Eruption: The Concept of Feel as a Framework for Human-Machine Co-Creativity

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Abstract

Guitar ”feel”, the subtle timing, dynamics, and articulation choices that define expressive guitar playing, remains an underexplored domain in computational creativity research. Inspired by the landmark Van Halen solo guitar piece, *Eruption*, this paper proposes a computational framework treating ”feel” as a multi-modal dynamic structured language. Various methodologies are presented for capturing the nuances of ”feel” using micro timing analysis, note-level envelope tracking, and spectrotemporal features, enabling AI models to emulate or perturb a guitarist’s style. The dual-phase system combines both emulation and provocation, challenging musicians to explore new creative territory. Preliminary results suggest machine-guided variations can elicit expressive responses beyond habitual patterns. This study situates ”feel” as a fertile test bed for exploring real-time human-machine co-creativity in instrumental performance.

Introduction

Guitar ”feel”, encompassing timing, dynamics, articulation, and subtle deviations, is central to the unique expressiveness of performance. Unlike strictly quantised MIDI playing, feel incorporates intentional microtiming shifts and dynamic nuance, providing human musicians with their distinctive voice. As exemplified by the solo piece, *Eruption* by Edward Van Halen, the expression of ”feel” is both technically advanced and emotionally linked.

Computational creativity has extensively modeled text, poetry, or rap (Valença and Calegario, 2025, Olatunji et al., 2025), but instrumental ”feel” remains relatively unformalised. It can be postulated that modeling ”feel” computationally can inspire musicians through adversarial co-creativity, where AI-generated perturbations provoke exploration of new timing and phrasing.

A framework treating guitar ”feel” as a structured domain is presented for human-machine co-creativity, combining phrase segmentation, feature extraction, statistical analysis, and real-time alignment techniques. This research advances computational creativity beyond symbolic or text-based domains into nuanced instrumental performance.

Approach

Guitarist Choice

In this pilot study, a number of guitarists playing live performances of the *Eruption* solo by Edward Van Halen were chosen: One professional player heavily influenced by the playing style of Van Halen (Dweezil Zappa) and three other randomly chosen renditions by other guitarists (Tina S, Joshua Jones, and Kmac). Each guitarist was compared phrase-by-phrase in a pairwise manner using a variety of digital signal processing methods highlighted in the *Analysis* section.

Feature-Based Comparison

Phrase-level features were normalised (z-scored) and aggregated into a combined feature matrix for the pool of chosen guitarists. Principal Component Analysis (PCA) was used to visualise distributions and K-Means clustering ($k = 2$) was calculated to detect stylistic grouping between guitarist phrasing, via a silhouette score to quantify cluster separability (Fig. 1).

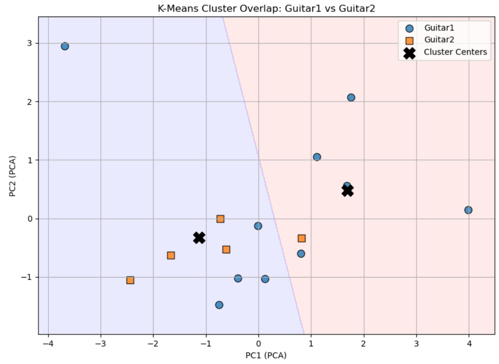

Figure 1: PCA of combined phrase features, coloured by guitarist (Guitar 1 = Edward Van Halen, Guitar 2 = Dweezil Zappa). Separation indicates stylistic differences in phrasing and dynamics.

Phrase Segmentation and Feature Extraction

To analyse phrasing between pairs of guitarists a segmentation pipeline was developed using RMS energy contours. Here, the RMS (Root Mean Square) energy is defined as a quantitative measure of the average power or “loudness” of a signal and is a useful metric of guitarist dynamics in this context. Silence thresholds were computed from the 25th percentile of the energy distribution, enabling detection of phrase boundaries via significant low-energy pauses exceeding a user-defined threshold (e.g., 0.3 seconds). This yielded temporally aligned phrase lists for each guitarist:

$$\text{Phrases} = \{(t^i_{\text{start}}, t^i_{\text{end}})\}_{i=1}^{N}$$

Where:

$t =$ time.

$N =$ total number of phrases.

For each phrase, various features were extracted:

- **Dynamics**: RMS energy, peak amplitude, dynamic range.
- **Spectral/ Audio features**: Mean spectral centroid (Tonal brightness) and bandwidth.
- **Rhythmic features**: Estimated tempo by beat tracking in each phrase.

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This approach is proposed to capture expressive characteristics critical to ”feel” modeling. For demonstrative purposes, only the plot outputs for Edward Van Halen versus Kmac are shown, giving clearer insights into the *differences* [PCA/ K-Means clustering (Fig. 2), RMS energy (Fig. 3), Spectral bandwidth distribution (Fig. 4), and MIDI phrase alignment (Fig. 7)] and *similarities* [Tempo/BPM distribution (Fig. 5) and Phrase-by-phrase dynamics trajectory (Fig. 6)] of their respective playing skills.

Dynamics and Spectral Comparisons

To assess stylistic contrasts in specific expressive dimensions, stylistic features were generated:

- Boxplots comparing RMS (Root Mean Square) energy across phrases, in order to measure loudness dynamics.
- KDE (Kernel Density Estimate) plots showing spectral centroid (Tonal brightness) and bandwidth distributions, by calculating an approximation of the data distribution for easier visualisation.
- Phrase-by-phrase RMS energy trajectories to track dynamics evolution, throughout the solo.
- Pairwise scatter plots of all feature pairs to identify correlated expressive strategies.

These analyses reveal nuanced differences in phrasing aggression (dynamics) and tonal brightness (spectral centroid analysis) when comparing the solo across guitarists.

Analysis

PCA and Clustering

Phrase features were normalised and analysed using Principal Component Analysis (PCA) for dimensionality reduction (Fig. 2). K-Means clustering ($k = 2$) separated stylistic patterns between players, with silhouette scores quantifying separation.

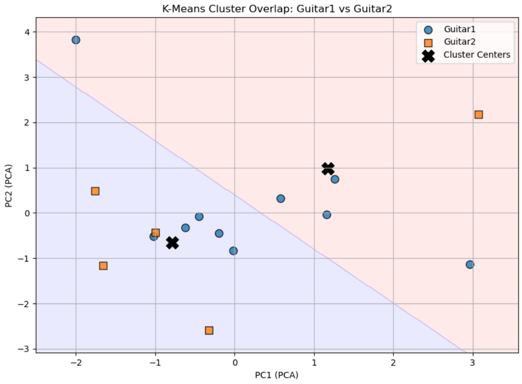


Figure 2: PCA of phrase features from Guitar 1 (Edward Van Halen) and Guitar 2 (Kmac), with K-means clusters and decision boundary.

Dynamics and Spectral Analyses

RMS Boxplots (Fig. 3), kernel density estimates (KDEs) and Tempo distribution plots provided insights into energy, spectral distributions (Fig. 4), and tempo (Fig. 5), revealing systematic differences in expressive dynamics and tone.

Interestingly, The double spectral bandwidth peak of Guitar 1 in (Fig. 4) shows tonal evidence of Edward Van Halen’s ”Brown Sound” (legendarytones.com, 2023.)

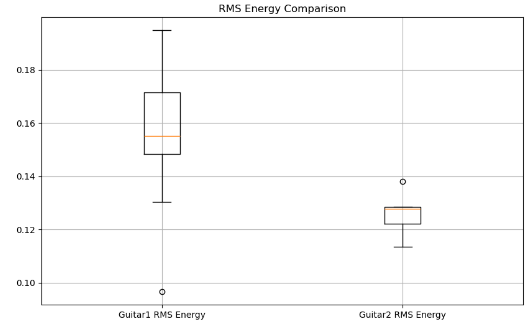


Figure 3: RMS energy comparison between Guitar 1 (Edward Van Halen) and Guitar 2 (Kmac) phrases.

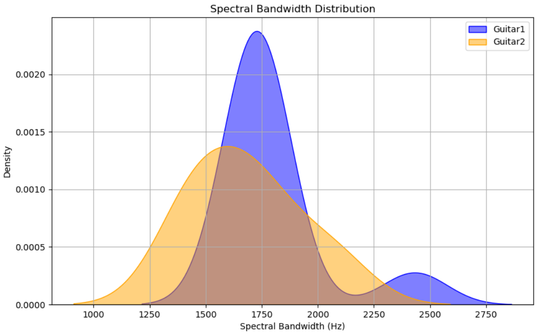


Figure 4: Spectral bandwidth distributions show tonal brightness differences (Guitar 1 = Edward Van Halen. Guitar 2 = Kmac.

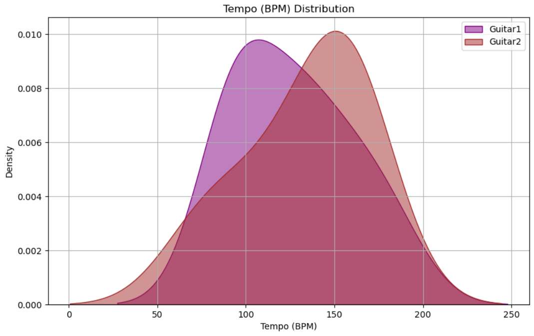


Figure 5: Tempo/ BPM differences between Guitar 1 (Edward Van Halen) and Guitar 2 (Kmac).

Phrase Dynamics Trajectory

Playing dynamics were modeled using phrase-by-phrase RMS trajectories which tracked dynamic evolution over the performance. This visualisation of expressive arcs can be mapped to conventional musical terms such as crescendo, where the music rises in loudness and intensity, and diminuendo, where the music decreases in loudness (Fig. 6).

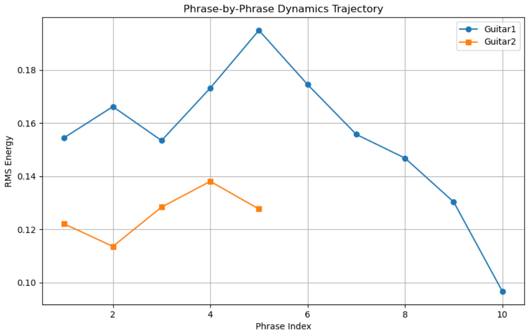


Figure 6: Phrase-by-phrase dynamics trajectory (Guitar 1 = Edward Van Halen. Guitar 2 = Kmac).

MIDI Note Accuracy and Pitch Analysis

To measure note-level accuracy, pYIN pitch tracks were extracted and converted to MIDI note numbers. Note-by-note pitch deviations were calculated in cents and defined correctness within a tolerance window (e.g., ±10%):

$$\text{Accuracy} = \frac{\sum \mathbf{1}_{\{|f_{\text{test}} - f_{\text{ref}}| \leq \text{tol}\}}}{N} \times 100\%$$

Where:

f_{test} = predicted frequency.

f_{ref} = reference frequency.

tol = tolerance.

Accuracy calculations were repeated across multiple tolerances (1%–50%), producing accuracy profiles reflecting intonation precision.

Batch-wise MIDI Phrase Analysis

MIDI note trajectories were compared phrase-by-phrase. Within each phrase, time-aligned MIDI tracks were plotted from both guitarists, exposing pitch contours and expressive deviations at high resolution. This allowed evaluation of micro-intonation and ornamental differences across phrases, critical for detailed ”feel” characterisation. MIDI note tracks were extracted using the python library Librosa and its pYIN function for each phrase and plotted for granular pitch trajectory comparisons, enabling micro-intonation level analysis (Fig. 7).

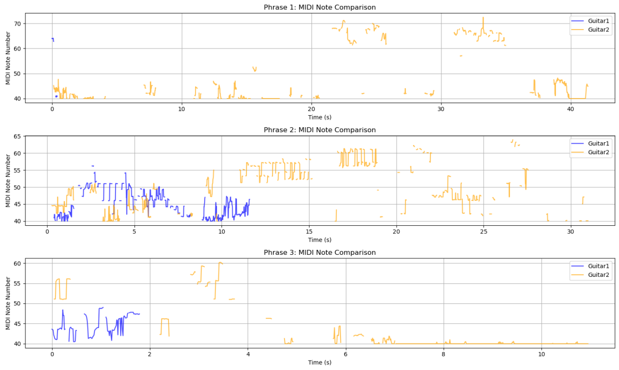
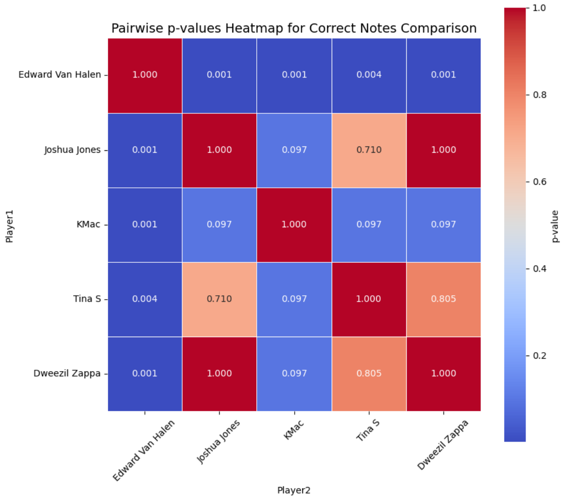


Figure 7: MIDI note comparison (Guitar 1 = Edward Van Halen, Guitar 2 = Kmac).

Statistical Evaluation of Note Accuracy

Accuracy rates at multiple tolerance levels were compared across guitarists using Mann-Whitney U-tests. Heatmaps of pairwise p-values (Fig. 8) assessed whether accuracy distributions differed significantly, contextualising pitch precision relative to the reference guitarist (Edward Van Halen).

As expected, Van Halen and Zappa have distinctly different phrasing styles, whereas Tina S and Joshua Jones were more similar to Zappa rather than Van Halen.



	Edward Van Halen	Joshua Jones	KMac	Tina S	Dweezil Zappa
Edward Van Halen	1.000	0.001	0.001	0.004	0.001
Joshua Jones	0.001	1.000	0.097	0.710	1.000
KMac	0.001	0.097	1.000	0.097	0.097
Tina S	0.004	0.710	0.097	1.000	0.805
Dweezil Zappa	0.001	1.000	0.097	0.805	1.000

Figure 8: Pairwise p-value heatmap comparing note accuracy distributions across guitarists. Significant differences highlight stylistic disparities in pitch execution.

Time-Stretch-Based Phrase Realignment

To probe co-creativity through phrasing, phrase-level time-stretching was implemented. The Guitarist 2 (Kmac) phrases were adjusted in duration to match the timing of Guitarist 1 (Edward Van Halen) using the *pyrubberband* python library:

$$\text{rate} = \frac{d_{\text{G2}}}{d_{\text{G1}}}, \quad y_{\text{stretched}} = \text{TimeStretch}(y_{\text{G2}}, \text{rate})$$

Where:

d_{G1}: The duration of the first audio segment (Group 1 / Source).

d_{G2}: The duration of the second audio segment (Group 2 / Target).

rate: The resulting speed ratio.

Reconstructing the Guitarist 2 (Kmac) performance with that of the phrasing for Guitarist 1 (Edward Van Halen) facilitated investigation of "feel" alignment and exploration of potential hybrid creative expressions.

Dynamic Time Warping (DTW) Onset Alignment

Dynamic Time Warping (DTW) is a technique that elucidates the optimal, non-linear onset mapping of musical notes between two time-series, analysing phrase alignment and syncopated timing differences between the two datasets.

Phrase and onset timings were compared before and after time-stretch realignment. DTW distances were computed between onset sequences to quantify temporal alignment improvement:

$$D_{\text{DTW}} = \text{DTW}(\text{onsets}_{\text{G1}}, \text{onsets}_{\text{G2}})$$

Where:

$\text{onsets}_{\text{G1}}, \text{onsets}_{\text{G2}}$: Sequences of audio onset timestamps for Group 1 and Group 2.

$\text{DTW}(\ldots)$: The Dynamic Time Warping alignment function.

D_{DTW}: The resulting alignment distance score (lower values indicate higher similarity).

Onset plots (Fig. 9) illustrate alignment trajectories, revealing how realigned phrases can improve timing alignment.

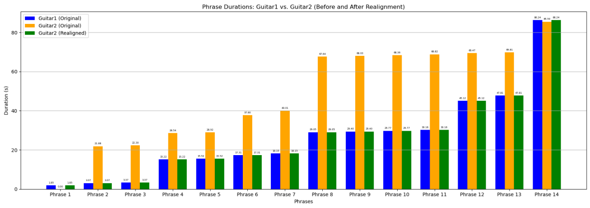


Figure 9: DTW-based onset alignment of the playing style of Kmac with regard to Edward Van Halen: Before (left of centre) and after (right of centre) time-stretching. Lines connect matching onsets across guitarists.

Creative Potential of Realignment

Combining timing alignment (DTW), pitch accuracy metrics, and dynamic/spectral feature distributions offers a comprehensive view of stylistic overlap and divergence. By reconstructing performances with alternative phrasing (Fig. 10), the proposed method demonstrates how AI-based alignment can generate new, hybrid interpretations, laying the groundwork for co-creative improvisation tools.

Together, alignment analysis (DTW, pitch accuracy) and the richer feature landscape allow the proposed system to detect stylistic overlap and divergence to reconstruct performances with alternative phrasing, thus allowing the development of AI-generated hybrid interpretations and co-creative improvisation tools.

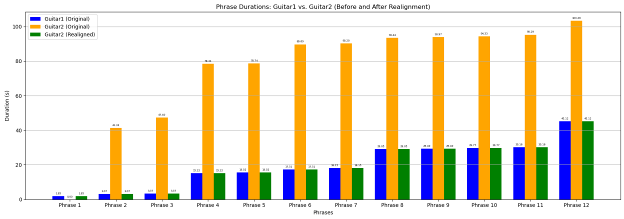


Figure 10: Illustration of note-level time stretching to force alignment: although durations match, no explicit feedback on timing errors is stipulated.

Reinforcement Learning for Cadence Adaptation

To further support active learning of expressive timing, integrating reinforcement learning (RL) is proposed as a coaching advancement into the co-creative tool. As shown schematically in Fig. 11, the system can compare the player note onsets against a target beat grid. During practice, each performance episode yields a reward or penalty based on timing similarity:

- **Reward**: Assigned when the learned phrase note timings align closely with the target cadence, reinforcing accurate timing.
- **Penalty**: Applied when note timing deviates beyond a threshold from the target beat grid.

Over repeated iterations, the RL agent can adapt to the evolving cadence of each player and provide personalised feedback, dynamically adjusting difficulty (e.g., Presenting stricter timing thresholds) as the learner improves.

This approach combines:

- **Error-based learning**: Encouraging self-correction by highlighting timing mismatches.
- **Incremental progression**: Gradually refining timing precision demands the player advances.
- **Co-creative guidance**: Offering useful and inspirational suggestions that are neither rigid corrections nor purely passive evaluations.

Such an RL-enhanced system has the potential to accelerate skill acquisition by balancing challenge and support, adapting in real-time to each learner's unique phrasing tendencies.

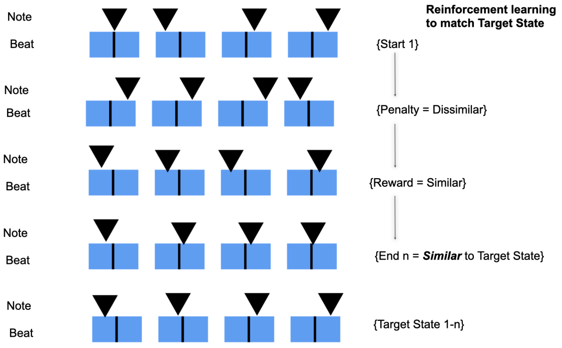


Figure 11: Conceptual diagram of reinforcement learning for beat-cadence adaptation: penalties discourage timing dissimilarity while rewards reinforce alignment with the target cadence.

Conversely, beat-level or cadence-based alignment strategies that highlight discrepancies in timing without forcibly correcting them offer an opportunity for active learning. By presenting the player with visual and auditory evidence of how their phrasing diverges from a reference performance, they can iteratively adjust their playing to develop internal timing and groove sensitivity.

The findings suggest that:

- Pure time-stretching fosters mechanical reproduction but not adaptive timing learning.
- Cadence-aware systems that expose timing misalignments encourage active engagement with "feel".
- Combining beat analysis with dynamic feedback enables players to progressively refine their sense of timing and phrasing.

Future educational tools should favour interactive systems that visualise and sonify beat-level differences, promoting deliberate practice of timing rather than relying on automatic note-duration correction alone. This approach aligns with motor learning literature emphasising the importance of error-based feedback in skill acquisition (Schmidt et al., 2018).

Music, ”Feel”, and Brain Dynamics

”Feel” in guitar performance is not only a mechanical or stylistic phenomenon, but also deeply intertwined with neural processes. Research in music neuroscience shows that expressive timing and dynamics recruit brain networks involved in motor planning, prediction, and affective processing (Large and Palmer, 2002; Zatorre et al., 2007).

EEG scans of players listening to performances of *Eruption* by Edward Van Halen (Fig. 12) show increased beta wave (13–30 Hz) activity over the frontal-temporal electrodes AF7, AF8, TP9, and TP10 during the rapid phrases. This pattern is consistent with the engagement of predictive-timing mechanisms that are known to modulate activity in the temporal-parietal and frontal association cortices during complex rhythmic perception (Giraud and Poeppel, 2012; Zatorre and Zarate, 2012).

In contrast, EEG recorded during the less technically accurate rendition of Eruption by Kmac (Fig. 13) reveals reduced beta wave coherence and elevated theta wave (4–8 Hz) variability at the same electrodes. These changes suggest a greater cognitive load or uncertainty when the listener must resolve timing irregularities in the music.

These findings suggest:

- Expressive timing enhances motor and predictive processing, reflected in beta wave dynamics.
- Deviations from expected timing patterns increase theta variability, indicating greater cognitive load.
- Combining computational ”feel” modeling with EEG-informed metrics could yield adaptive co-creative systems that respond to musicians’ neural states in real time.

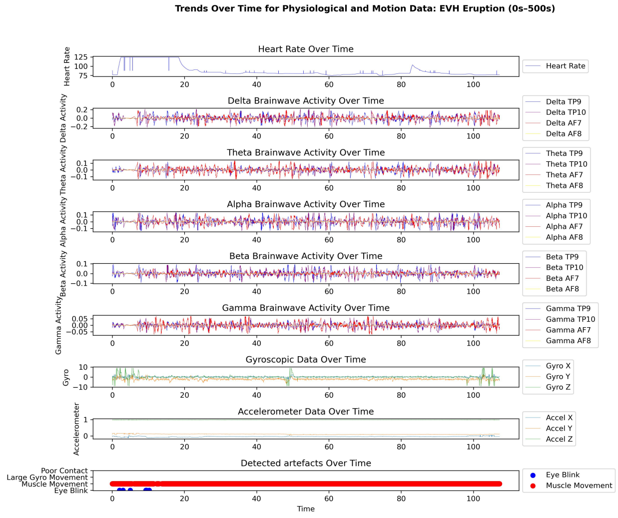


Figure 12: Sample EEG spectrogram during the Van Halen rendition of *Eruption*: Increased beta wave synchrony aligns with precise microtiming and enjoyment of the piece.

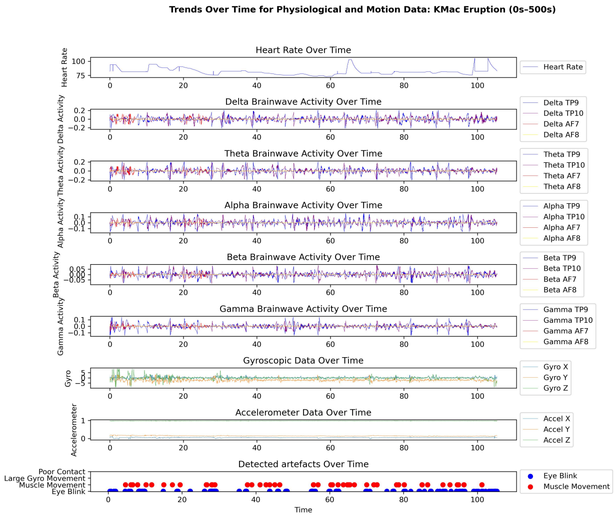


Figure 13: Sample EEG spectrogram during the Kmac rendition of *Eruption*: Less consistent beta wave activity reflects timing uncertainty. More muscle artefacts are seen, showing greater levels of fidgeting. The heart rate amplitude increase aligns with timing errors.

This integration of musical ”feel” and neural dynamics supports a richer, brain-aware approach to human-machine co-creativity, where systems can sense and respond to the cognitive state of performers, fostering deeper engagement.

Discussion

The proposed approach demonstrates that microtiming, dynamics, and pitch trajectories can be operationalised as computational features, providing a quantitative basis for modeling expressive guitar ”feel”. By segmenting performances into phrases, extracting nuanced timing deviations, and analysing spectral and dynamic characteristics, a heatmap-based feature space (Fig. 8) is created capable of distinguishing stylistic differences and similarities among guitarists. This can be used as a learning prompt to suggest guitarists who play in similar styles, and have a target ”feel” that a learner would want to emulate and absorb into their playing style. Conversely, this analytical approach could also be utilised to suggest influential guitarists with near-similar or totally dissimilar styles, in order to both inspire and challenge creativity.

This computational representation of ”feel” enables not only objective comparisons but also the generation of model-driven feedback tailored to the expressive nuances of the individual musician, aligning with previous findings that timing and dynamics are central to musical identity (Palmer, 1997; Repp, 1995).

Time-stretch-based phrase realignment shows promise as a tool for exploring creative possibilities in co-improvisation, enabling performers to experience how their phrasing interacts with alternative timings. However, as the analysis highlights, relying solely on time-stretching can undermine the pedagogical value of active timing correction by removing the learner’s opportunity to engage with and internalise beat deviations. Prior work on sensorimotor learning underscores the importance of error-based feedback for durable skill acquisition, suggesting that systems should present discrepancies rather than mask them (Maes et al., 2014; Schmidt et al., 2018).

The integration of EEG-based brain dynamics into the framework offers interesting avenues for adaptive co-creative systems. Increased beta wave synchrony during precise timing reflects temporal-parietal and frontal association cortical processing during complex rhythmic perception(Giraud and

Poeppel, 2012; Zatorre and Zarate, 2012), while elevated theta variability may signal cognitive overload during poorly aligned phrases. By incorporating real-time EEG or other neurophysiological measures, co-creative tools could dynamically modulate their challenge level or feedback modality based on a performer's engagement and cognitive state, consistent with principles of affective computing (Picard, 1997)and flow induction (Csikszentmihalyi, 1990).

Combining beat/cadence alignment with reinforcement learning (RL) mechanisms represents a promising approach to personalised timing instruction. By rewarding alignment with a target cadence and penalising deviations, an RL-based system can adaptively guide players toward precise timing while preserving their autonomy to experiment with expressive microtiming. Such an approach addresses a key limitation of static correction-based systems, which often fail to foster the exploratory practice essential for developing a personal sense of groove (Witek, 2017).

Overall, these findings suggest that effective human-machine co-creativity tools should combine precise computational models of microtiming with interactive, adaptive feedback mechanisms that encourage active learning. By integrating neural measures, dynamic beat alignment, and RL-driven guidance, future systems can better support both technical skill acquisition and the development of an authentic expressive voice. This integrative framework has potential applications beyond guitar performance, offering a general model for supporting co-creative learning in other musical and motor skills domains.

Media links

The source tracks are publicly available as 16 bit, 44.1 kHz sampled audio.

- EdwardVanHalen
- DweezilZappa
- TinaS
- JoshuaJones
- Kmac

Python version and libraries

Processing and analysis was carried out using bespoke Python 3.12.2 code.

Utilising the following libraries:
librosa 0.11.0, matplotlib 3.10.8, numpy 2.3.5, pandas 3.0.1, pydub 0.25.1, pyrubberband 0.4.0, scikit-learn 1.8.0, seaborn 0.13.2

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