



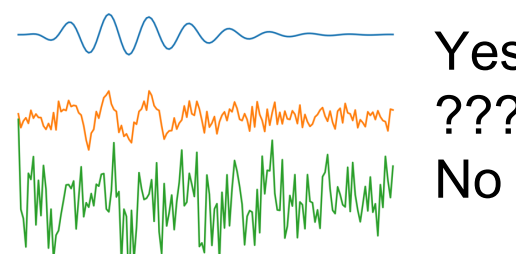
Detecting Individual Auditory Brainstem Responses (ABRs)

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Goal

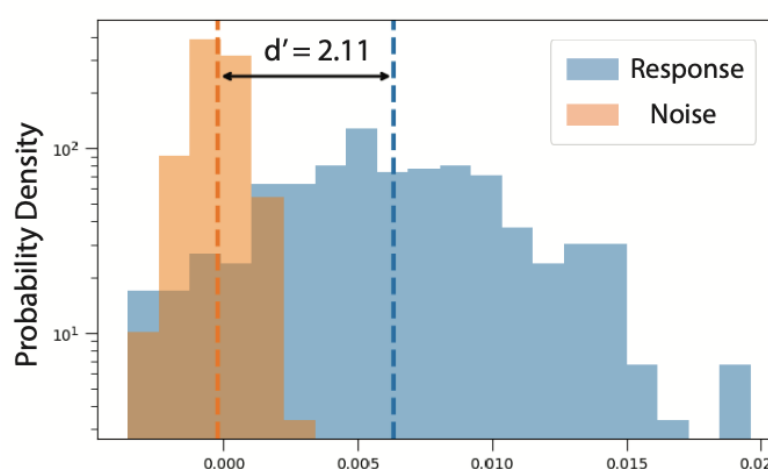
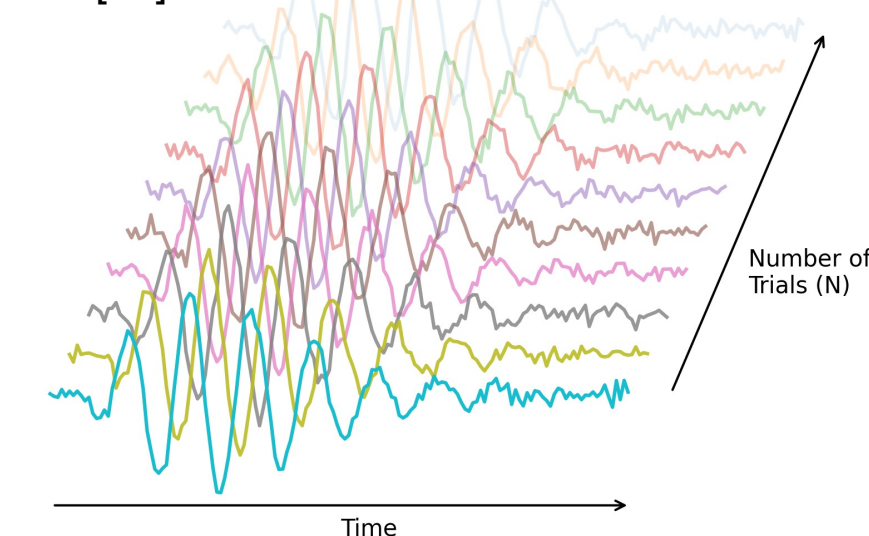
Detect presence of auditory brainstem responses (ABRs)
Reduce test time
Explain tradeoffs
Automated test
Guarantee performance



Signal Model^a

$w_i = s + \eta_i$ Synthetic data: constant signal plus white noise

$\text{Var}[\eta_i] = \sigma^2$



Estimate discriminability with Cohen's d' . This allows us to build a rigorous statistical model to predict thresholds.

Covariance Options^b

$F_{ij} = w_i w_j$	Full covariance	✗ Too Noisy
$C_i = w_i \sum_j w_j$	Matched filter	✗ Biased
$J_i = w_i \sum_{j \neq i} w_j$	Jackknife matched filter	✓ Just right

We average the N trials in an experiment to form a matched filter, the optimal linear detector (Van Trees, 2001).

We use jackknifing to remove the self-similar noise term.

Approach^c

We propose inter-trial similarity: Is there an underlying signal that appears in all the waveforms? We measure similarity with covariance (unnormalized correlation).

The conventional ways to detect ABR signals are by visual inspection; various morphological approaches; or by measuring a statistic of the average waveform, such as the power of the average waveform (**POTAW**). Averaging reduces noise while retaining the signal, but this poster shows that covariance is a stronger measure (better d' , lower thresholds, consequently fewer trials needed to achieve desired accuracy.)

We start by deriving estimates of the mean and variance for a single trial and a single point in time, and from these measures we can estimate the distance between the two distributions (with and without the signal) as described by Cohen's d' . Furthermore, we derive the signal levels and number of trials needed to achieve any desired d' . This simple model of per-trial discrimination allows us to understand the relationship between signal (s) and noise levels (σ^2), and then derive the number of trials needed to reach the desired discriminability.

We extend the single-point theory in three necessary directions. We extend the theory 1) to multiple looks, much like the POTAW method, where we decide based on N measurements in an experiment, 2) to the entire waveform, and finally 3) to results for colored noise.

We do not address the psychoacoustic question: How do we predict a hearing threshold (a perceptual question) from the electrical signal? In this work we highlight the dependence on the number of trials that is implicit in many such predictions from ABR signals. We expect the analysis in this work will lead to better psychoacoustic predictions.

Single Point^d

Theory¹ (orange line)

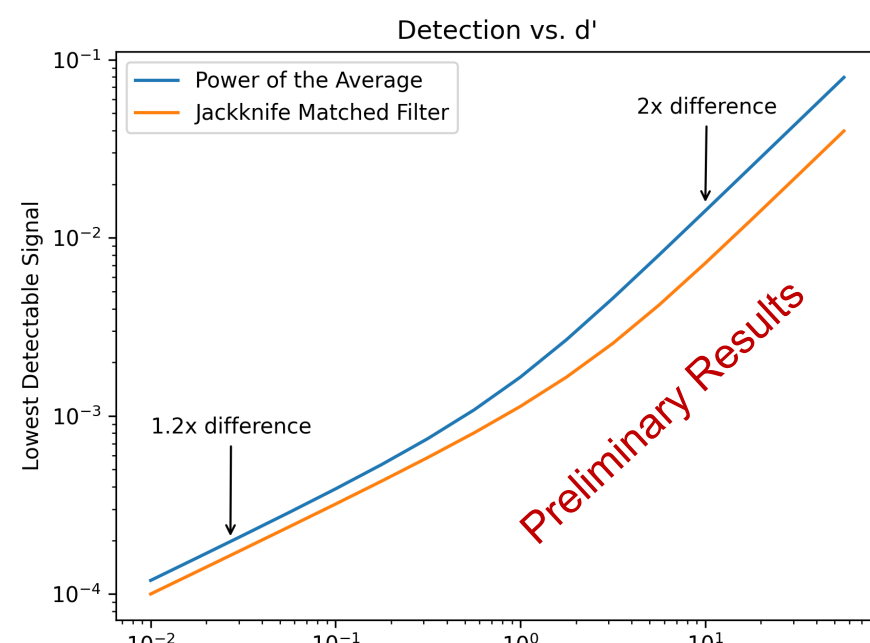
We derive the mean, variance and then d' for a single trial of the jackknife matched filter (J), assuming our signal model. The closed-form expressions match the simulations.

s^2

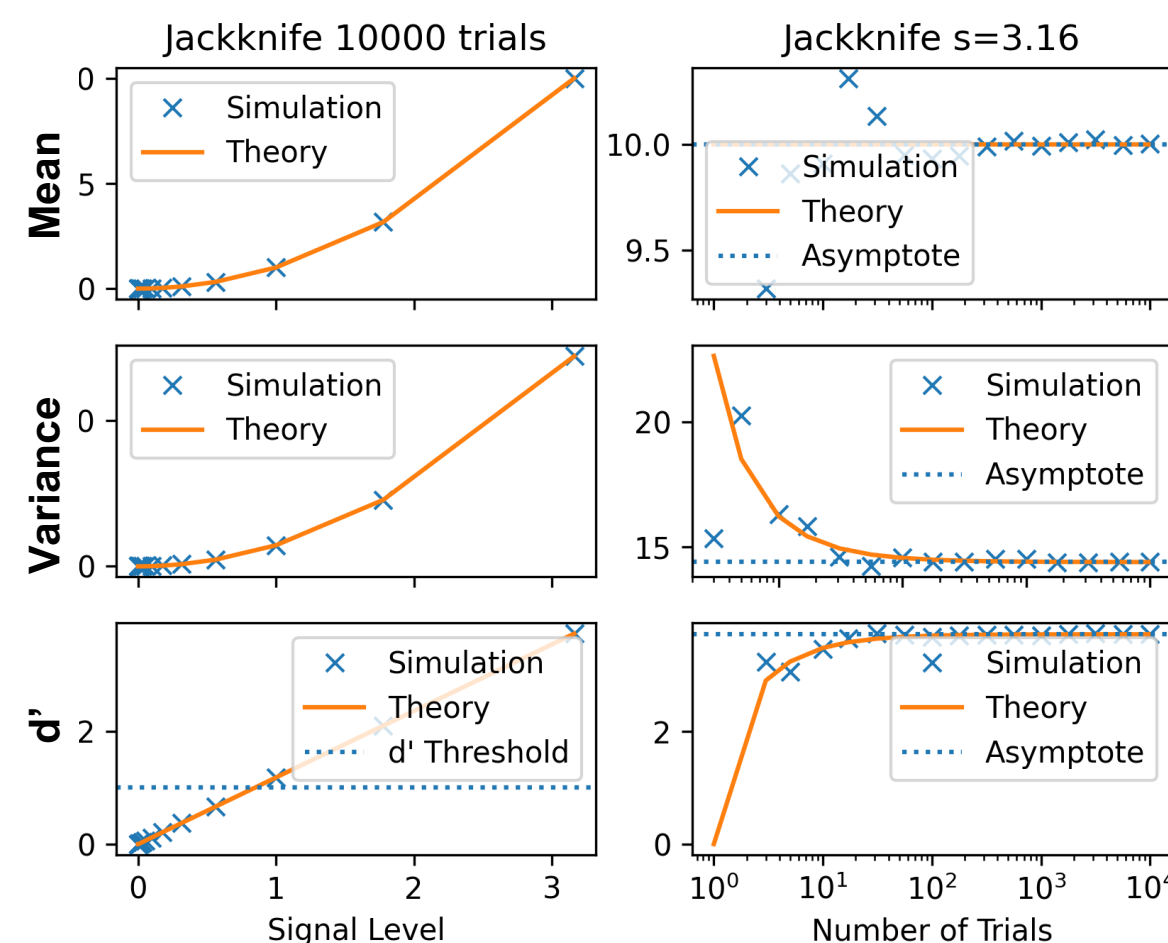
$$s^2 \sigma^2 (1 + 1/(N-1)) + \sigma^4 / (N-1)$$

$$\frac{\sqrt{2} s^2}{\sqrt{\frac{2\sigma^4}{N-1} + \frac{s^2 \sigma^2}{N-1} + s^2 \sigma^2}}$$

Asymptote ($N \rightarrow \infty$) $d'_\infty = \frac{\sqrt{2} s}{\sigma}$



Simulations (blue x)



Given an expression for d' in terms of s, σ , and N, we can compute the signal level (s) need to achieve the desired d' . Here we compare signal detection thresholds for POTAW and covariance,

Depending on the desired d' , the covariance approach is up to 2x more sensitive than POTAW, i.e. POTAW needs a higher signal level to reach the desired d' than covariance.

Multiple Looks^e

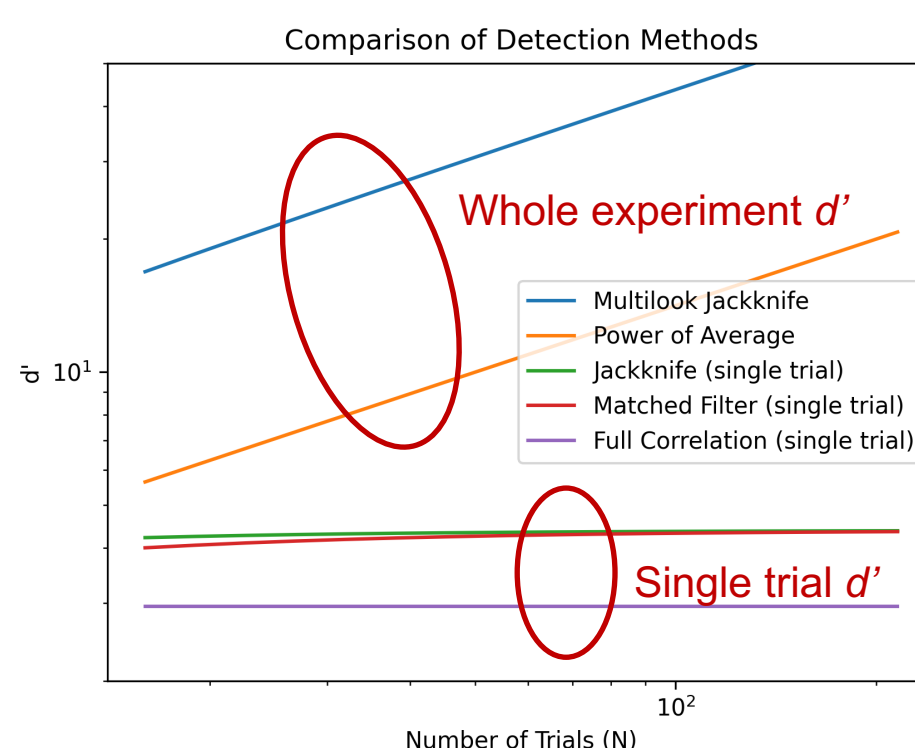
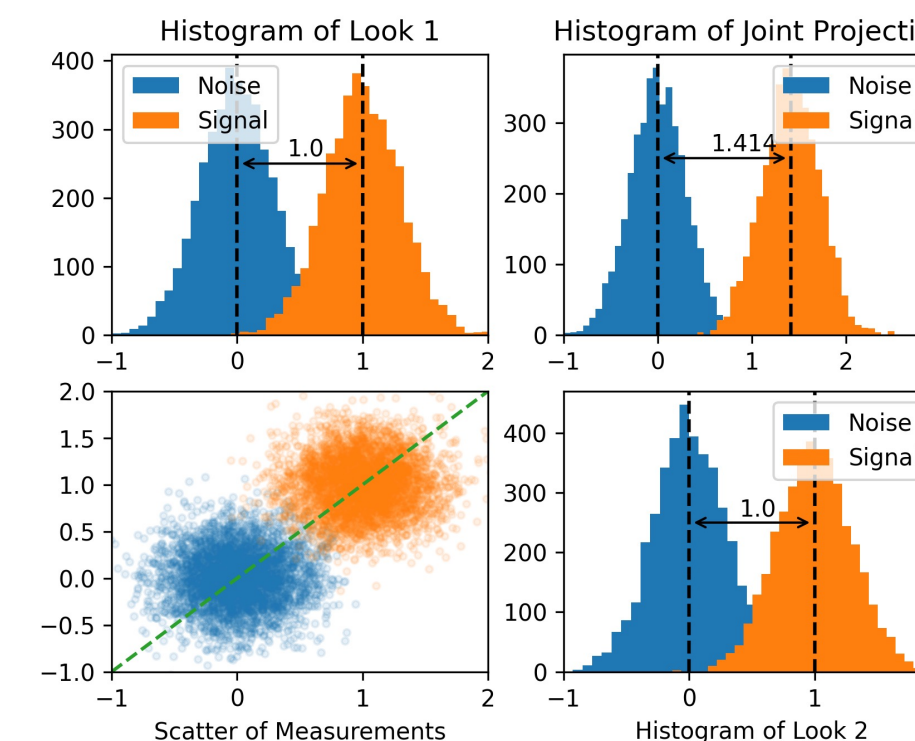
The theory to the left calculates d' for a single trial. But we are more interested in a whole experiment with multiple (N) looks or trials. These trials increases d' by the \sqrt{N}

$$d'_N = d'_1 \sqrt{N}$$

This is like a t-test, but calculating d' allows us to compare POTAW and various forms of covariance.

The single trial d' asymptotes, as shown to the left and right. Detecting the ABR signal with multiple (N) trials increases d' by \sqrt{N} . The jackknifed matched filter still gives larger d' increased sensitivity (reducing the threshold) than SOTAW

Experiment parameters: $s=3.1$, $\sigma^2=1$



We also extend the analysis, computing means, variances, and d' for the normal case: we have an entire waveform s_j over time.

Asymptotically, d' is linearly related to the vector magnitude of the latent signal.

$$d' = \frac{\sqrt{2} \sqrt{\sum_j s_j^2}}{\sigma}$$

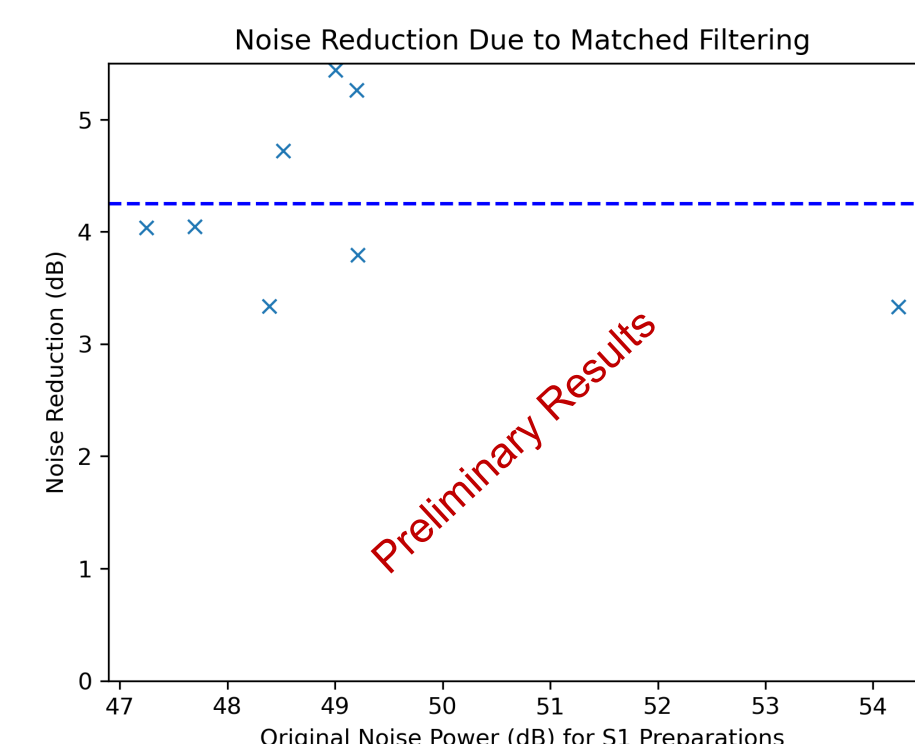
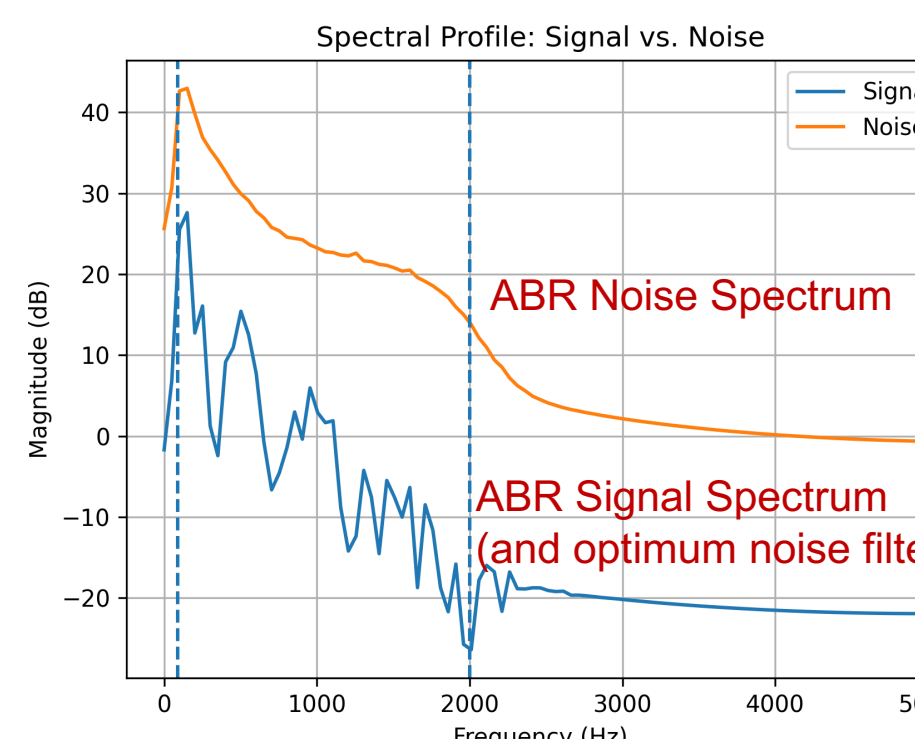
Entire Waveform^f

We do the same analysis in the Fourier domain. \tilde{s}_i and σ_i^2 are the amplitude of the signal and the power of the noise in a Fourier frequency bin. We calculate d' as

$$d' = \frac{\sqrt{2} \sum_i \tilde{s}_i \tilde{s}_i^*}{\sqrt{\sum_i \sigma_i^2 \tilde{s}_i \tilde{s}_i^*}}$$

Now the spectral noise in the d' calculation is scaled by the signal level (circled).

Data from Bidelman (upper right) shows the spectrum of the signal and the noise for one preparation. We filter the noise with the signal profile, to calculate how much noise is removed by the matched filter. The plot to the right shows the noise reduction due to the matched filter for several of his S1 data. An overage the filter removes an additional 4.2dB of noise over a conventional 90-2000Hz bandpass filter.



Conclusions

- Panel a: Demonstrated value of d' statistic Robust yardstick for comparison
- Panel b: Measure similarity via inter-trial covariance (unnormalized correlation)
- Panel e: Explains dependence on number of trials (N) Explicit tradeoff between accuracy and number of trials
- Panel f: Every waveform point counts Better than single-point measures

Most Importantly

- Panel d: Covariance is more sensitive than POTAW Signal threshold is 1.2 to 2x smaller (better) with covariance
- Panel g: Covariance is a matched filter, the optimum noise filter Noise power is scaled by signal power ~4.24dB noise reduction with Bidelman's S1 data

References:

Bidelman (2018), Test-Retest Reliability of Dual-Recorded Brainstem ...
Van Trees (2001), Detection, Estimation, and Modulation Theory

¹The detailed derivations are in a paper nearing completion. Send email to malcolm@ieee.org for a preprint.