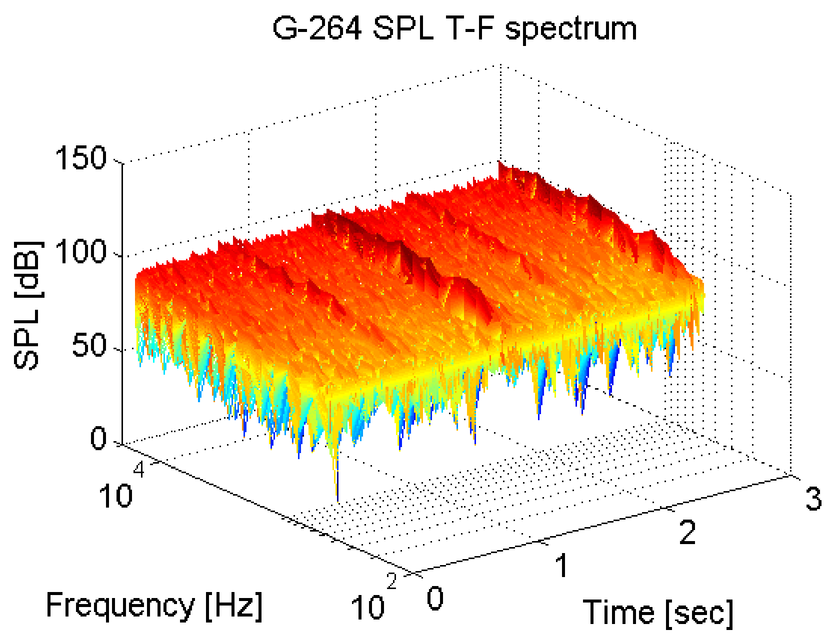

Figure 7. T-F representation of noise G264 T-F obtained from AWT.

As it was mentioned earlier, each implementation of the AWT (see Eq. (3)) obtains the time history of the 1/3 octave SPL of the center frequency at $\omega = \frac{\eta}{s}$ (Zhu & Kim, 2006). Figs. 8 and 9 show six 1/3 octave time histories obtained for G263 and G264 at the center frequencies 0.5. 1, 2, 4, 8, 16 KHz, at which NIHL of chinchillas were measured. This set of six 1/3 octave time histories are used as the basic T-F information to calculate the noise metrics.

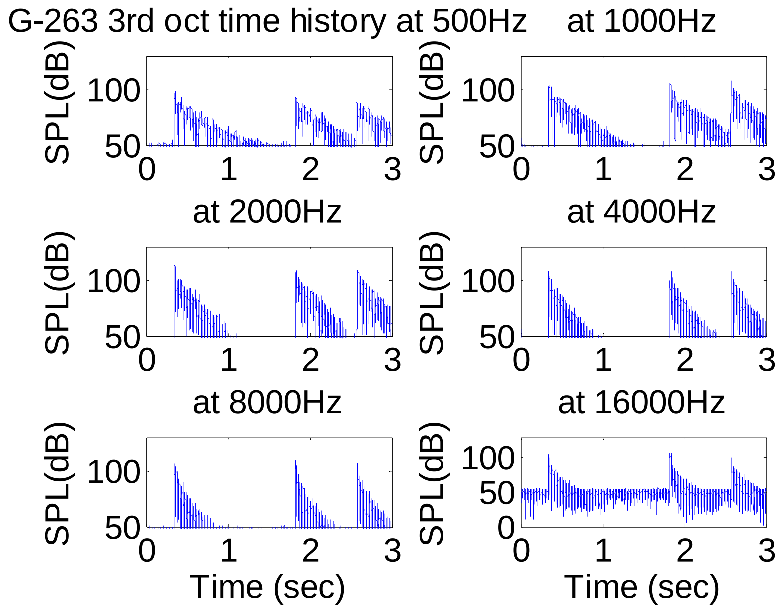

Figure 8. 1/3 octave time histories of noise G263 at 0.5, 1, 2, 4, 8 and 16KHz.

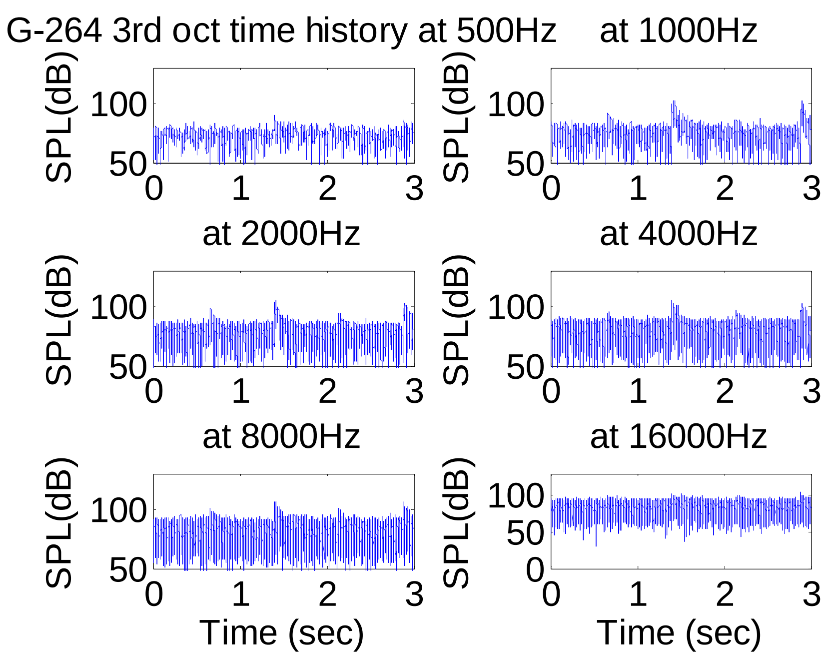

Figure 9. 1/3 octave time histories of noise G264 at 0.5, 1, 2, 4, 8 and 16KHz.

2.4 Design of Noise Metrics

Six basic forms of noise metric were designed to reflect T-F characteristics of noises in uniquely different ways; then varied to a total of 14 metrics. These metrics are calculated from the six 1/3 octave time histories obtained by applying the AWT to the noise. Therefore, these noise metrics are obtained as functions of frequency. The definitions of the metrics are as follows.

Metric 1: Equivalent SPL $L_{eq}(\omega)$: It has the same definition as the conventional L_{eq} except that it is calculated as a function of frequency. The time averaged pressure $P_{eq}(\omega)$ is calculated as follows.

$$P_{eq}(\omega) = \sqrt{\int_0^T \left(P(\omega,t)\right)^2} \tag{8}$$

where, $P(\omega,t)$ is the 1/3 octave pressure time histories obtained at the aforementioned 6 frequencies. $L_{eq}(\omega)$ is obtained as:

$$L_{eq}(\omega) = 10\log_{10}\left(\frac{P_{eq}(\omega)^2}{P_{ref}^{\ 2}}\right) \tag{9}$$

Metric 2: The frequency domain kurtosis $\beta(\omega)$: The kurtosis, a statistical quantity that represents the impulsiveness of the event, is calculated from each 1/3 octave SPL time history. Kurtosis of a time series is defined as:

$$\beta(\omega)=\frac{\sum_{i=1}^{N}\left(x_{i,\omega}-\bar{x}_{\omega}\right)^{4}}{\left(\sum_{i=1}^{N}\left(x_{i,\omega}-\bar{x}_{\omega}\right)^{2}\right)^{2}} \tag{10}$$

where, $x_{i,\omega}$ is the 1/3 octave time series and N is the number of time points. The kurtosis obtained from the total sound pressure was used as the metric in the noise exposure study by Hamernik and Qiu (Hamernik & Qiu, 2001; Hamernik et al., 2003; Lei et al., 1994; Lei & Hamernik, 1995).

Metric 3: $L_{\max}(\omega)$: Maximum SPL of each 1/3 octave time history is used as a metric based on the assumption that the hearing loss may depend on the maximum level of the frequency component. The 95% value of the SPL distribution histogram is taken as the maximum SPL.

Metrics 4 – 8: Dynamic sound pressure level $L_d(\omega)$: The basic form of these metrics is defined as:

$$L_d(\omega)=L_m(\omega)+K\Delta L(\omega) \tag{11}$$

where $L_m(\omega)$ is the mean value of the SPL of the noise, $\Delta L(\omega)$ is the dynamic fluctuation of the SPL defined as the difference between $L_{\max}(\omega)$ and $L_m(\omega)$, and K is a magnifying factor greater than 1. The design weights the dynamic component of the SPL more heavily than the static component based on the logic that the dynamic component is more detrimental than the static component to the failure of a dynamic system. Metrics 4 through 8 are defined by taking the values of K=2,3,4,5, and 10.

Metrics 9-13: Modified equivalent SPL $L_{em}(\omega)$: The basic definition is defined as follows:

$$P_{em}(\alpha,\omega)=\frac{1}{T}\left[\int_0^T \left\langle p(\omega,t)-p_o\right\rangle^{\alpha} dt\right]^{1/\alpha},\ L_{em}(\omega)=20\log\left(\frac{P_{eq}(\alpha,\omega)}{P_{ref}}\right) \qquad (12)$$

where p_o is the threshold pressure, $p(\omega,t)$ is the pressure value of the 1/3 octave time history of SPL, T is the averaging time, and the exponent α reflects the non-linearity of the damage mechanism. $\left\langle p(\omega,t)-p_0\right\rangle$ is a singular function defined as:

$$\left\langle p(\omega,t)-p_0\right\rangle=0 \text{ if } p(\omega,t)\le p_o,\ \left\langle p(\omega,t)-p_0\right\rangle=p(\omega,t)-p_o \text{ if } p(\omega,t)>p_o \qquad (13)$$

Equation (4.10) assumes that the noise contributes to the hearing loss only when its level exceeds the threshold pressure p_o. Using a higher α value has an effect of weighting higher pressures more heavily. Currently, 0.282 Pa is used for p_o , which corresponds to the SPL of 80 dB. Metrics 9 through 13, respectively, are obtained by calculating with α =2,3,4,5, and 10.

Metric 14: Normalized weighted exposure time $\bar{T}_w(\omega)$: This definition is obtained by applying the 3 dB exchange rule to *each time interval* to each 1/3 octave time history. For each unit time interval of size Δt;

- If $p(\omega,t)$ is the same as the threshold value p_0, the weighted time interval $\Delta t_{w,i}(\omega)=\Delta t$.

- If $p(\omega,t)$ is higher than the threshold value by 3 dB, the weighted time interval

$\Delta t_{w,i}(\omega) = 2\Delta t$; by 6 dB, $\Delta t_{w,i}(\omega) = 4\Delta t$, and so on.

- If $p(\omega,t)$ in the interval is lower than the threshold value by 3 dB, the weighted time interval $\Delta t_{w,i}(\omega) = \Delta t / 2$, by 6 dB, $\Delta t_{w,i}(\omega) = \Delta t / 4$, and so on.

Finally, $\overline{T}_w(\omega) = \sum_{i=1}^{N} \Delta t_{w,i}(\omega) / T$, where T is the length of the time series and N is the number of time intervals.

2.5 Preliminary Study of the Exposure Test Data

Figs. 10 and 11 show averaged values of the PTS, TTS, OHC and IHC losses measured from groups G263 and G264. As it is seen, the four NIHL indicators have all different frequency dependencies. Out of the four indicators PTS is selected as the NIHL parameter to study the correlation with the noise metrics in this study because it is a direct indication of the hearing loss.

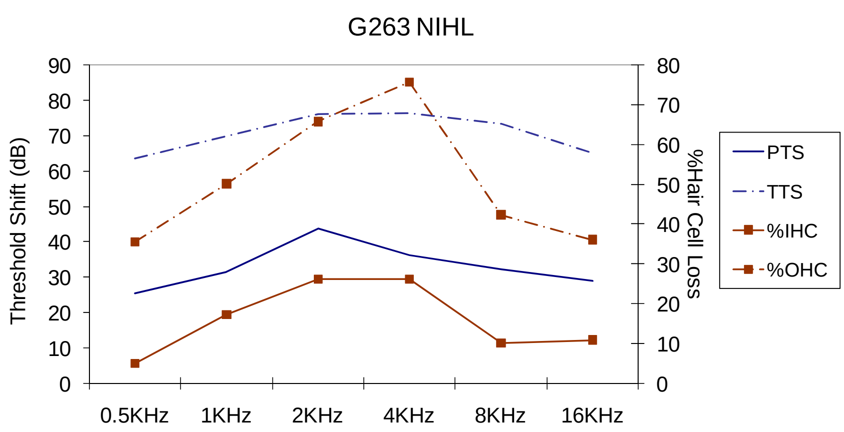

Figure 10: Averaged hearing loss data from chinchillas exposed under G263.

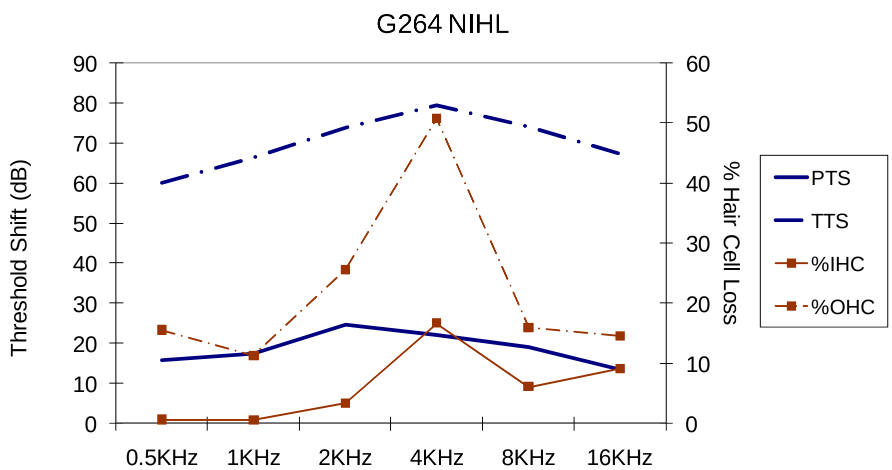

Figure 11: Averaged hearing loss data from chinchillas exposed under G264.

Six of the 14 metrics are plotted with the PTS data obtained from G263 group as functions of frequency in Fig. 12. It is seen visually that $L_d\left(\omega\right)$ and $L_{em}\left(\omega\right)$ give good correlations with PTS for this particular group.

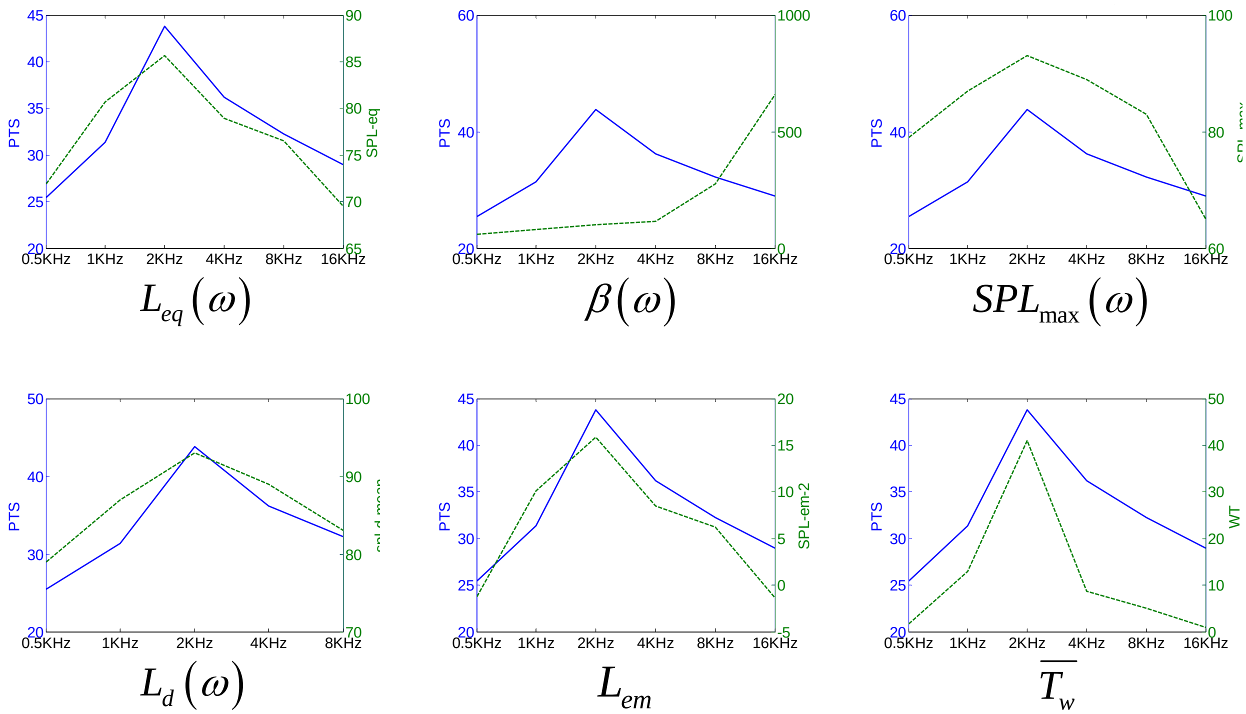

Figure 12. Measured PTS and six metrics of noise G263

Fig. 13 shows box plots of the PTS data measured at 6 frequencies from 18 chinchilla groups. Boxes represent inter-quartile ranges, horizontal lines represent the median, whiskers represent the largest and smallest values and '+' symbols represent outliers defined as the points outside of 1.5 box lengths from the end of the boxes, It is seen that the measured PTS data have quite large statistical variations, as it is frequently in animal test data. Because of the high statistical variations, median values are used instead of mean values in the ensuing correlation study.

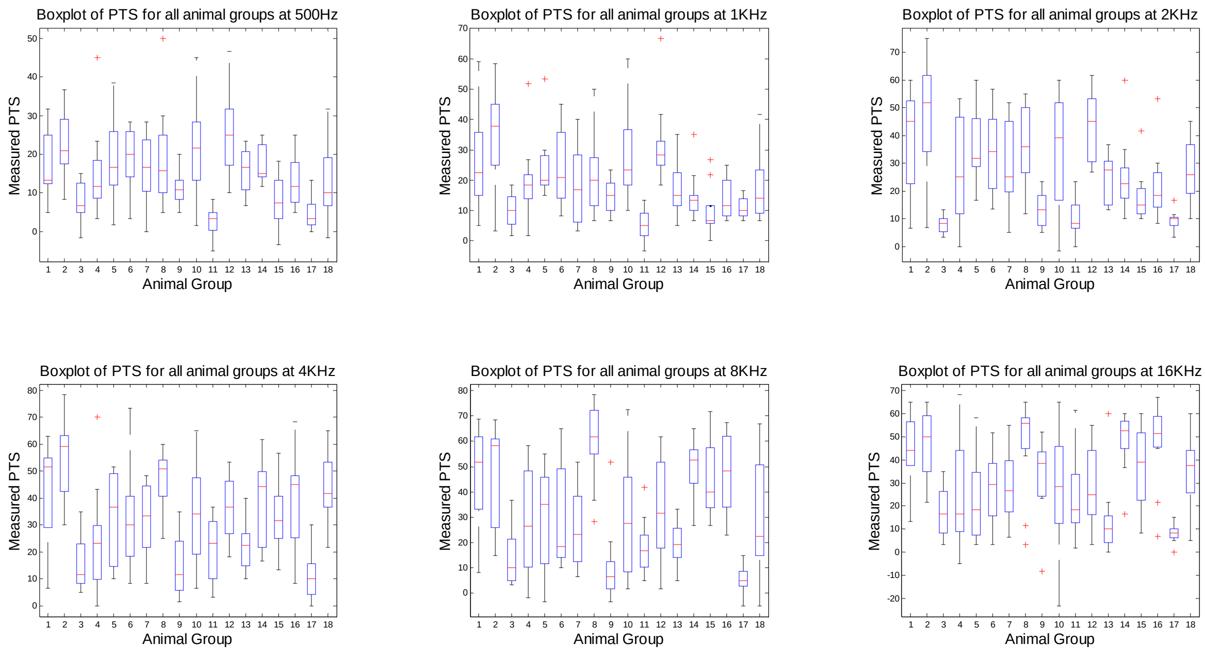

Figure 13. Box plots of measured PTS of 18 groups of chinchillas at 0.5, 1, 2, 4, 8, 16 KHz.

2.6 Correlation Study of the Noise Metrics

Definition of Correlations: The 14 noise metrics were compared for their correlations with the NIHL data obtained by Hamernik and Qiu. The data that was used in this initial study was obtained from 214 chinchillas divided into 18 groups exposed to respectively different types. The details of the exposure data used for the correlation study are found in Table 1.

The linear correlation between the observed PTS and the metric value is calculated as follows [109]:

$$\rho_{mp} = \frac{E\left[(m_i - \overline{m})(P_i - \overline{P})\right]}{\sigma_m \sigma_p} \tag{14}$$

where, E implies the expectation, m_i and P_i are the values of metric and PTS of the ith pair of the data, $\overline{m}$ and $\overline{P}$ are their respective averages, and σ_m and σ_p are their respective standard deviations. A correlation value 1 indicates a perfect correlation and a value of 0 indicates no correlation.

The noise metric and the average PTS of the animal group are obtained for 18 noises / animal groups at 6 frequency points; therefore in 18 x 6 matrices. Let matrix $m_i(g_1:g_{18}, f_1:f_6)$ is the ith noise metric calculated and matrix $PTS(g_1:g_{18}, f_1:f_6)$ is the average PTS measured. The three correlations used in the study are defined as follows.

<u>Frequency correlation</u> indicates how well the metric and PTS are correlated as functions of frequency for each noise group. Therefore, 18 frequency correlations are calculated for each of the 14 metrics. For example, the frequency correlation of L_{eq} (1st metric) of the second animal group (G264 in Table 1) is calculated from 6 pairs of the metric-PTS data ($m_1(g_2, f_1:f_6)$; $PTS(g_2, f_1:f_6)$) by using Eq. (6). The relationship between L_{eq} and average PTS of group G264 are shown in Fig. 6 (a) as functions of frequency, and Fig. 6 (b) in a scatter plot. If the metric and the PTS were perfectly correlated, all points in Fig. 6(b) would have located on a straight line.

<u>Noise correlation</u> indicates how well the metric and the average PTS of animal groups are correlated for the 18 noises at each frequency. Therefore, 6 noise correlations are calculated for each metric. For example, the noise correlation of L_{em2} (9th metric) at 1

KHz (2nd frequency) is calculated from 18 pairs of data ($m_9(g_1 : g_{18}, f_2)$; $PTS(g_1 : g_{18}, f_2)$) by using Eq. (6). A metric-PTS scatter plot similar to Fig. 6 (b) will be obtained but with 18 points.

Overall correlation indicates the overall performance of the given metric. The overall correlation is calculated from the combined data set of the above two cases. The correlation is calculated from Eq. (6) using 108 (18 x 6) pairs of data ($m_9(g_1 : g_{18}, f_1 : f_6); PTS(g_1 : g_{18}, f_1 : f_6)$). A single correlation value is obtained for each metric. Overall correlations were used to compare the metrics to select the best noise metric.

Comparison of Frequency Correlations

Considering the position theory of the basilar membrane responses, it is logical to expect good correlations between the frequency dependencies of the NIHL and the noise metric. A metric with a good frequency correlation will enable assessing the NIHL risk as a function of frequency. Fig. 14 shows the correlations of the 14 metrics calculated as such for 18 noises in a color map, in which a darker color represents better correlation. Noise index in the horizontal axis indicates the noise the animals were exposed (see Table 1), and metric index in the *y*-axis indicates the afore-mentioned 14 noise metrics. An ideal metric would have good correlations with all 18 noises.

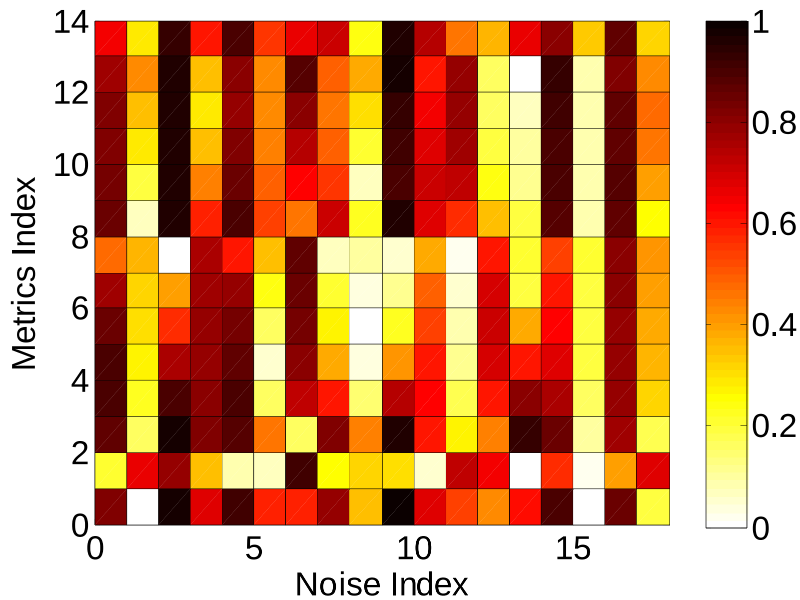

Figure 14. Correlation across frequencies between the PTS and noise metrics.

For some unknown reason, no metric gave good correlations for noise G264 and G269 (index 2 and 16). The averaged correlation values of the 14 metrics re shown in Table 2. The two metrics that showed the highest correlation values are identified as metric 14 ($\overline{T}_w$) with averaged correlation of 0.614 and metric 1 (L_{eq}) with averaged correlation of 0.606. It is also seen that all five modified equivalent SPL ($L_{em}(\omega)$ with $\alpha = 2, 3, 4, 5, 10$) show almost as good correlations as the top two metrics. Correlation values of these two metrics are plotted in Fig. 15, which clearly show bad correlations with animal groups 2 and 16. Examination of the measured NIHL data did not reveal any abnormality for these groups; however the examination was of limited nature because the data is from a past study.

Metric Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Averaged Correlation	0.606	0.394	0.596	0.575	0.517	0.476	0.443	0.380	0.565	0.555	0.561	0.563	0.573	0.614

TABLE 2: Averaged correlation of metrics

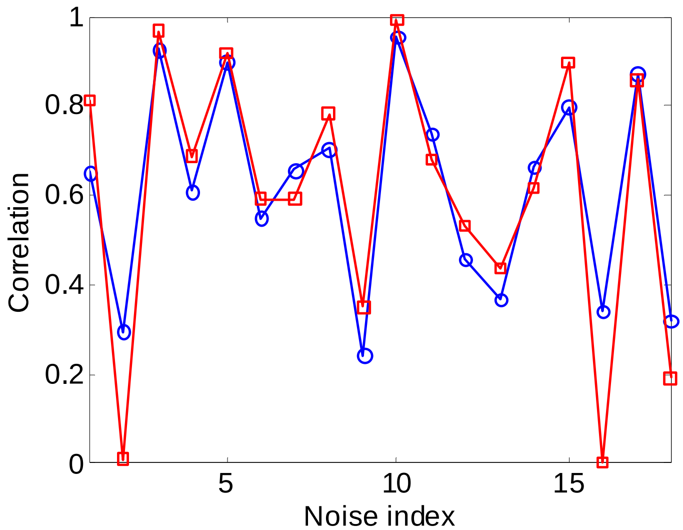

Figure 15. Correlation of two metrics with best across-frequency correlations. Solid line, $\bar{T}_w(\omega)$; dashed line, $L_{eq}(\omega)$.

Frequency correlations can also be calculated from the A-weighted metrics. The A-weighting can be applied to the six 1/3 octave SPL time histories obtained from the AWT. Using these time histories to calculate the metrics, A-weighted metrics can be calculated. The correlation results when A-weighting is used are shown in Fig. 16. Table 3 shows the averaged correlations of the metrics calculated from A-weighted data. The top two metrics in this case are identified as $L_{\max}$ (metric 3) with averaged correlation of 0.62, and $L_d\left(K=2\right)$(metric 4) with averaged correlation of 0.572. The best two A-weighted metrics are plotted in Fig. 17. While L_{max} gives a better correlation than the best non-weighted metric ($\overline{T}_w$), it is seen that the metrics calculated from non-weighted time histories give generally better correlations in general. Therefore, it is decided to use non-weighted time series for the further correlation study.

Metric Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Averaged Correlation	0.535	0.394	0.620	0.572	0.506	0.502	0.511	0.510	0.490	0.486	0.489	0.496	0.528	0.541

TABLE 3: Averaged correlation between A-weighted metrics and PTS

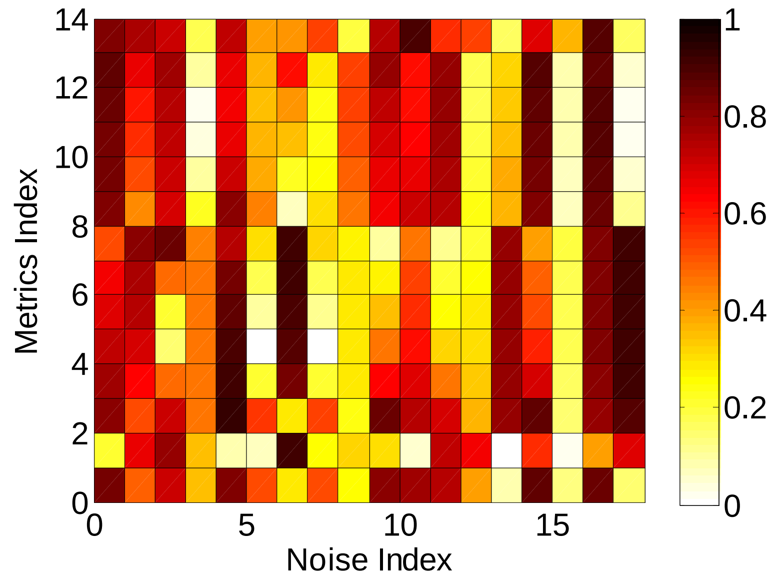

Figure 16. Frequency correlations when A-weighting is used.

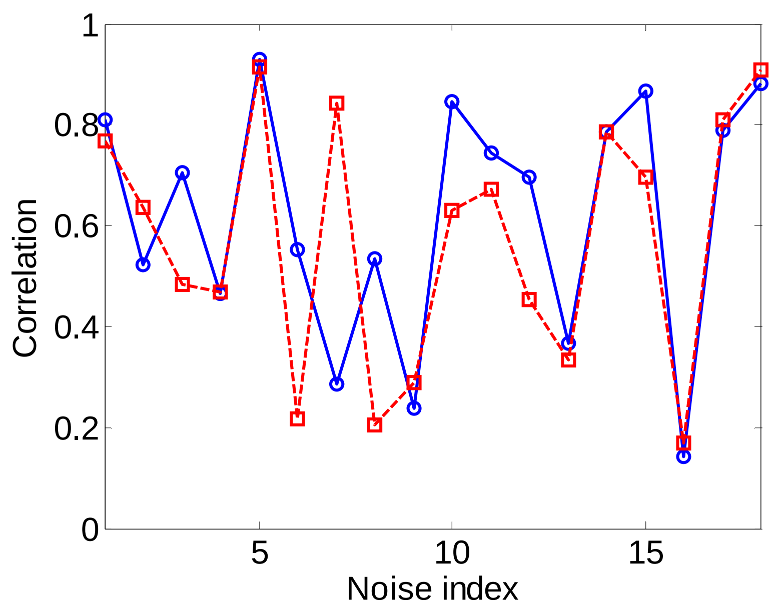

Figure 17. Correlation of two metrics with best across-frequency correlations when A-weighting is used, solid line, $L_{\max}$; dashed line, $L_d\left(K=2\right)$.

Comparison of Overall Correlations

An ideal noise metric should have the good frequency correlation as well as the noise correlation. Such a metric will enable accurate assessment of the exposure risk to noises of any temporal or spectral characteristics as a function of frequency. The combined overall correlation calculated from all 108 data points, 6 frequency points by 18 noise groups, can be used to identify the best metric in that sense. Table 4 shows the overall correlations values of the 14 metrics calculated from 108 pairs of the PTS data and calculated metric values. When the initial data set composed of 18 noise groups (see Table 1) is used, metrics L_{em2}, L_{em3} and L_{em4} (L_{em} with α =2,3,4) showed the best *overall correlations*, 0.525, 0.52 and 0.51. The traditional metric L_{eq} had the *overall correlation* of 0.48.

Metric Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Corre-lation	0.488	0.056	0.421	0.199	0.127	0.100	0.086	0.062	0.503	0.502	0.494	0.486	0.476	0.382

TABLE 4: Overall correlation values calculated for non-weighted metrics. Top 2 metrics are L_{em} with $\alpha = 2$ (0.503) and L_{em} with $\alpha = 3$ (0.502)

Based on this data, L_{em2} (L_{em} with α =2) is considered as the best metric. An additional advantage of L_{em2} is that it can be interpreted the same way as the traditional metric L_{eq} for noises of high SPL. For example, L_{em2} changes by 3-dB when L_{eq} of the noise changes by 3-dB.

Comparison of Noise Correlations

Correlations can also be calculated for the data of 18 noise groups for a fixed frequency. In this case, the correlations are calculated from 18 pairs of $\{x\}$ and $\{y\}$ data. $\{x\}$ is the median values of the PTS of the 18 animal group and $\{y\}$ is the metric values of the 18 noises used to expose the group. The correlation calculated in this way indicates the ability of the noise metric to represent NIHL risks of different type of noises.

Fig. 18 shows noise correlations of the 14 metrics calculated at 6 frequencies. 5 variations of $L_{em}(\omega)$ are identified as the metrics that give good noise correlations. The noise correlation L_{em2}, the selected metric, calculated from the initial data set composed of 18 noise groups is shown in Fig. 19. It I seen that the correlation is very poor at two frequencies, 500 Hz and 1 KHz. As it is seen in Fig. 18, noise correlations of all other metrics were very poor at these two frequencies.

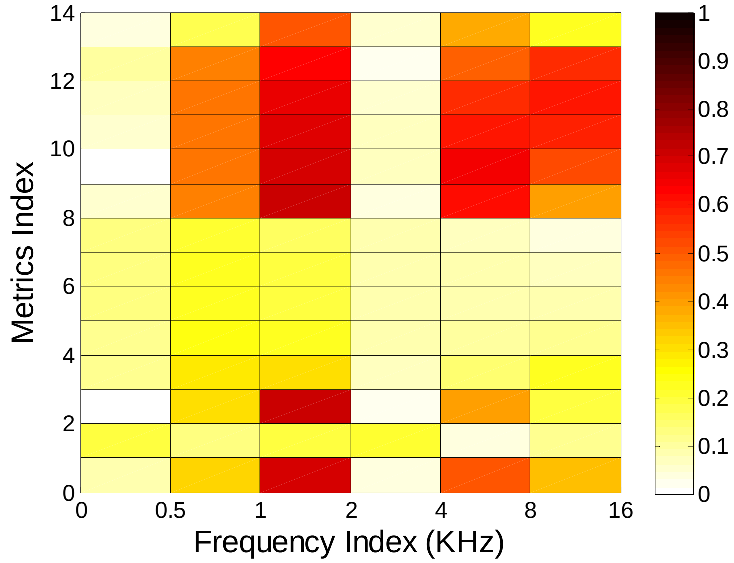

Figure 18. Correlations across noises between the PTS and noise metrics.

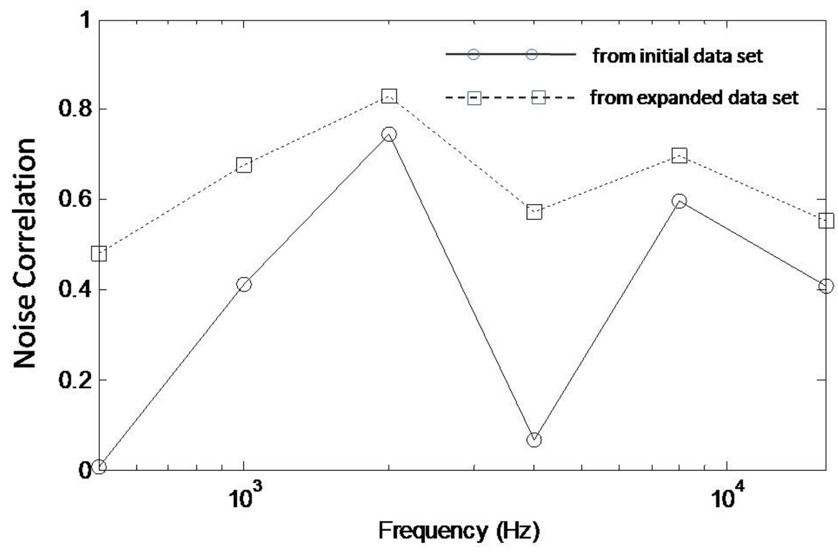

Figure 19. Noise correlations of L_{em2} of 6 frequency components calculated from the initial data set and expanded data set

The poor correlations at 0.5 KHz and 4 KHz contributed to lowering the *overall correlation*. To understand the cause of this problem, the PTS-L_{eq} scatter plots for all individual animals were made at 6 frequency points as seen in Fig. 20. The scatter plots were made by matching L_{eq} calculated each of the 18 noises and the PTS value of the animals in the group. Therefore, there are 214 data points. The examination reveals that the L_{eq} levels of all 18 noises are in much narrower narrow ranges at these the two frequencies than they are at other frequencies. The range is only 12 dB at 500 Hz and 10 dB at 4 KHz while the ranges are about 20 dB or higher at all other frequencies.

It is believed that this made the data to be used for the calculation of the correlation ill-conditioned. For an extreme example, if all chinchillas were exposed to the noises that have exactly at the same metric value, the points in the PTS – metric scatter plot will form a horizontal line, which will result in giving zero-valued correlation between the noise and metric.

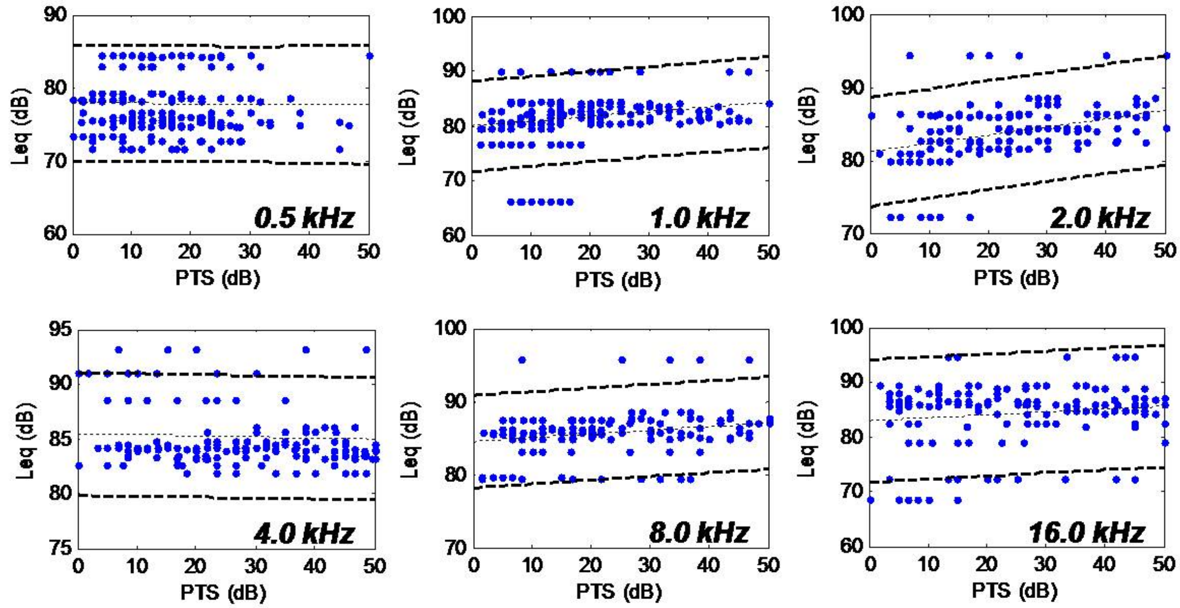

Figure 20. PTS-L_{eq} scatter plots at six frequencies

To correct this problem, the chinchilla noise exposure test data conducted with noises of lower levels was added to expand the range of the data. Table 5 shows the information of the additional test data, which was obtained from 61 chinchillas exposed to 5 different noises of 90 and 95-dBA. The data sets were added to the original data from 18 animal groups shown in Table 1. The expanded data is composed of a total of 275 chinchillas exposed to 23 different noises. This expanded data set was used for the rest of the study.

Fig. 19 compares the *noise correlations* calculated at 6 frequencies using the initial data set composed of 18 noise groups and from the expanded data set composed of 6 noise groups. The comparison shows significant improvement of the *noise correlations*, especially at 0.5 KHz and 4 KHz. This suggests that the frequency-by-frequency risk assessment of the noise, which this proposed research aims, has a good possibility of success.

The scatter plots of the PTS-L_{em2} for all frequency points of the original and expanded datasets are shown in Fig. 21(a) and (b). The plot of the original set in Fig. 21 (a) is composed of 108 points (18 groups x 6 frequencies), while the plot of the expanded set in Fig. 21 (b) is composed of 138 points (23 groups x 6 frequencies). Comparison of the figures shows substantial improvement of the *overall correlation*. The actual value of the overall correlation improved from 0.525 (original data) to 0.680 (expanded data), which is a quite good correlation considering wide subject-to-subject variations of the data observed often animal test data (Cody et al., 1983).

Noise	No. of chinchillas	Time Kertosis	SPL (dBA)
G-47	12	3	90
G-48	11	32	90
G-56	11	35	90
G-57	15	3	95
G-58	12	41	95

Table 5. Additional Exposure Test Data Measured with Lower Exposure Levels

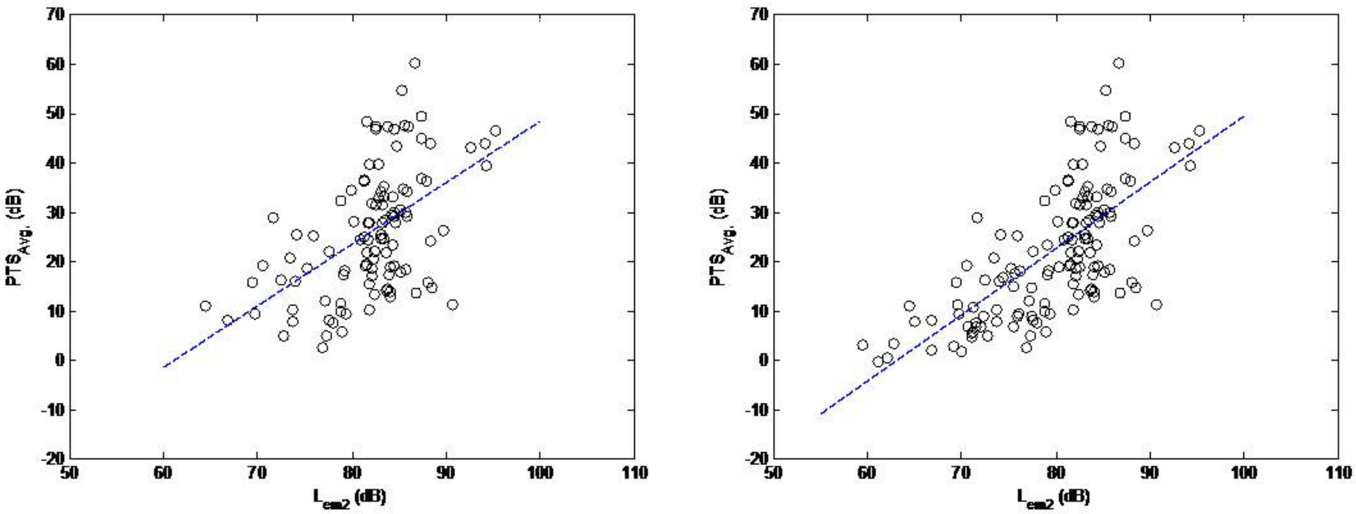

Figure 21. PTS-L_{em2} scatter plots used to calculate the overall correlation of L_{em2}: (a) plot of the initial data (214 chinchillas of 18 groups), (b) plot of the expanded data set (275 chinchillas of 23 groups)

III. Design of Future NIHL Study and Test Protocol

The proposed research is a part of the long-term effort of the PI to develop an improved NIHL risk assessment procedure for human. The long-term research plan composed of four stages is briefly explained in the following. The stages (1) and (2) were completed during this project. The stages (3) and (4) are future researches.

(1) Preliminary Research to Develop Basic Signal Analysis and Simulation Techniques

In preparation for the long-term research program, basic analysis and simulation tools to be used in the risk assessment procedure were developed. The AWT, a special version of the wavelet transform, was developed as the basic signal analysis tool to characterize the noise [28-30]. An auditory system simulation model of human was developed based on the AHAAH model. The model will be modified to a chinchilla model in the proposed research. A transfer function based method was developed to calculate the stapes displacement in response to the given noise by using measured transfer functions. The method can be applied to chinchilla, human, guinea pig and cat. See Section C, *Preliminary Studies*, for more details.

(2) Development of the General Noise Metric for Chinchillas

This stage of the research was conducted as the NIOSH R-21 project that is being reported. Fourteen metrics were designed to reflect effects of temporal and spectral changes of the noise in uniquely different ways. The noise metric best correlated with PTS of chinchillas induced by diversely different types of noise was identified based on the correlation study. The metric enables more accurate representation of the risk of highly transient noises such as an impulsive noise as well as steady, broadband noises.

(3) Development of the General Noise Risk Assessment Procedure for Chinchillas:

In this stage, a chinchilla version of the general noise risk assessment procedure will be developed as a prototype of the human version procedure to be developed in the future. The general noise metric developed in the previous research and a new concept called the equal auditory risk metric (EARM) curves will be the core concepts of the procedure. The procedure will be validated by using a set of chinchilla noise exposure data that was not used for the development of the procedure. Utilizing the experience gained through the development of the procedure during this research, a detailed research plan will be made for the development of the risk assessment procedure for human.

(4) Development of the Human Version of the Risk Assessment Procedure

As the final goal of the long-term plan, the human version of the NIHL risk assessment procedure will be developed and validated. The procedure will contribute to improving occupational health of workers in the United States as well as other nations by enabling more accurate assessment of the risk of industrial noises including impulsive and complex noises.

Results and Discussion

A special version of the AWT developed in this research is an ideal signal analysis tool that can be applied to the development of the noise metric. The AWT will be used as a part of the noise guideline in the future. The signal analysis method developed in this work can be used as a basic tool for the noise exposure research and noise risk analysis methods.

Fourteen different designs of noise metrics were studied to identify a more general form of noise metric that be used to for more accurate assessment a of risks of impulsive or complex noises. The metrics were designed so that they reflect time-frequency characteristics of the noise in uniquely different ways. The 14 noise metrics were evaluated initially based on their correlations with an existing animal noise exposure study data obtained from 18 groups of chinchillas exposed to respectively different types of noise of 100-dBA.

Noise metrics were calculated with and without using A-weighting, resulting in un-weighted and A-weighted noise metrics. It was seen that un-weighted noise metrics showed generally better correlations with PTS data than A-weighted metrics. This contradicts with the current practice of using the A-weighted SPL as the metric.

Three types of correlations of the noise metrics were calculated, which are frequency correlation, noise correlation and the overall correlation. When no frequency weighting is used, $\overline{T}_w(\omega)$ and $L_{eq}(\omega)$ were identified as the metrics that showed best correlations with measured PTS across frequencies. All modified equivalent SPLs, $L_{em}(\omega)$, $\alpha = 2, 3, 4$, 5 and 10 showed nearly as good frequency correlations. Two modified equivalent SPL, $L_{em}(\omega), \alpha = 4$ and 5 showed best noise correlations. For the overall correlations, $L_{em}(\omega), \alpha = 2$ and 3 were identified as the best metrics, which had correlation values of 0.503 and 0.502. The traditional metric $L_{eq}(\omega)$ calculated as a function of frequency also showed relatively a good overall correlation value of 0.488.

It was found that all noise metrics have very poor noise correlations at 0.5 KHz and 4 KHz. Inspecting the L_{eq} - PTS relationship, it was found that the range of the noise level the 18 noises used in the original exposure data was too narrow at those two frequencies. To correct the problem, additional test data obtained from 61 chinchillas exposed to 5 different noises of 90 and 95-dBA was added to expand the data set. Correlation study was conducted by statistically comparing the metric values calculated from the noise and the PTS measured in the chinchillas exposed to the noise. The overall and noise correlations showed substantial improvement. For example, the overall correlation of L_{em2}

improved from 0.525 (original data) to 0.680 (expanded data),

Based on the correlation study, metric $L_{em}(\omega)$ with $\alpha = 2$ calculated from un-weighted SPL time histories is considered as the best metric to assess risk of a wide range of noises including impulsive and complex noise. An additional advantage of L_{em2} is that it can be interpreted the same way as the traditional metric L_{eq} if the SPL of the noise is sufficiently high, as in most cases in that NIHL is concerned.

Conclusion

A special type analytic wavelet transform (AWT) developed for transient signal analysis of noises and an improved noise metric identified for the future noise guidelines are two major contributions of this research.

The AWT, a special type of the wavelet transform, has not been widely used despite its many advantages. We developed a special version of the AWT that is ideal for *transient noise signal* analysis. The method will serve as the signal analysis tool to assess the exposure risk to general type of noises.

By utilizing the unique capability of the AWT, fourteen designs of advanced forms of noise metrics were developed and compared. The noise metrics were calculated from the 1/3 octave SPL time histories obtained with AWT, therefore are functions of time and frequency. Correlation study conducted utilizing the PTS data measured from chinchillas exposed to a total of 21 different noises identified metric L_{em2} as the best noise metric.

L_{em2} is a metric defined by modifying L_{eq} to account for the noise only when its instantaneous SPL exceeds the given threshold value.

Development of an improved noise guideline is the future research that can be extended from this work. The signal processing method and the noise metric developed and identified in this research will serve as the basis of the new noise guideline to be developed in the future.

References

*Ahroon, W. A., Hamernik, R. P., & Davis, R. I. (1993). Complex noise exposures: An energy analysis. *The Journal of the Acoustical Society of America*, *93*(2), 997-1006.

*ANSI S3.38-1986. *Draft american national standard – method of the evaluation of the potential effect on human hearing of sounds with peak A-weighted sound levels above 120 decibels and peak C-weighted sound pressure levels below 140 decibels*

*Blakeslee, E. A., Hynson, K., Hamernik, R. P., & Henderson, D. (1977). Interaction of spectrally-mismatched continuous and impulse-noise exposures in the chinchilla. *The Journal of the Acoustical Society of America*, *61*, S59.

*Cody, A. R and Robertson, D. (1983). “Variability of noise-induced damage in the guinea pig cochlea: electrophysiological and morphological correlates after strictly controlled exposures,” Hearing Research, 9, 55-70.

*Daubechies, I. (1992). *Ten lectures on wavelets*. Philadelphia: SIAM.

*Davis, R.I., Ahroon, W.A. and Hamernik, R.P. (1989). “The relation among hearing loss, sensory cell loss and tuning characteristics in the chinchilla,” Hearing Research, 41, 1-14.

*Dunn, D. E., Davis, R. R., Merry, C. J., & Franks, J. R. (1991). Hearing loss in the chinchilla from impact and continuous noise exposure. *The Journal of the Acoustical*

Society of America, *90*(4 Pt 1), 1979-1985.

*Grossmann, A., & Morlet, J. (1984). Decomposition of hardy functions into square integrable wavelets of constant shape. *SIAM Journal on Mathematical Analysis, 15,* 723-736.

*Hamernik, R. P., Ahroon, W. A., Henderson, D., & Salvi, R. J. (1987). The interaction between continuous and impulse noise: Frequency effects. *The 2Nd International Conference on the Combined Effects of Environmental Factors*, Koyei, Kanazawa, Japan. 1-20.

*Hamernik, R. P., Ahroon, W. A., & Hsueh, K. D. (1991). The energy spectrum of an impulse: Its relation to hearing loss. *The Journal of the Acoustical Society of America, 90*(1), 197-204.

*Hamernik, R. P., Ahroon, W. A., Hsueh, K. D., Lei, S. F., & Davis, R. I. (1993). Audiometric and histological differences between the effects of continuous and impulsive noise exposures. *The Journal of the Acoustical Society of America, 93*(4 Pt 1), 2088-2095.

*Hamernik, R. P., Ahroon, W. A., Patterson, J. H.,Jr, & Qiu, W. (2002). Relations among early postexposure noise-induced threshold shifts and permanent threshold shifts in the chinchilla. *The Journal of the Acoustical Society of America*, *111*(1 Pt 1), 320-326.

*Hamernik, R. P., Henderson, D., Crossley, J. J., & Salvi, R. J. (1974). Interaction of continuous and impulse noise: Audiometric and histological effects. *The Journal of* *the Acoustical Society of America, 55*(1), 117-121.

Hamernik, R. P., & Hsueh, K. D. (1991). Impulse noise: Some definitions, physical acoustics and other considerations. *The Journal of the Acoustical Society of America, 90*(1), 189-196.

Hamernik, R. P., & Qiu, W. (2000). Correlations among evoked potential thresholds, distortion product otoacoustic emissions and hair cell loss following various noise exposures in the chinchilla. *Hearing Research, 150*(1-2), 245-257.

*Hamernik, R. P., & Qiu, W. (2001). Energy-independent factors influencing noise-induced hearing loss in the chinchilla model. *The Journal of the Acoustical Society of America, 110*(6), 3163-3168.

*Hamernik, R. P., Qiu, W., & Davis, B. (2003). The effects of the amplitude distribution of equal energy exposures on noise-induced hearing loss: The kurtosis metric. *The Journal of the Acoustical Society of America, 114*(1), 386-395.

*Hunt, W. J., Hamernik, R. P., & Henderson, D. (1976). The effects of impulse level on the interaction between impulse and continuous noise. *Trans. Am. Acad., 82*, 205-308.

*ISO-1999 (Ed.). (1990). *Acoustics – determination of occupational noise exposure and estimation of noise-induced hearing impairment* (2nd ed.). Geneva, Switzerland: Reference No. ISO 1999:

Kim, J., Welcome, D. E., Dong, R. G., Joon Song, W., & Hayden, C. (2007). Time–

frequency characterization of hand-transmitted, impulsive vibrations using analytic wavelet transform. *Journal of Sound and Vibration, 308*(1-2), 98-111.

*Martin, A. M. (1975). The equal energy concept applied to impulse noise. *Unknown,*

*Nilsson, R., Dunn, D. E., Erlandsson, B., Brenner, J., Hakanson, H., Ivarson, A., et al. (1983). Conclusions from animal experiments on the effects of steady-state and impulse noise. *Of the Fourth Internatinal Congress,* Milano, Italy. 159-170.

*NIOSH. (1996). *Preventing occupational hearing loss – a practical guide, cincinnati, OH: U.S. department of health and human service*Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH) Publication No. 95-105.

*Passcheir-Vermeer, W. (1983). Measurement and rating of impulse noise in relation to noise-induced hearing loss, in *noise as a public health problem*. Proc. of the Fourth International Congress, Milano Italy. 143-157.

*Patterson, J. H.,Jr. (1991). Effects of peak pressure and energy of impulses. *The Journal of the Acoustical Society of America, 90*(1), 205-208.

*Roberto, M., Hamernik, R. P., Salvi, R. J., Henderson, D., & Milone, R. (1985). Impact noise and the equal energy hypothesis. *The Journal of the Acoustical Society of America, 77*(4), 1514-1520.

*Starck, J., & Pekkarinen, J. (1987). Industrial impulse noise: Crest factor as an additional parameter in exposure evaluation. *Appl.Acoust, 20*, 263-274.

*Starck, J., Toppila, E., & Pyykko, I. (2003). Impulse noise and risk criteria. *Noise & Health, 5*(20), 63-73.

*Taylor, W., Lampert, B., Pelmear, P., Hemstock, I. and Kershaw, J. (1984). "Noise levels and hearing thresholds in the drop forging industry," J. of Acoustic Society of America 76(3): 807-819.

*Thiery, L., & Meyer-Bisch, C. (1988). Hearing loss due to partially impulsive industrial noise exposure at level between 87 and 90 dB(A). *J. of Acoust. Soc. Am., 84*, 651-659.

*Voigt, P., Godenhielm, B., & Ostlund, E. (1980). Impulse noise - measurement and assessment of the risk of noise induced hearing loss. *Scandinavian Audiology.Supplementum, (Suppl 12)*(Suppl 12), 319-325.

*Zhu, X., & Kim, J. (2005). Application of the analytic wavelet transform to time-frequency analysis of highly impulsive sound signals. *2005 SAE Noise and Vibration Conference*, Traverse City, MI.

*Zhu, X., & Kim, J. (2006). Application of analytic wavelet transform to analysis of highly impulsive noises. *Journal of Sound and Vibration, 294*(4-5), 841-855.

Publications Resulted from the Research

Journal Publication

Zhu, X., Kim, J., Song, S.H., Murphy, W., "Development of a Noise Metric for Assessment of Exposure Risk to Impulsive and Complex Noises," Accepted by J. of Acoustic Society of America[1]

Conference Proceeding Papers

Song, W., Kim, J., "Comparative Study on the Response of Human Middle Ear Models," Noise-Con 2008, July 2008, Dearborn, MI.[2]

Zhu, X., Kim, J., "Application of Analytic Wavelet Transform to Transient Signal Analyses", 2007 SAE Noise and Vibration Conference, St. Charles, IL, May 2007, Paper No. 2007-01-2321.[2]

Murphy, W., Zhu, X., Kim, J., "Study of the Effect of Hearing Protectors for Military Noises based on Time-Frequency Analysis by Analytic Wavelet Transform," 2006 Internoise, Honolulu, Hawaii, December 2006.[2]

Ph.D. Dissertation

Xiangdong Zhu, "Development and Application of Analytic Wavelet Transform Technique with Special Attention to Risk Assessment of Impulsive Noises", May 2008[1,2]

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[1] Specific Aim 2. Development of the Noise Metric

[2] Specific Aim 1. Development of the Analytic Wavelet Transform