

UC San Diego

UC San Diego Previously Published Works

Title

Identifying Pitch Errors in Music Through a Musician's Brain Waves (EEG)

Permalink

<https://escholarship.org/uc/item/0tg6g743>

Journal

2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 00

Authors

Kim, Anthony

Uppal, Abhinav

Gano, Kameron

et al.

Publication Date

2025-10-08

DOI

10.1109/smc58881.2025.11343296

Copyright Information

This work is made available under the terms of a Creative Commons Attribution License, available at <https://creativecommons.org/licenses/by/4.0/>

Peer reviewed

Identifying Pitch Errors in Music Through a Musician’s Brain Waves (EEG)

Anthony Kim¹, Abhinav Uppal², Kameron Gano², and Gert Cauwenberghs²

Abstract—Understanding how the brain processes musical pitch errors is key to advancing music perception and auditory rehabilitation. This pilot study (N=1) examined neural responses to pitch deviations in a trained musician using a portable dry-electrode electroencephalography (EEG) system. The participant listened passively to seven 10-second violin excerpts with systematically varied pitch errors: none, medium, or high. EEG data were recorded, preprocessed, and analyzed for oscillatory patterns in the beta band across temporal and central brain regions. Findings revealed a graded increase in right-temporal beta power with error magnitude, alongside distinct temporal dynamics suggesting a sequential process: initial detection of deviations, evaluation of error severity, and adjustment of predictive models. These results highlight a potential cascade in passive pitch-error processing, extending prior work on active performance to naturalistic listening contexts. This work offers preliminary insights into the neural basis of pitch perception and suggests applications in music education and auditory training, though further research with larger cohorts is needed to confirm these findings.

I. INTRODUCTION

Accurate detection of pitch deviations is fundamental to both the perception and production of music. In everyday listening, musicians continuously monitor incoming auditory input and compare it against internal pitch templates, allowing them to detect even subtle tuning errors and maintain correct intonation of notes. A deeper understanding of the neural dynamics that support passive pitch monitoring could therefore benefit a wide range of applications such as music education or auditory rehabilitation.

Many electroencephalography (EEG) studies of pitch-error processing have focused on active performance: musicians generating notes and then detecting their own slips [1]–[3]. These investigations have revealed that oscillatory beta-band activity tracks self-generated deviations [3], suggesting a role in predictive coding and sensory-motor integration [4]. For instance, studies on pianists have shown that beta-band oscillations are linked to error prediction during performance [3], while event-related potential (ERP) components indicate rapid monitoring prior to errors [2]. Additionally, beta-band oscillations have been implicated in predicting pitch changes during auditory perception [5], highlighting their broader role in auditory predictive coding across both active and passive contexts. However, the brain’s response to externally imposed pitch errors, encountered during passive

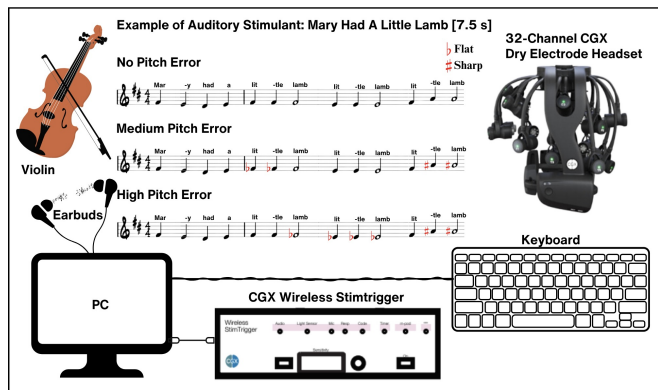


Fig. 1. Experimental setup and the structure of the auditory stimuli used in this work. The setup includes a PC connected to a 32-channel CGX Quick-32r dry-electrode headset, which records EEG data at 500 Hz with a reference electrode at A1 and a ground at the inner left earlobe, following the 10-20 system with impedance below 2500 k Ω . The PC delivers seven 10-second violin excerpts to a musician (N=1), each presented under one of three pitch accuracy conditions: (a) No Pitch Error (0 errors across the excerpt), (b) Medium Pitch Error (2–4 errors across the excerpt), and (c) High Pitch Error (5–6 errors across the excerpt). Each condition is repeated three times across the seven pieces, totaling 21 trials per condition. Musical note onsets, including pitch errors in the Medium and High conditions, are marked using a CGX Wireless StimTrigger for precise EEG alignment. Baseline EEG is recorded for 30 seconds after each randomized sequence of 21 excerpts, with the participant resting in silence with eyes closed; resting state is repeated three times. Images of the CGX hardware were sourced from the CGX website and user manual.

listening, remains under-explored, despite some evidence of expectancy violation processing in perception [6]. We address this gap with a portable dry-EEG paradigm to examine graded, passive pitch-error processing in a naturalistic musical context. We selected the violin for its continuous pitch profile, which allows for fluid, expressive intonation similar to human speech. Unlike the fixed pitch steps of the piano, this quality makes the violin especially suited for studying subtle pitch deviations in contexts that more closely resemble natural musical and vocal expression. By presenting a trained musician with seven 10-second violin excerpts containing systematically varied half-step pitch deviations (a frequency ratio of $2^{1/12}$), we capture real-time neural signatures using the benefits of dry electrodes.

Our pilot study identifies a sequential cascade of beta-band dynamics across left-temporal, right-temporal, and central sites—regions associated with auditory processing and frontal executive functions—that appears to flag, weight, and update pitch-accuracy predictions during passive listening.

¹Torrey Pines High School, 3710 Del Mar Heights Rd, San Diego, CA 92130, USA

²Chien-Lay Department of Bioengineering, UC San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA
Contact: auppal@ucsd.edu

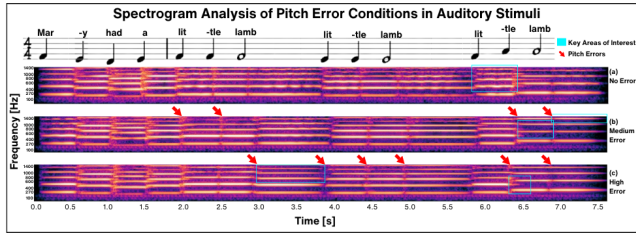


Fig. 2. The spectrogram of an 8-second violin excerpt of "Mary Had a Little Lamb" illustrating frequency dynamics under three pitch accuracy conditions: (a) No Pitch Error (0 errors), (b) Medium Pitch Error (2–4 errors), and (c) High Pitch Error (5–6 errors). Cyan boxes highlight key frequency differences, and red arrows mark pitch-error onsets in the Medium and High conditions. Spectrograms were generated in Audacity with the following settings: Bark scale (1–1500 Hz), spectrogram parameters (2048 window size, Hann window, zero-padding factor of 2), and Roseus color scheme (gain: 20 dB, range: 80 dB, high boost: 0 dB/dec).

II. METHODS

Seven 10-second violin excerpts were presented to a musician participant ($N = 1$) under three pitch accuracy conditions: (1) No Pitch Error (0 errors), (2) Medium Pitch Error (2–4 errors), and (3) High Pitch Error (5–6 errors). Each of the seven pieces was presented three times under each condition, yielding 21 trials per condition (7 pieces $\times$ 3 repetitions). After each excerpt, the participant provided feedback via keyboard (0 = unenjoyable, 1 = enjoyable), though these responses were not analyzed in this study and were collected for potential future analysis of subjective experience. Baseline EEG was recorded for 30 seconds after each randomized sequence of 21 excerpts, with the participant resting in silence. These baseline recordings served to prevent subject fatigue between sequences and to provide a reference of the subject's brain activity in a resting state with eyes closed and no movement, ensuring the accuracy of the subsequent data. This process was repeated three times. EEG data were recorded at 500 Hz using a 32-channel CGX dry-electrode headset (ref: A1, ground: inner left earlobe). Note onsets, including pitch errors in Medium and High conditions, were marked via a CGX Wireless StimTrigger for precise alignment with EEG data. Preprocessing included a 1 Hz high-pass filter, 60 Hz sinusoidal regression, manual interpolation of four noisy channels identified via visual inspection of raw EEG data for excessive noise or flatline signals, and ocular artifact removal via Fast Independent Component Analysis (FastICA; sklearn, MNE-Python). EEG data were processed using a custom pipeline optimized for dry-electrode systems, including filtering, artifact correction, and spectral analysis. Electrodes followed the standard 10-20 system, with impedance below 2500 k Ω . Power spectral density (PSD) was smoothed using a Savitzky–Golay filter.

EEG data were epoched from -0.2 to $+0.8$ s around specific note onsets. To retain comparable musical context, No Pitch Error and High Pitch Error epochs were generated from the same note onsets across different trials—centering on incorrect notes in the High Pitch Error condition (5–6 errors per trial) and their corresponding, correct versions in the No Pitch Error condition. The Medium Pitch Error condition was

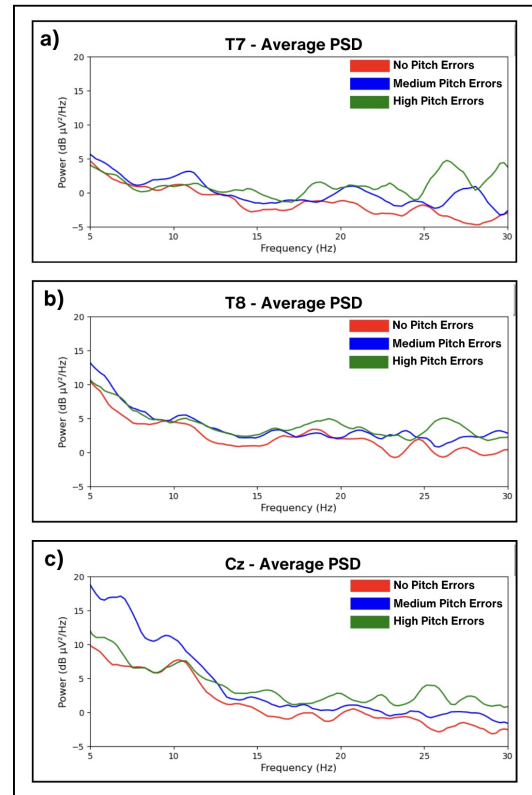


Fig. 3. Power Spectral Density (PSD) analysis of EEG signals across three pitch accuracy conditions: No Pitch Error (0 errors, red), Medium Pitch Error (2–4 errors, blue), and High Pitch Error (5–6 errors, green). PSDs are averaged across all epochs within each condition from seven 10-second violin excerpts, with each condition repeated three times across the seven pieces, yielding 21 trials per condition. (a) PSD for the T7 (left temporal) channel, (b) PSD for the T8 (right temporal) channel, and (c) PSD for the Cz (central) channel. EEG data preprocessing included a 1 Hz high-pass filter, 60 Hz sinusoidal regression, manual interpolation of four noisy channels, and ocular artifact removal via FastICA. PSDs were computed using Welch's method (0.5 s window, 50% overlap) over the 5–30 Hz frequency range and smoothed with a Savitzky–Golay filter.

not used for event-related desynchronization/synchronization (ERDS) analysis and noisy epochs were excluded by visual inspection of bad segments.

Power Spectral Density (PSD) (Fig. 3) was computed using Welch's method (0.5 s window, 50% overlap) over 5–30 Hz per epoch. PSD was averaged across all epochs within each condition (correct note epochs for No Pitch Error; pitch-error epochs for Medium and High). Results for PSD and ERDS focused on T7, T8, and Cz channels in the beta range (15–30 Hz). Topographic maps (Fig. 4) visualized scalp-wide PSD (0–50 Hz) for each condition, averaged across epochs for beta sub-bands (15–20 Hz, 20–25 Hz, 25–30 Hz). For Event-Related Desynchronization/Synchronization (ERDS) (Fig. 5), epochs were categorized into "No Pitch Error" (using the selected note onsets from the No Pitch Error condition) and "Pitch Error" (using the incorrect note onsets from the High Pitch Error condition only). ERDS in the beta band (15–30 Hz) was computed via Morlet wavelets (6 frequencies/octave, 0.5 s window) and normalized to a -0.2 to 0 s baseline.

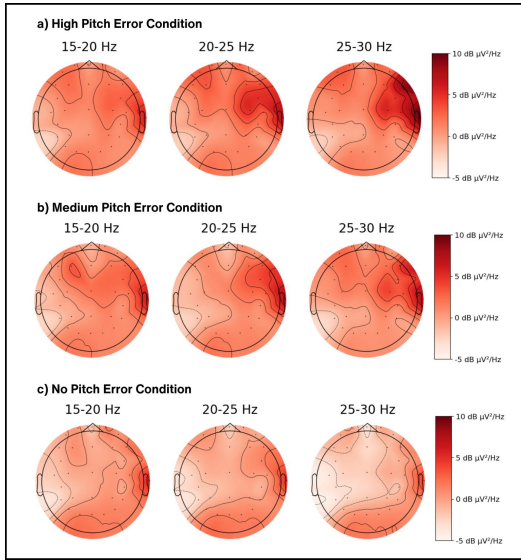


Fig. 4. EEG topographic maps of power spectral density (PSD) across beta sub-bands (15–20 Hz, 20–25 Hz, and 25–30 Hz) for three pitch accuracy conditions: (a) High Pitch Error (5–6 errors), (b) Medium Pitch Error (2–4 errors), and (c) No Pitch Error (0 errors). These maps visualize scalp-wide PSD (0–50 Hz) for each condition, averaged across all epochs within each condition from seven 10-second violin excerpts, with each condition repeated three times across the seven pieces, yielding 21 trials per condition. EEG data preprocessing included a 1 Hz high-pass filter, 60 Hz sinusoidal regression, manual interpolation of four noisy channels, and ocular artifact removal via FastICA. Noisy epochs were excluded prior to averaging.

III. RESULTS

Power Spectral Density (PSD) analysis revealed frequency-dependent modulations across EEG channels T7, T8, and Cz in response to pitch errors (Fig. 3). In T7 (left temporal region) (Fig. 3a), the medium pitch error condition exhibited greater power in the 5–12 Hz range, while the high pitch error condition displayed the highest power in the 15–30 Hz range, with a notable drop between 25–30 Hz. In T8 (right temporal region) (Fig. 3b), the medium pitch error condition showed increased power between 5–10 Hz, whereas the high pitch error condition dominated from 17–27 Hz, followed by the medium pitch error condition. The no pitch error condition exhibited the lowest power across this range. Quantitatively, there was a mean PSD increase of 2.4 dB in the beta band (15–30 Hz) at T8 between the no pitch error and high pitch error conditions. In Cz (central region) (Fig. 3c), the medium pitch error condition demonstrated greater power from 5–12 Hz, while the high pitch error condition surpassed other conditions in the 15–30 Hz range.

Topographic mapping of power spectral density across beta sub-bands (15–20 Hz, 20–25 Hz, and 25–30 Hz) illustrated a progressive increase in power within right-lateralized central and temporal regions as pitch error magnitude increased (Fig. 4). Notably, the high pitch error condition exhibited the greatest power in the 25–30 Hz range, with the medium pitch error condition showing broader engagement of cortical areas. Additional power increases were observed near central regions, particularly in the high error condition.

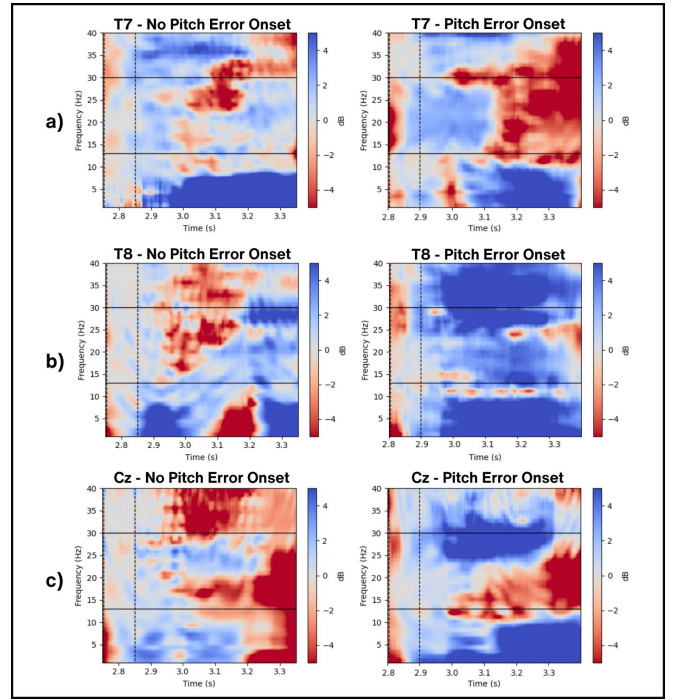


Fig. 5. Event-Related Desynchronization/Synchronization (ERDS) plots illustrate beta-band dynamics (15–30 Hz) across T7 (left temporal), T8 (right temporal), and Cz (central) EEG channels during auditory pitch processing. Subplots (a) show T7 responses, (b) show T8 responses, and (c) show Cz responses, comparing No Pitch Error (left, 0 errors) and Pitch Error (right, High [5–6 errors] condition only). The dashed vertical line marks note onset, with the beta band highlighted in a black rectangle. EEG data were epoched from -0.2 to $+0.8$ s around note onsets, preprocessed with a 1 Hz high-pass filter, 60 Hz sinusoidal regression, manual interpolation of four noisy channels, and ocular artifact removal via FastICA. ERDS was computed via Morlet wavelets (6 frequencies/octave, 0.5 s window), normalized to a -0.2 to 0 s baseline, and averaged within each condition. The ERDS scale (-5 to 5) represents power changes, with blue indicating synchronization and red indicating desynchronization.

Event-Related Desynchronization and Synchronization (ERDS) analysis revealed distinct temporal dynamics in the beta band (15–30 Hz) across the selected channels (Fig. 5). At T7, a pronounced desynchronization was observed approximately 250 ms post-error onset (Fig. 5a). In T8, synchronization in the beta band (15–30 Hz) was evident, with additional synchronization extending into higher frequencies (30–40 Hz) (Fig. 5b). At Cz, a robust synchronization in the beta band (15–30 Hz) occurred around 400 ms post-error onset, preceded by a brief desynchronization in the lower beta range (15–20 Hz) starting at approximately 200 ms (Fig. 5c). These findings suggest a sequential activation pattern: an initial flagging of pitch deviations in the left temporal region (T7), followed by magnitude weighting in the right temporal region (T8), and subsequent updating of predictive models in the central region (Cz).

IV. DISCUSSION/CONCLUSION

This single-subject pilot study explored the neural dynamics of passive pitch-error processing in a trained musician using a 32-channel dry-electrode EEG system. By analyzing responses to violin excerpts with systematically varied

pitch errors, we observed a sequential pattern of beta-band oscillatory activity across left-temporal (T7), right-temporal (T8), and central (Cz) regions. These findings may indicate a potential three-stage cognitive process: (i) flagging pitch deviations, (ii) weighting their magnitude, and (iii) updating predictive models. This pattern appears to align with beta-mediated error signals observed in active performance studies [1], [3] and parallels ERP severity effects in auditory processing [7], potentially extending these mechanisms to passive listening contexts. For example, research on pianists has demonstrated beta-band involvement in error prediction [3], while error severity modulates neural responses in both active and observed contexts [7].

The early beta desynchronization at T7, peaking around 250 ms post-error onset, may reflect the initial detection of pitch deviations, consistent with the left temporal region's role in fine-grained auditory analysis [8]. The subsequent increase in beta power at T8, which scaled with error magnitude (mean PSD increase of 2.4 dB between no-error and high-error conditions), could indicate the evaluation of error severity, possibly linked to holistic auditory perception. Finally, the beta rebound at Cz approximately 400 ms post-error onset might suggest the updating of internal predictive models [4], [5], supported by evidence that beta oscillations modulate with pitch predictability [5] and sensory predictions [4]. Together, these dynamics point to a possible coordinated neural process for handling pitch errors during passive listening. The participant's musical training may have heightened sensitivity to pitch deviations, potentially amplifying beta-band responses, as suggested by studies like [8].

These preliminary results have potential implications for music perception and rehabilitation. In music education, understanding pitch-error processing could inform teaching strategies, while in auditory rehabilitation, it might aid in developing interventions for pitch discrimination. Given the single-subject design, these findings are preliminary and require validation with a larger cohort. Future studies will expand the sample size to enhance reproducibility and statistical power, including diverse participants and musical stimuli from various instruments to validate and extend these findings.

REFERENCES

- [1] C. Maidhof, A. Pitkäniemi, and M. Tervaniemi, "Predictive error detection in pianists: a combined ERP and motion capture study," *Frontiers in Human Neuroscience*, vol. 7, p. 587, 2013.
- [2] C. Maidhof, M. Rieger, W. Prinz, and S. Koelsch, "Nobody Is Perfect: ERP Effects Prior to Performance Errors in Musicians Indicate Fast Monitoring Processes," *PLoS ONE*, vol. 4, no. 4, p. e5032, 2009.
- [3] M. Herrojo Ruiz, F. Strübing, H.-C. Jabusch, and E. Altenmüller, "EEG oscillatory patterns are associated with error prediction during music performance and are altered in musician's dystonia," *NeuroImage*, vol. 55, no. 4, pp. 1791–1803, 2011.
- [4] L. H. Arnal and A.-L. Giraud, "Cortical oscillations and sensory predictions," *Trends in Cognitive Sciences*, vol. 16, no. 7, pp. 390–398, 2012.
- [5] A. Chang, D. J. Bosnyak, and L. J. Trainor, "Beta oscillatory power modulation reflects the predictability of pitch change," *Cortex*, vol. 106, pp. 248–260, 2018.
- [6] C. Maidhof, N. Vavatzanidis, W. Prinz, M. Rieger, and S. Koelsch, "Processing expectancy violations during music performance and perception: an ERP study," *Journal of Cognitive Neuroscience*, vol. 22, no. 10, pp. 2401–2413, 2010.
- [7] C. Albrecht and C. Bellebaum, "Slip or fallacy? Effects of error severity on own and observed pitch error processing in pianists," *Cognitive, Affective, & Behavioral Neuroscience*, vol. 23, no. 4, pp. 1076–1094, 2023.
- [8] R. Behroozmand, N. Ibrahim, O. Korzyukov, D. A. Robin, and C. R. Larson, "Left-hemisphere activation is associated with enhanced vocal pitch error detection in musicians with absolute pitch," *Brain and Cognition*, vol. 84, no. 1, pp. 97–108, 2014.