Neural Habituation of the Mismatch Response Predicts Pattern Detection and Speech Discrimination in Infants

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BACKGROUND & SIGNIFICANCE

The development of speech perception, including speech discrimination, depends partially on early exposure to and experience with highly salient and behaviorally relevant acoustic input. Our previous research has highlighted the importance of quality sound access for the development of speech discrimination in infants as young as one month of age. Specifically, we have demonstrated that the speech evoked mismatch response (MMR_{SE}) is modulated by discrimination difficulty and may be useful in predicting later behavioral outcomes in infants. However, there is wide variability in discrimination outcomes that may affect the utility of MMR_{SE} as a biomarker; for example, the absence of a response may not be an accurate indicator of discrimination but a reflection of the still developing neural generators for engaging in and completing the task.

OBJECTIVE

We examined the time-frequency representation of the MMR_{SE} (TF-MMR_{SE}) as a function of the number of trials elapsed from the last deviant stimulus to determine whether the evoked potential magnitudes preceding a deviant trial could predict the identification of a difference response and whether such differences might correlate with later behavioral outcomes.

METHODS

Participants

Hearing Loss (HL)
- N = 40
- Age (MMR): 3.4 (0.9) mo
- Age (VRISD): 8.9 (3.9) mo

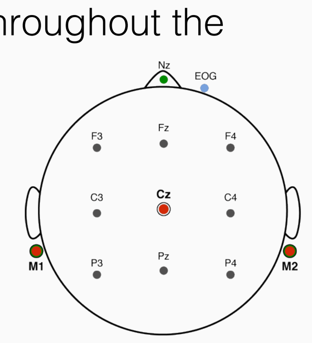
Normal Listeners (NL)
- N = 47
- Age (MMR): 3.3 (1.1) mo
- Age (VRISD): 8.3 (1.6) mo

Stimulus parameters

- Two stimulus contrasts: /a-i/ and /ba-da/
- P(deviant) = 0.15
- 0.5s duration per sound
- Pitch matched at 204 Hz
- Equated for loudness
- 70dBA in sound field

Electroencephalography

- Continuous EEG was recorded during sleep throughout the session
- 11 electrode montage
- Nasion (Nz) reference during acquisition
- Ocular activity (EOG) was monitored for wakefulness & REM state
- EEG was rereferenced to the linked mastoid channels after artifact rejection.
- Final ERPs analyzed from Cz
- ERPs transformed to time-frequency via CWT (64 log-spaced scales, 1-18 Hz)



1. HABITUATION EFFECTS

Effects of habituation on the TF-MMR_{SE}

1a. Trial selection

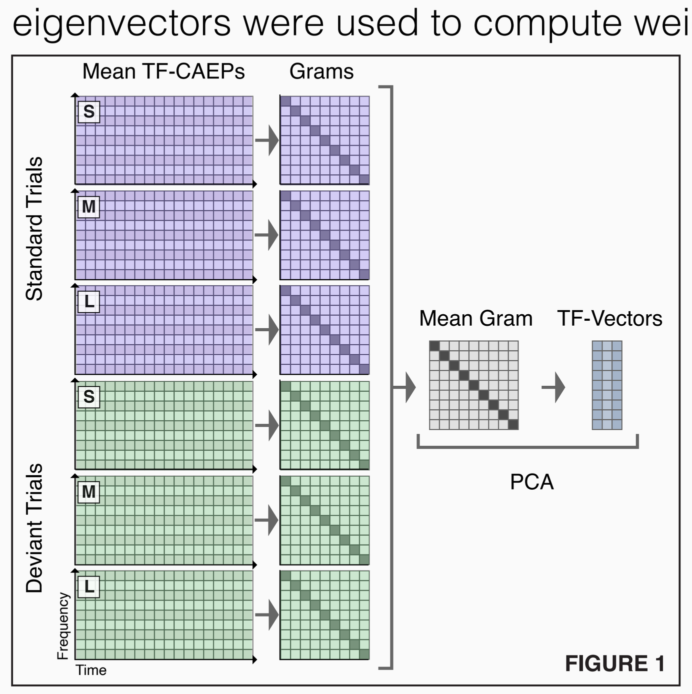
To examine the effects of habituation on the TF-MMR_{SE}, ERP trials were binned into three groups based on the number of standard trials that had elapsed since the previous deviant stimulus. The three habituation groups are labeled as short, medium, and long, referring to the time or number of elapsed standard trials:

- Short (S): 2 - 4 trials
- Medium (M): 5 - 7 trials
- Long (L): 8 - 11 trials

Trial bins were created separately for standard and deviant trials. After binning the trials, we computed the mean TF Coherence response for each set of bins.

1b. Analysis

We used an extension of classical multidimensional scaling known as DISTATIS to test for generalized effects of habituation on all responses (i.e.,irrespective of hearing group or contrast type). Each set of retained responses was transformed into a grammian, or "gram" matrix, which is a normalized representation of the spectral-temporal covariances in the TF response. A principal component analysis (PCA) of the mean grammian was used to identify three eigenvectors that, together, explained 82.7% of the total variance amongst all responses. These three eigenvectors were used to compute weighted scores for each response, which were then treated as dependent variables for group comparison. **Figure 1** (left) shows a schematic illustration of the DISTATIS approach for analysis.



RESULTS: HABITUATION EFFECTS

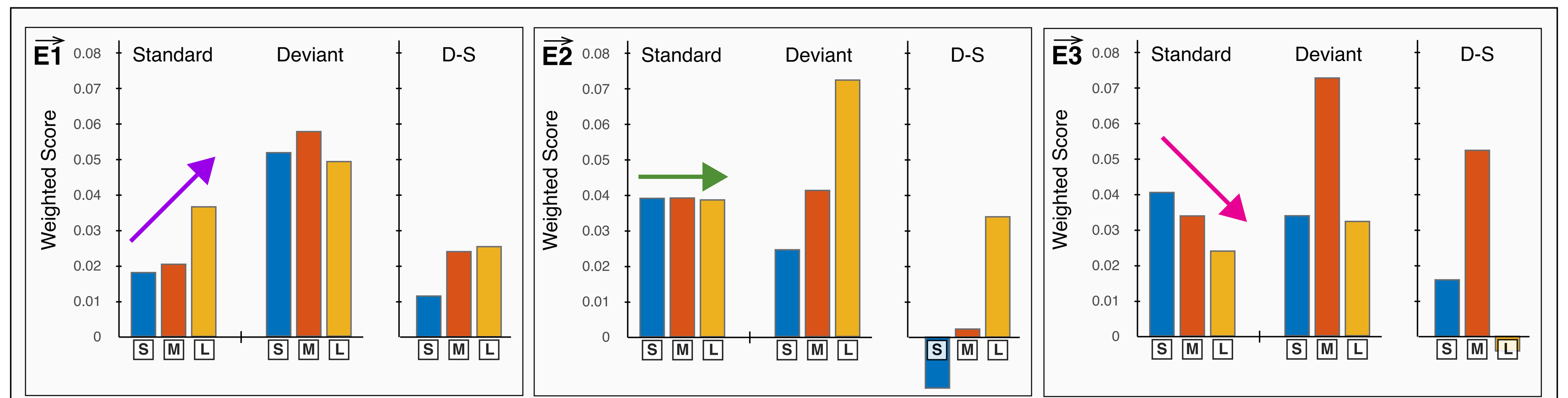


Figure 2 (above) shows the weighted scores for each selected eigenvector, E1, E2, and E3. Each panel depicts two trial groups: standard trials (left column group), deviant trials (center column group), and their differences (deviant minus standard, right column group). Each column group depicts the weighted score for each of three habituation groups: short (blue bars), medium (red bars), and long (gold bars). The arrows over each of the standard groups are schematic and are plotted to highlight the observed habituation effects. Note that while E1 and E3 clearly demonstrate habituation of the standard trials, the effect in E2 appears to be driven by the deviant trials.

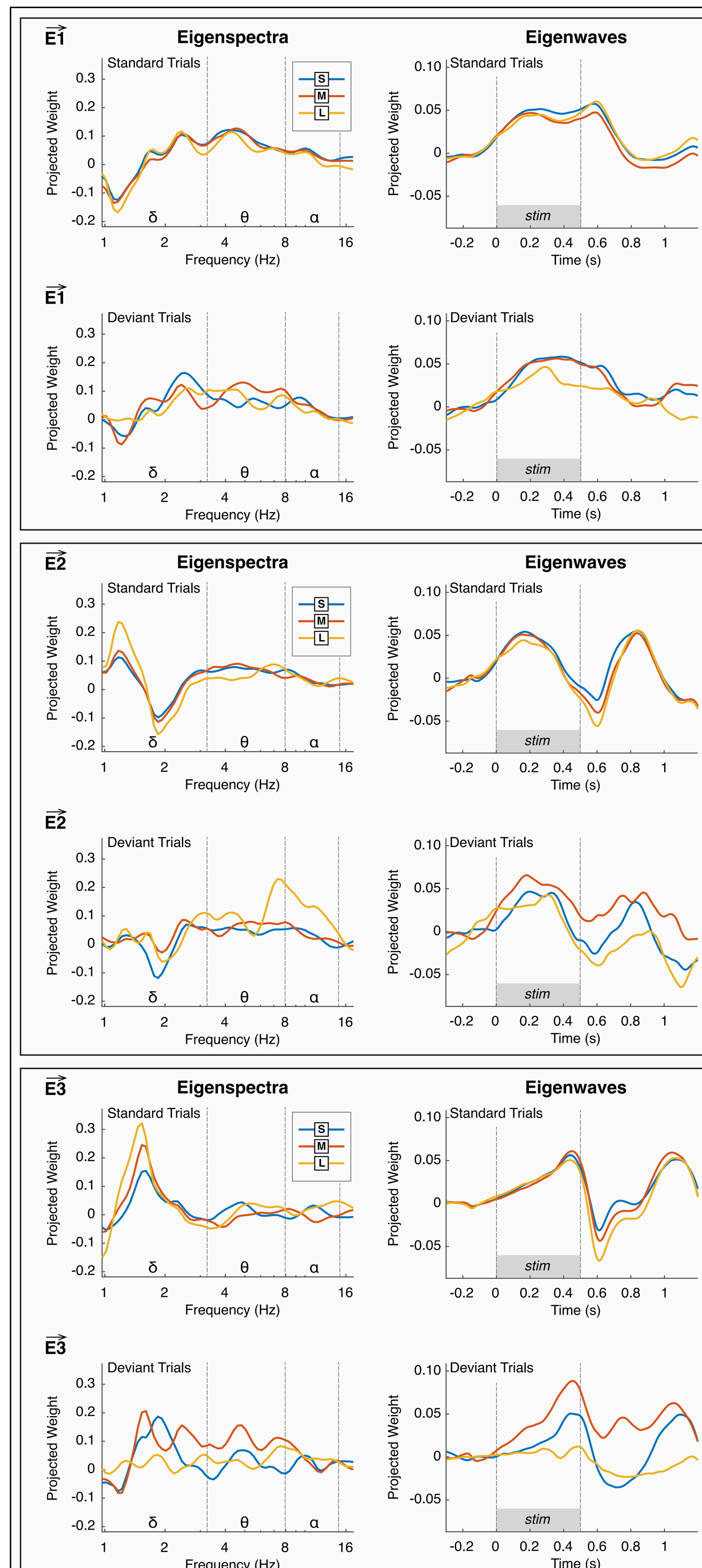


Figure 3. Spectral and temporal projections for each selected eigenvector, E1, E2, and E3. Each panel depicts two trial groups: standard trials (top row) and deviant trials (bottom row), and each habituation group: short (blue lines), medium (red lines), and long (gold lines).

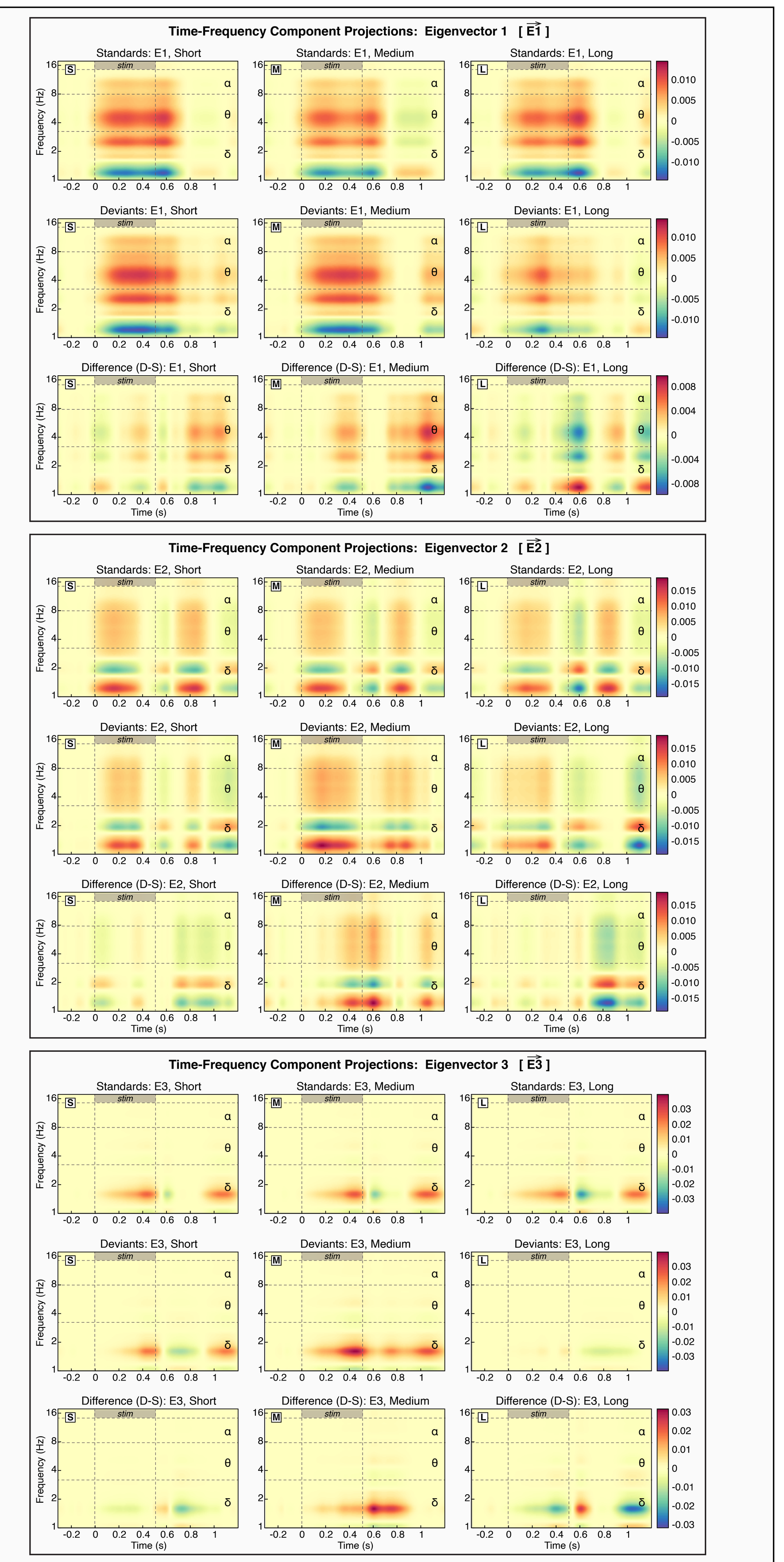


Figure 4. Time-frequency (TF) component projections for each selected eigenvector, E1, E2, and E3. Each panel depicts two trial groups: standard trials (top row), deviant trials (middle row), and their differences (deviant minus standard, bottom row), and each habituation group: short (left column), medium (center column), and long (right column).

2. PREDICTING DISCRIMINATION OUTCOMES

Predicting behavioral discrimination outcomes

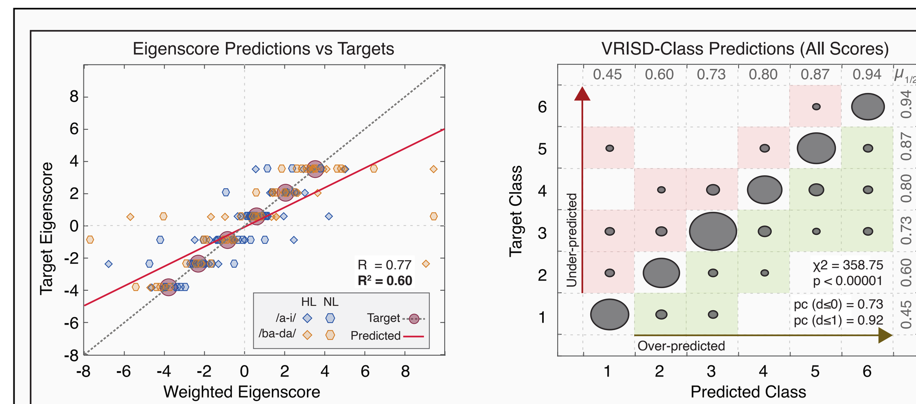
2a. Testing behavioral discrimination

To examine whether scaled TF-MMR_{SE} responses might be predictive of later behavioral performance, each subject was administered the Visual Reinforcement Infant Speech Discrimination test (VRISD) approximately 6 months after EEG testing. The VRISD PC Max score for each subject and contrast was treated as the dependent variable in a pattern classification analysis. VRISD scores were grouped into six groups based on the PC Max scores (see Figure 5). The goal of the classifcation algorithm was to predict individual VRISD scores from the corresponding TF-MMR_{SE} grammian matrix.

2b. Classification analysis

The grammian matrix for each TF-MMR_{SE} response (deviant minus standard; all trials) was treated as the predictor variable in a classification analysis of the corresponding VRISD score. We applied a semi-supervised learning algorithm extended from the family of multiclass support vector machine (SVM) algorithms. The goal of this algorithm was to find a set of weights that, when multiplied by a given grammian, results in a score that predicts membership in one of the six VRISD score groups (i.e., the closest median score from each group). Results of the classification algorithm were compiled in a contigency table and were tested for significance using the Chi-square test for independence of groups.

RESULTS: MMR → VRISD PREDICTIONS



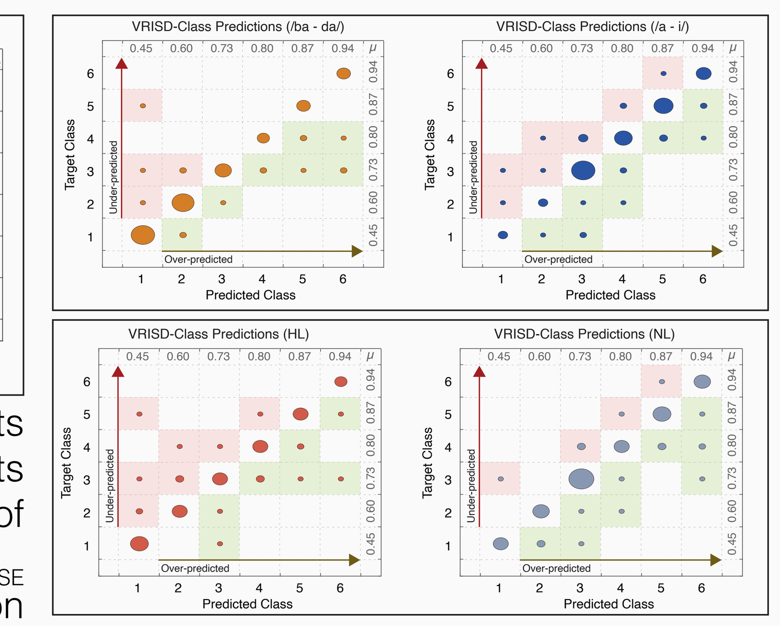


Figure 5 (above) shows VRISD prediction weights and predicted score classes. The left panel depicts the weighted eigenscore (abscissa) as a function of the target eigenscore (ordinate) for each TF-MMR_{SE} response. The right panel depicts classification accuracy for all responses. The values shown at the top and right of each class segment are the median VRISD scores for the corresponding target class (row or column). The radius of each circle is proportional to the number of observations at the corresponding coordinate position (predicted vs target). **Figure 6** (right) shows the classification results parsed by speech contrast (upper panels) and by hearing group (lower panels).

CONCLUSIONS

These results revealed a habituation effect corresponding with the time elapsed from the last deviant trial and changes in the frequency and magnitude of the TF-MMR_{SE}. These results also revealed a significant correlation between the TF-MMR_{SE} response and later VRISD scores. Taken together, these results suggest that acoustic audibility and salience are both necessary but not sufficient for speech discrimination and that discrimination is dependent on the brain's ability to recognize and adapt to complex stimulus patterns.

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