Non-negative Matrix Factorization Improves the Efficiency of Recording Frequency-Following Responses in Normal-Hearing Adults and Neonates

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INTRODUCTION

- The scalp-recorded frequency-following response (FFR) is an electroencephalographic (EEG) measurement that has been widely used to evaluate how the human brain perceives and tracks changes in the fundamental frequency (F0) and its harmonics with periodic speech stimulations (Hart & Jeng, 2021; Krizman & Kraus, 2019; Skoe & Kraus, 2010).
- Despite the usefulness of the FFR, one major challenge still exists. This challenge is related to the negative influences of different kinds of noise that are embedded in a recording. Because the FFR is a small-amplitude response (usually ≤ 100 nV) (Jeng et al, 2011; Lemos et al., 2021; Skoe & Kraus, 2010), any kind of noise, either environmental or physiological in nature, may have substantial and adverse effects on the signal-to-noise ratio of a recording.
- The non-negative matrix factorization (NMF), first reported by Lee and Seung (Lee & Seung, 1999), is a machine learning algorithm for extracting parts-based representations (i.e., separating different components of a mixture).
- In this study, we developed a new source separation NMF (SSNMF) algorithm that does not require any supervised training by integrating a source separation constraint (i.e., a rule dictating how each component is computed) in the conventional NMF algorithm.

METHODS

Participants

- Fifteen American adults (10 females and 5 males, 20-33 years old) and 15 American neonates (6 girls and 9 boys, 1-3 days after birth)

Stimulus

- An English vowel /i/ with a rising frequency contour (F0 ranging from 102 to 140 Hz) was utilized to elicit FFRs.
- 70 dB SPL for adults and 65 dB SPL for neonates

Recording

- 3 gold-plated surface recording electrodes
  - High forehead, right mastoid, and low forehead
- Participants resting or fast-asleep prior to recording
- 8000 accepted sweeps for each recording

Preprocessing

- 100, 250, 500, 1000, 2000, 3000, 4000, 5000, 6000, 7000, and 8000 sweeps were randomly selected from a pool of the 8000 accepted sweeps.
- This resulted in a total of 11 nSweep conditions to be analyzed.
- 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 subsequently concatenated as input signals in the SSNMF algorithm

SSNMF Model

Architecture

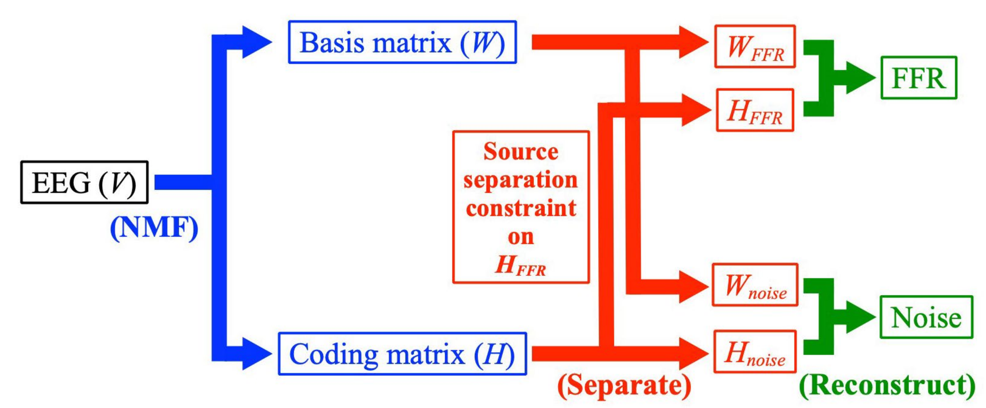

Figure 1. Design of a SSNMF algorithm. The SSNMF algorithm was based on two assumptions: (1) each EEG recording was a mixture of FFR and noise, and (2) an FFR was present with similar magnitudes in each recording sweep.

Optimization

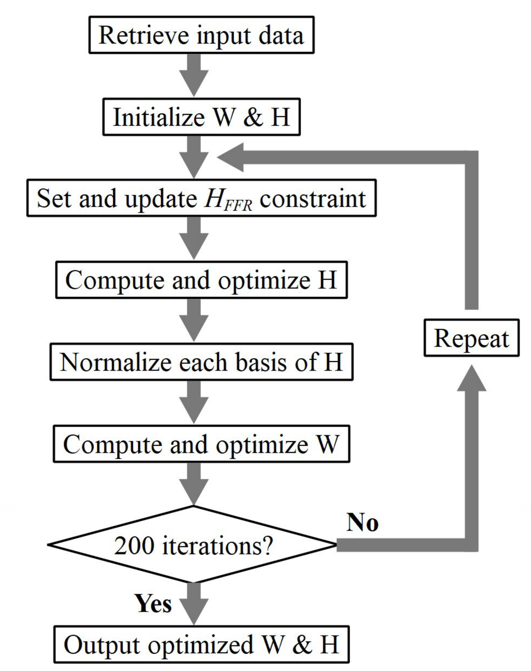

Figure 2. Procedural steps of an iteration cycle.

Example Outcome

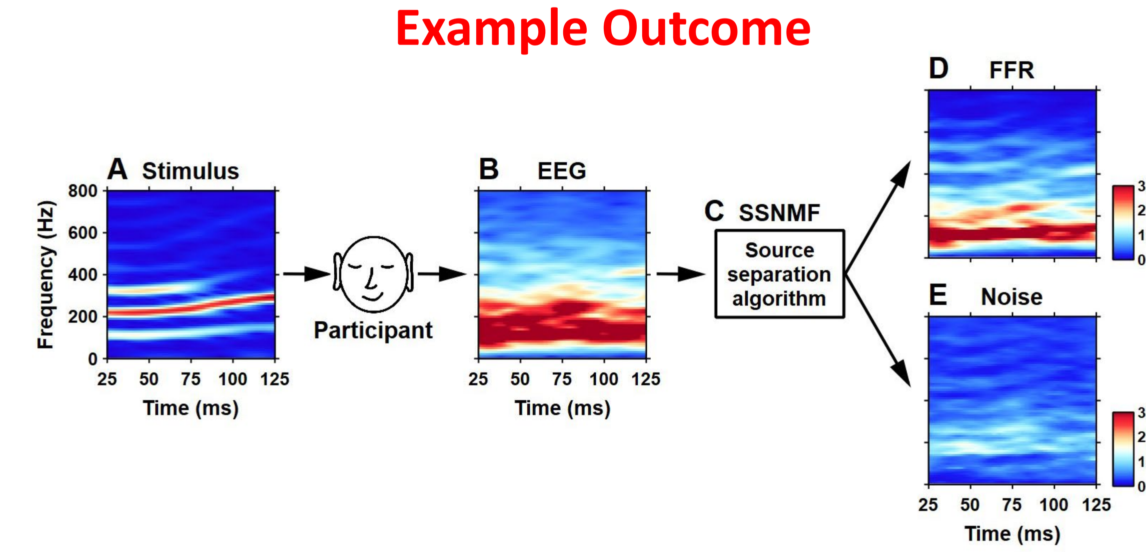

Figure 3. A typical example of the SSNMF decomposition. These grand-averaged spectrograms were obtained from fifteen adult participants when the 500 sweeps were included in the averaging procedure.

RESULTS

Source Separation

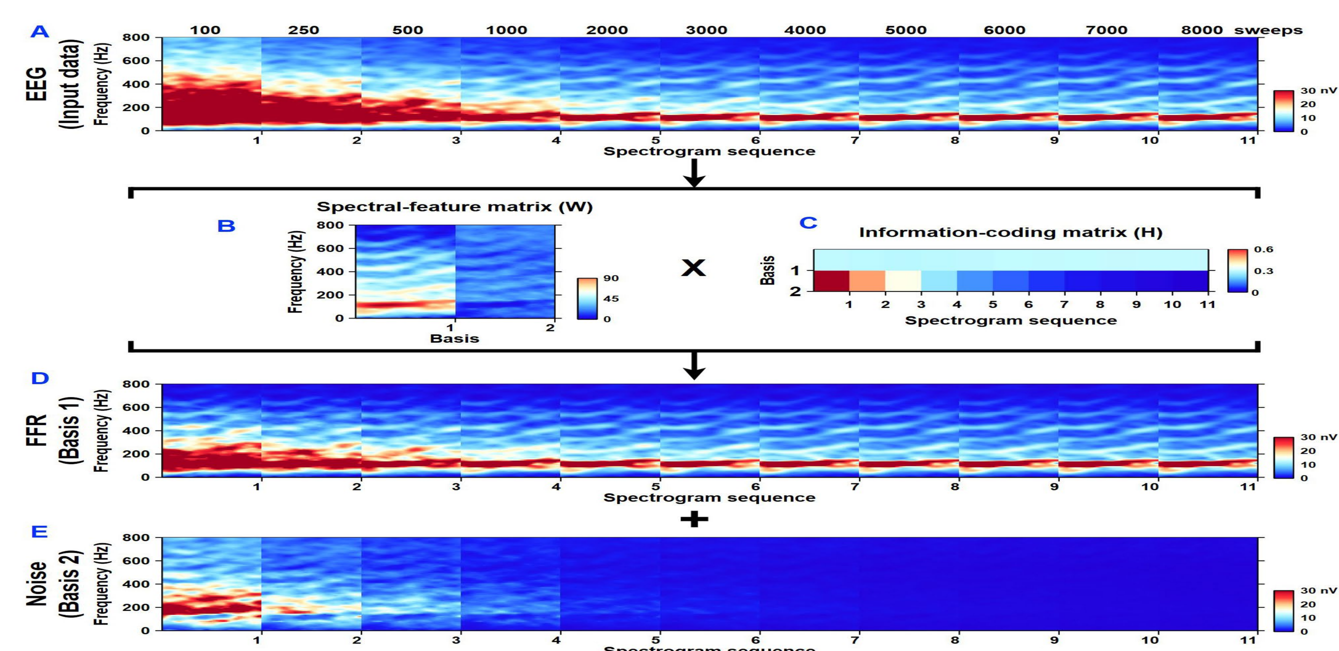

Figure 4. Application of the SSNMF algorithm on EEG recordings obtained in adult participants. Grand-averaged spectrograms of the input data (A), spectral-basis matrix (B), information-coding matrix (C), enhanced FFR (D), and extracted noise (E).

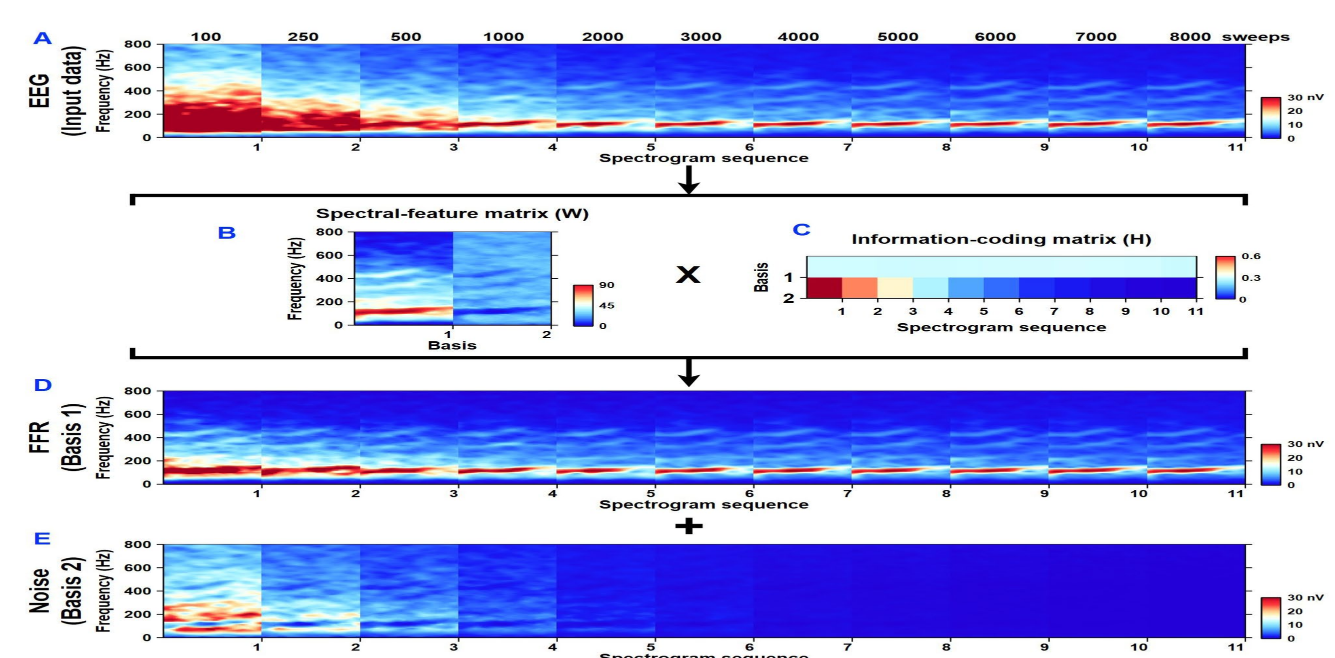

Figure 5. Application of the SSNMF algorithm on EEG recordings obtained in neonatal participants. Grand-averaged spectrograms of the input data (A), spectral-basis matrix (B), information-coding matrix (C), enhanced FFR (D), and extracted noise (E).

Model Performance

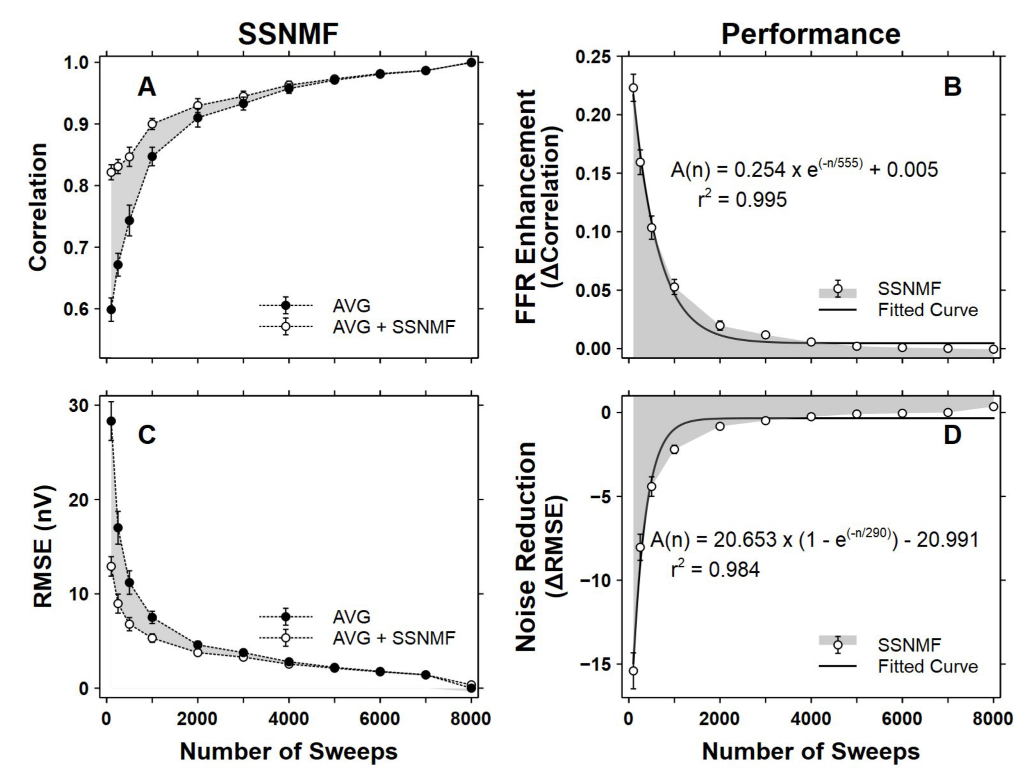

Figure 6. SSNMF performance in adult participants.

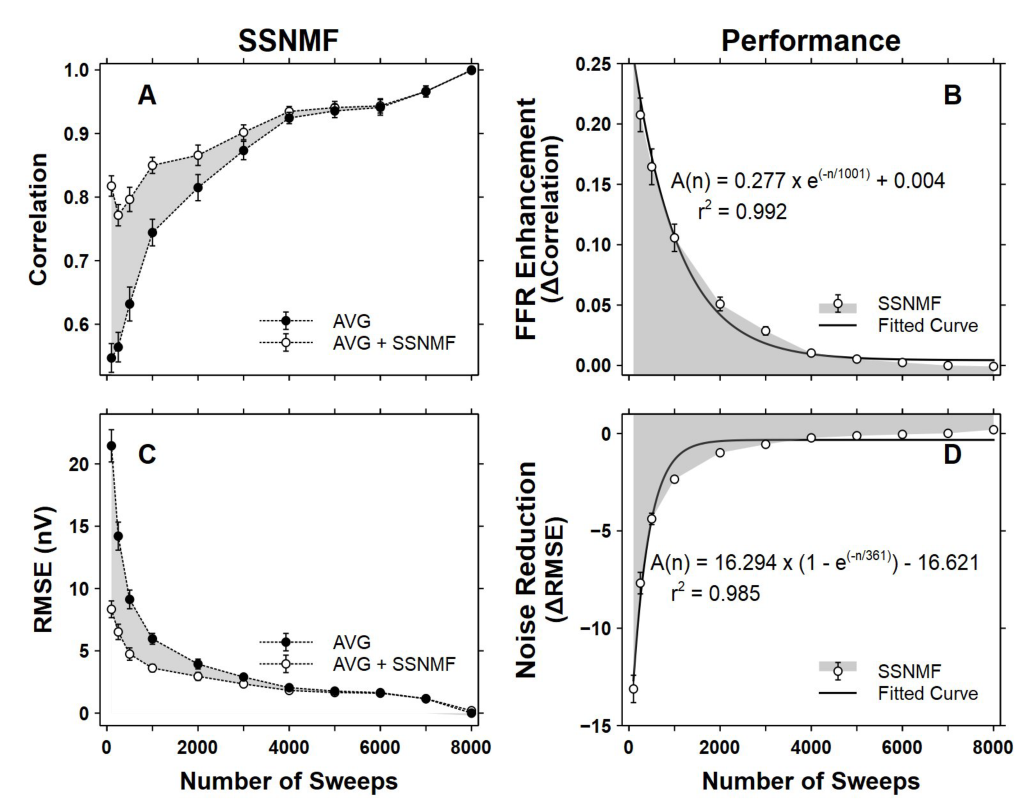

Figure 7. SSNMF performance in neonatal participants.

DISCUSSION

- Effectiveness of the SSNMF algorithm is visualized in the sweep series of amplitude spectrograms derived from adult and neonatal recordings.
- The SSNMF decomposition has successfully enhanced the visibility of the FFR and removed additional noise from each recording. Such improvements are examined and modeled through exponential curve fitting of FFR Enhancement and Noise Reduction trends with increasing number of sweeps.
- Applications of the SSNMF algorithm on FFR recordings may prove to be useful in assessing pitch processing and neuroplasticity mechanisms in the human brain for individuals during their adulthood and immediate postnatal days.
- Limitations of this study and future directions
  - Although the SSNMF algorithm does not require any training data, performance of this algorithm relies on the quality and information that are embedded in the input spectrograms.
  - 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.
- 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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