

# Rhythmic Perception and its Neural Correlates

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**Abstract**— Experimental animals will be trained, using a conditioned avoidance paradigm, on variants of a rhythm discrimination task, whereby they must identify a target click train with a distinct rhythmic pattern in a sequence of reference click trains with a different pattern. The click trains will be interleaved with naturalistic, modulated band-pass noise that will allow for system identification analysis of neural temporal response properties. Through a comparison of neural responses during behavior and passive listening to these acoustic stimuli, the study aims to gain better insight into the neural basis and perception of rhythm and also will explore how neural representations in auditory cortex adaptively change to permit the discrimination of distinct rhythmic patterns.

## Index Terms

IOI: Inter-onset-interval  
GBA: Gamma Band Activity  
STRF: Spectro-temporal-receptive field

## I. INTRODUCTION

Several powerful effects of music have been discovered through observation, but are being rediscovered scientifically. Musicians and therapists have long been aware of music's unique and powerful effects. Current efforts to discover how music is processed and its neural correlates can lead to a deeper understanding of both the brain and music's effects can be better understood.

The neural timing mechanisms utilized in rhythm comprehension are critical for rhythm perception and discrimination. This study aims to analyze how rhythm is processed, specifically in specialized auditory areas of the cerebral cortex.

This study seeks insight into how the auditory system processes rhythm by analyzing data collected from naïve animals listening to rhythmic stimuli. Comparing neural and physical representations of specific rhythms allow comparisons to be made that give insight to such processing. Additionally, comparisons were made between physical waveforms and neural spike trains to explore whether or not there is a linear transformation. This is accomplished through neural spike train analysis, utilizing van Rossum comparison techniques [7].

Data was recorded from multiple cortical areas of the ferrets' brain using passive electrodes to measure electric

potential. The data was then converted into matrices in MATLAB format and later processed to generate visually interpretable data. Van Rossum spike train analysis is used based on desirable results from previous studies.

Due to the specific function and tuning of each neuron, it would there is not sufficient evidence to solidify judgments on the basis of such a small collection of cells and time-constrained analysis. However, this study can be used as a basis for future studies investigating the neural representation of rhythm.

## II. METHODS

### A. Subjects

Several ferrets that have been trained on varying auditory discrimination tasks were recorded from in the Auditory Cortex. The tasks that they were trained on were independent of rhythm discrimination. All animals were in healthy conditioned and procedures abided by all animal testing regulations and were in coherence with mandates from the head veterinarian at the University of Maryland.

### B. Auditory Stimuli.

Rhythms were generated in MATLAB and contained eight clicks within one second, so that they could not be discriminated through click count or absolute duration. The rhythms were classified by the following names: Isochronous, Gallop, African, Hip-Hop, and Fritz Groove. A set of new rhythms was formed through averaging these initial rhythms with an isochronous rhythm by means of IOI. These additional stimuli allowed for changes toward isochronous to be evaluated on the neural level. All original rhythms were compared relative to each other by five members in the lab to see that the rhythms were clearly distinct to a human ear. An additional isochronous rhythm was included in the stimuli set to reveal variability within a neurons firing.

#### TABLE 1.

*8 Hz Rhythm(Over one second duration):*

Isochronous:

[0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125]

Fritz:

[0.06 0.19 0.125 0.06 0.19 0.125 0.06 0.19]

Fritz(\*):

[0.0925, 0.1575, 0.1250, 0.0925, 0.1575, 0.1250, 0.0925, 0.1575]

African:

[0.125 0.15 0.1 0.075 0.15 0.1 0.15 0.15]

African(\*):

[0.1250, 0.1375, 0.1125, 0.1000, 0.1375, 0.1125, 0.1375, 0.1375]

Hip-Hop:

[0.2 0.05 0.125 0.05 0.125 0.1 0.1 0.25]

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Hip-Hop(\*)

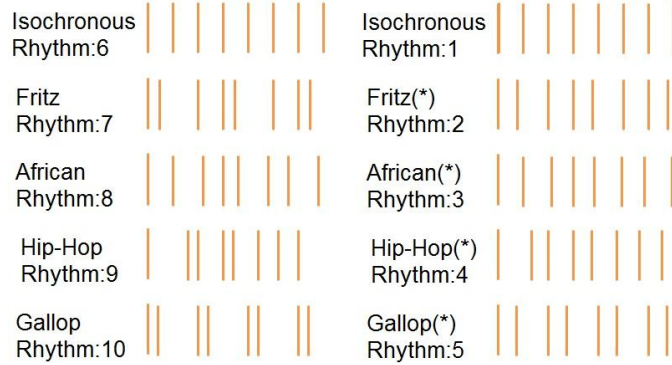
[0.1625, 0.0875, 0.1250, 0.0875, 0.1250, 0.1125, 0.1125, 0.1875]

Gallop:

[0.05 0.2 0.05 0.2 0.05 0.2 0.05 0.2]

Gallop(\*)

[0.0875, 0.1625, 0.0875, 0.1625, 0.0875, 0.1625, 0.0875, 0.1625]



(\*) denotes original rhythm was averaged with isochronous

C. Procedure.

Naïve animals were played rhythms in a random order at 70db. Within each trial, the one second stimulus was repeated three times for each rhythm. Recordings were taken in a double walled sound insulated room, with thin 3MΩ tungsten electrodes inserted into Auditory Cortex. Tuning curves and cell responses were measured. An in ear speaker was used to play the stimulus to two female ferrets who had been previously trained on auditory discrimination tasks that were independent of rhythm. There was one recording session for each animal. One recording used an independently moveable four electrode array. The other recording used an implanted thirty two electrode array. The electrodes used were tungsten. Data was recorded from 11 tuned and characterized cells using all rhythm stimuli MATLAB. Four of these cells were from the four electrode array and the other seven were from cells in the thirty-two-fixed- position electrode array that responded to the rhythmic stimuli. Recordings from the thirty-two electrode array had 15 trials and the four electrode array had twenty trials.

For the four electrode array, neurons were located through slowly progressing electrodes until spikes became apparent. Once detected, there was time left for the brain to decompress and settle, so that measurements remained accurate and did not deviate over the course of a recording. Typically each electrode found one to two neurons. The data was then sorted to find the predominant neuron firing prior to processing cells so individual neuron analysis could be conducted.

32 Channels Apparatus:

Diameter: 125μm  
 Depth: 700um (~layer 4)  
 Impedance: 2-3M MΩ  
 Sampling Rate: 25kHz  
 Bandpass filter: 300-7kHz

4 Channels Apparatus:

200 μm  
 150-1200 μm  
 3 MΩ

Overall Sampling Rate: 1kHz

D. van Rossum Analysis

A neural spike train can be represented by a vector containing zeroes and ones (however there can be higher number should there be multiple spikes within one unit of the sampling rate). In van Rossum's "A Novel Spike Distance," an effective method is described for comparing these spike trains. Spike trains are convolved with an exponential decay function. The two are then subtracted and squared. For the purpose of this study, the difference between two spike trains is normalized by the difference between the two isochronous spike trains. Thus, leaving easier comparisons because of the relative difference of '1'. For the purpose of this study the '1' can represent different due to noise.

Figures from [7]:

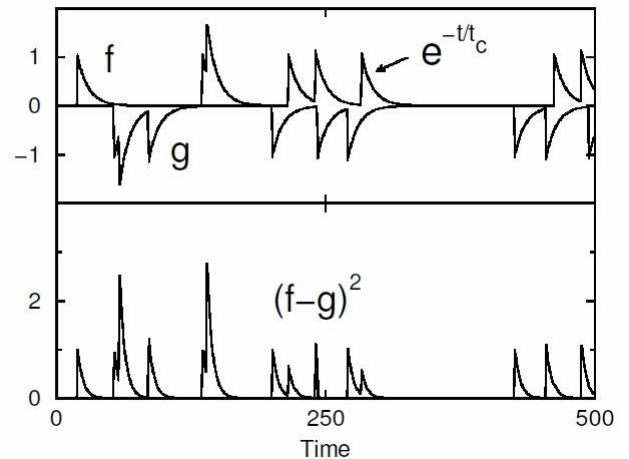
EQUATION 1.

$$f(t) = \sum_i^M H(t - t_i)e^{-(t-t_i)/t_c}$$

FIGURE 2.

Heavyside function(Impulse) convolved with exponential decay

A Novel Spike Distance



Squared difference between convolved spike trains

This comparison has the huge benefit of modifying the time constant based on the importance of grouping spikes, and neglecting minor offsets. For instance, with tau as a small integer value, a minor difference in spike trains(i.e. few millisecond delay, but identical responses otherwise) would

result is a misleading number. If tau is increased this problem is easily avoided.

### III. RESULTS

#### A. Neurophysiological responses to rhythmic stimuli of a naïve ferret

There were 11 cells from which data was collected. There was only sufficient time to adequately analyze four of these cells. One of the cells displayed 1-1 firing in response to the acoustic stimuli, two had onset responses, and one cell had an onset/offset response. Only the 1-1 cell had a linear STRF and the remaining cells had non-linear STRFs.

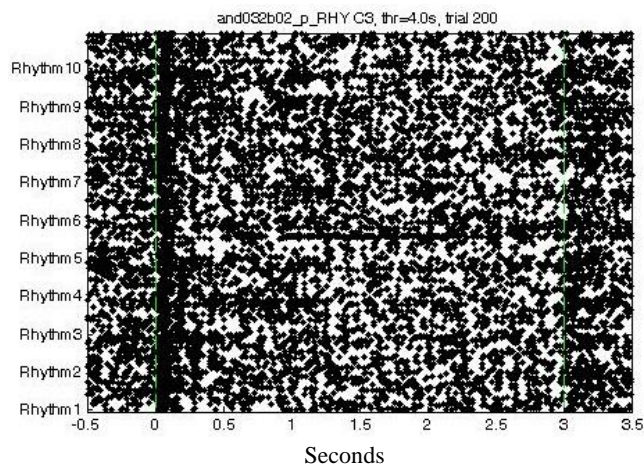
Cell 1's response is shown in figures 2a-e. The cell has a non-linear STRF and low frequency tuning curve. This cell displayed a clear onset/offset response.

Responses in Auditory cortex do not show a 1-1 representation of the incoming acoustic stimuli. An example is shown in cell 1 in figure 2a, where gallop(\*) displays a greater distance to the isochronous than gallop does. This is surprising because my initial hypothesis was that there would be linear mapping between rhythms and their neural representation. Instead the representation of the sound is transformed by filter properties of each neuron.

$$G(*) = (I+G)/2$$

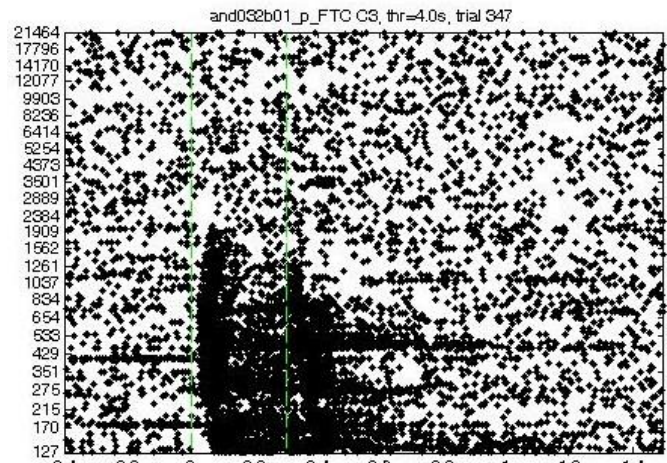
Physically G(\*) is halfway between G and I, and is calculated with the inter-click-interval vector.

FIGURE 2a.



Raw data displaying cell firing over twenty trials. This cell displays a strong onset and offset response

FIGURE 2b.



Frequency tuning curve showing strong onset and offset responses from 127-1800Hz

FIGURE 2c.

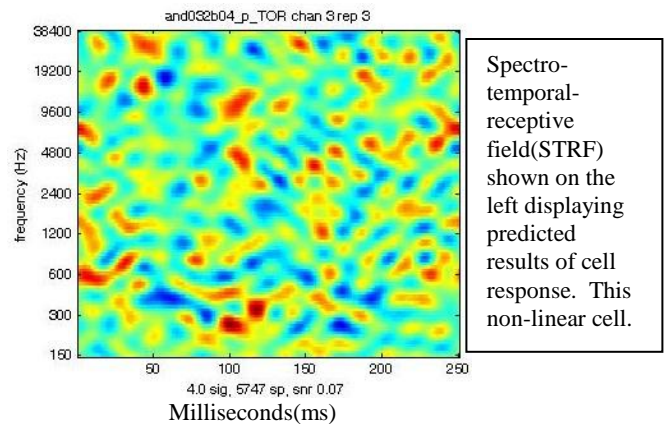


FIGURE 2d.

Mean Spiking Over 20 trials for Channel 3

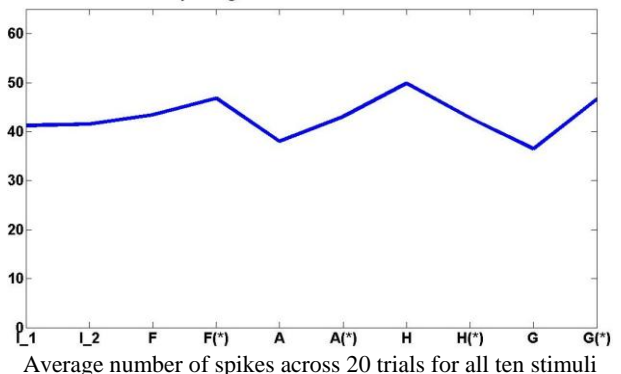
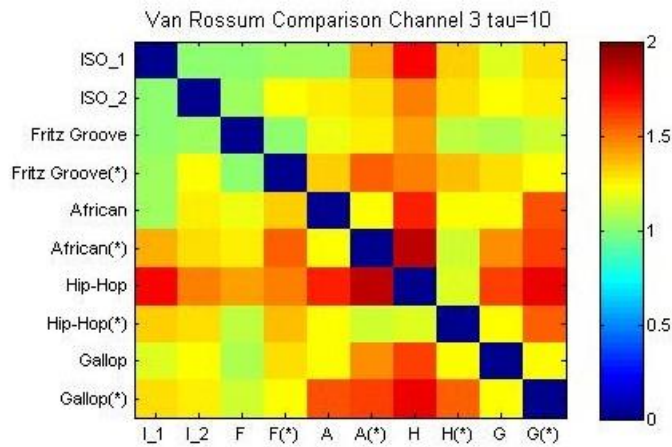


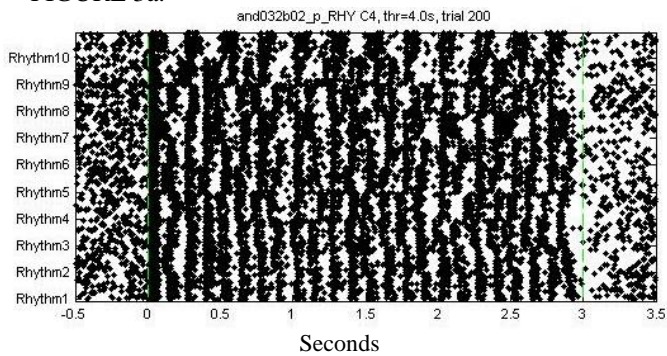


FIGURE 2e.



Van Rossum comparison matrices, displaying (dis)similarity with the difference between the two ISOs being normalized to one. Dark blue means an exact stimulus match.

FIGURE 3a.



Raw data displaying cell firing over twenty trials. This was the only cell found that shows a direct firing correlation to stimulus

FIGURE 3b.

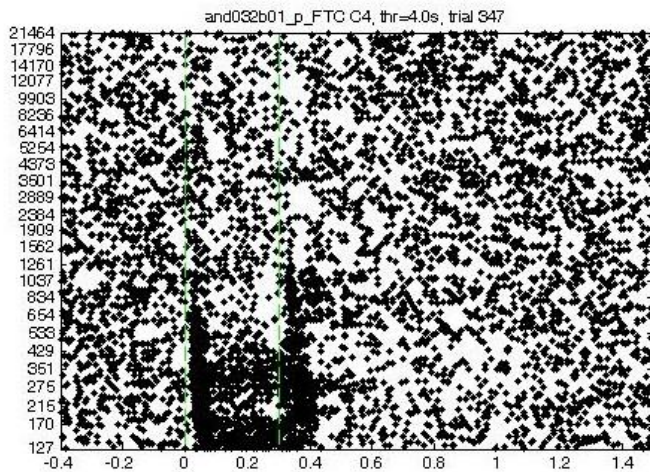


FIGURE 3c.

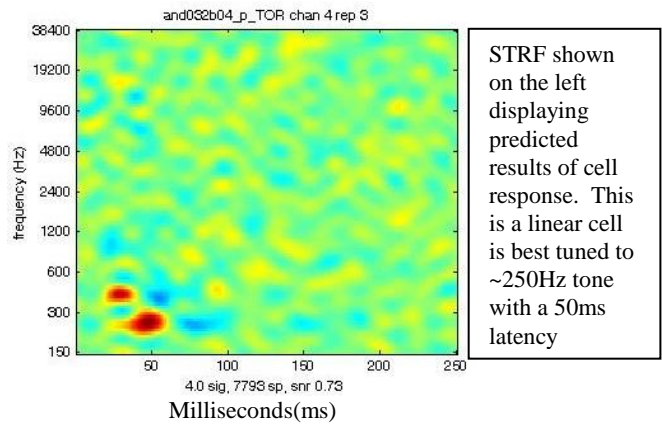


FIGURE 3d.

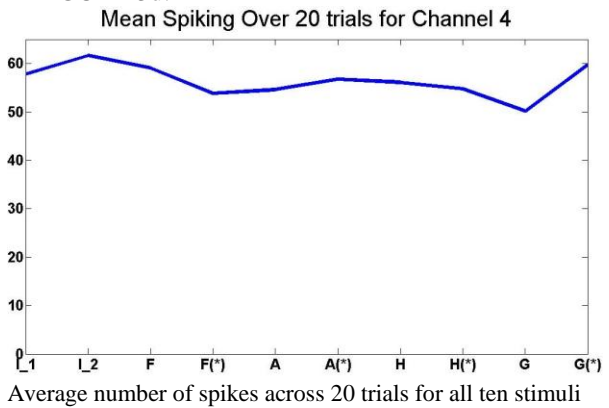
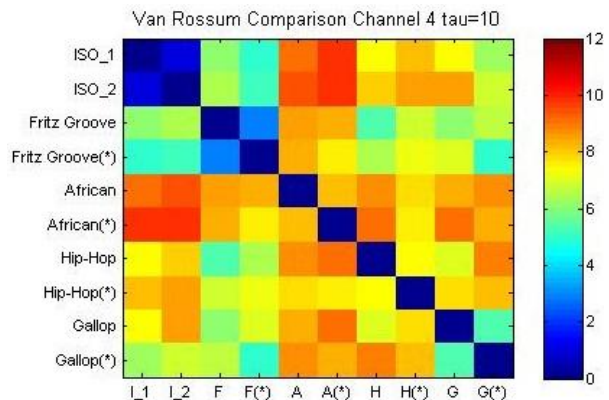


FIGURE 3e.



Van Rossum comparison matrices showing that Fritz Groove and Fritz Groove(\*) are closer in neural representation than Gallop and Gallop(\*) relatively. The expanded color axis represents more separation amongst the spike trains collectively.

Cell 2's response is shown in figures 3a-e. The cell have a linear STRF and low frequency tuning curve. Additionally, this was the only cell that displayed 1-1 firing when presented the rhythmic stimuli.

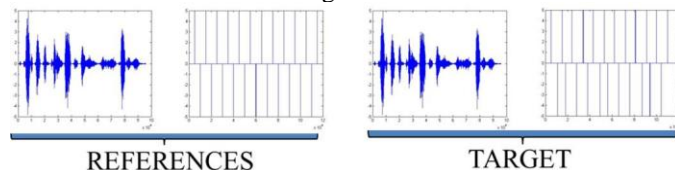
Despite the cell 2's unique tuning and response to stimuli (direct vs. onset) there are still general similarities with cell 1. One might not expect the relationships between the two isochronous rhythms to be comparable in cell 1 and 2. However, there is clear evidence that both cells have fire to the two isochronous rhythms more closely than any other pair of stimuli.

There was insufficient time for complete analysis of the additional 7 cells.

### B. Behavioral Data

Only one of the two ferrets who were trained showed evidence of learning to discriminate rhythms. It was successful in making these discriminations when the target was only 12dB louder than the reference stimulus over the course of eight weeks of training. This shows the difficulty for ferrets to learn rhythm discrimination tasks. Adequate training would probably take several more months. An example of training stimulus is shown below:

FIGURE 4. Behavioral Training



The reference sounds consisted of one second of speech-modulated noise followed by one second of a 30Hz isochronous rhythm. The target was one second of speech-modulated noise followed by one second the galloping rhythm. \*Speech-modulated noise consists of broadband noise(2-3kHz) that was modulated to simulate syllabic expressions.

## IV. DISCUSSION/CONCLUSION

These preliminary data while suggestive, do not lead to direct conclusions. The van Rossum difference of the two isochronous rhythms can be considered inner cell variability and can only be classified as noise in these studies. This is from of the lack of physiological data to support notions such as an animal attention or lack thereof.

To progress, Auditory Cortex does not have a one-to-one spiking correlation with rhythmic stimuli. Data and other studies hint at encoding to a varied rate with a specific integration window. There are several possible explanations that I will allude to through expanding upon previous studies for future research.

## V. FUTURE RESEARCH

Once behavioral data can be combined with neurological data more definite correlations may be drawn. Therefore there should be a priority on an effective method for training

animals on a rhythm discrimination task and allowing for adequate time so that the trained animal can perform the task while being recorded from. This would allow for greater classification of the 'noise-factor' shown between the two isochronous rhythms. Examples of classification potentially include animal attention, or distress.

Additionally, the processing of rhythm is unique in that it's highly dependent upon timing and utilizes two parallel timing mechanisms[11]:

- Absolute timing through the cerebellum and olivocerebellar network

- Relative timing through the basal ganglia and straito-thalamo-cortical network

In this study I have focused on relative timing by making efforts to keep rhythms fixed at 8Hz and limited to a 1 second duration. However, future studies could observe neural responses to changes in gap and time durations (i.e. extra time at the end of stimuli and elongating notes to give a greater absolute timing duration).

To fully understand the neural pathway that rhythm takes, recording should be taken simultaneously from such timing mechanisms and the Auditory Cortex. If gamma-frequencies are also looked for then it's a possibility to calculate delay times on the basis of rhythmic difficulty.

Another study could look at neural pathways between primary and secondary auditory areas to reveal parallel processing in accordance to the belt-parabelt-model commonly accepted in auditory neuroscience [3]. Such data could potentially display much higher order processes other than rhythm identification or discrimination. A study could be to observe functions during communal musical performance. This would observe how one concentrates on a specific rhythm or collection of rhythms when there is an abundance of complex inputs. Following such, would be how one generates a rhythm internally that complements external rhythms (the drum-circle problem). Further applications of such a study include observing how we adaptively change focus when interacting with rhythms in the surrounding environment.

Some recent observations ( Large et al. 2009, 2011) found rhythm comprehension in humans is correlated with neural spiking bursts measured by electroencephalography (EEG). He finds that gamma-band activity(GBA; 20-60Hz) can be used as communication between areas of the brain and used to predict tone/beat onsets. This is important because future experiments could use Fourier analysis on a collection of cells' neural spike trains to reveal if GBA is present. Assuming that the prior occurs, it would be interesting to observe any changes in this bursting frequency as a result of stimulus change. Large mentions that this response could have a 500ms delay, however such a delay was not included in my data analysis [4,9].

E.W. Large divides the gamma-band activity into two categories: induced and evoked. This is very logical because induced would imply a psychological isochronous beat used to anticipate a beat. However evoked GBA is phase locked in

response to the actual stimulus, following the beat. Large alludes that when induced and evoked approach each other there you reach a greater comprehension of rhythmic stimuli. A future study could inhibit GBA in a ferret trained on a rhythm discrimination task and see if the task can be completed successfully.

Large proposes several orders of keeping time. For example an 8 Hz beat typically has three isochronous levels depicted by counting schemes below:

1 2 3 4 5 6 7 8

1 2 3 4 1 2 3 4

1 2 1 2 1 2 1 2

Further studies could specifically look for neural patterns generated in the ferret in attempt to match differing levels of temporal structure [4].

A field that should be integrated in order to draw more powerful conclusions is computational music theory. Mathematical modeling combined with music theory can allow for rhythmic stimuli comparisons that accurately reflect differences, while considering important temporal structure of a rhythm. Such comparison can allow for more accurate relative difference comparisons with neural spike trains and perhaps reveal unique transformations [12].

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His motivation for psychoacoustics research stems from his passion for listening and playing music. Specifically his interest in rhythmic perception and its neural correlates comes from his main instrument of drums/percussion. He strives to learn more about the brain and music so that he understands both of which better. He is currently a member of the Audio Engineering Society(AES) and IEEE.