Titel123

Marc Pabst

How does the brain process and represent successive sound in close temporal proximity? By investigating mismatch negativity (MMN) components, prior research (Sussman & Gumenyuk, 2005; Sussman, Ritter & Vaughan, 1998) has suggested that temporal proximity plays an important role in how sounds are represented in auditory memory. Here, we investigate how predictability affects the election of mismatch negativity components in auditory sequences consisting of two tones (frequent tone A = 440 Hz, rare tone B = 494 Hz, fixed SOA 100 ms). In the predictable condition, tones are presented in a fixed order whereas in the unpredictable condition, standards and deviants are presented in a pseudo-random order. We expect to find that B tones in the unpredictable condition will elicit a significant MMN while B tones in the predictable conditions will not. A repeating five-tone pattern was presented at several stimulus rates (200, 400, 600, and 00 ms onset-to-onset) to determine at what temporal proximity the five-tone repeating unit would be represented in memory. The mismatch negativity component of event-related brain potentials was used to index how the sounds were organized in memory when participants had no task with the sounds. Only at the 200-ms onset-to-onset pace was the five-tone sequence unitized in memory. At presentation rates of 400 ms and above, the regularity (a different frequency tone occurred every fifth tone) was not detected and mismatch negativity was elicited by these tones in the sequence. The results show that temporal proximity plays a role in unitizing successive sounds in auditory memory. These results also suggest that global relationships between successive sounds are represented at the level of auditory cortices.

# Introduction

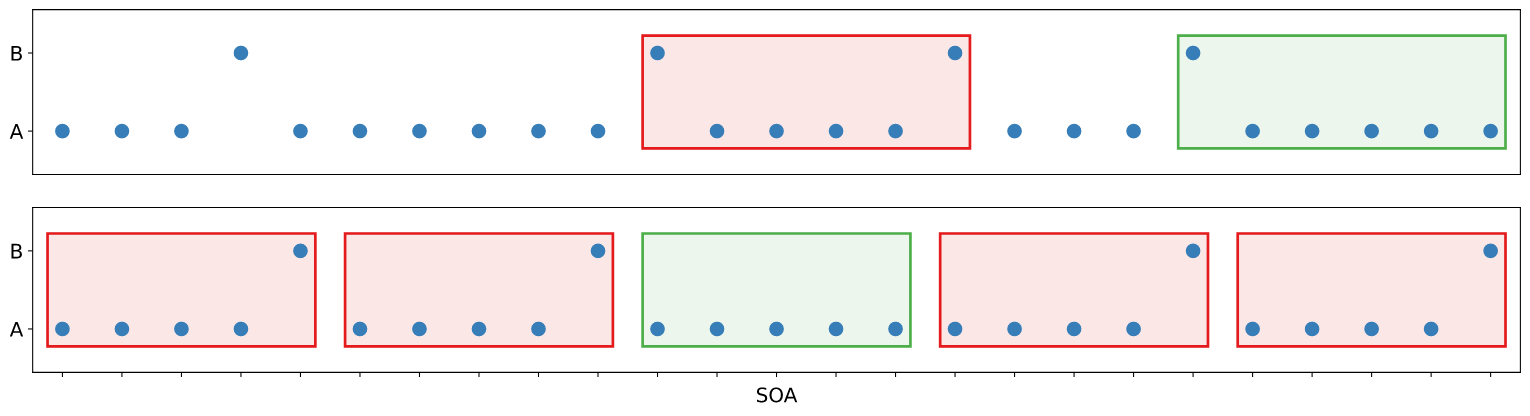
# Methods

## Data Acquisition

### Participants

For study 1, 24 participants were recruited.

### Stimuli



Auditory stimuli in two different condition

Stimuli consisted of pure sinusodial tones with a duration of 50 ms (including a 10 ms cosine on/off ramp), presented isochronously at a stimulation onsets asynchrony (SOA) of 100 ms for study 1 and 150 ms for study 2. Participants where seated in a electromagnetically shielded and sound-proofed cabin while administering a total of 40 blocks containing a mixture of frequent 440 Hz tones (“A” tones) and infrequent 449 Hz tones (“B” tones). In one half of the blocks, tones were presented in pseudo-random order (e.g. AAABABA}, “random” condition), while in the remaining block tones followed a simple pattern in which a five-tone-sequence of four frequent tones and one infrequent tone (i.e. AAAAB) was repeated cyclically (“predictable” condition). The ratio of frequent and infrequent tones was 1/10 for both conditions. Additionally, within the predictable condition, 10% of designated (infrequent) B tones were replaced by A tones, resulting in sporadic five-tone sequences consisting solely of A tones (i.e. AAAAA). In the random condition, randomly arranged tones were interspersed with sequences mimicking aforementioned patterns from the predictable condition (BAAAAB and BAAAAA).

In Study 1, a total of 2000 tones for (4000 tones Study 2) was delivered to each participant.

### Data Acquisition

Electrophysiological data was recorded from active Silver-silver chloride (*Ag*-*AgCl*) electrodes using an ActiveTwo amplifier (BioSemi B.V., Amsterdam, The Netherlands). Acquisition was monitored online to ensure data quality. A total of 39 channels were obtained using a 32-electrode-cap and 7 external electrodes. Scalp electrode locations conformed to the international 10–20 system. Horizontal and vertical eye movement was obtained using two bipolar configurations with electrodes placed around the lateral canthi of the eyes and above and below the right eye. Three additional external electrodes were placed on the tip of the nose and at the left and right mastoid sites. Data was sampled at 512 Hz and on-line filtered at 1000 Hz.

## Analysis Pipeline

Data prepossessing was implemented using a custom pipeline based on the *MNE Python* software package (Gramfort, 2013) using *Python 3.7*. All computations were carried out on a cluster operated by the University Computation Center of the University of Leipzig. Code used in thesis is publicly available at <https://github.com/marcpabst/xmas-oddballmatch>.

### Bad Channel Detection and Interpolation

Firstly, EEG data was subject to the ZapLine procedure (de Cheveigné, 2020) to remove line noise contamination. A fivefold detection procedure as described by Bigdely-Shamlo et al. (2015) was then used to detect and subsequently interpolate bad channels. This specifically included the detection of channels thain contain prolonged segments with verry small values (i.e. flat channels), the exclusion of channels based on robust standard deviation (deviation criterion), unusualy pronounced high-frequency noise (noisiness criterion), and the removal of channels that were poorly predicted by nearby channels (correlation criterion and predictability criterion). Channels considered bad by one or more of these methods were removed and interpolated using spherical splines (Perrin et al., 1989). Electrode locations for interpolations were informed by the BESA Spherical Head Model.

### Independent Component Analysis

Given the power spectral density of EEG data, the estimation independent components (ICs) by independent component analysis (ICA) would be strongly influenced by high-frequency noise that is ususally considere brain-irrelevant [reference]. To mitigate this effect, a 1-Hz-high-pass filter (134th order hamming-windowed FIR) was applied prior to ICA (Winkler et al., 2015).

To further reduce artifacts, Artifact Subspace Reconstruction (ASR, Mullen et al., 2015) was used to identify parts of the data with unusual characteristics (bursts) which were subsequently removed. ICA was then carried out using the *Picard* algorithm (Ablin et al., 2018, 2017) on PCA-whitened data. To avoid rank-deficiency when extracting components from data with one or more interpolated channels, PCA was also used for dimensionality reduction to obtain full-ranked data.

The EEGLAB (version 2020.0, Delorme & Makeig, 2004) software package and the IClabel plugin (version X.Y, Pion-Tonachini et al., 2019) were used to automatically classify estimated components. Only components clearly classified (i.e. confidence above 50%) as resulting from either eye movement, muscular, or heartbeat activity were zeroed-out in the mixing matrix before inversely transform ICs.

### Filtering

In line with recommendations from Widmann et al. (2015), a bandpass filter from 0.1 Hz to 30 Hz was applied (Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation).

### Epoching and Averaging

Continuous data was epoched into 400 ms long segments around stimulus onsets. This included a 100 ms pre-stimulus interval which was used to perform baseline correction by subtracting its mean amplitude from each epoch. The AutoReject software package (Jas et al., 2017) was used to reject bad epochs. The AutoReject algorithm uses cross-validations and basyan optimaziation to calculate channel-wise peak-to-peak amplitude thresholds that minimizes the root mean square error (RMSE) between the mean (after removing the trials marked as bad) and the median of the data (including all trials). For epochs where only a small subset of channels exceeded the critical threshold, bad channels were interpolated instead of removing the whole epoch.

## Statistical Analysis

# References

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