

# A resonator model predicts temporal orienting in rhythmic music

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## Introduction

Many sounds within the acoustic environment — e.g. music, speech, non-human animal calls — contain periodic structure. Dynamic Attending Theory (DAT) posits that, in rhythmic contexts, attending rhythms — endogenous oscillations of neural resources — become entrained to external stimulus rhythms (Jones & Boltz, 1989; Large & Jones, 1999), thereby orienting attention to salient time positions. In the current study, we examine whether a computational model of temporal attention (Tomic & Janata, 2008), built around systems of reson filters (a damped linear oscillator), predicts dynamic attention. We do so by combining our computational model with a psychophysical mapping of attentional allocation in musical auditory scenes.

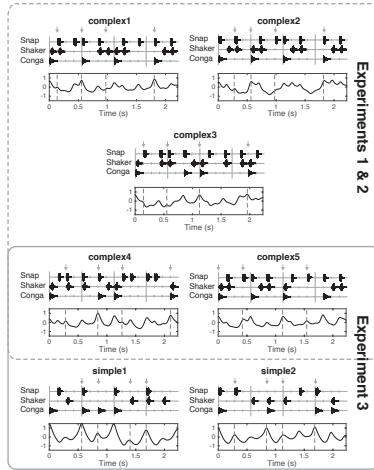
## Methods

**Participants:** UC Davis undergraduates; all normal hearing

- Experiment 1: N = 28; 12 musicians ( $\geq 3$  yrs training)
- Experiment 2: N = 38; 13 musicians
- Experiment 3: increment n = 25 (15 musicians), decrement n = 29 (13 musicians)

**Stimuli:** Multi-timbre percussion patterns continuously looped.

Transient intensity deviants placed at temporal positions of varying resonator-modeled salience.



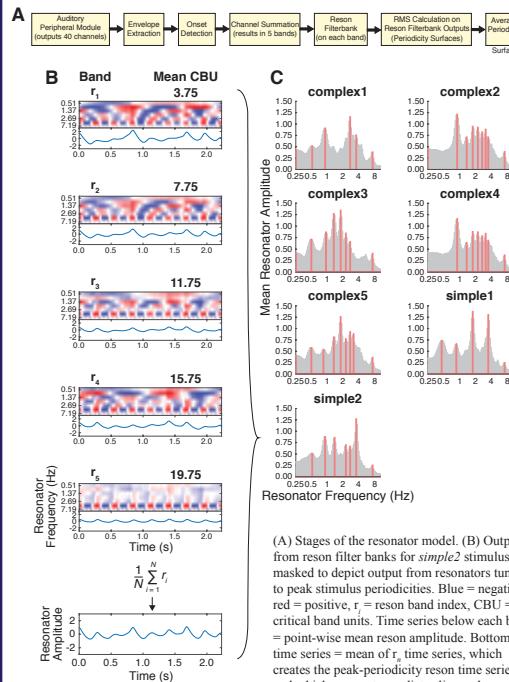
Top rows: Stimulus rhythms. Downward arrows = probe positions.  
Time series below each pattern = modeled salience dynamics.

### Procedure:

- 1 of 4 time points randomly chosen to probe with intensity deviant (increment or decrement, depending on experiment) every 2 to 3 loop iterations.
- Magnitude of intensity change determined dynamically via ongoing threshold estimation (tracked separately for each position).
- Separate block for each stimulus. Block ends once all thresholds converge.
- Prior to experiment task, baseline threshold obtained in isochronous context (Exp 3).

## Modeling Temporal Salience

We modeled stimulus periodicity structure and temporal salience using Tomic & Janata's (2008) resonator model.



(A) Stages of the resonator model. (B) Output from reson filter banks for simple2 stimulus, masked to depict output from resonators tuned to peak stimulus periodicities. Blue = negative, red = positive,  $r_i$  = reson band index, CBU = critical band units. Time series below each band = point-wise mean reson amplitude. Bottom time series = mean of  $r_i$  time series, which creates the peak-periodicity reson time series, and which we use to predict salience dynamics.  
(C) Mean Periodicity Profiles (MPPs) depict prominent periodicity frequencies by averaging reson energy (RMS) across time. Red bars = peak periodicities.

## Data Analysis

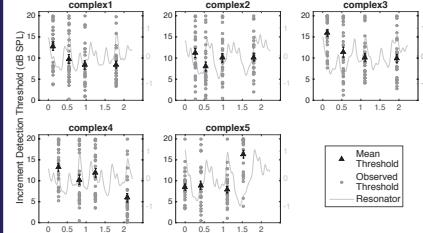
**Adaptive threshold.** We measured participants' detection thresholds separately at each probed temporal position. We used the Zippy Estimation by Sequential Testing (ZEST; Marvit et al., 2003) adaptive threshold procedure, which employs Bayes Theorem to adjust stimulus intensity and converge upon a threshold based on a participant's preceding responses. Lower detection threshold = greater perceptual sensitivity.

**Statistical analyses.** Effects examined using linear mixed-effects models:

$$\text{Threshold}_j = \beta_0 + \beta_1 \text{Resonator}_i + \beta_2 \text{Musicianship}_i + \beta_3 \log_{10}(\text{Block}_i) + \beta_4 \text{Resonator}_i^* \text{Musicianship}_i + b_{ij} + b_{2j} + \epsilon_j$$

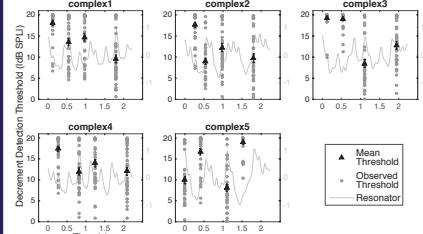
## Results

### Experiment 1 - Increment Detection

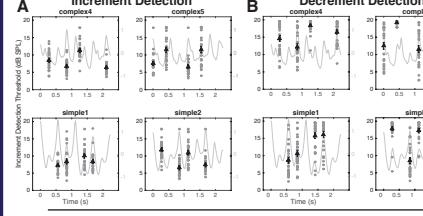


Detection thresholds as a function of temporal position and resonator amplitude.

### Experiment 2 - Decrement Detection

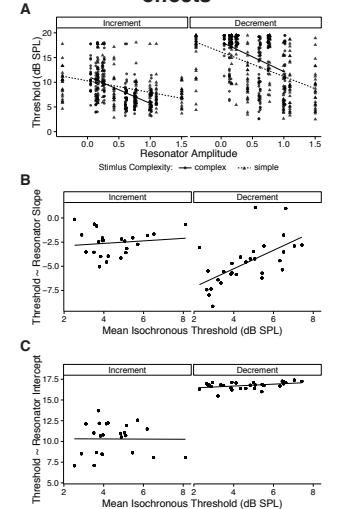


### Experiment 3



Experiment 1 (Increment Detection)		Experiment 2 (Decrement Detection)	
Parameter	Est.	Parameter	p-value
Reson. amplitude	-2.68	< .001	
log <sub>10</sub> (Block #)	4.80	< .001	
Experiment 3 (Increment Detection)		Experiment 3 (Decrement Detection)	
Resonator amplitude	-5.83	< .001	
Metrical complexity	3.59	< .001	
Resonator frequency	-3.15	< .001	
Experiment 4 (Decrement Detection)		Experiment 4 (Increment Detection)	
Resonator amplitude	-8.81	< .001	
Metrical complexity	-1.82	.003	
Baseline isochronous threshold	0.48	.032	
Block #	0.71	< .001	
Resonator*baseline threshold	0.63	.048	

## Stimulus- and individual-level effects



(A) Thresholds ~ resonator as a function of stimulus complexity.  
(B) Participant-level threshold ~ resonator regression slopes as a function of their isochronous baseline thresholds.  
(C) Participant threshold intercepts as a function of baseline thresholds.

## Conclusion

We provide a new, alternative method for modeling temporal attention combined with an ecological approach for psychophysically mapping salience dynamics in auditory scenes. Our results show that output from reson filters can predict the the dynamic allocation of attention in rhythmic contexts. This effect replicated across 4 samples of participants, increment and decrement probes, and varying levels of metrical complexity. Our results are consistent with a theoretical oscillatory mechanism of temporal attention.

## References

- Jones, M. R., & Boltz, M. (1989). Dynamic attending and responses to time. *Psychological Review*, 96(3), 459-491.
- Large, E. W., & Jones, M. R. (1999). The dynamics of attending: How people track time-varying events. *Psychological Review*, 106(1), 119-159.
- Marvit, P., Florencio, M., Baus, S. (2003). A comparison of psychophysical procedures for level-discrimination thresholds. *J Acoust Soc Am*, 113(6), 3348-61.
- Tomic, S. T., Janata, P. (2008). Beyond the beat: Modeling metric structure in music and performance. *J Acoust Soc Am*, 128(6), 4024-41.