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Enhancements for Loose Particle Detection in Loudspeakers

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ABSTRACT

During loudspeaker production, particles may become trapped in the loudspeaker motor and voice coil vicinity, resulting in a distinctive defect that is easily heard, but difficult to detect by traditional test and measurements.

We found that a Sine Sweep Stimulus followed by a High Pass Filter and RMS Envelope Analysis efficiently detected Loose Particles and Rub & Buzz defects.

The remaining problem is how to reduce the effect of background noise, and get more reliable results. Statistical descriptors such as Crest Factor, Skewness, and Kurtosis are first investigated. Experimental results are given and the different tools are compared.

New enhancements are described that increase effectively the overall immunity to background noise and discrimination of the method.

1. INTRODUCTION

During loudspeaker production, particles may become trapped in the loudspeaker motor and voice coil vicinity, resulting in a distinctive defect that is easily heard, but difficult to detect by traditional test and measurements.

As described in our previous paper [1] we found that a Sine Sweep Stimulus followed by a High Pass Filter and RMS Envelope Analysis reliably detected Loose Particles and Rub & Buzz defects.

The Loose Particles (LP) algorithm is simple and efficient but has a drawback. In the presence of ambient noise, especially impulsive noise, false loose particles are counted that may end in a false reject for a good loudspeaker.

The challenge is to improve both the robustness against noise and also the reliability of the method.

Ideally, the algorithm should yield a value of zero for good speakers and an increasing value for an increasing number of loose particles, regardless of the background noise.

2. SUMMARY OF THE PROBLEM

2.1. Time-Frequency Analysis

In the recorded sound wave of a defective loudspeaker with loose particles, the fault appears as impulsive noises riding on the stimulus wave [Figure 1].

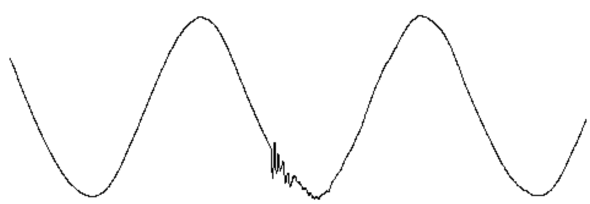

Figure 1: Detail of recorded time signal of a loudspeaker with a "Loose Particle" defect

Each of these impulses is produced when a loose particle hits the dust cap or voice coil component of the loudspeaker.

The loose particle hits appear at a low excitation frequency when the displacement of the diaphragm is large.

Regardless of the excitation frequency, these impulses occur at random times.

In a speaker with no loose particle fault [Figure 2], the time-frequency map shows only the stimulus signal and a few additional harmonics.

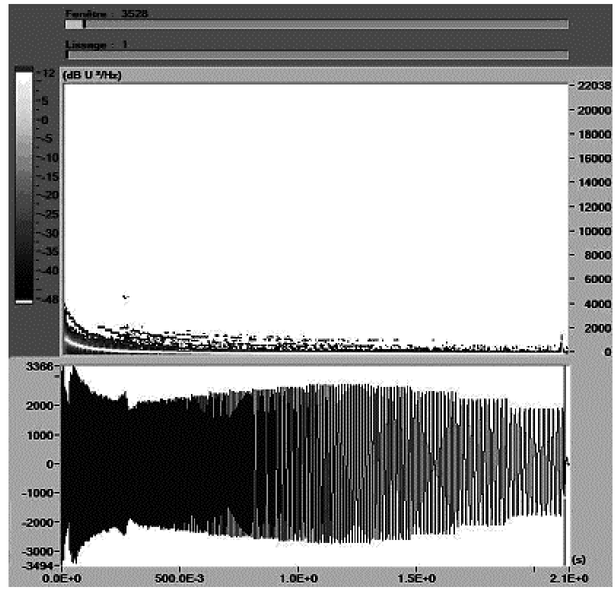

Figure 2: Good Speaker

In a speaker with an obvious loose particle fault, the loose particles hit randomly in time, and appear as short-time transients with a wide spectrum [Figure 3].

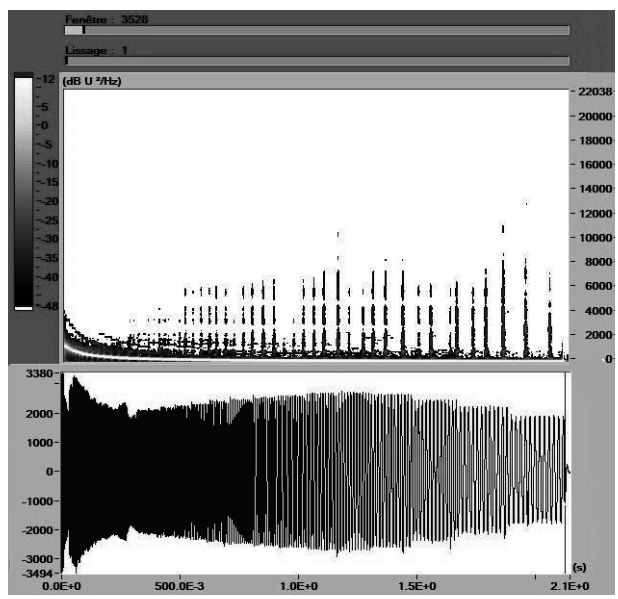

Figure 3: Loose Particles

Note: the two figures above are obtained by Short Term Fourier Transform (STFT) with the same window settings. The X Axis is a time scale, the Y Axis is a linear frequency scale, and the Z Axis is the Energy

Spectrum Density in dB as a grayscale (60 dB dynamic).

2.2. Current LP Algorithm

In the current method as described in our previous paper [1], a swept-sine at low frequency (typically around and below the resonant frequency) is used as a stimulus to excite the loose particles and reveal the defect. The purpose of the LP algorithm is to detect wide-band impulses added to a low frequency sine.

The current LP algorithm is in three steps:

1. High-pass filtering
2. RMS Envelope Calculus
3. Threshold Detection and Peak Count

High-pass filtering

A high-pass filter removes the sine stimulus signal so that only the impulses remain. The frequency cut-off is set to the maximum frequency of the swept-sine. The filter used is a 4^{th} order Bessel recursive filter.

RMS Envelope Calculus

After filtering, the residual LP signal remains. In order to detect the peaks of acoustic energy due to the loose particles, the RMS envelope of the signal is then calculated.

A running RMS integration is used and follows the steps:

1. Square the filtered signal to get instantaneous power
2. Obtain the power envelope by an exponential running average
3. Square root the power envelope to get the RMS envelope

Threshold Detection and Peak Count

The final step of the LP algorithm is the detection of valid peaks in the envelope. The valid peaks are those that exceed a certain threshold for a minimum duration. Both threshold and minimum duration are essential to discriminate the LP impulses against the background noise.

The peaks are then counted and used as an indicator of the severity of the LP defect.

2.3. Results

The SoundCheck™ measurement system was used to apply the Loose Particle Detection Method to the following loudspeakers:

- Good woofer
- Woofer with loose particles (borderline case)
- Woofer with loose particles (obvious case)

For each of these, the following are shown:

- A graph with the envelope of the filtered time signal and the threshold of detection
- The number of loose particles impacts detected (#LP)

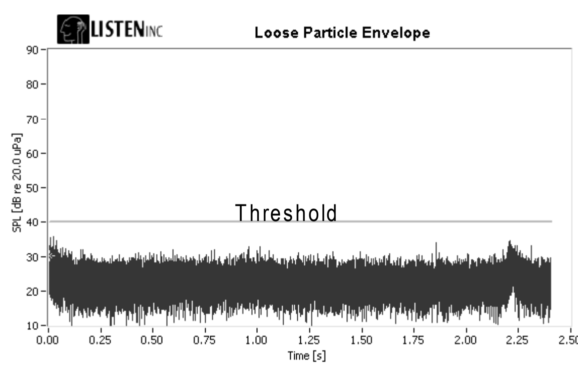

Figure 4: Good Woofer. #LP: 0

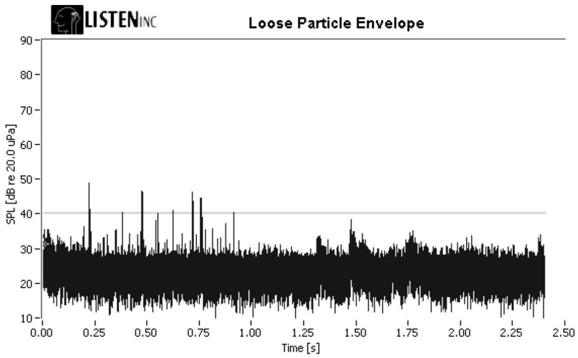

Figure 5: Borderline Case. #LP: 8.

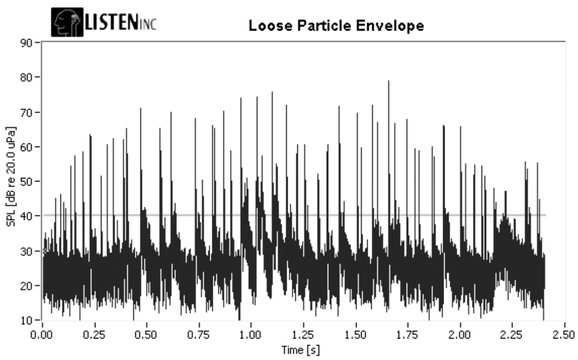

Figure 6: Obvious case. #LP: 290

2.4. Limitations to Overcome

In a quiet environment such as an anechoic chamber or even in the presence of stationary noise, this method gives good and reliable results. In addition, this method is very sensitive; even barely audible defects are detected.

However in a factory or production facility, there is likely to be impulsive background noises from air compressors or other factory equipment. This may cause false detection of loose. Figure 7shows the time envelope of a good speaker contaminated by a handclap, and a similar speaker with loose-particles.

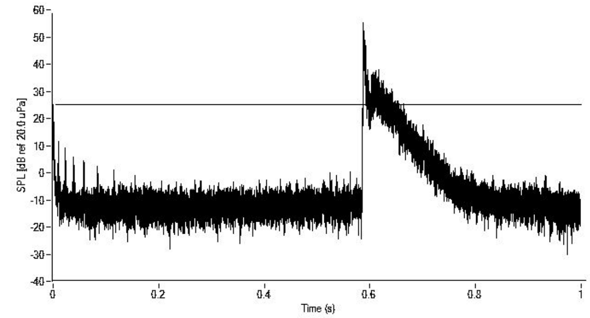

Figure 7: Good Speaker with Handclap on. #LP: 62

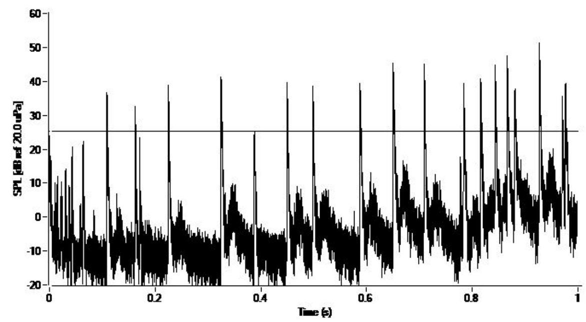

Figure 8: Speaker with Loose-particles. #LP: 48

This demonstrates that the current LP algorithm detects more loose particles in a simple handclap than in the bad speaker. The threshold (horizontal black line at 25 dB) is crossed 62 times by the handclap impulse because of the noise superimposed.

The LP algorithm alone does not discriminate enough against transient noise.

3. ENHANCEMENTS

3.1. Theory of Statistical Descriptors

One possible enhancement of the LP algorithm is the use of statistical analysis to measure the spikiness of the LP signal.

These techniques are used in faulty bearing detection, which is a similar problem to loose particles [1].

Mean and Median

Let’s define first the basics.

Let's consider a record **X** of N samples of the signal x:

X = $[x_0, x_1, \ldots, x_{N-1}]$

For that record, the **Mean** is defined by:

$$\mu_x = \bar{x} = \frac{1}{N}\sum_{i=0}^{N-1} x_i$$

The **Median** of **X** is the value x_M, which is exceeded by half of the samples x_i. M is an index between 0 and N-1.

The median can be different from the mean. For a Gaussian distribution of the samples, the median and the mean are identical.

RMS and Crest-factor

The **RMS** value is defined by:

$$\mathrm{RMS_x} = \sqrt{\overline{\mathrm{x}^2}}$$

The square of the RMS level is homogeneous to the power of the signal x (for a given impedance).

The RMS is different from the standard deviation, which is:

$$\sigma_x = \sqrt{\overline{x^2} - \bar{x}^2} = \sqrt{RMS_x^2 - \mu_x^2}$$

For an acoustical signal, the mean μ_x is null and the standard deviation is equal to the RMS level.

The **Crest-Factor** is defined by:

$$C_x = \frac{Max(|x|)}{RMS_X}$$

It is the simplest and most intuitive measure of spikiness. A spike that has a high maximum value compared to his RMS level, has a high crest-factor .

For a sine the crest-factor is √2 and for a Gaussian noise it is about 5.

Skewness

The Skewness of the record **X** is given by**:**

$$S_x = \frac{\overline{(x-\bar{x})^3}}{\sigma_x^3}$$

The Skewness measures the asymmetry of the histogram of **X** values.

The histogram in Figure 9 skews toward the right; the higher values are more frequent than the lower values, therefore the Skewness is positive.

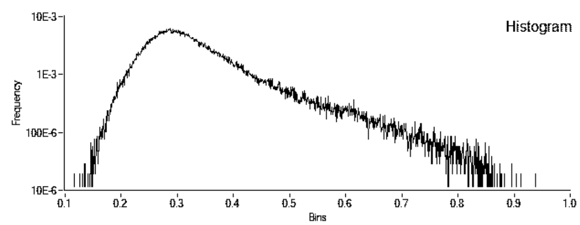

Figure 9: Skewness = 1.8

For a Gaussian noise [Figure 10], the Skewness is null, because the histogram is symmetric.

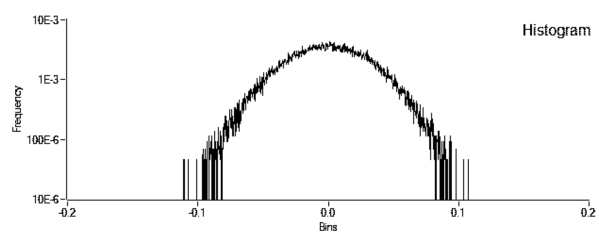

Figure 10: Skewness = 0

Kurtosis

The Kurtosis of the record **X** is given by**:**

$$K_x = \frac{\overline{(x-\bar{x})^4}}{\sigma_x^4}$$

K_x gives a measure of the spread of the histogram. Because of the even power present in the formulae, extreme amplitudes (both high and low) are heavily weighted.

For Gaussian noise as in Figure 10, the Kurtosis is equal to 3.

For a signal full of spikes, such as Figure 11, the Kurtosis is much higher.

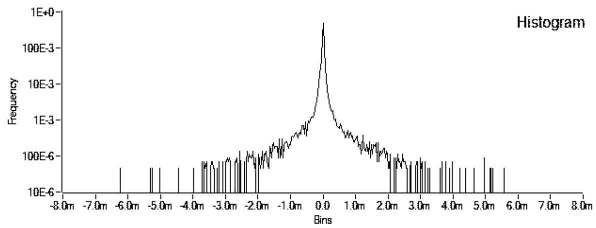

Figure 11: Kurtosis = 297

Kurtosis is also a popular tool for faulty bearing detection in the machine industry.

Note

Crest-factor, Skewness, and Kurtosis are shape factors that qualify the shape of the histogram of a record, regardless of the amplitude or power of the signal.

3.2. Experimental Results

The statistical descriptors, Crest-factor, Skewness, and Kurtosis were applied to different speaker records. The speakers are in 5 groups of increasing defect severity:

- Good: no audible LP defects
- Borderline LP: barely audible LP defects
- LP: fair amount of LP defects
- R&B: rub & Buzz defect
- R&B+LP: Rub & Buzz + LP defects

We also include two records with handclap to test the case of impulsive background noise (“Good+Clap”, “LP+Clap”). The speakers are all similar woofers.

The statistics are applied first on the time envelopes issued from the actual LP algorithm. The results are given in Figure 12.

The same tools are also applied directly to the raw LP signal for comparison. The results are given in Figure 13.

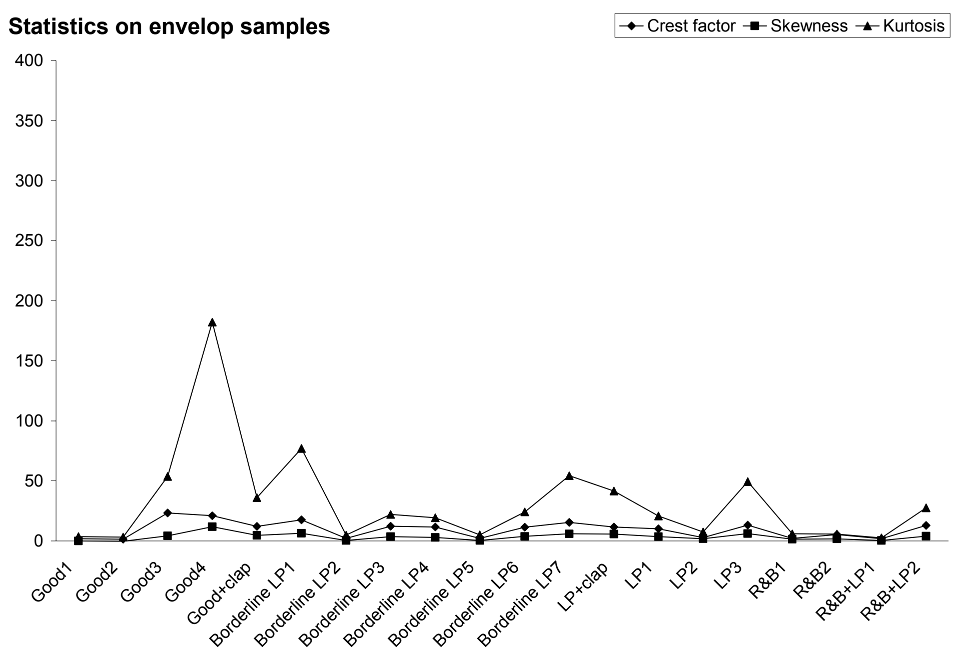

Figure 12: Statistics applied to envelop samples

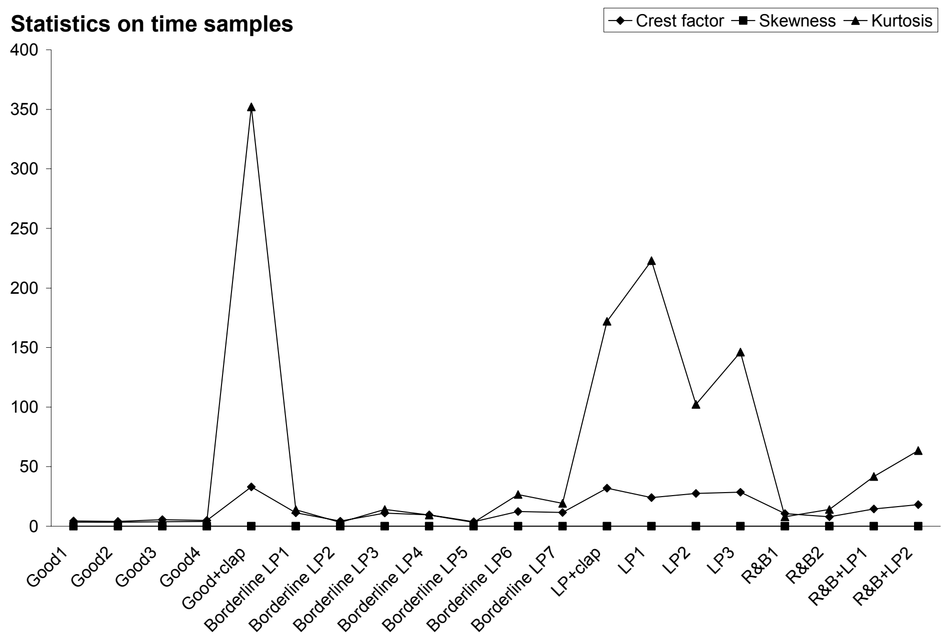

Figure 13: Statistics applied to time samples

3.3. Comparison of Statistical Descriptors

First of all Kurtosis is the most sensitive to spikiness.

For envelope analysis, the results are bad for all of the descriptors: good and borderline speakers get higher values than bad speakers.

When applied directly to the time signal, Kurtosis yields satisfactory results (except the particular case of "good + clap". Kurtosis is a good indicator of LP defect. Crest Factor could be a second choice. Skewness is almost null for all time signals because their histograms are symmetrical around 0.

Nevertheless a major drawback remains, as shown by the "good + clap" record: these tools are too sensitive to impulsive background noise. One single handclap yields higher figures than numerous LP or R&B spikes. The main problem is that these methods doe not detect and count events.

This inherent susceptibility to transient background noise makes these tools not suitable for process control in a factory environment.

3.4. Description of New LP Algorithm

The previous results confirm that our first approach based on event detection and counting was likely to yield better results. Consequently we decided to try and refine our current LP algorithm. Returning to Figure 7, the LP analysis of the handclap counts 62 LP. Because it is a handclap the event should not even be counted once.

To improve robustness against noise, the following enhancements are introduced.

FFT-Filtering

First of all, the stimulus sine has to be filtered out and the envelope of the residual signal obtained.

In the spectral domain, it is easier to set the stimulus to zero, which occurs at low frequencies in the spectrum. At the same time, by zeroing out the negative frequencies and taking the inverse FFT, we get the envelope of the time signal to analyze. This achieves a complete cancellation of the stimulus compared to attenuation that occurs with a recursive filter. A better envelope of the LP signal is obtained than with RMS detection. More specifically, the analytical equivalent of a damped sine impulse, as a LP tick, is a damped exponential impulse. When that pulse is converted to dB, the damped part becomes a straight line. (Figure 15)

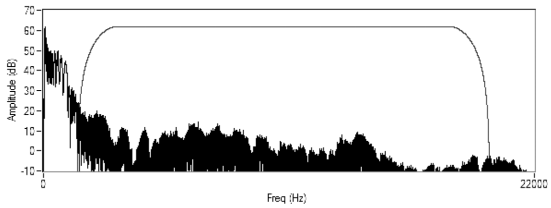

Figure 14: Spectrum of LP Speaker response + filter window

The complete FFT-filter algorithm is:

1. Make the FFT of X,

2. Apply a window to remove the stimulus and the negative frequencies ,

3. Take the inverse FFT to get the analytical time signal Y,

4. Calculate the magnitude of Y

|Y| is the envelope of the high-pass residual defect signal.

Nowadays, FFT algorithms no longer depend on a power of two and are much faster. Although an FFT may be slower than recursive filtering, the calculus time involved is short enough for post-processing purposes (typically one tenth of a second for a one second record).

dB-Median Filter

The detection algorithm will benefit from a smooth energy envelop of the LP signal.

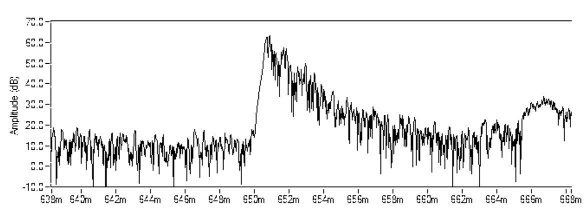

Figure 15: LP pulse

On a dB scale a LP pulse looks like a saw tooth (see Figure 15). This is due to the fact that the impulse response of the speaker and its dust cap are roughly a damped sine.

The ideal way to ensure a clean detection is to smooth out the noise without altering the shape of the LP pulses. A traditional filter is not able to achieve this.

A non-linear filter such as a running median has interesting properties. The principle of the filter is to yield the median amplitude of a running block on the signal **X**:

y_i= Median[x_{i-r}, x_{i-r+1},…, x_i,…, x_{i+r-1}, x_{i-r}],
with 2r+1 ≡ “Averaging” Time

The median filter preserves the attack edge, the release slope, and the duration of the pulse. In the figure below we see the result of the median filter on the pulse of the previous figure.

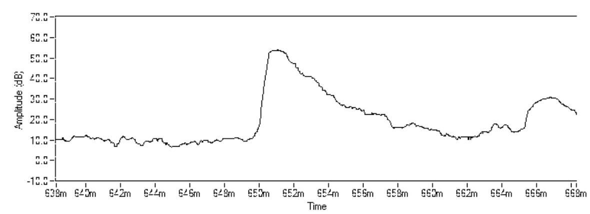

Figure 16: Smoothed LP Pulse

These properties make the dB-Median filter valuable for peak detection.

Hysteresis Threshold Detection

To diminish the number of false events a hysteresis is added to the trigger logic. To be counted, a pulse must exceed the attack threshold and also go under a release threshold of a lesser value. The difference between the attack and release threshold is the hysteresis of the trigger (see Fig. 17).

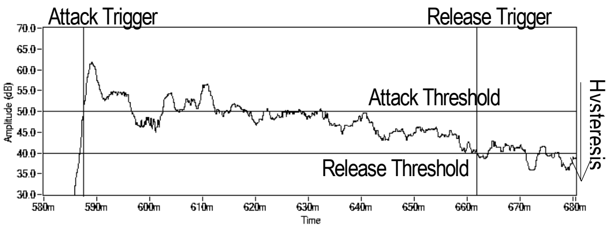

Figure 17: Threshold with Hysteresis

As one can easily see, when the hysteresis is set larger than the noise, only one pulse is detected.

Discrimination on duration

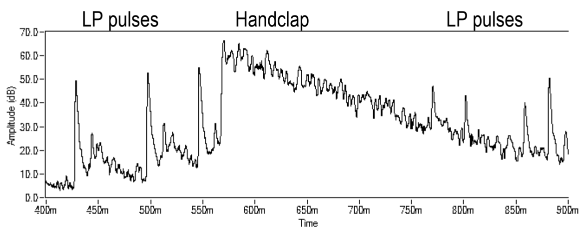

Figure 18: Loose Particles + Hand-Clap

In the figure above we see a handclap mixed with LP pulses. The duration of the handclap is obviously much longer than for the LP pulses. Therefore, another enhancement to the detection algorithm is made on the duration of the pulse detected: the duration has to be within a certain range to be counted. The pulses are discarded if they are either too short or too long. That way the range can be set to fit the duration of the LP pulses (e.g. between 4 and 40 ms), the handclap is ignored because its duration is greater than 200 ms.

New LP Algorithm

Therefore the new LP Algorithm is:

1. FFT filtering to get the envelope of the LP signal.

2. dB-median smoothing of the LP signal

3. Threshold detection of pulses with hysteresis and pulse duration selectivity.

4. Count of the detected pulses.

3.5. Comparison with the Previous LP Algorithm

To compare them effectively the two algorithms have been applied on the same set of woofer samples for statistics.

The number of LP detected for each record is given in the two following graphs.

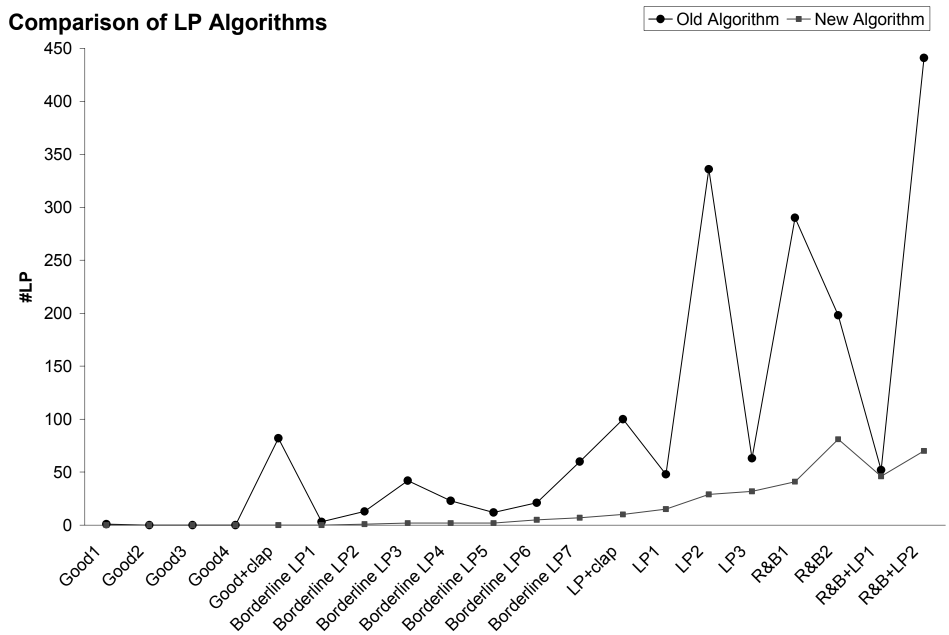

Figure 19: #LP detected with old & new algorithm

Note: to ease comparison, the X-axis is the same for Figure 12, Figure 13, Figure 19.

First, the overall number of peaks detected is much smaller with the new algorithm due to the better selectivity of the new method. In fact with the old method, each peak yields several detections because of noise. This is can clearly be seen in Figure 8. This sensitivity to noise explains why certain LP records yield more counts than R&B cases. R&B should give the higher results because there is a click for each stimulus period.

Then for the old algorithm there is the “good + clap” case (Figure 7): the amount of LP detected puts it in the range of fair LP cases. It is a good example of false detection due to impulsive background noise.

With the new algorithm the “good + clap” is measured as zero counts along with the other good speakers (Figure 19). The number of LP counts increases logically as the severity of the defect increases (good, borderline, LP and R&B).

This demonstrates that the new algorithm offers a significant improvement over the earlier technique for loose particle detection in noisy environments.

4. FURTHER DEVELOPMENTS

Based on this work, and our previous paper [1], some potential enhancements may be pursued in the following directions:

- Tracking notch filter, or model-based methods to obtain a more complete LP signal and increase the S/N of the analysis
- Matching filter or pattern recognition to detect the LP peaks with more discrimination.
- As mentioned before [1], psychoacoustic filters to detect peaks as humans would perceive it

5. CONCLUSION

To improve our LP algorithm we tried global statistical descriptors to get a measure of spikiness. Crest-factor, skewness, and kurtosis were used. We established that kurtosis worked best. In a quiet environment kurtosis proved to be straightforward and reliable to detect and quantify Loose Particles defects.

When faced with impulsive noise, kurtosis and others statistical indicators lead to false detection. Even one single handclap gives a higher kurtosis than loose particles noise. The main problem is that these methods do not detect and count events.

So that confirmed that our first approach based on event detection and counting, was the better approach.

Our initial algorithm was improved it in 3 ways:

- Complete removal of excitation sine by FFT filtering
- dB-median smoothing of residual signal, that remove noise and oscillation, while preserving the shape of pulses
- Enhanced threshold detection of pulses with hysteresis and pulse duration selectivity.

The new algorithm has been demonstrated to offer significant improvements over earlier methods for the measurement of loose particle and Rub & Buzz defects. It is significantly less sensitive to noise, even impulsive noise. These improvements make it particularly suited for production line speaker testing.

6. REFERENCES

[1] S.Temme, P.Brunet, E. Chakroff, “Loose Particle Detection in Loudspeakers”, Presented at the AES115th Convention, New-York, 2003 October 10–13