Reverse Correlation Uncovers Spectral Representations of Tinnitus

Alec Hoyland, Nelson Barnett, Benjamin W. Roop, Adam C. Lammert†

Abstract**—— *Goal*: Make tinnitus characterization better. *Methods*: Use reverse correlation and compressed sensing. *Results*: Cool and fun results! Much data, very wow! *Conclusions*: Alec and Adam are cool and smart.**

Index Terms**—reverse correlation, tinnitus**

Impact Statement**—30 words on significance**

I. Introduction

TINNITUS—the perception of sound (*e.g.* ringing, buzzing) in the absence of an external stimulus—affects over 50 million people in the U.S., a third of which experience functional cognitive impairment and substantial reduction in quality of life [1], [2]. Primary treatment options for tinnitus are currently limited by a lack of methods for accurately characterizing the internal sounds experienced by patients. Tinnitus treatment typically involves *sound therapy*, a form of habituation therapy, which involves target exposure to external sounds to attenuate the perception of tinnitus or to encourage patients to perceive their tinnitus as a neutral stimulus [3]. Critically, treatment outcomes have been repeatedly shown to improve when the external sounds used in sound therapy are closely informed by the internal tinnitus experience of the patient [4]–[7], specifically, its component frequencies that constitute the *psychoacoustic tinnitus spectrum* (PTS). However, existing methods for characterizing the PTS rely on reductionist assumptions concerning the nature of tinnitus sounds (*e.g.* that they are pure tones or have small-width Gaussian spectra) and produce characterizations that are correspondingly bias and incomplete when compared to the spectral variety of tinnitus percepts—less than 50% of tinnitus patients report their tinnitus sounding like "ringing" [2]. There is a pressing need for methods to more completely characterize the PTS [1], [8], [9], to further improve treatment outcomes for patients suffering from tinnitus.

We utilize *reverse correlation* approach to characterize the PTS more completely, without the strong biases introduced by existing methods. Reverse correlation is a widely-accepted method for unconstrained and unbiased estimation of latent neural representations (*e.g.* neural receptive fields) based on the white-noise method for black-box system identification [10], [11]. This method has been used to characterize the psychophysical processes of perception in vision (*e.g.* faces) and audition (*e.g.* phonemes) [12]–[14] all on the basis of stimulus-response data [15], [16]. In reverse correlation, subjects are presented with richly-varying random stimuli (*e.g.* white noise) and make simple "yes/no" responses about whether they perceive a particular signal (*e.g.* their tinnitus percept). Internal representations, such as the PTS, can be estimated by regressing subject responses against the stimuli over many trials. Despite widespread use in characterizing neural and cognitive representations, reverse correlation has never been used for tinnitus characterization.

Our long-term goal is to improve outcomes for patients suffering from tinnitus by providing a validated clinical assay, based on the demonstrated capabilities of the reverse correlation approach, that clinicians can use to accurately and efficiently characterize the individualized perceptual experience of tinnitus. Our guiding hypothesis is that reverse correlation will produce PTS estimates that patients will consistently report as being similar to their own tinnitus experience. The rationale for this work is that accurate and efficient characterization of the PTS can inform individualized tinnitus treatment with enhanced habituation therapies.

II. Materials and Methods

Software code used for the experiments and analysis was written in MATLAB (Mathworks, Inc., Natick, Massachusetts) and is freely available at https://github.com/alec-hoyland/tinnitus-project/. The code depends on [17]–[19].

A. Stimulus Generation

To generate stimuli, we partition the frequency space $f \in [100,\ 13{,}000]$ Hz into 8 mel-spaced frequency bins so that each bin is perceptually different to a listener [20]. For each stimulus, we randomly select $[2, 7]$ bins with equal probability to be "filled" with power 0 dB. Unfilled bins are set to -100 dB. The inverse Fourier transform of the spectrum yields a 500-ms stimulus waveform.

Before arriving at this method, we ran an *in-silico* hyperparameter sweep over nine stimulus generation methods and hundreds of hyperparameter values (*cf.* Supplementary Information).

This work was supported in part by the University of Massachusetts Center for Clinical and Translation Science Pilot Project Program 2022, grant no. GRANT NUMBER.

Mr. Hoyland is a graduate student in the Department of Biomedical Engineering at Worcester Polytechnic Institute (WPI). Mr. Nelson Barnett is a research assistant at WPI. Mr. Benjamin W. Roop is a research scientist at MIT Lincoln Laboratory. Dr. Lammert is an Assistant Professor in the Department of Biomedical Engineering at WPI.

† Corresponding Author

Code is freely available at https://github.com/alec-hoyland/tinnitus-project/. Data are available upon request.

B. Reconstruction Analysis

A subject performing n trials with b frequency bins produces a stimulus matrix $\Psi \in \mathbb{R}^{n \times b}$ and a response column vector $y \in 1, -1^n$, where 1 corresponds to a "yes" response and -1 to a "no."

The linear regression solution is given by the normalized inner product of the stimulus matrix and the responses (Eq. 1). Intuitively, this implies that the reconstruction, x, is a linear combination of the randomly-generated stimuli that lies closer in simularity to the "yes" stimuli than the "no" ones [13].

$$\hat{x} = \frac{1}{n}\Psi y \tag{1}$$

C. Synthetic and Random Subjects

Two *in-silico* experiments were run with synthetic and random subjects.

The synthetic subject used a template-matching algorithm. Given the target signal spectrum (for either "buzzing" or "roaring"), $s \in \mathbb{R}^t$, and the stimulus matrix in the spectral domain, $\Psi \in \mathbb{R}^{n \times t}$, each element of the synthetic response vector, $y_s \in 1, -1^n$ is defined as:

$$r_i = \begin{cases} 1 & \text{if } \Psi_i^{\mathrm{T}} s \geq Q(0.5; \Psi_i^{\mathrm{T}} s) \\ -1 & \text{otherwise} \end{cases} \tag{2}$$

for $i \in 1, \ldots, n$, where $Q(x,y)$ is the quantile function for $x \in [0,1]$, given the empirical distribution of the simularity calculation $Psi^{\mathrm{T}} s$. Thus, the 50% most-similar stimuli receive a "yes" response and the 50% least-similar stimuli receive a "no" response. Due to the nature of this calculation, the synthetic subject has full-knowledge of all stimuli before making responses.

The random subject chooses responses at random, with a 50% probability of "yes":

$$r_i = \begin{cases} 1 & \text{if } X > 0.5 \\ -1 & \text{otherwise} \end{cases} \tag{3}$$

where $X \in [0,1]$ is a uniform random variable.

D. Experiment

We recruited $N = 10$ subjects for the experiment with healthy hearing from $[100,\ 13{,}000]$ Hz. Subjects used Sennheiser PXC 550 over-the-ear headphones and manually adjusted loudness using sample stimuli before performing the task (Sennheiser GmbH & Co. KG, Wedemark, Germany).

The subjects performed an AX paradigm binary choice task in 2 blocks of 100 trials with breaks between blocks, for a total of 200 trials per experimental condition. For each trial in the experiment, the subject listened to an auditory target signal followed by one of the randomly generated stimuli. The subject was instructed to press the J key if the stimulus sounded similar to the target signal and the F key if the stimulus did not (Fig. 1).

The target signals were drawn from online examples from the American Tinnitus Association, representing the range of tinnitus experiences (American Tinnitus Association, Vienna, Virginia). We selected two example tinnitus waveforms from their website: "buzzing" and "roaring". In this way, the AX experiment mimicked comparing a randomly-generated stimulus to an internal perception of tinnitus, however the known target signals unify across subjects and provide a gold-standard to benchmark against.

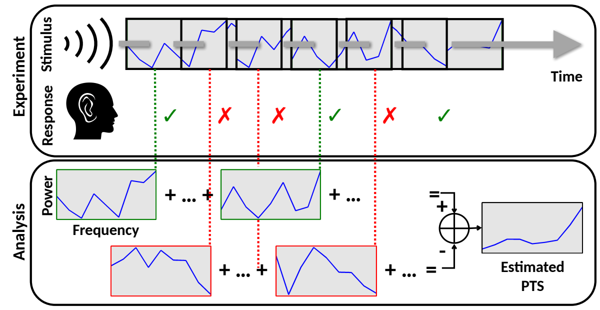

Fig. 1. Diagram of the experimental paradigm. The subject listens to a priming target signal, then a stimulus. They compare the mental model of the stimulus to the mental model of the target signal, before making a binary choice about the two signals' similarity.

III. Results

Subjects performed an AX-paradigm reverse correlation experiment using ATA tinnitus examples as the target sounds. We reconstructed the PTS using the responses and stimuli from the experiments using L_2 linear regression. Figure 2 shows the tonotopic bin representation of the reconstructions compared to the ground-truth target representation.

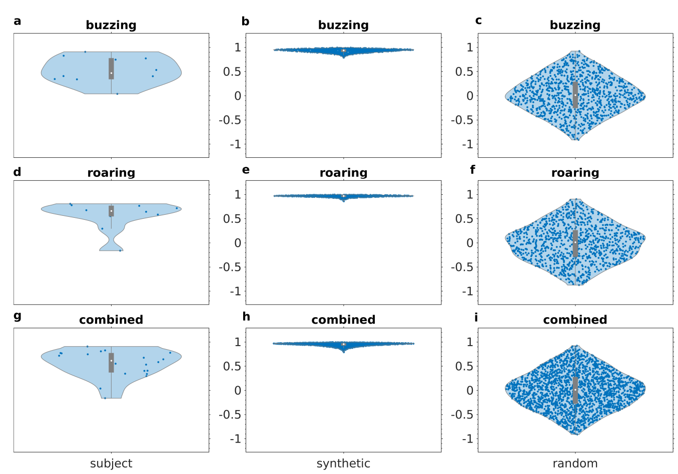

Fig. 2. Compressed sensing improves tinnitus signal reconstruction in human experiments. **(a)** depicts the ground truth (g.t.) bin representation for the "buzzing" example tinnitus spectrum, the reconstructions given the responses to stimuli in the AX experiment using linear regression (LR) and compressed sensing (CS) reconstruction algorithms, and the results of a synthetic subject (*cf.* Supplementary Information), also using the CS algorithm. **(b)** shows simular data for the "roaring" example tinnitus spectrum. For both conditions, CS results in a less noisy reconstruction that captures the salient spectral information of the target tinnitus signals.

RECONSTRUCTION ACCURACY

Tinnitus Type	Subject #	r^2 LR	r^2 CS
Buzzing	1	0.062	**0.138**
Roaring	1	0.208	**0.331**
Roaring	2	0.625	**0.839**
Buzzing	2	0.311	**0.508**

TABLE I. Compressed sensing produces higher quality reconstructions than L_2 linear regression. The table shows Pearson's r^2 values for linear regression-based (LR, *cf*. Eq. 1) and compressed sensing-based (CS, *cf*. Eq. **??**) reconstruction algorithms. CS improves performance in all cases and in the case of subject 2 in the "roaring" condition, produces extremely high-fidelity reconstructions.

IV. CONCLUSION

We applied reverse correlation to the novel domain of psychoacoustic tinnitus spectrum reconstruction and improved reconstruction performance (PTS) up to 2x using compressed sensing. Using our reconstruction algorithm, the experiment required only 2,000 trials for quality reconstruction results which is a 10x improvement over reverse correlation results in similar domains [13]. Subjects finished the experiment within two hours, indicating that this procedure is feasible as an "outpatient medical test" to characterize the PTS of a subject, a crucial step in diagnosis and treatment [1], [8], [9]. After fine-tuning, we will use this algorithm to characterize the PTSes of clinical tinnitus patients to help in the treatment of patients and to further understanding of tinnitus.

Results from human subjects are far below the synthetic baseline, indicating that some improvements can be made to boost human performance. The simplicity of the mathematical model for the synthetic subject (and its favorability towards the problem) leads to a synthetic subject that accounts for each tonotopic bin with equal attentiveness, does not suffer fatigue, and never changes its threshold for positive vs. negative responses. The experiment asks subjects to rate each stimulus as similar or dissimilar to the target tinnitus signal. This can lead to "threshold drift," where the decision threshold between positive and negative assignments to stimuli change as the experiment goes along. While the AX paradigm protects against this effect somewhat by playing the target sound before each decision stimulus, subjects self-reported feeling unsure that they were making consistent decisions. In future investigations, we will use a two alternate forced choice (2AFC) paradigm, where a subject is provided two stimuli after the cue, and chooses the more similar one. All chosen stimuli get positive responses assigned and non-chosen stimuli get negative responses assigned (CITE?). Reconstructions can proceed normally, using both the positive and negative responses.

mention closed-loop/ML?

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