Multiple Microphone Miracles: Rejecting Unwanted Data from Your Measurements

Stephen Hambric[1]
Hambric Acoustics, LLC
Asheville, NC USA

Chad Walber
Michigan Technological University

Andrew Taggart
PCB Piezotronics

ABSTRACT

Single microphones may not be able to distinguish a sound source of interest from others in the vicinity, detect a source in windy environments, or measure faint signals which may be below the microphone noise floor. However, adding just a single additional microphone can help resolve all these issues. This paper reviews how ICP microphones work and explains their noise floors. Next, we'll show you how to combine the signals from two or more microphones to tell one source from another, filter unwanted sources (like flow-induced pressures) from data, and reduce noise floors to measure very low signals. We process the signal pairs using cross-spectral analysis to calculate the coherence between the signals. The coherence can help extract a desired signal or reject undesired ones.

1. INTRODUCTION

All integrated circuit piezoelectric (ICP) sensors function the same way. A fluctuating electrical charge is converted into a voltage by a Resistor-Capacitor (RC) circuit. The voltage is then amplified by a transistor before it is transmitted to a Data Acquisition System (DAS). You can learn more about how ICP sensors work, along with their upper and lower limits, in [1]. Figure 1 shows the measured noise floor of an ICP accelerometer, representing the lowest signals you can measure with a single sensor. At very low frequencies, noise floors are dominated by thermal fluctuations which induce false signals. Although these fluctuations can affect vibration measurements, they are lower than the threshold of human hearing (20 Hz). Above 20 Hz the primary source of noise within a sensor is caused by noise within the transistor. The good news is that the resistor and transistor background noise in each sensor are independent of other sensors, meaning that the noise floors from two sensors are *statistically uncorrelated*. We can use this statistical independence to our advantage with coherent signal processing.

[1] hambricacoustics@gmail.com

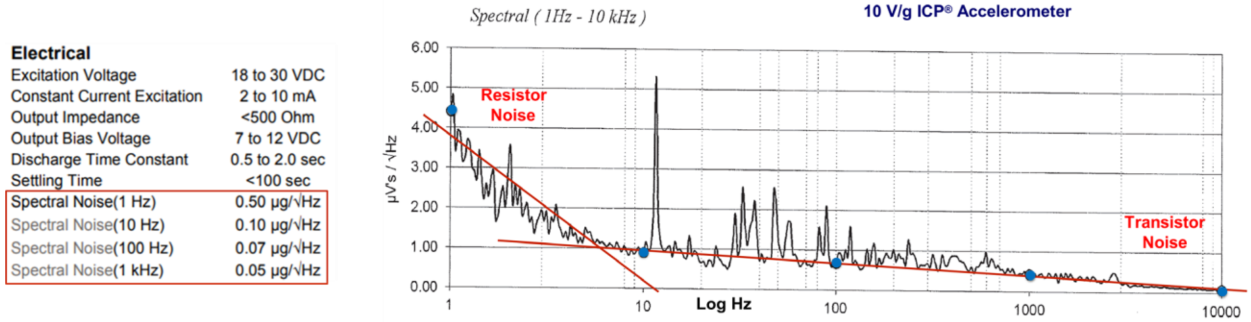

Figure 1: Noise floor of an ICP accelerometer.

2. COHERENT SIGNAL PROCESSING

Coherent signal processing (CSP) is well understood and explained by many authors [see references 2-4, for example]. Let's start with signal processing of one signal where we compute the power spectrum by averaging Fast Fourier Transforms (FFTs) over many short time blocks. This is usually shown as the expected value of the product of the signal X and its complex conjugate for each frequency, averaged over time T :

$$G_{xx}(f) = \lim_{T\to\infty} \frac{2}{T} E\{X^*(f,T)X(f,T)\}. \tag{1}$$

Power spectra are averaged and only appropriate for signals which are reasonably statistically stationary over time. Figure 2 shows an online spectral processing demonstrator on the hambricacoustics.com website. Four seconds of data, comprised of white noise and a single tone, are processed into a Power Spectral Density (PSD). The important processing parameters used here are:

- The Sampling rate (fs): 16,384 Hz
- Window length: 1 second (by specifying four time blocks to subdivide the overall time record)
- Windowing: Rectangular
- Overlap: None

We won't discuss windowing or overlap here, although both are useful in signal processing. In general, using a shorter window length allows you to obtain more averages and thus potentially improve statistical confidence. However, shorter windows mean wider frequency bandwidths, so there is a trade-off between the number of averages and the frequency details you can resolve. For simplicity, this demonstration uses a rectangular window with no overlap.

The statistical theory behind coherent signal processing can be complicated, but in simple terms, if you average the products of the FFTs of two signals X and Y over many time blocks, the underlying uncorrelated signals average to nearly nothing, leaving the correlated signals. The cross-power spectrum is

$$G_{xy}(f) = \lim_{T\to\infty} \frac{2}{T} E\{X^*(f,T)Y(f,T)\}. \tag{2}$$

Note that you can only perform this calculation for data acquired on the same system at the same sampling rate. In some cases, for example when each microphone is corrupted by independent random noise sources (like wind), a simple cross spectrum will give you a reasonable estimate of the spectrum of a sound source. We'll see an example of this later.

Figure 2: Online signal processing demonstrator at hambricacoustics.com. The time history is on the top, and the power spectrum on the bottom.

The coherence between the two signals is the ratio of the square of the amplitude of the cross spectrum and the product of the autospectra of the two signals:

$$\gamma_{xy}^2(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f)G_{yy}(f)}. \tag{3}$$

Coherence ranges from 0 (X and Y are completely uncorrelated) to 1 (X and Y are identical). Here's the good part: you can use the coherence to either extract the correlated portions of the X and Y signals as the Coherent Output Power (COP):

$$COP(f) = \gamma_{xy}^2(f)G_{yy}(f), \tag{4}$$

or remove the correlated signals, resulting in the Incoherent Output Power (IOP):

$$IOP(f) = (1 - \gamma_{xy}^2(f))G_{yy}(f). \tag{5}$$

Here's a simple demonstration: three sinusoidal signals (the desired signal) are corrupted by pink background noise. We used Matlab to synthesize 30 seconds of data for two microphones. Both mics measured the sinusoids, and each heard its own uncorrelated pink noise signal (incoherent between both mics). Figure 3 shows the PSDs of the sinusoidal signal and one of the pink noise signals. Figure 4 shows the coherent and incoherent output powers of the first microphone. The underlying sinusoids are clear, but there is some residual background noise in the coherent signal. This is because the averaging process did not completely eliminate the uncorrelated noise. Repeating the calculation with longer time records provides more averaging and lowers the background noise.

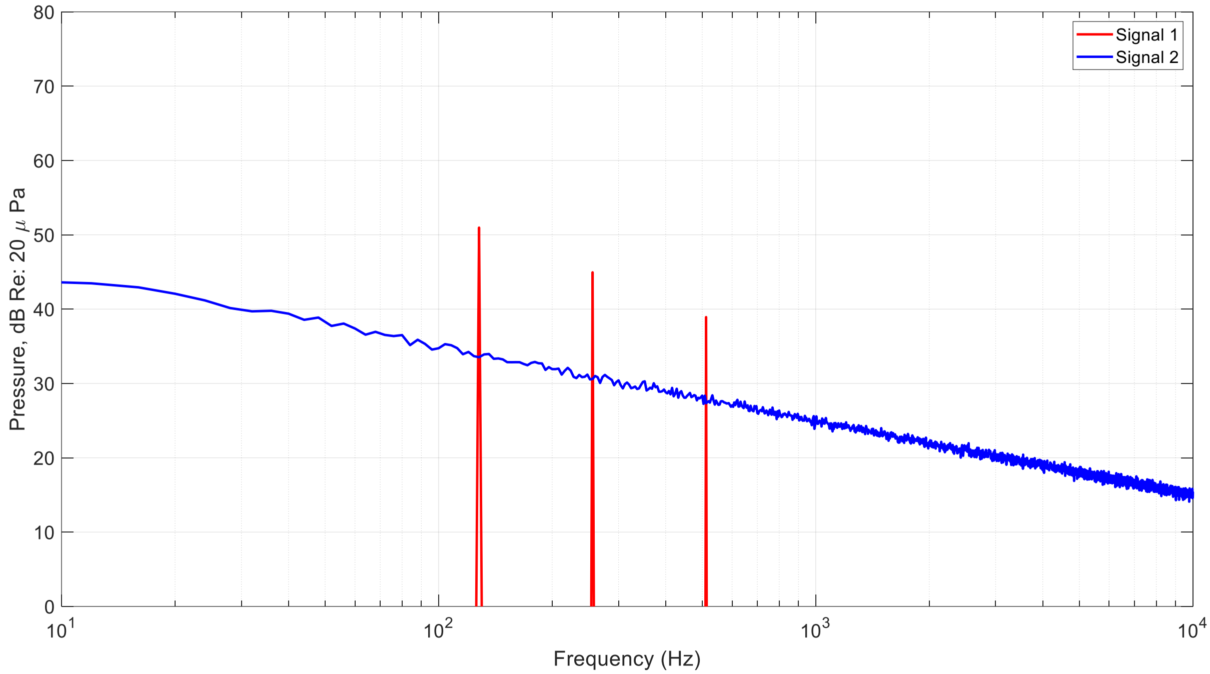

Figure 3: A sinusoidal signal (three sinusoids between 100 and 1000 Hz) in red with pink noise background in blue. The microphones measure the sums of the sinusoids and the pink noise.

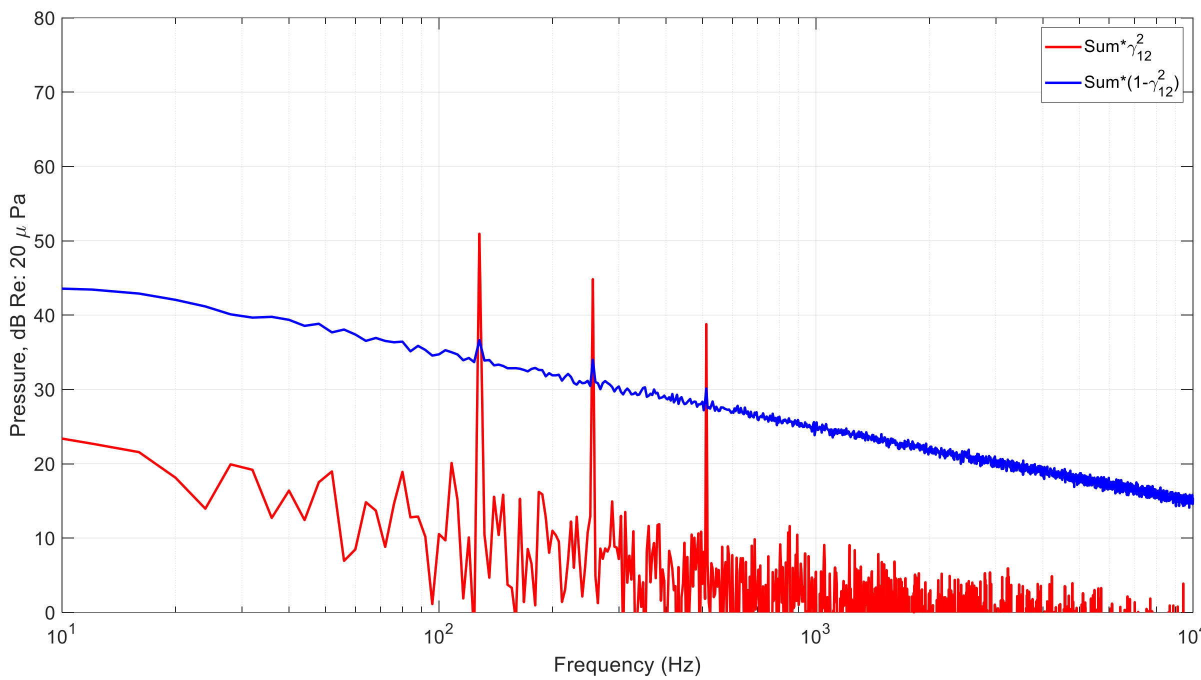

Figure 4: Coherent (red) and incoherent (blue) signals extracted. Some residual background noise remains in the COP which can be reduced with more averaging over long times.

3. DEMONSTRATIONS

3.1. Wind Noise Removal

For this demonstration, we use audio files from the BBC archives [5]. You can find an amazing number of free high-quality stereo .wav files, most sampled at 44.1 kHz and higher. We've extracted 30 seconds of fairly steady sound from London's Heathrow airport[2], which includes several aircraft taxiing, taking off, and landing, along with 30 seconds of wind noise[3], which is also reasonably consistent over time. Recall that the cross-spectral and coherence methods assume the sound is fairly consistent over time and relies on averaging to eliminate uncorrelated signals.

Figure 5 shows the autospectra of one channel of the airport noise (original signal), one channel of wind noise, and the sum of the two. The airport noise is a combination of strong tones from aircraft engines at multiple frequencies, along with broad-band humps of engine sound. The wind noise causes a broad spectral hump centered near 100 Hz. This hump is related to the wind speed (faster wind speeds shift the peak frequency higher), as well as the size of the wind turbulence (larger turbulent eddies generate lower frequency sound). All flow-induced sound decreases with frequencies above the hump.

The total measured signal shows that the wind noise exceeds the airport noise below about 500 Hz, and artificially increases the broad-band levels at all frequencies. The wind can be eliminated with a simple cross-spectral calculation, provided the two microphones are placed fairly far apart and oriented perpendicular to the wind flow. This orientation ensures that turbulent eddies are uncorrelated between the mics. (If the mics are placed in the wind flow direction, eddies will pass by both mics with a short phase delay and will remain coherent.)

Figure 6 compares one channel of the original signal with the CSD of both channels (with independent wind signals added to both). The simple CSD averages out the wind noise very well for frequencies above 30 Hz. Below 30 Hz, some of the wind noise remains. This could be reduced further with longer time records (recall the simple example earlier). Figure 6 also shows the IOP (Equation 5) of one of the signals which matches the individual wind noise autospectrum. There are other applications where the flow-induced signal is of interest, such as measuring flow-induced wall pressures in pipes and channels [6]. Using IOP eliminates any coherent acoustic plane waves which may be propagating within the pipe. Conversely, CSDs or COP may be used to eliminate flow-induced wall pressures and return the acoustic plane wave spectra.

3.2. Removing Unwanted Sources

Now, let's use coherence to remove unwanted sound from other sources. In this demonstration, we use BBC sound files for an industrial motor[4] (the desired sound source) and a car engine[5] (the unwanted source). Figure 7 shows the individual autospectra of both sources along with their sum. The car engine corrupts the spectrum below about 200 Hz and also slightly near 5 kHz. Placing a second microphone close to the car engine allows us to compute coherence and use it to remove most of the unwanted signals. In this example, we assume the second microphone location causes the industrial motor sound to be 10% lower than that at the primary microphone. Figure 8 compares the uncorrupted industrial motor spectrum with that computed using the IOP approach (which removes any signals coherent between the mics). The 'cleaned' spectrum is much improved, but slightly lower than the original spectrum. This is because some of the desired signal remains in the mic close to the car engine and was removed using the IOP.

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[2] https://sound-effects.bbcrewind.co.uk/search?q=07017060, London Heathrow Airport

[3] https://sound-effects.bbcrewind.co.uk/search?q=NHU05039063, blustery wind

[4] https://sound-effects.bbcrewind.co.uk/search?q=07059073, electronic sounds, motor hum

[5] https://sound-effects.bbcrewind.co.uk/search?q=07023057, BMC car

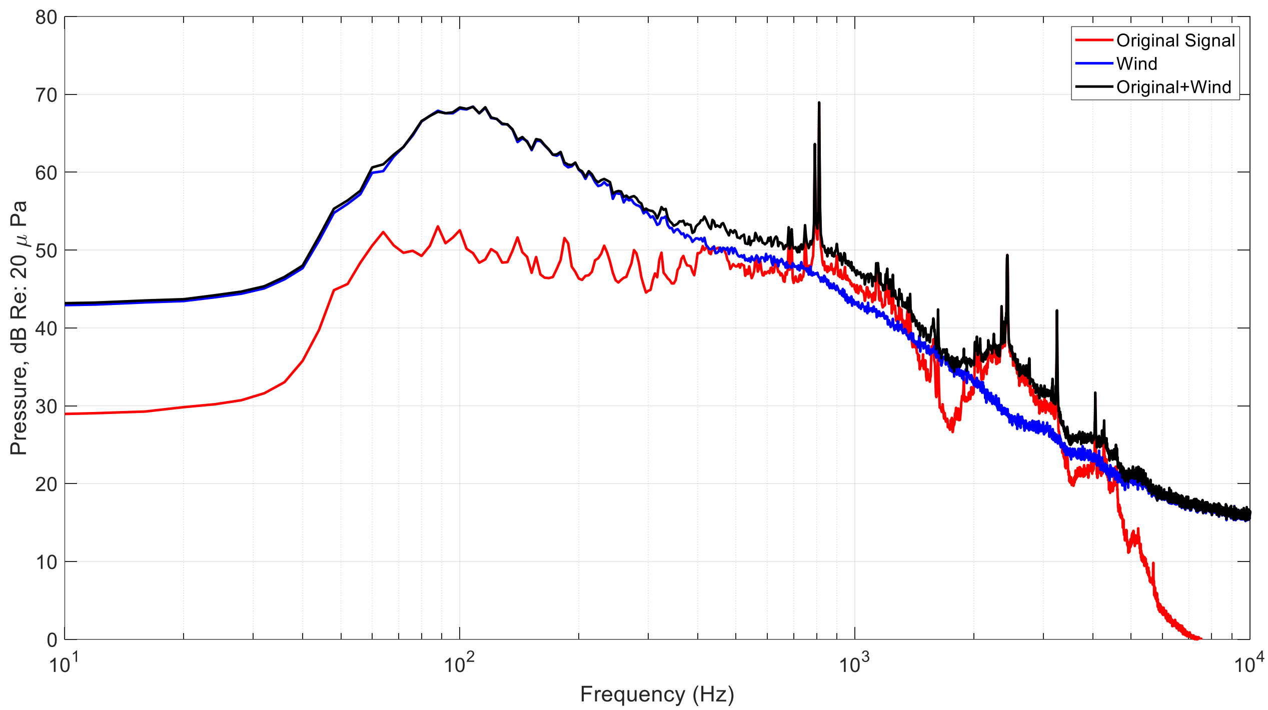

Figure 5: Autospectra of airport sound (red), wind in one microphone (blue), and sum (black).

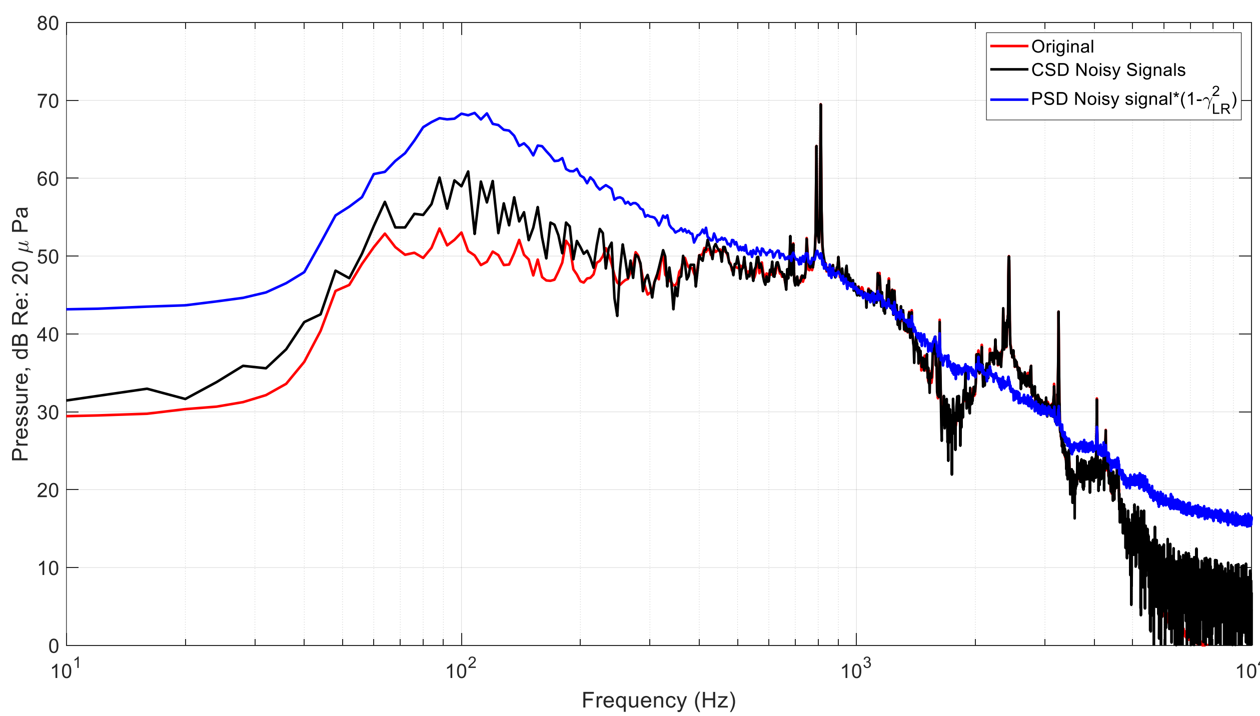

Figure 6: Autospectra of airport sound (red), cross-spectral density between the two mics (black), and uncorrelated spectral density of the wind at one of mics (blue).

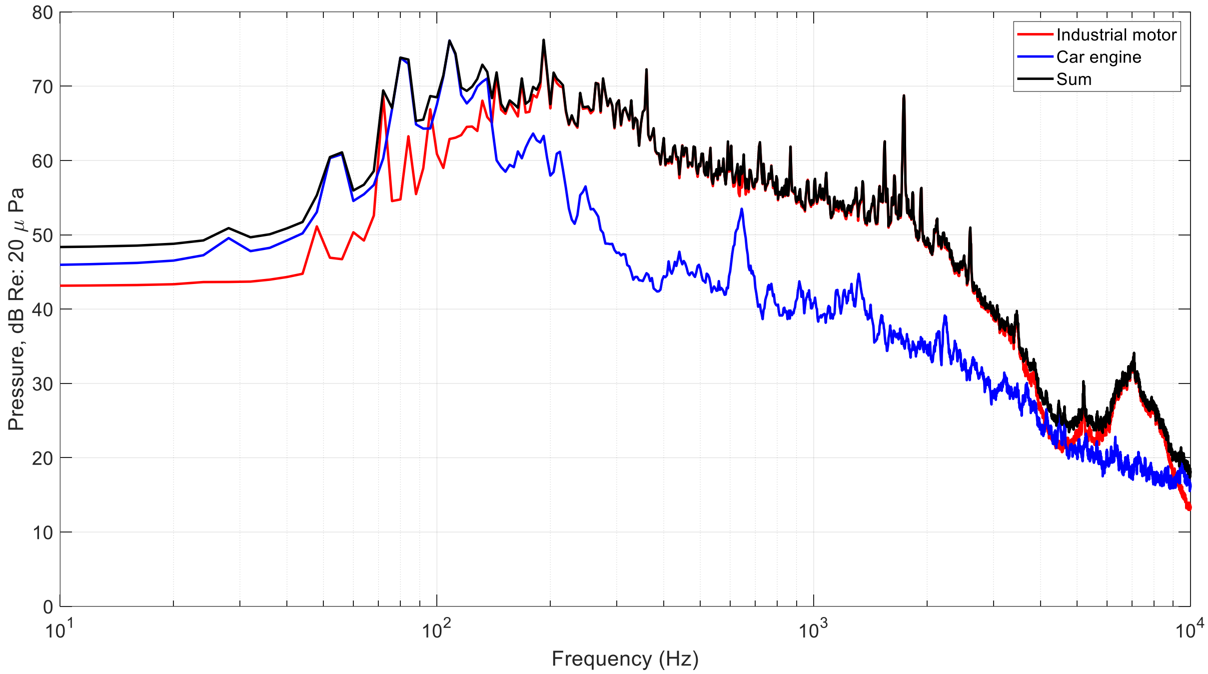

Figure 7: Autospectra of industrial motor (red), a nearby car engine (blue), and the sum (black).

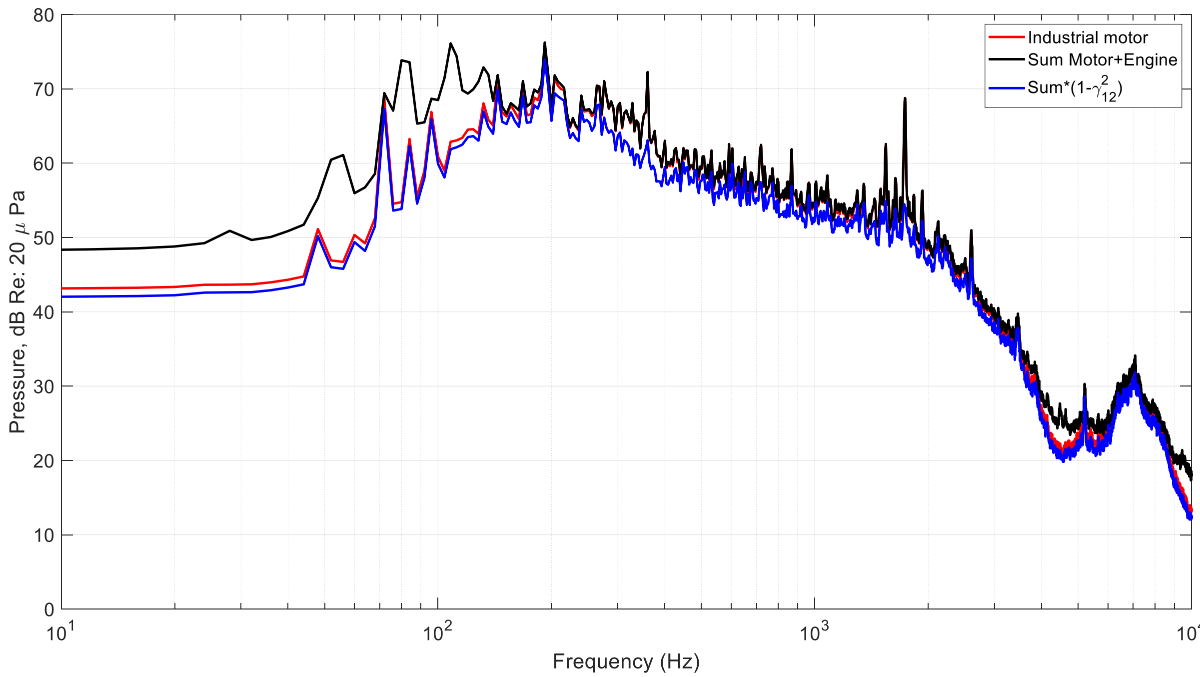

Figure 8: Autospectra of industrial motor (red), sum of motor and engine (black), and IOP (blue).

3.3. Reduced Noise Floors

Recall that an individual ICP sensor's noise floor is caused by localized disturbances within the sensor housing that induce random signals in the sensor electronics. These floors are completely uncorrelated with those in other sensors. We can therefore use COP to effectively lower our noise floors and measure very low signals. Figure 9 shows PCB's published Z-weighted[6] and A-weighted noise floors for p/n 378B02 ½ inch free-field microphone. Sensor noise floors are measured in very quiet chambers with data acquisition systems (DAS). These DAS have their own noise floors, which are typically well below those of the sensors.

Some applications require measuring faint signals, in some cases below an individual microphone's noise floor. In this application, a faint signal of about -40 dB Re: 20 μPa was generated but cannot be measured by a single mic. Figure 10 shows two microphones held together with double-sided hook and loop tape. Special care was taken to make sure they were electrically isolated, and that the vents on the preamplifiers were not blocked. The microphone assembly was inserted into a quiet test chamber (Figure 11) which was placed in a quiet anechoic room. Data were acquired on a National Instruments NI-9234 system at a sampling rate of 51.2 kHz.

Figure 12 shows the individual autospectra of each microphone compared to the published PCB noise floor data (in symbols at one-third octave center frequencies). The levels are all consistent as expected[7], and there is no evidence of the faint 1 kHz tone. The COP, however, significantly reduces the noise floor by eliminating the incoherent internal electronic noise, clearly revealing the quiet 1 kHz tone. Further reductions are possible by increasing the time record length. This phenomenon applies to all PCB ICP microphones, as the internal electronics are all similar.

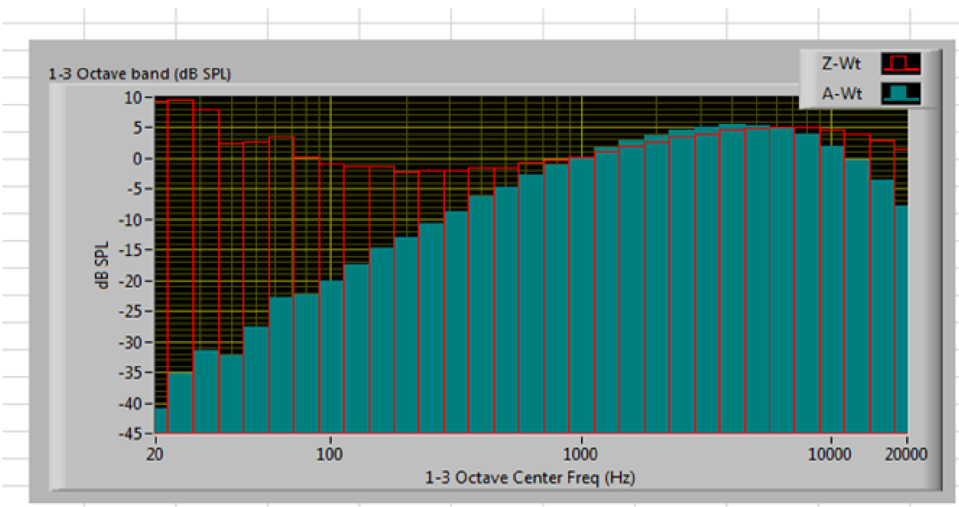

Figure 9: Noise floor of a PCB ½" free-field 378B02 microphone.

[6] Z-weighting implies no weighting.

[7] There is some low frequency broad-band background noise below about 70 Hz, but it does not affect the measurements at higher frequencies.

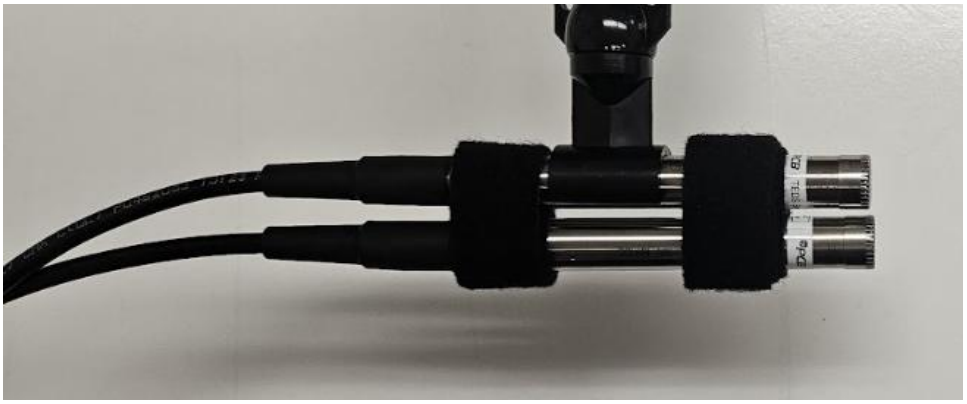

Figure 10: Two electrically isolated PCB 378B02 microphones with unblocked pre-amplifier vents.

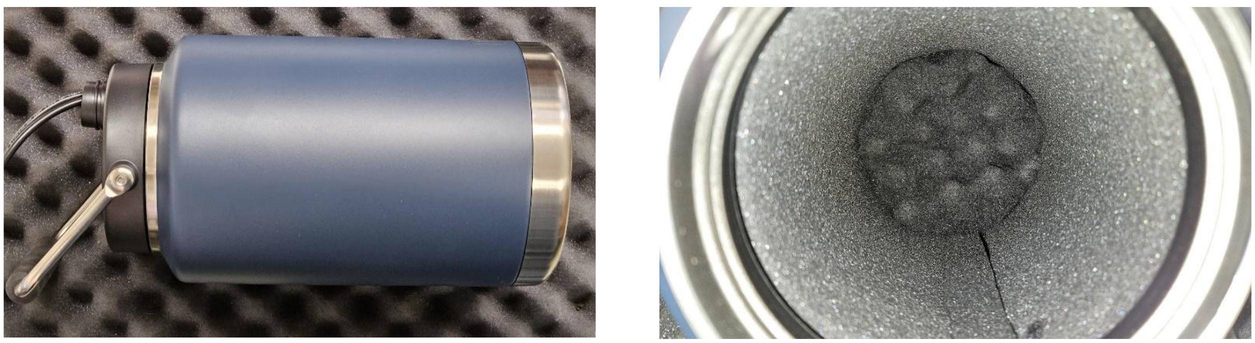

Figure 11: Quiet test chamber with microphone pair mounted in lid (left).

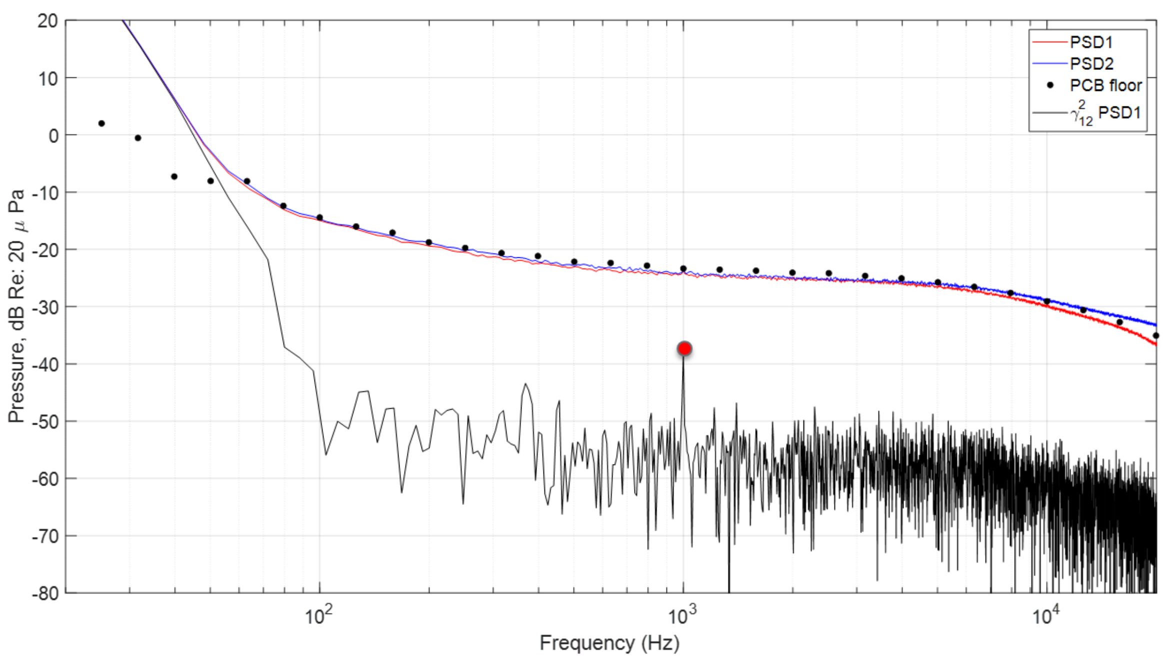

Figure 12: Individual microphone autospectra compared to PCB published noise floor and coherent output power between both mics (black). Faint 1 kHz tone is evident in the COP (red symbol).

4. SUMMARY AND CONCLUSIONS

Using two microphones for your measurements, simultaneously acquired on a DAS at consistent sampling rates, allows you to use cross-spectral processing to:

- extract desired signals in windy environments,
- remove unwanted signals by placing the second microphone close to a corrupting source, and
- measure faint signals below a single microphone's noise floor.

These methods work for signals that are reasonably consistent over time. They rely on averaging over multiple time blocks to estimate coherence, which is then used to compute coherent or incoherent output power.

These principles can also be applied to any other ICP sensor. You can even combine microphone and accelerometer signals the same way. For example, place an accelerometer on the surface of either a source of interest, or an unwanted source. Simply compute the coherence of the accelerometer and microphone signals, and either remove or accentuate the portion correlated with the accelerometer.

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5. BBC Sound Effects website: sound-effects.bbcrewind.co.uk
6. Lauchle, G.C., and Daniels, M.A., Wall pressure fluctuations in turbulent pipe flow, *Physics of Fluids*, 30 (10), 3019-3024 (1987).