

Running Title: Paradigm to simultaneously record MMR and cABR

Validating a new paradigm for simultaneously assessing mismatch response and complex
auditory brainstem response

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Highlights

- Speech perception requires interactions between cortical and subcortical processes
- Our new paradigm records concurrent MMR (cortical) and cABR (subcortical)
- MMRs for Native vs. Nonnative speech sounds are decoded by a machine-learning model
- cABR for different speech stimuli are also reliably decoded
- Replicate and extend past studies with much fewer trials and shorter experiment time

Abstract

Speech sounds are processed in the human brain through intricate and interconnected networks of cortical and subcortical structures, yet it remains largely unknown how these different levels of auditory processing interact with one another. Two neural signatures, one largely from cortical sources (mismatch response, MMR) and one largely from subcortical sources (complex auditory brainstem response, cABR) are critical for assessing language acquisition, as they both show a sensitivity to high-level linguistic information. To understand how cortical-subcortical interactions influence speech perception, MMR and cABR must be measured within the same paradigm, yet few studies have accomplished this due to their distinct recording prerequisites. This study aims to validate our novel paradigm that concurrently captures both signals by meeting the benchmarks of significant decoding accuracies for (1) MMR between Native and Nonnative speech contrasts and (2) cABR to three speech sounds. Using EEG, we observed a decoding accuracy of 71.8% between Native vs. Nonnative MMR, achieved higher than 97.5 percentile against the null distribution. A significantly larger Native MMR was shown in the expected time window, replicating past research. A significant decoding accuracy of 81.8% was found for cABR. A high stimulus-to-response cross-correlation within 10 ms suggested that cABR closely tracks speech sounds. These findings demonstrate that our paradigm reliably captures both MMR and cABR, with much fewer trials and shorter experiment time. This study paves the way to understanding cortical-subcortical interactions for speech and language processing with the potential to serve as an ideal clinical assessment tool particularly in early development.

Keywords:

Mismatch response, Auditory brainstem response, Speech perception, Recording paradigm

Introduction

Humans can identify a variety of complex sounds in their surroundings, among them, comprehending speech sounds stands as a fundamental aspect of our human experiences. To understand the linguistic meaning of a speech sound and acquire a language, humans must perceive critical acoustic features in the dynamic speech signal. This feat cannot be achieved without the intricate and interconnected networks of cortical and subcortical structures along the central auditory pathway (Bidelman, 2015; Escera, 2023; Kraus & White-Schwoch, 2015), yet it remains largely underexplored how these networks interact to support language acquisition.

Past studies have investigated speech processing in both cortical and subcortical levels along the auditory pathway using scalp-recorded neural activities, measured with non-invasive and temporally sensitive M/EEG. Most brain studies and prominent speech perception models (e.g. dual stream model by Hickok & Poeppel, 2000, 2004, 2007) focused on cortical mechanisms (see a recent review by Bhaya-Grossman & Chang, 2022). One well-studied cortical neural signature is the mismatch response (MMR), predominantly localized to the inferior frontal cortex and superior temporal cortex, reflecting neural sensitivity to sound changes, including phonetic contrasts (Garrido et al., 2009; Näätänen et al., 2007). Critically, MMR has been shown to be modulated by language experience. For example, research has found that listeners have a discriminable, mostly larger, MMR to phonetic contrasts in their native language than in nonnative languages (Näätänen et al., 1997; Sharma & Dorman, 1999, 2000; Zhang et al., 2005; Zhao, 2022). This divergence emerges early in life and is crucial for subsequent language development (Zhao et al., 2021; Zhao & Kuhl, 2022), making MMR a valuable neural indicator to predict language abilities in early childhood. The conventional approach for eliciting MMR involves hundreds of sound repetitions in an oddball paradigm, in which a sequence of repeated

Standard sounds is randomly interspersed with one or multiple types of Deviants, or oddball sounds (Näätänen et al., 2004). MMR can be observed by comparing averaged evoked response between discriminable Deviants to the Standards, typically between 100 to 250 ms after the Deviants. The conventional oddball paradigm's dependence on a high number of trials often leads to long recording times and participant boredom, making it especially challenging for infants and kids.

Another neural signal, the complex auditory brainstem response (cABR), originating primarily from subcortical structures, has recently gained attention for its role in early-stage auditory processing of speech sounds. In contrast to the conventional view of cABR as a passive mechanism for faithful transcription of acoustic properties (Krizman & Kraus, 2019; Skoe & Kraus, 2010), recent studies have revealed its adaptability through higher-level music and language experiences (Bidelman et al., 2011; Zhao & Kuhl, 2018; Krishnan et al., 2005; Krishnan & Gandour, 2009; Llanos et al., 2017; Ou et al., 2023; Reetzke et al., 2018; Wong et al., 2007; see Escera, 2023 for a thorough review). For instance, studies have shown that speakers of tonal languages or highly skilled English-speaking musicians exhibit cABRs tracking the pitch of lexical tones, surpassing the capabilities of non-tonal language speakers or nonmusicians (Bidelman et al., 2011; Krishnan et al., 2005; Krishnan & Gandour, 2009; Llanos et al., 2017; Ou et al., 2023; Wong et al., 2007). In addition, research on English-speaking adults who underwent a short-term, intensive lexical tones training revealed alterations in neural pitch tracking of lexical tones, as evidenced by changes in the cABR (Reetzke et al., 2018). Our recent study delved into the cABR in English- and Spanish speakers and found that their cABRs are influenced by their language experience (Zhao & Kuhl, 2018). Furthermore, studies have found an effect on cABR from experiences and learning as early as in infancy and childhood (Anderson

et al., 2015; Llanos et al., 2022; Novitskiy et al., 2022; Skoe et al., 2015; Zhao, 2022). These findings suggest that cABR, mainly attributed to subcortical processes (yet still under debate, see our Discussion), plays a crucial role in speech and language comprehension from an early age.

Despite the significance of both MMR and cABR in speech and language processing research, the relationship between them for encoding linguistic information remains unclear due to the absence of concurrent recording paradigms. This scarcity is primarily attributed to the latency of each neural signal and thus the distinct recording requirements for subcortical cABR and cortical MMR. The subcortical cABR is relatively weak when collected on the scalp for M/EEG, thus often requiring thousands repetition of sounds (Skoe & Kraus, 2010) to observe an effect. The short latency of cABR, less than 10 ms, makes it possible to record sufficient trials with a short Inter-Stimulus Interval (ISI) in reasonable test time in order to observe the effect. In contrast, cortical MMR, with a slower response time (100 to 250 ms), requires a longer ISI to prevent contamination from subsequent trials. The challenge lies in the inherent discrepancy of the required length of ISI and number of repetitions for MMR and cABR, making it time-consuming to measure both in the same paradigm. To date, only a few studies have recorded cortical-subcortical responses in the same experiment (Bidelman, 2015; Coffey et al., 2021; Krishnan et al., 2012; Novitskiy et al., 2023; Woods et al., 1993), but even less have tested the linguistic effects across different speech sounds. Coupled with the demand for time efficiency when studying developmental populations, there is a pressing need for a more efficient paradigm that sufficient data can be gathered for both MMR and cABR within a shorter timeframe.

The goal of this study is to establish a time-efficient paradigm to simultaneously measure cortical MMR and subcortical cABR to speech sounds. Building upon Bidelman (2015), where in a single speech stimulus was presented in clusters with accelerating and decelerating ISI, our

study instead roves across 3 speech sounds in clusters (Figure 1). With this approach, we can assess MMR using sounds at the border between clusters with longer ISIs and we can also assess cABR using the tokens in the middle of a cluster with shorter ISIs and larger number of repetitions. Specifically, the three speech sounds vary on the voice onset time (VOT), where /ba/ sounds serve as the Standards, and /pa/ and /mba/ sounds are the Deviants, generating a Native phonetic contrast in English (i.e. /ba/ vs. /pa/) and a Nonnative phonetic contrast in English (i.e. /ba/ vs. /mba/). Critically, the two Deviants follow the same temporal structure, making the two MMRs comparable.

To validate our paradigm, we considered the following result patterns as benchmarks. For MMR, we aimed at replicating previous findings that show a distinct MMR in Native versus Nonnative speech contrasts with statistically significant decoding accuracy. Specifically, we expected a larger MMR to Native than the Nonnative phonetic contrasts happening around 100 to 250 ms after the change (Garrido et al., 2009; Näätänen et al., 2007). For cABR, given the scarcity of cABR and language effect for replication, our goal is to demonstrate that cABR to the three speech sounds recorded in this paradigm could be decoded with statistically significant accuracy. Moreover, we expected a high signal-to-noise ratio such that there is a clear cABR waveform and reasonable stimulus-to-response cross-correlation and lag within 10 ms for each of the speech sounds (Krizman & Kraus, 2019).

Materials and Methods

Participants

Nineteen monolingual English-speaking adults were recruited (13 females, 6 males, 0 nonbinary, mean age = 24.32, std age = 3.11 years old). One subject was excluded due to

technical issues. All subjects were right-handed and reported no known hearing, language or speech difficulties. All experimental procedures were approved by the University of Washington Institute Review Board. All participants were given informed consent and were compensated monetarily for their time and effort.

Speech stimuli

Bilabial stop consonants with varying VOTs were synthesized by the Klatt synthesizer in Praat software (Boersma and Weenink, 2009) (Figure 2b, 2c, 2d). The syllable with 0 ms VOT was first synthesized with a 2 ms noise burst and the vowel /a/. The duration of the syllable is 90 ms. The fundamental frequency of the vowel /a/ began at 95 Hz and ended at 90 Hz. Silent gaps were added after the initial noise burst to create syllables with +10 ms (sound like /ba/) and +40 ms (sound like /pa/) VOTs. A 40 ms pre-voicing was added before the noise burst to create -40 ms VOT (sound like /mba/). The total durations for the +10 ms, +40 ms and -40 ms stimuli were 100 ms, 130 ms and 130 ms, respectively. The fundamental frequency for the pre-voicing portion was 100 Hz. Perception of the synthesized syllables was validated on adult speakers in a previous study using identification and discrimination tasks (Zhao & Kuhl, 2018).

The syllable with +10 ms VOT was used as the Standards, the syllables with +40 ms and -40 ms VOT were used as Deviants. The +10 ms VOT/+40 ms VOT stimulus contrast represented a native phonemic contrast between /ba/ and /pa/, therefore the stimulus with +40 ms VOT is from here on referred to as the Native Deviant. On the other hand, the +10 ms VOT/-40 ms VOT stimulus contrast is a phonemic contrast in nonnative languages, such as Spanish, but not in English. Therefore, the stimulus with -40 ms VOT is from here on referred to as the Nonnative Deviant.

Paradigm

In each trial, several of the same speech sounds were presented (randomly selected to be between 8-14 sounds). See Figure 1 for the illustration. The interstimulus-intervals (ISIs) gradually shortened from 500 ms to 50 ms then back to 500 ms with jitters across the ISIs, minimizing the predictability of the timing of the next stimulus. As a stimulus was played through the trial, memory trace was developed for that speech sound. The first stimulus in the next trial after the last stimulus in the current trial thus represented a stimulus change that is equivalent to the stimulus change in a classic oddball paradigm. This pair of sounds were used to calculate MMR. The middle tokens of a cluster (the third token to the third to the last token) were presented in alternating polarities with short ISIs between them and were suitable for the calculation of cABR. There were in total 400 trials, recorded in two separate runs (each took 12 minutes) with a brief break. Within each run, there were 100 trials of /ba/, and 50 trials of /mba/ and /pa/ each. We only presented the analysis from the first run (i.e. 200 trials), which was deemed sufficient and optimal to address our research goals. The Deviant trials /pa/ or /mba/ were presented in randomized order and interleaved with the Standard /ba/ trial.

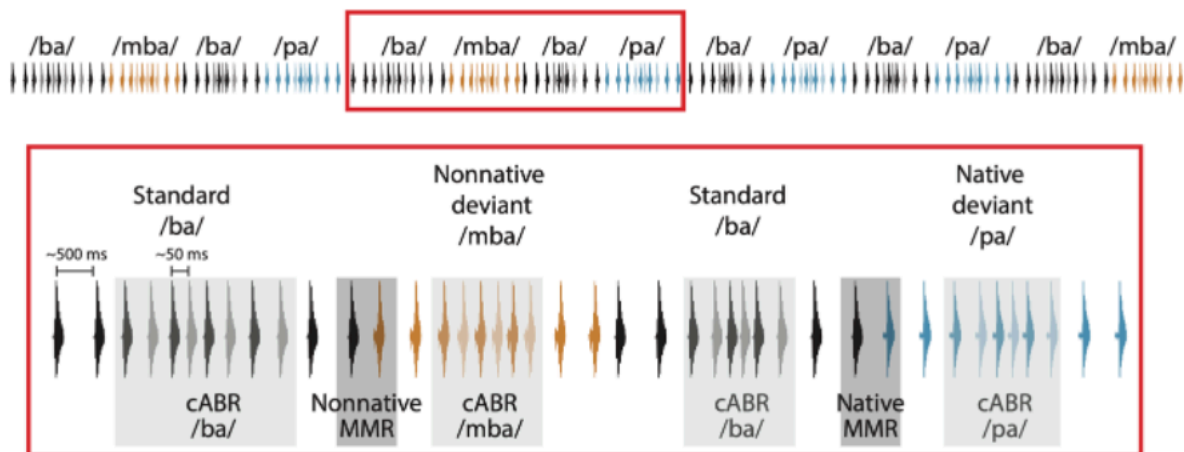


Figure 1. The dual-recording paradigm captures MMR between the clusters and captures cABR within the cluster. Each cluster has 8 to 14 sounds of the same speech stimuli, including sounds with +10 ms VOT (/ba/ like, served as the Standards for MMR, painted in black), +40 ms VOT (/pa/ like, served as the Native Deviants, painted in blue) and -40 ms VOT (/mba/ like, served as the Nonnative Deviants, painted in orange). In each cluster, the presenting rate accelerates in the first half and decelerates in the second half with randomized ISIs. The grey rectangles marked the sounds used to compute MMR (highlighted in dark grey) and cABR (highlighted in light grey), respectively. The sound tokens painted in lighter color were the ones with reversed polarity to cancel out the microphonic responses.

Procedures

Standard EEG electrode placement for cABR was used with one electrode placed on CZ, the ground electrode on the center of the forehead, and the reference electrode on the right earlobe. The impedance of the electrodes averaged across subjects was 6.02 k Ω with a standard deviation of 2.41 k Ω .

MEG recordings were completed inside a magnetically shielded room (MSR) (IMEDCO America Ltd., IN), using a whole-scalp MEGIN TRIUX™ neo system with 204 planar gradiometers and 102 magnetometers. Five head-position indicator (HPI) coils were attached to identify head positions under the MEG dewar at the beginning of each block. Three landmarks (LPA, RPA and nasion) and the HPI coils were digitized along with 100 additional points along the head surface (Isotrak data) with an electromagnetic 3D digitizer (Fastrak®, Polhemus,

Colchester, VT, USA). In addition, a pair of electrocardiography sensors (ECG) was placed left and right arms to record cardiac activity and three pairs of electrooculogram (EOG) sensors were placed horizontal and vertical to the eyes to record saccades and blinks. All data were sampled at 5 kHz. The sounds were delivered from a TDT RP 2.7 device (Tucker-Davis Technologies, Alachua, FL, USA), controlled by custom Python software on a HP workstation, to insert earphones. The stimulus was processed such that the RMS values were referenced to 0.01 and it was further resampled to 24,414 Hz for the TDT. The sounds were played at the intensity level of 75 dB through tubal insert phones (Model TIP-300, Natus Neurology, Pleasanton, CA, USA). The participants listened passively and watched silent videos during recording.

Preprocessing

For the purpose of this study to validate the paradigm, only EEG data were analyzed. Future studies will focus on MEG data and its relationship with the EEG data. All EEG data processing was done using the MNE-python software v1.5 (Gramfort et al., 2014). For the MMR analysis, the raw EEG recordings were low-pass filtered at 50 Hz with the fourth order Butterworth filter. The continuous EEG signals were then epoched from 100 ms before stimulus onset to 600 ms after stimulus onset to have enough length to calculate MMR, with a baseline from -100 to 0 ms. The epochs that include a peak-to-peak amplitude larger than $100e-6$ volt were excluded. The evoked responses of the Standards and the Deviants were separately computed by averaging across the epochs. Native and Nonnative MMRs were calculated by subtracting the evoked responses of the Standards from the Deviants for both Native and Nonnative contrasts.

For the cABR analysis, the raw EEG recordings were notch filtered at 60 Hz and its harmonics up to 2000 Hz in order to remove the line noise. The EEG signals were band-pass

filtered at 80 Hz to 2000 Hz with the fourth order Butterworth filter. The EEG signals were then epoched from 20 ms before stimulus onset to 200 ms after stimulus onset, with a baseline from -20 to 0 ms. The epochs that include a peak-to-peak amplitude larger than $35e-6$ volt were excluded. The cABR of Standard /ba/, Native Deviant /pa/ and Nonnative Deviant /mba/ were calculated by averaging across epochs, respectively.

Statistical analysis

MMR analysis.

Machine learning decoding model.

To test whether the paradigm elicits discriminable MMRs for Native vs. Nonnative phonetic contrasts, a machine-learning based method that utilized the time series was employed. Specifically, a linear model based on logistic regression was trained to classify each individual's MMR into the Native vs. Nonnative categories. Data at every time instant between 0 and 250 ms (Garrido et al., 2009; Näätänen et al., 2007) were used as features in the model. The features were first standardized by scaling with mean and standard deviation. Then a five-fold cross-validation was used to avoid overfitting and to evaluate the scores. The accuracy was averaged across all scores. To further evaluate the accuracy, we shuffled the correspondence between data and labels and performed the decoding process 500 times to generate the null distribution. We examined the significance of the originally obtained decoding accuracy by comparing it to the 97.5 percentiles of the null distribution. The machine-learning analyses were done using the open source scikit-learn package (Pedregosa et al., 2011) in conjunction with the MNE-python software.

Cluster-based Permutation test.

A cluster-based permutation test was conducted on the MMRs (Maris & Oostenveld, 2007) to test if the Native and Nonnative MMRs are significantly different from each other between 0 and 250 ms (Garrido et al., 2009; Näätänen et al., 2007). This procedure utilized a nonparametric cluster method for calculating corrected p -values to address the multiple comparison problem in EEG data. The null distribution was generated by randomizing the sign flip 1024 times. In each permutation, the time instants exceeding the t -threshold that corresponds to a p -value of 0.05 were selected. The largest cluster of time instances was retained to build the null distribution. The “clusters”, namely the time windows, of our original data were compared to the null distribution to test for statistical significance. The cluster-based permutation test was done using MNE-python software (Gramfort et al., 2014).

cABR analysis.

Machine learning decoding model.

The identical linear model and procedure employed in decoding MMR were also utilized for cABR. The only difference was that the cABR classification process involved three syllables (a three-way classification), as opposed to the binary classification between Native and Nonnative for MMR.

Stimulus-to-response cross-correlation.

To test how close the cABR tracks audio signals, the audio waveform and its corresponding cABR, including the onset response to the noise burst and frequency-following response (FFR) to the vowel, were visualized for each speech sound (Figure 2b, 2c, 2d). In addition, a cross-correlation was computed to quantify the relationship between the audio waveforms and cABR time series averaged across individuals. The audio signals were resampled

to match the EEG recording sampling rate. The audio waveforms and cABRs were first standardized and then normalized with the unity peak (i.e. the autocorrelations at zero lag equal 1). Cross-correlation was then computed to account for any delay between neural and audio signals. The cross-correlation between each speech waveform and corresponding cABR was done from 20 ms after the noise burst to exclude the onset response (Krizman & Kraus, 2019; Russo et al., 2004). This was done using open-source scipy package with correlate functions (Virtanen et al., 2020).

Results

Mismatch Response

A negatively going peak was observed after we subtracted the evoked response of the Standards from the Deviants for both Native and Nonnative contrasts (Figure 2a). A linear classifier decoded the difference (0 to 250 ms) to Native versus to Nonnative speech contrast with 71.8% accuracy, which is 21.8% higher than the 50% chance level for binary classification. This decoding accuracy was deemed significant as it was higher than 97.5 percentile of the null distribution (67.3%). Further, a significantly larger MMR in Native than Nonnative contrast ($p < 0.05$) was observed from around 160 ms to 200 ms after the Deviants, examining using cluster-based permutation test. This significant time window is consistent with previous findings of MMR (Garrido et al., 2009; Naatanen et al., 2007). The results from the two types of analyses provide converging evidence demonstrating that our new paradigm can elicit MMR to Native versus Nonnative speech sounds that reflect the linguistic effects, replicating existing literature (Näätänen et al., 1997; Sharma & Dorman, 1999, 2000; Zhang et al, 2005; Zhao, 2022).

Complex Auditory Brainstem Response

For the three speech sounds, cABR faithfully tracked the noise burst onset, VOT, and the periodic pulses of the vowel (Figure 2b, 2c, 2d). The cABR was delayed for about 9 ms after the audio stimuli as can be seen in Figure 2. The max normalized cross-correlation coefficients between each speech waveform and corresponding cABR were 0.345 (lag 9.2 ms) for /ba/ sound, 0.357 (lag 9.2 ms) for /mba/ sound, and 0.322 (lag 9.0 ms) for /pa/ sound.

The same linear model was applied to classify cABR to the three speech sounds with different VOTs (i.e. +10 ms, +40 ms and -40 ms). A decoding accuracy of 81.8%, which is 48.5% higher than the 33.3% chance level for 3-way classification. This decoding accuracy was deemed significant as it is higher than 97.5 percentile of the null distribution (48.2%). We further tested cABR decoding accuracy with the average of fewer trials. The linear model still decoded the three speech sounds with 72.2% accuracy for cABR averaged across 100 trials and 53.8% accuracy averaged across 50 trials, consistent with recent literature (Llanos et al., 2017).

These results showed that our new paradigm captured cABR of the three different speech sounds, evident by the decoding accuracy significantly higher than the chance level, as well as the high stimulus-to-response cross-correlation with short lags within 10 ms.

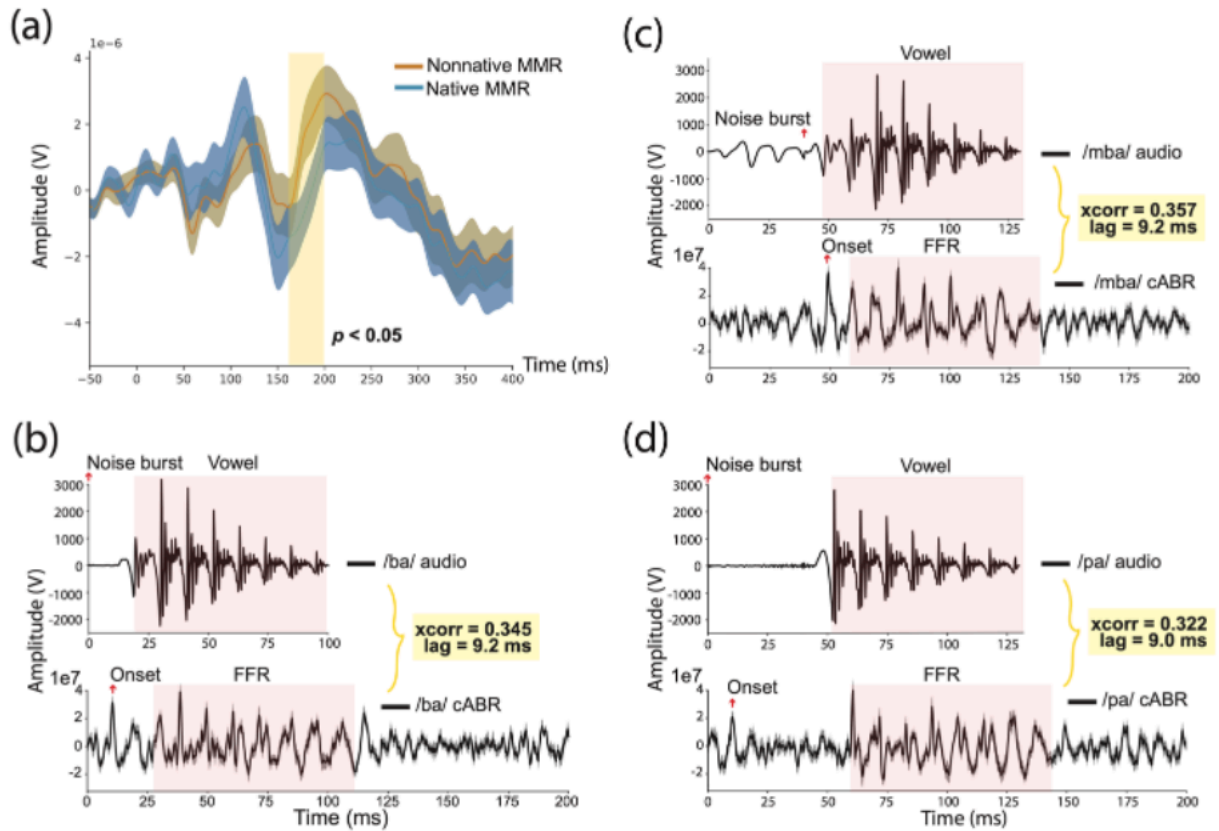


Figure 2. MMR and cABR recorded in our new dual-recording paradigm. (a) MMR to Native (blue) and Nonnative (orange) speech contrast. The decoding accuracy for the binary classification was 71.8 %. The statistically significant ($p < 0.05$) time points with cluster-based multiple comparison correction were highlighted in yellow. The audio signal and corresponding cABR of the three speech sounds with +10 ms VOT (b), +40 ms VOT (c) and -40 ms VOT (d). The decoding accuracy for the three-way classification was 81.8 %. The red arrow indicates the noise burst of the audio signal and its corresponding cABR onset response. The red rectangle indicates the vowel of the audio signal and the corresponding FFR.

Discussion

This study aimed to concurrently record MMR and cABR to meaningful phonetic sounds using a new recording paradigm. Native MMR can be differentiated from Nonnative MMR with 71.8% accuracy, achieving higher than 97.5 percentile against the null distribution, using a data-driven machine learning model. There was a significantly larger MMR in Native contrast compared to Nonnative contrast in 160 ms to 200 ms after the Deviants with the cluster-based permutation test, consistent with previous studies (Garrido et al., 2009; Näätänen et al., 2007).

cABR to the three speech sounds were differentiated from each other with 81.8% accuracy, again achieving higher than 97.5 percentile against the null distribution. We verified the signal-to-noise of the waveform qualitatively (see Figure 2) and quantitatively by examining the maximal normalized stimulus-to-response cross-correlation (Bidelman, 2015; Krizman & Kraus, 2019). The present findings validate our paradigm by achieving predefined benchmarks. This study holds significance as it is among the first few to simultaneously assess subcortical and cortical processes (Bidelman, 2015; Krishnan et al., 2012; Novitskiy et al., 2023; Woods et al., 1993), paving the way to study how linguistically meaningful speech sounds are processed along the central auditory pathway.

The practical advantages of our methodology could have a great impact on future research and clinical applications. First, our recording paradigm required fewer trials than other studies, while still proven sufficient to gather ample cABR and MMR data to achieve significant decoding accuracy by machine learning algorithms. Our study utilized only 200 trials of data, taking about 12 minutes to complete. Specifically, MMR computation involved just 50 trials of Standards and Deviants, while showing similar results to our recent study using 150 trials (Zhao, 2022). Interestingly, the difference between Native and Nonnative MMR was reduced in the second half of the experiment, while cABR was not affected (not reported in this paper), likely due to fatigue and boredom across time. This suggests an optimal recording duration of less than 15 minutes. For cABR, we calculated responses using 200 middle tokens for each of the three speech sounds, which is notably more efficient compared to our previous research (3000 repetitions for each speech sound, Zhao & Kuhl, 2018), and many other cABR studies (1000 – 6000 repetitions, as per Skoe & Kraus, 2010). Second, the concurrent recording of MMR and cABR offers the additional benefit of observing the neural responses of the same subject in a

single session, eliminating the need for the subject to return on a different day. This helps prevent potential variations in neural activity states and reduces the likelihood of participant withdrawal. One caveat, as noted in Bidelman (2015), is that using stimulus clusters for recording MMR and cABR is not inherently simultaneous, given the use of tokens with longer ISI for measuring MMR and other tokens with shorter ISI for recording cABR. However, recording MMR and cABR by the same tokens is very slow due to the recording requirements for the MMR and cABR (Krishnan et al., 2012; Woods et al., 1993) and could not feasibly be applied in most research. Therefore, our dual-recording design remains essential for recording MMR and cABR in the same paradigm with maximized time efficiency. The time efficiency and same-session recording is particularly advantageous for subjects with limited tolerance for prolonged recordings, such as infants who are only awake and compliant for a short duration (Clarke et al., 2022).

The concurrent recording of MMR and cABR in our paradigm is critical to advance the theoretical understanding of speech perception in several ways. First, cortical and subcortical responses deserve equal attention regarding high-level cognitive processes. Most studies only focus on cortical mechanisms (so called "cortical myopia", first mentioned by Parvizi & Kastner, 2018), while increasing cases demonstrate that subcortical processes are also shaped by auditory experiences, attention control, and language learning (see Escera, 2023 for a thorough review). The faster growth of subcortical auditory system compared to the cortex is particularly critical in early language learning, further highlighting the need to elucidate subcortical mechanisms (Moore & Linthicum, 2007; Novitskiy et al., 2023). Our study puts equal weights to cortical and subcortical responses to linguistically meaningful speech sounds. The immediate next step is to test the linguistic effects on cABR recorded in our paradigm, while it is not the main focus of the

present study. Secondly, new perspectives are being raised to challenge the existing understanding of MMR and cABR. For example, a fMRI study has found some “mismatch-like” responses to change detection originating from subcortical structures, such as the medial geniculate body (MGB) and the inferior colliculus (IC) (Cacciaglia et al., 2015), but it remains unclear how these subcortical mismatch signals are related to the conventional MMR localized to the cortex. Moreover, recent MEG studies discovered a large cortical contribution to speech-related cABR, specifically frequency following response (FFR), from the auditory cortex (Coffey et al., 2016, 2019). Contrary to these findings, using EEG, Bidelman (2018) suggests opposite patterns such that subcortical structures dominate FFR to speech sounds. The inconsistencies among these findings again highlight the need for future research to understand the intricacies between cortical and subcortical regions in speech processing.

For the purpose of validating the paradigm, it is sufficient to only report the data from a single-channel EEG. Future works will seek to replicate our paradigm with other neuroimaging techniques such as MEG. Compared with EEG, MEG is less susceptible to movement artifacts, and exhibits superior precision in source localization. Therefore, MEG has great potential to unlock deeper insights into cortical-subcortical interactions and their contributions to scalp-recorded brain signals. Our immediate next step is to test whether MEG captures comparable MMR and cABR to EEG in adults, and hopefully reconcile the inconsistencies in the M/EEG literature. The current study is our first step to target outstanding questions about cortical-subcortical interactions in speech perception. Ultimately, future work will investigate the subcortical-cortical mechanisms during early language acquisition in infants by utilizing our time-efficient paradigm with passive and objective MEG recording.

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