Silent Interval Degrades Machine Learning in Extraction of Human Frequency-Following Responses

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INTRODUCTION

- Frequency-following response (FFR) is a measure used to evaluate how the brain processes and monitors changes in the fundamental frequency and its harmonics with speech stimulations [1].
- The FFR is a small response that can be disrupted by noise. It is difficult to collect a visually identifiable response because thousands of recording sweeps are required to outweigh the noise.
- The source separation non-negative matrix factorization (SSNMF) model is a specific type of machine learning that integrates a source separation constraint [2]. By clustering periodic energies, SSNMF increased FFR visibility with decreased noise disturbances.
- The silent interval is the time between the offset of one stimulus and the onset of the next one. It contains the ongoing EEG activity, not the response [3]. While the silent interval may help improve the signal-to-noise ratio of a recording, it also contains no response. Thus, the influence of silent interval on SSNMF model remains unexplored.
- The goal of this study is to determine the influence of silent interval on the SSNMF performance.

METHODS

Participants

- Twenty-three native speakers of English (19 females and 4 males; M age = 22.78, SD = 1.83 years).

Stimulus

- A pre-recorded English vowel /i/ (with a rising fundamental frequency contour) was utilized to elicit FFRs.
- 70 dB SPL, monaural stimulation to the right ear.
- 150 ms silent interval between adjacent stimuli.

Procedure

- 3 gold-plated surface recording electrodes.
  - High forehead, right mastoid, and low forehead.
- Participants resting or fast-asleep during recording.
- 8000 artifact-free recording sweeps from each participant.

Data Analysis

- Utilized custom scientific programing in the Python language.
- To better isolate the spectral energies at the fundamental frequency contour and its harmonics, continuous brainwaves were digitally filtered (Butterworth, bandpass 90-1500 Hz, 24 dB/octave).

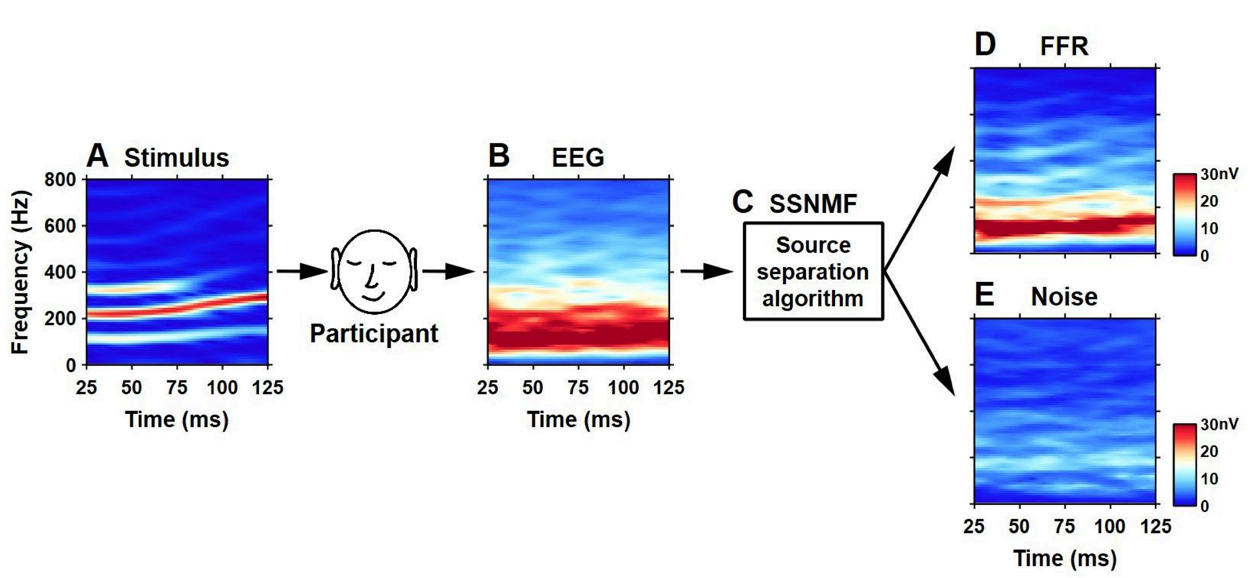

*Figure 1. A typical example of the SSNMF decomposition. **A.** Amplitude spectrogram of the stimulus. **B.** Grand-averaged spectrogram before SSNMF decomposition. **C.** SSNMF components. **D.** Grand-averaged spectrogram of the targeted FFR. **E.** Grand-averaged spectrogram of the noise.*

RESULTS SSNMF – NO SILENT INTERVAL

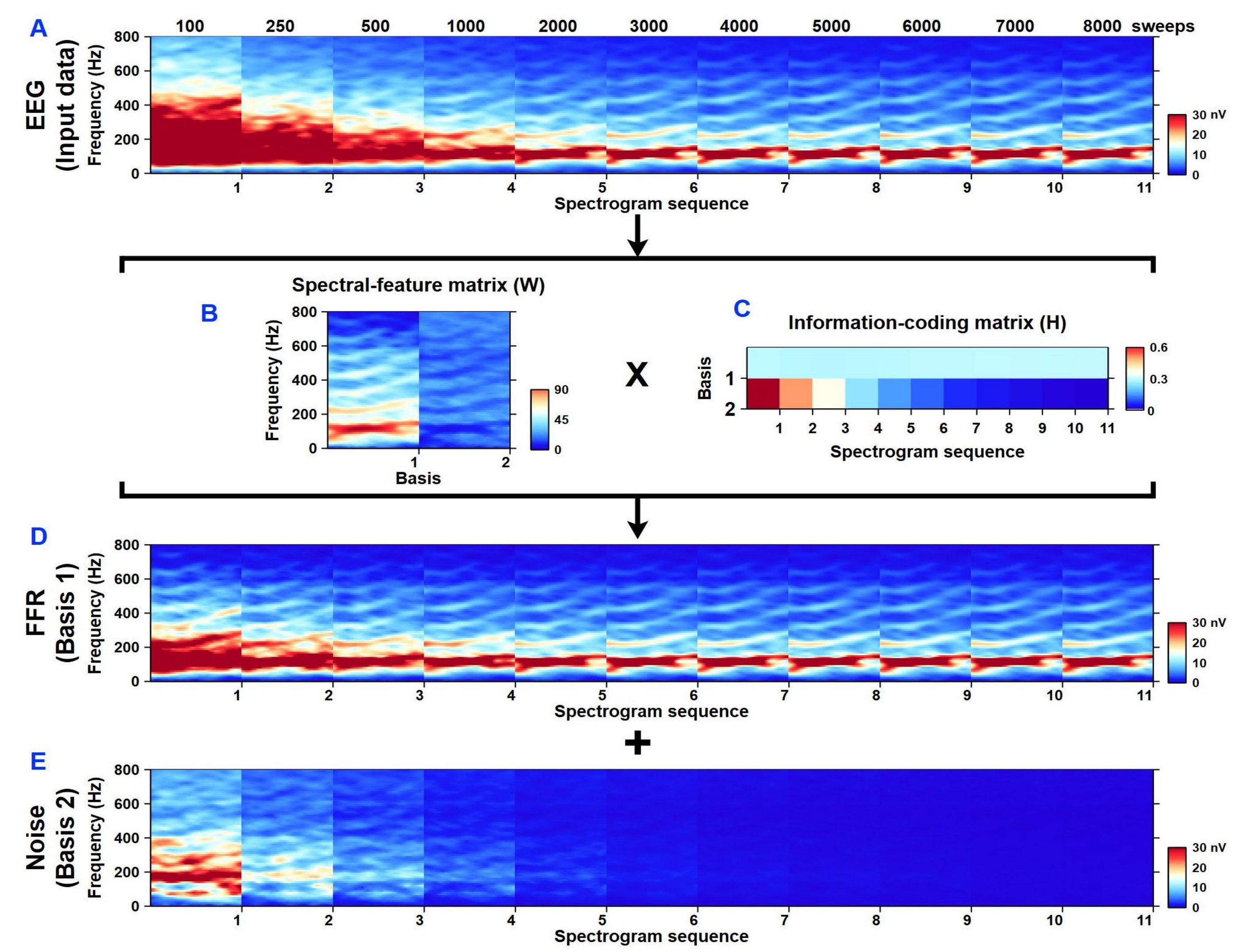

*Figure 2. Application of the SSNMF model on EEG recordings with no silent interval. **A.** Grand-averaged spectrograms of the input data **B.** Spectral-basis matrix. **C.** Information-coding matrix. **D.** Enhanced FFR. **E.** Extracted noise.*

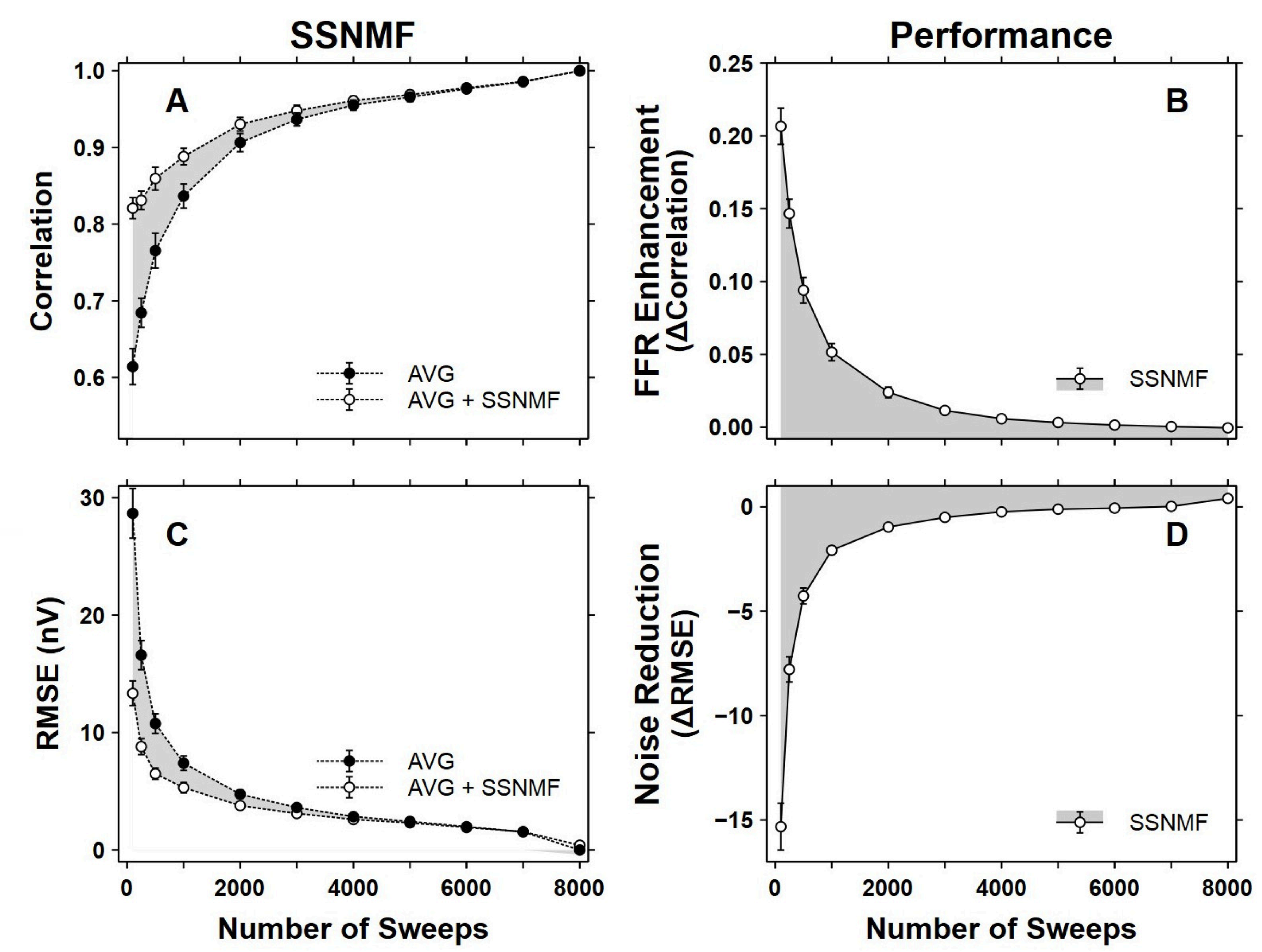

*Figure 3. SSNMF performance. **A.** Correlation coefficients before (AVG) and after (AVG+SSNMF) the SSNMF decomposition. **B.** FFR Enhancement as a function of the number of sweeps. **C.** RMSEs before and after the decomposition. **D.** Noise Reduction with increasing number of sweeps.*

RESULTS SSNMF – 150ms SILENT INTERVAL

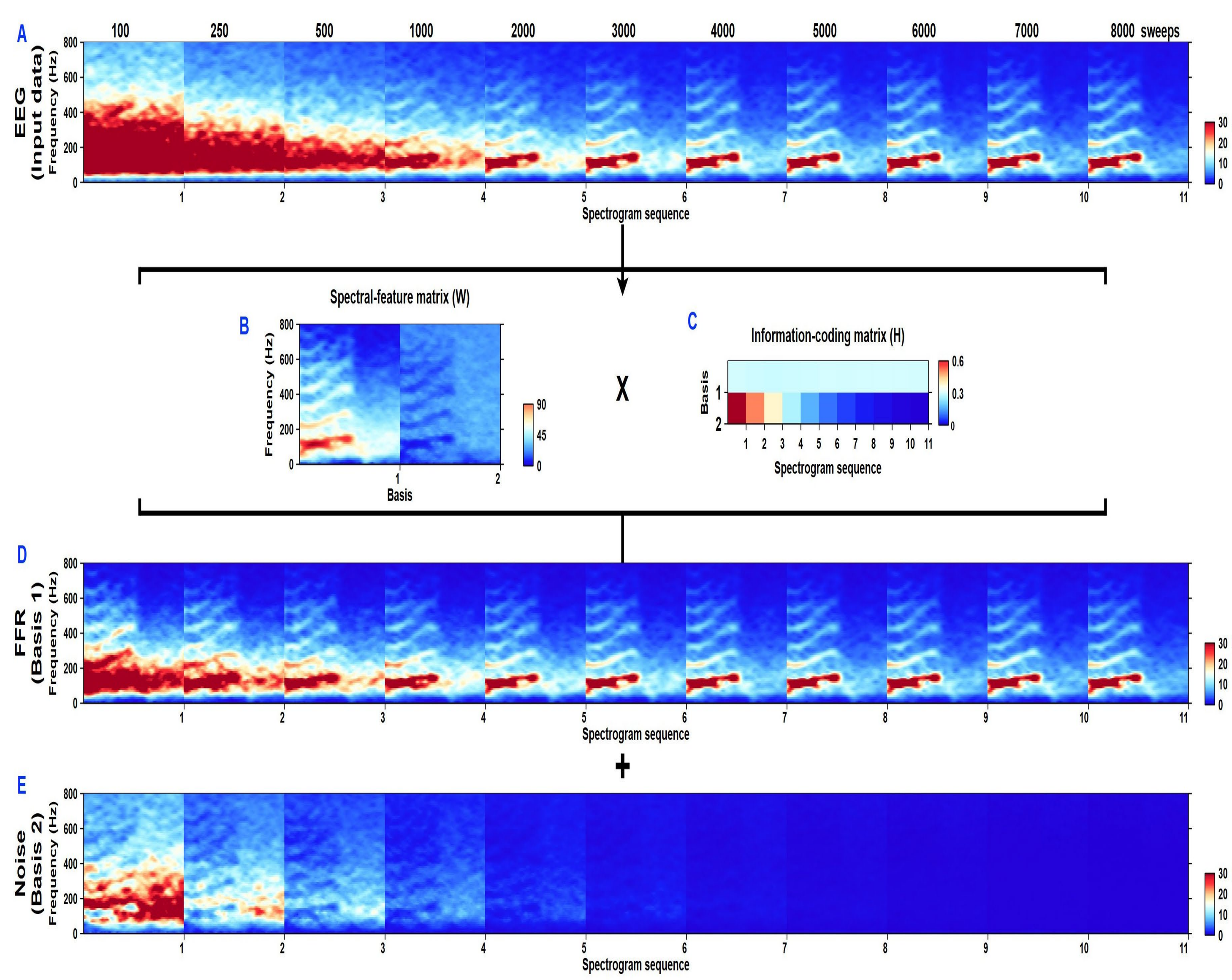

*Figure 4. Application of the SSNMF algorithm on EEG recordings with a silent interval of 150ms. **A.** Grand-averaged spectrograms of the input data **B.** Spectral-basis matrix. **C.** Information-coding matrix. **D.** Enhanced FFR. **E.** Extracted noise.*

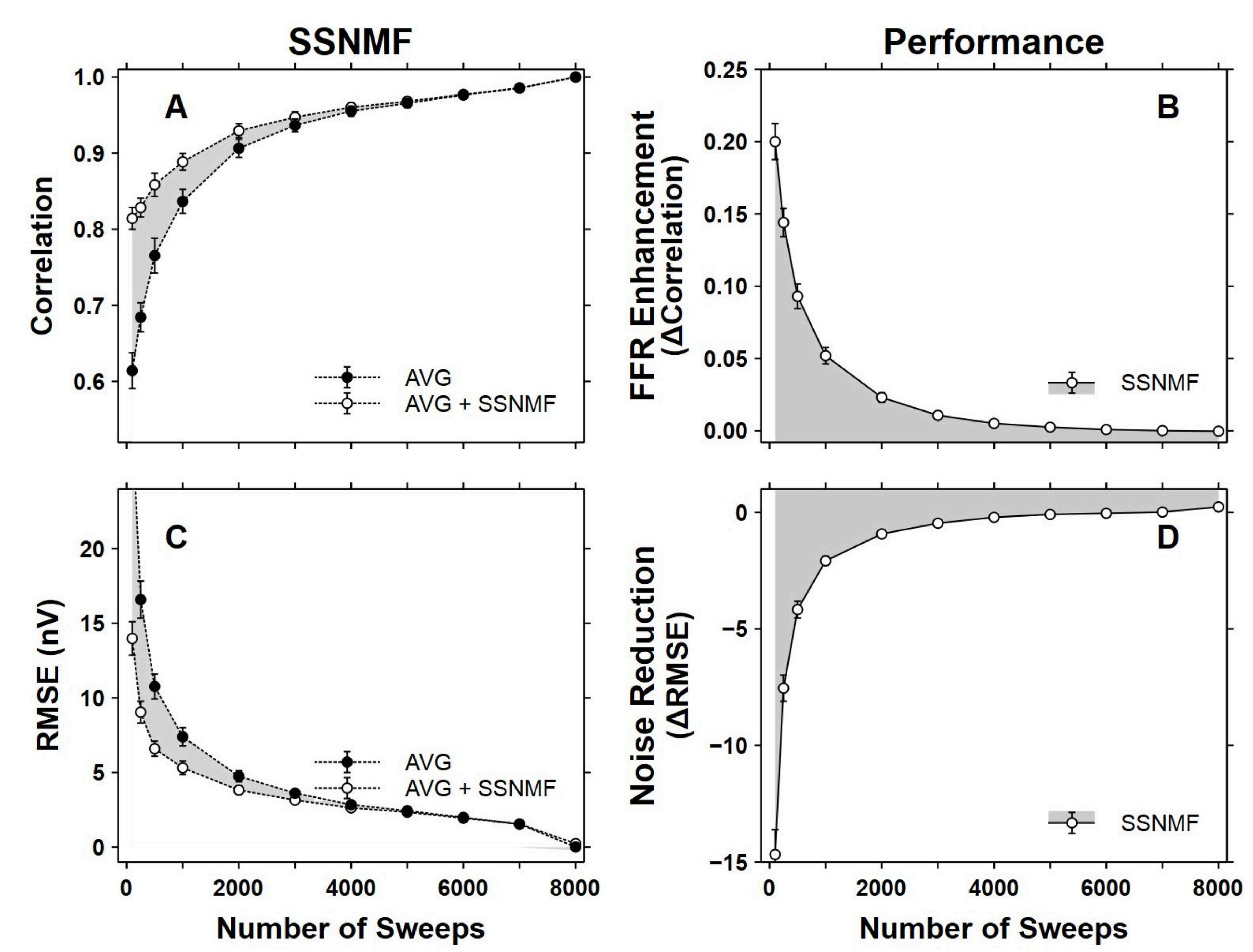

*Figure 5. SSNMF performance with a silent interval of 150ms. **A.** Correlation coefficients before (AVG) and after (AVG+SSNMF) the SSNMF decomposition. **B.** FFR Enhancement as a function of the number of sweeps. **C.** RMSEs before and after the decomposition. **D.** Noise Reduction with increasing number of sweeps.*

Overall Net Effect

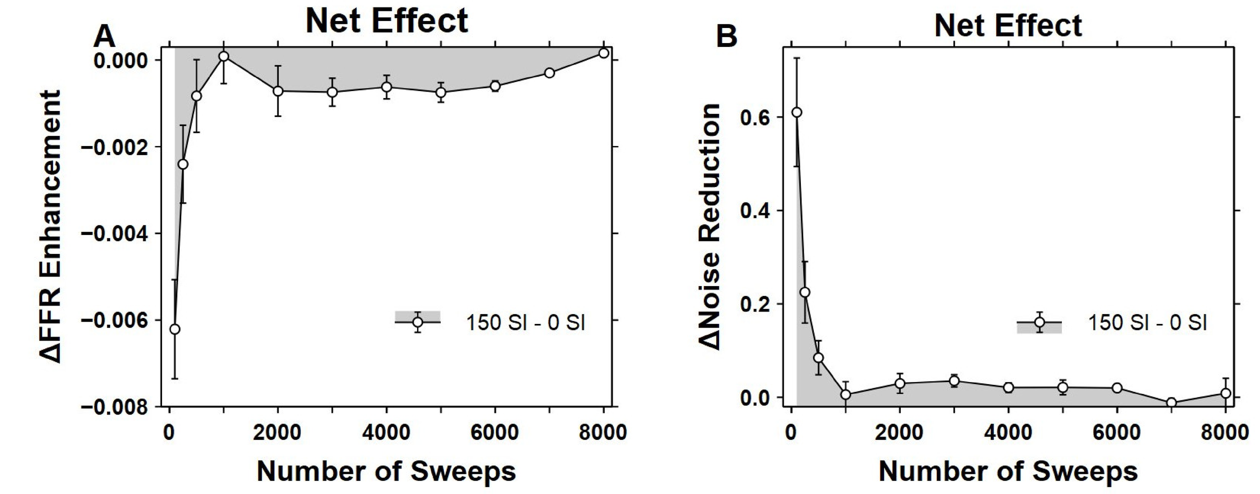

*Figure 6. Overall Net Effect across 11 conditions regarding FFR Enhancement and Noise Reduction. **A.** The net effect is negative in terms of FFR enhancement across the 11 nsweeps conditions, this shows a significant degradation of the SSNMF model performance with the inclusion of the 150 ms silent interval. **B.** The net effect is positive in terms of noise reduction across the 11 nsweeps conditions, this shows there is a decrease in the ability to reduce noise with the inclusion of a 150 ms silent interval.*

- A two-way repeated measures analysis of variance (ANOVA) showed a statistical significance on the silent interval on the model performance in terms of FFR Enhancement [$F(1, 22) = 11.532$, $p = 0.003$, $\eta_p^2 = 0.344$, *power* = 0.900] and Noise Reduction [$F(1, 22) = 24.200$, $p < 0.001$, $\eta_p^2 = 0.524$, *power* = 0.997].

DISCUSSION

- SSNMF algorithm without a silent interval can be used to extract the targeted response from noise, thus improve the efficiency of FFR recordings.
- A significant degradation was observed in extraction of FFRs that a 150 ms silent interval was included in the SSNMF model when compared no silent interval was included in the model.
- By eliminating the need of a silent interval, we found that the current SSNMF algorithm is the most streamlined process in reducing noise from the FFR recording.
- Without the inclusion of a silent interval, FFR Enhancement and Noise Reduction capabilities are best refined.
- This study lays a foundation for researchers to further investigate machine learning models and how to further improve their efficiency and effectiveness in decreasing noise.

ACKNOWLEDGMENTS

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