Auditory Processing: Effects of Silent Intervals on the Extraction of Human Frequency-Following Responses Using Non-Negative Matrix Factorization

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INTRODUCTION

- The Frequency-Following Response (FFR) is a scalp-recorded electroencephalographic (EEG) measurement that can be used to evaluate how the human brain processes important acoustic features of an incoming signal (Krizman & Kraus, 2019; Skoe & Kraus, 2010).
- Recent studies have focused on the applicability of various Machine Learning (ML) models in FFR research (Hart & Jeng, 2021; Llanos et al., 2019; Xie et al., 2019). Although the attempts to use ML models in identifying FFRs have produced fruitful results, none of them are designed to enhance the visibility of an FFR.
- The Non-Negative Matrix Factorization (NMF) algorithm is the foundation of a conventional ML model (Lee & Seung, 1999). Inspired by the potential of the NMF algorithm and driven by the desire to enhance the visibility of an FFR, Jeng and colleagues (2023) developed a Source-Separation Non-Negative Matrix Factorization (SSNMF) algorithm that built upon the capabilities of the conventional NMF algorithm. The SSNMF algorithm successfully increased FFR visibility and decreased noise disturbance by clustering energies that demonstrate a consistent pattern of spectral amplitudes.
- Silent intervals have traditionally been thought of as soundless gaps between adjacent acoustic stimuli. With the advent of the newly developed SSNMF algorithm, it is still unclear whether these intervals will significantly affect FFR extractions.

METHODS

Participants

- 23 adults (19 females, 4 males; 22.8 ± 1.8 years old).

Stimulus

- An English vowel /i/ with a rising frequency contour (F0 ranging from 102 to 140 Hz) was utilized to elicit FFRs.
- The stimulus has a duration of 150 ms.
- The silent interval between the offset of a stimulus and the onset of the next was fixed at 150 ms.
- 70 dB SPL to the right ear.

Recording

- 3 gold-plated surface recording electrodes.
  - High forehead (non-inverting), right mastoid (inverting), and low forehead (ground).
- 8000 accepted sweeps for each recording.

Data Analysis

- 100, 250, 500, 1000, 2000, 3000, 4000, 5000, 6000, 7000, and 8000 sweeps were randomly selected from a pool of the 8000 accepted sweeps.
- The averaged time waveform of each nSweep condition was converted to an amplitude spectrogram by using a narrow-band sliding-window technique.
- Amplitude spectrograms of the 11 nSweep conditions were concatenated as input signals in the SSNMF algorithm.

Algorithm Performance

- *FFR Enhancements* and *Noise Residues* were computed to estimate algorithm performance, while silent intervals were either included (i.e., the *WithSI* condition) or excluded (i.e., the *WithoutSI* condition) in the data analysis.

SSNMF Algorithm

Architecture

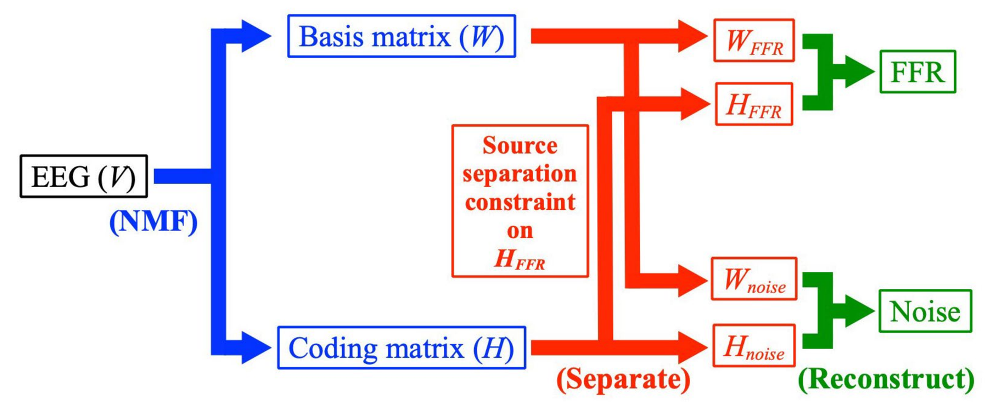

***Figure 1.** Design of a SSNMF Algorithm. The SSNMF algorithm was based on two assumptions: (1) each EEG recording was a mixture of FFR and noise, and (2) an FFR was present with similar magnitudes in each recording sweep.*

Optimization

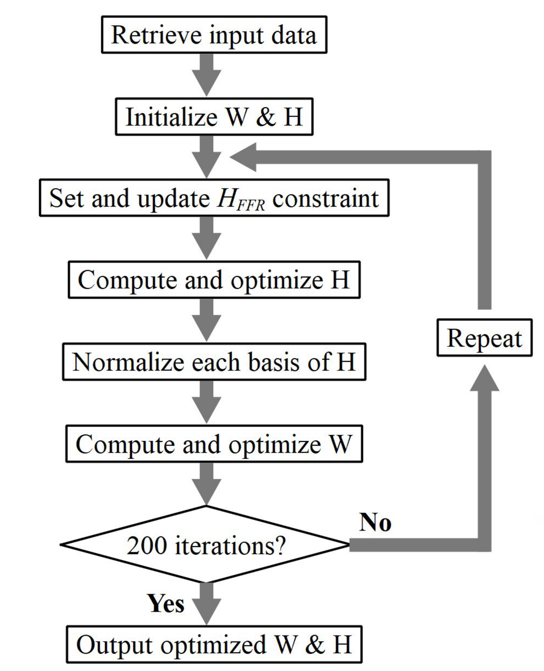

***Figure 2.** Procedural Steps of an Iteration Cycle.*

RESULTS

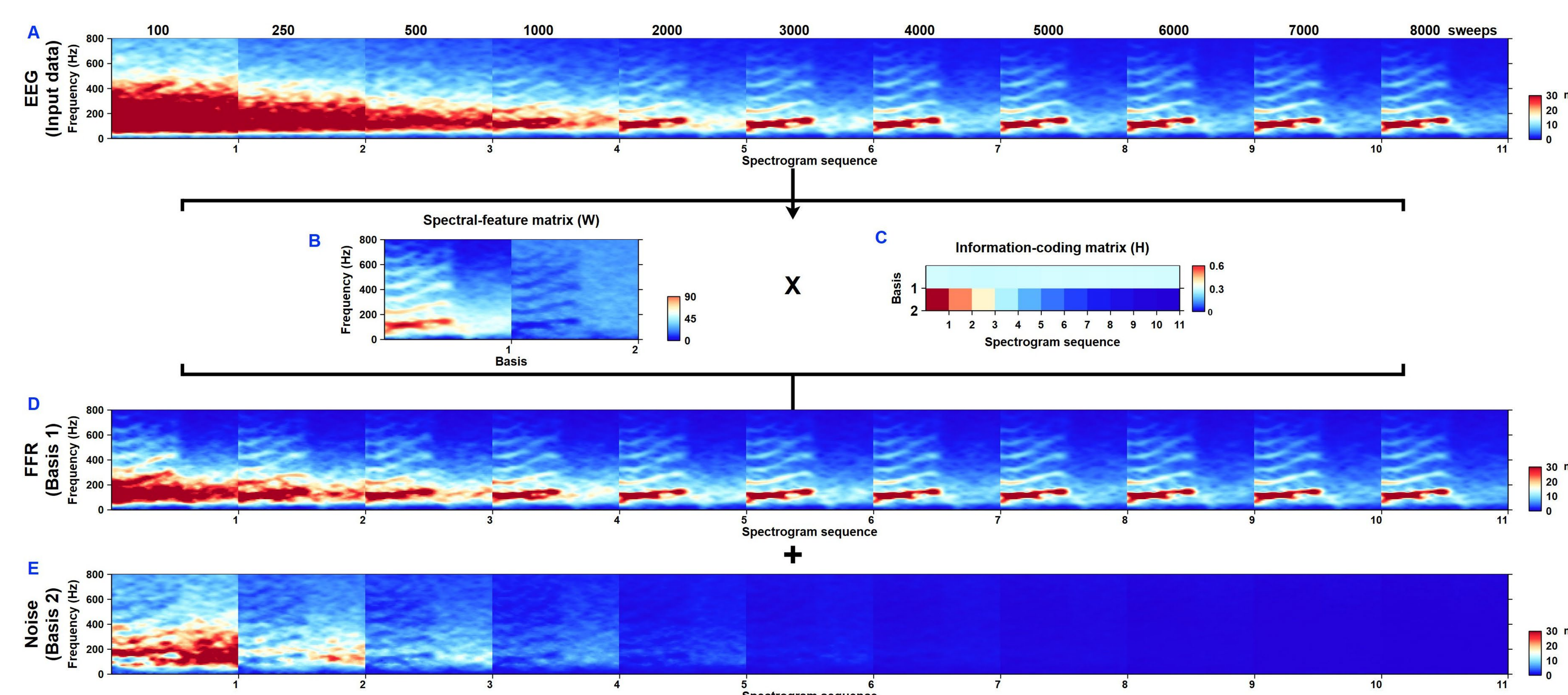

***Figure 3.** Application of the SSNMF algorithm on FFR recordings with Silent Intervals. Grand-averaged spectrograms of the input data (A), spectral-basis matrix (B), information-coding matrix (C), enhanced FFR (D), and extracted noise (E).*

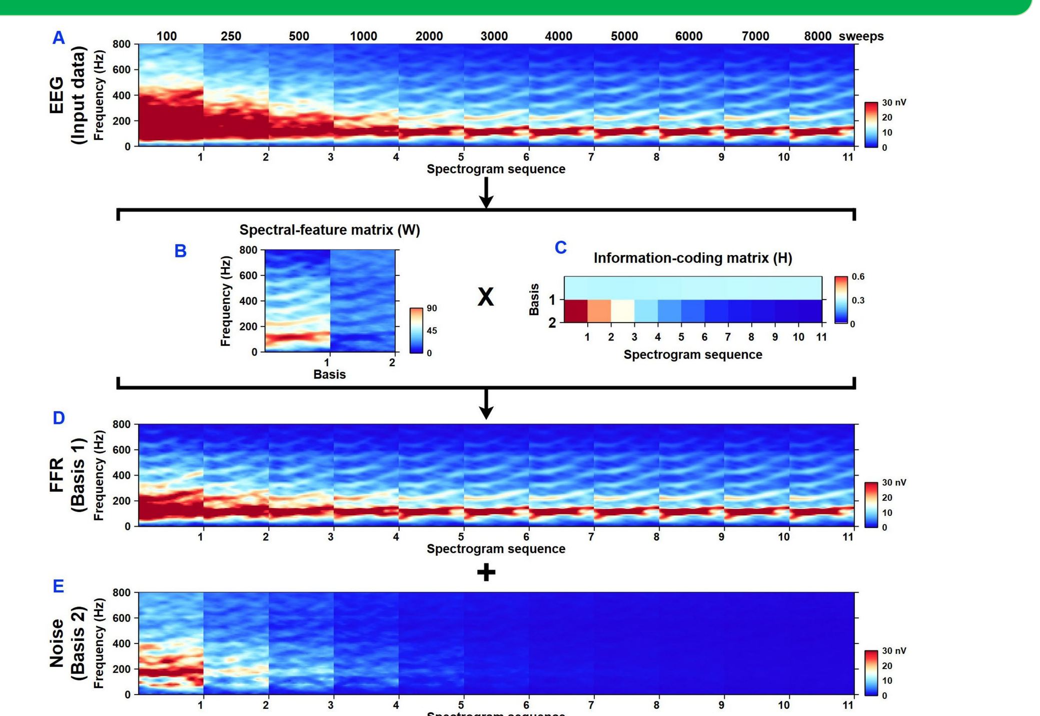

***Figure 4.** Application of the SSNMF algorithm on FFR recordings without Silent Intervals. Grand-averaged spectrograms of the input data (A), spectral-basis matrix (B), information-coding matrix (C), enhanced FFR (D), and extracted noise (E).*

Algorithm Performance (WithSI)

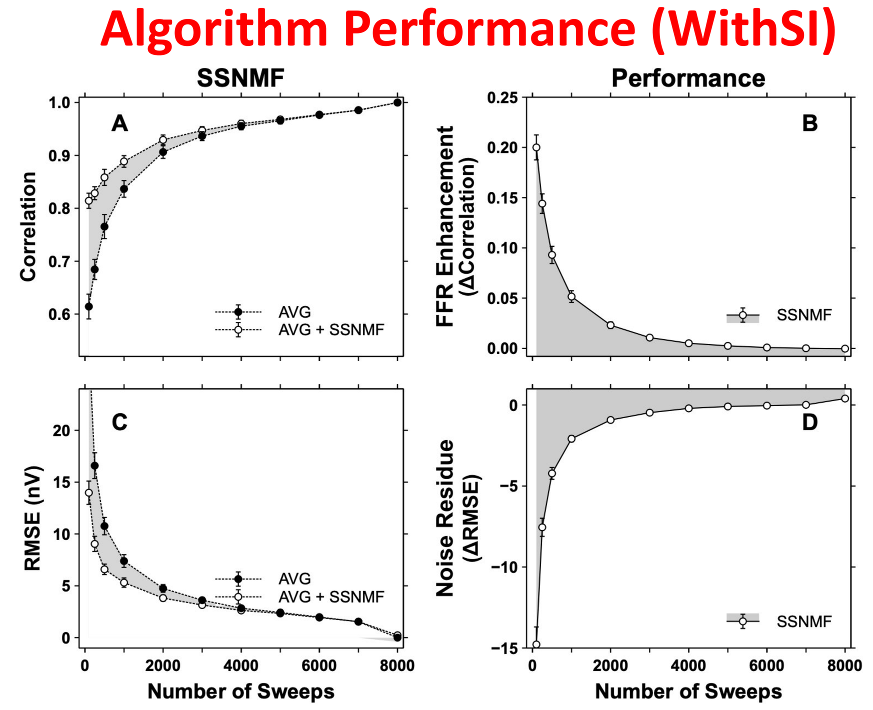

***Figure 5.** Algorithm Performance with Silent Intervals.*

Algorithm Performance (WithoutSI)

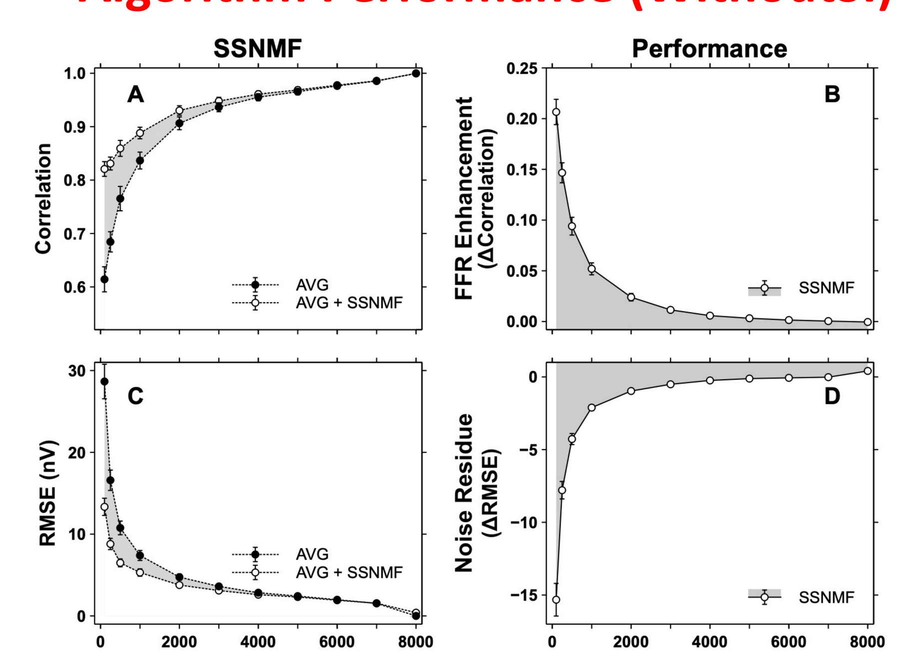

***Figure 6.** Algorithm Performance without Silent Intervals.*

Net Effects (WithoutSI – WithSI)

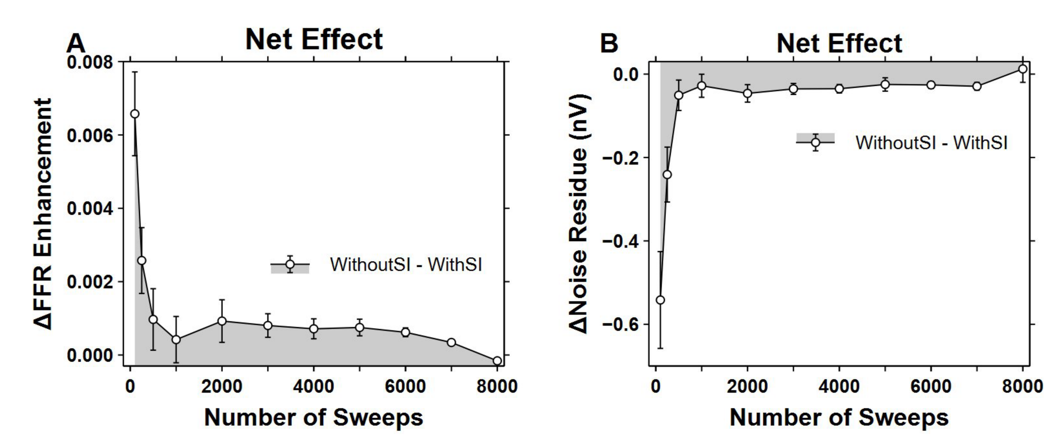

***Figure 7.** Effects of Silent Intervals on the SSNMF Algorithm Performance. Net effects of silent intervals in terms of ΔFFR Enhancement (A) and ΔNoise Residue (B).*

DISCUSSION

- A significant improvement ($p < 0.05$) was observed in the extraction of FFRs for all nSweep conditions, except for 8000 sweeps, when silent intervals were excluded from the SSNMF algorithm, as opposed to when silent intervals were included in the algorithm.
- Although improvements in algorithm performance were anticipated when no silent intervals were included, the extent to which the algorithm performance has improved was quite impressive, with a 11.78% increment in *FFR Enhancement* and a 20.69% decrement in *Noise Residue*.
- These results not only quantify the effects of silent intervals on the extraction of human FFRs, but also provide recommendations for designing and improving the SSNMF algorithm in future research.
- Limitations of this study and future directions
  - The applicability of this algorithm on different types of stimuli, such as the /da/ stimulus that has been widely used in FFR research, remains unexplored.
  - As the SSNMF can be combined with other ML models, the extent to which the effects of silent intervals on the algorithm performance may propagate and influence the outcome of other ML models remains unknown
- For clarity, the SSNMF algorithm written in the Python programming language and a sample recording are available on the first author's (FCJ) GitHub repository https://github.com/fjeng/ffr_ssnmf_feasibility.

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