Compressed Sensing for Characterization of Tinnitus

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***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*—compressed sensing, reverse correlation, tinnitus, barging into other people's fields and showing them up with MATH!**

***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. One limitation of reverse correlation is the sheer number of trials required to recover a good signal reconstruction. Classically, reverse correlation has required a large number of stimulus-response trials to yield accurate results (*e.g.* 20,000 trials in [13]), a property that makes reverse correlation time-consuming in a clinical setting.

We overcome this limitation of reverse correlation using *compressed sensing* (CS) to reconstruct the PTS with high fidelity using far fewer trials. Compressive sensing can reduce the number of trials required an order of magnitude compared to conventional estimation, thereby allowing for efficient and accurate characterization of tinnitus within a single clinical visit. Compressive sensing has gained broad recognition in medical imaging [CITE], due to its ability to reduce scan times without sacrificing image quality or introducing bias, and its promise for similarly improving reverse correlation has been recently demonstrated by our group *in-silico* [CITE].

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

A. Stimulus Generation

To generate stimuli, we partition the frequency space $f \in [100,\ 13{,}000]$ Hz into 100 mel-spaced frequency bins so that each bin is perceptually different to a listener [17]. For each stimulus, we randomly select 30 bins with equal probability to

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

be "filled" with power 0 dB. Unfilled bins are set to -20 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).

B. Theory

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." We assume that the PTS, $x \in \mathbb{R}^b$, is sparse in some basis $\Phi \in \mathbb{R}^{b \times b}$ (*cf.* Supplementary Information).

1) Linear Regression: 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].

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

2) Compressed Sensing: The one-bit compressed sensing reconstruction problem is:

$$y = \mathrm{sgn}(\Psi\Phi x) \tag{2}$$

which is an underdetermined system with infinite solutions. Compressed sensing says that when $\Theta = \Psi\Phi$ is sufficiently well-behaved (*e.g.* satisfies the restricted isometry property, which Gaussian and Bernoulli random matrices do with high probability, *cf.* [18]) that the sparsest solution $\hat{x}$ can be found by optimizing the l_1 norm of $\hat{x}$. We solve the optimization problem originally described by [19]:

$$\hat{x} = \min_{||x||_2 \leq 1} -\frac{1}{n}(\Theta x)^{\mathrm{T}} y + \lambda ||x||_1 \tag{3}$$

with tunable scalar parameter λ.

C. Experiment

We recruited $N = 2$ 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 20 blocks of 100 with breaks between blocks, for a total of $2{,}000$ 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.

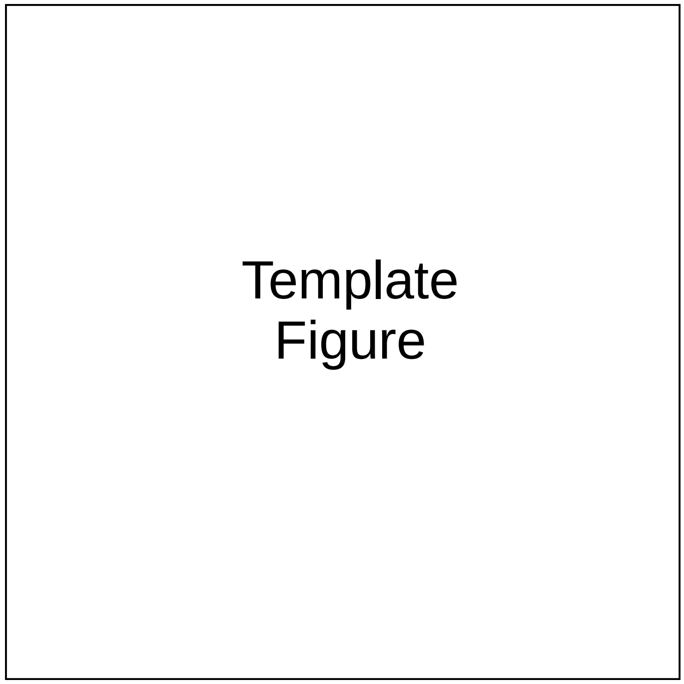

Fig. 1. Diagram of the experimental paradigm. The subject listens to a priming target signal, then a stimulus. They compare the mental model of the stimulus to the mental model of the target signal, before making a binary choice about the two signals' similarity.

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 both the L_2 linear regression and compressed sensing reconstruction algorithms. Figure 2 shows the tonotopic bin representation of the reconstructions compared to the ground-truth target representation.

Notes

1) Ben is way better at the experiment than Nelson. Sorry, Nelson.
2) CS results are consistently better than LR. Since this result doesn't necessarily hold for the synthetic experiment, it implies that CS' main contribution is *denoising* by countering human error [19], [20].
3) Is Pearson's r really the best way to measure accuracy? If you miss the big hump in either, I kind of think that we've failed. So maybe KL divergence, but then we have to normalize each spectrum to make probability distributions.

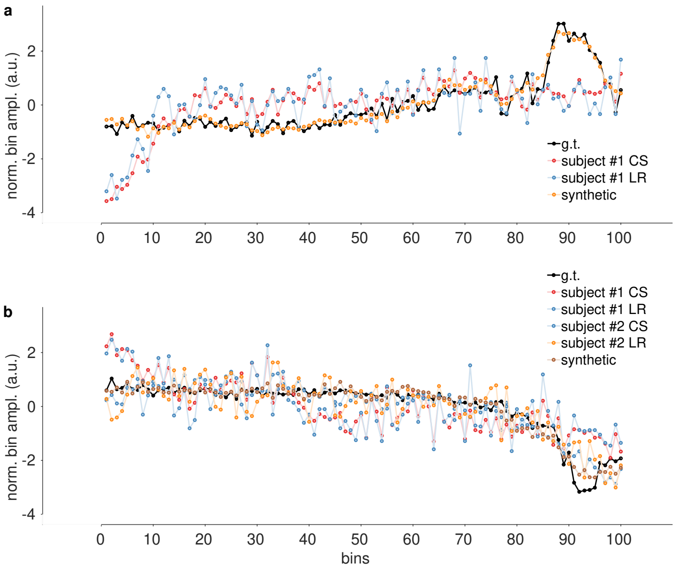

Fig. 2. Compressed sensing improves tinnitus signal reconstruction in human experiments. **(a)** depicts the ground truth (g.t.) bin representation for the "buzzing" example tinnitus spectrum, the reconstructions given the responses to stimuli in the AX experiment using linear regression (LR) and compressed 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**

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. 3) 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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