Audio Features Underlying Perceived Groove and Sensorimotor Synchronization in Music

Jan Stupacher
University of Graz, Austria

Michael J. Hove
Harvard Medical School; Fitchburg State University

Petr Janata
University of California, Davis

Running head: Audio Features of Groove

Author note

Jan Stupacher is supported by a DOC fellowship of the Austrian Academy of Sciences at the Department of Psychology, University of Graz. Michael J. Hove received support from National Institute of Mental Health grant T32-MH16259.

We would like to thank Stefan Tomic and Burke Rosen for assistance with Study 2, and Fabien Gouyon for making available the MATLAB scripts underlying the calculations of the beat salience and event density features described in Madison et al., 2011. We further thank Tom Schneider and Adrian Kunkel for recording the stimuli for Experiment 3.

Correspondence concerning this article should be addressed to Jan Stupacher, Department of Psychology, University of Graz, Universitaetsplatz 2/DG, 8010 Graz, Austria, e-mail: jan.stupacher@uni-graz.at, or Petr Janata, Center for Mind and Brain, University of California, Davis, 267 Cousteau Place, Davis, CA 95618, e-mail: pjanata@ucdavis.edu.

Abstract

The experience of groove is associated with the urge to move to a musical rhythm. Here we focus on the relevance of audio features, obtained using music information retrieval (MIR) tools, for explaining the perception of groove and music-related movement. In the first of three studies, we extracted audio features from clips of real music previously rated on perceived groove. Measures of variability, such as the variance of the audio signal's RMS curve and spectral flux (particularly in low frequencies) predicted groove ratings. Additionally, we dissociated two forms of event density, showing that an algorithm that emphasizes variability between beats predicted groove ratings better. In Study 2 we manipulated RMS levels and groove category (low, mid, and high groove) to confirm that perceived groove is not a function of loudness. In Study 3 we utilized novel music clips that manipulated the frequency of bass and bass drum (low vs. high) and attack time (short vs. long). Groove ratings and tapping velocities tended to be higher and tapping variability tended to be lower when the bass instruments had lower frequencies. The present findings emphasize the multifaceted nature of groove by linking audio and musical qualities to subjective experience and motor behavior.

Keywords: Experience of groove, entrainment, music information retrieval, loudness, variability

When listening to music we often move our bodies along with its rhythmic pulse. If the movement comes easily and the rhythm ‘feels right’, we are in a state that can be described as ‘in the groove’. Pressing (2002) defined groove as a temporal cognitive phenomenon that is characterized by the perception of a steady beat, the identification of recurring rhythmic patterns, and the induction of movements like foot tapping or dancing. The movement-inducing effects of groove have been emphasized by other musicologists (e.g., Iyer, 2002), in behavioral studies (Janata, Tomic, & Haberman, 2012; Hurley, Martens, & Janata, 2014), and validated in the form of motor evoked potentials in a recent TMS study (Stupacher, Hove, Novembre, Schütz-Bosbach, & Keller, 2013). Furthermore, the notion of, “wanting to move to music,” was used to define groove in experiments (e.g., Madison, 2006), and was the most common description of groove given by participants (Janata, Tomic, & Haberman, 2012). The degree to which different musical examples compel us to move is consistent across groups of individuals (Janata et al., 2012; Madison, 2006; Stupacher et al., 2013), and this consistency suggests that certain musical or auditory features are especially potent for engaging human motor systems.

From the music-feature perspective, a number of rhythmic features have been postulated to contribute to groove. High-groove music often has a repetitive rhythm (Pressing, 2002; Butler, 2006; Madison, Gouyon, Ullén, & Hörnström, 2011). The use of expressive timing deviations within the repeating structure emerged as an early and influential account of groove (Iyer, 2002; Keil, 1995; Keil & Feld, 1994; Prögler, 1995), though recent empirical studies aimed at testing this hypothesis have found that groove ratings decrease as magnitudes of microtiming deviations increase (Davies, Madison, Silva, & Gouyon, 2013; Frühauf, Kopiez, & Platz, 2013). In a recent theoretical paper, Merker (2014) provides an alternative interpretation of expressive microtiming by suggesting that ‘deviations’ from a regular rhythm with conventional metric subdivisions might actually be located on a fine-grained 'groove matrix' with canonical higher-order subdivisions of a fundamental frequency (repetition rate).

To induce the experience of groove, musicians use syncopated notes with short durations (Madison & Sioros, 2014). In listeners, moderate amounts of syncopation are especially effective in eliciting the sensation of groove: the relationship between syncopation and groove can be described by an inverted U-shaped function (Sioros, Miron, Davies, Gouyon, & Madison, 2014; Witek, Clarke, Wallentin, Kringelbach, & Vuust, 2014). Furthermore, the tempo of a sample of high-groove music averaged 115 beats per minute (Janata et al., 2012); a tempo that aligns with the frequency of general human locomotion (MacDougall & Moore, 2005).

Music information retrieval techniques have also been used to examine music-induced movement and ratings of groove. MIR algorithms operate directly on the audio recordings that a participant hears. Of interest is determining which features model psychological, neural, or musical processes. This type of approach has succeeded in modeling aspects of tonal cognition (Collins, Tillmann, Barrett, Delbé, & Janata, 2014) and timbre perception (Alluri & Toiviainen, 2010).

Among audio features, *spectral flux* (i.e., a measure of variability in the frequency spectrum over time) is correlated positively with the perceived activity of music (Alluri & Toiviainen, 2009). Greater *spectral flux* in low frequency bands (0-50 Hz, 50-100 Hz, 100-200 Hz) has been associated with more regular movement timing (Burger, Thompson, Luck, Saarikallio, & Toiviainen, 2012). Energy in low frequency bands is likely associated with a strong presence of bass drum and bass, instruments that predominantly drive musical groove (Butterfield, 2010; Iyer, 2002; Keil, 1995; Pressing, 2002). In dance music, the bass drum is especially powerful for movement induction (van Dyck, Moelants, Demey, Deweppe, Coussement, & Leman, 2013).

These results suggest a close connection between induced motor-system activity and energy in low frequency bands. Since the experience of groove depends on auditory-motor interactions and the desire to move with the underlying musical pulse, we expect that not only motor responses, but also the subjective experience of groove, is related to the energy in low frequency bands.

Aside from measures within spectral bands that presumably reflect the presence of instruments that are commonly associated with establishing the groove in music, features that more explicitly model metric and rhythmic properties are also correlated with subjective groove ratings. *Beat salience* (a measure of rhythmic periodicity based on the autocorrelation function of the signal representing the velocities of event onsets) and *event density* (a measure of the variability in the event onset velocity signal) have been identified as the best predictors of perceived groove across a range of genres (Madison et al., 2011). However, when calculated using the Music Information Retrieval Toolbox (MIR Toolbox) for MATLAB (Lartillot & Toiviainen, 2007), *event density* failed to predict groove ratings (Stupacher et al., 2013). In sum, MIR analyses suggest that spectral features (especially low frequency *spectral flux*) are linked to movement qualities, and that *event density* and *beat salience* may underlie groove ratings.

Despite reported links between MIR features, musical properties, behaviors associated with groove, and subjective judgments of groove, these interrelationships warrant more thorough examination, particularly in cases in which the same concept, e.g. *event density*, is invoked, but different modeling approaches are applied. Our objective for this paper, therefore, was to determine which audio features predict perceived groove ratings of naturalistic music (obtained from Janata et al., 2012), and to explicitly manipulate some of these features in experiments in order to determine their effects on subjective and sensorimotor measures of groove.

In the first of three studies, we tested the hypothesis that spectral features not only predict movement qualities (as shown by previous studies), but also groove ratings, and we investigated the relationships between different measures of *event density* (MIR *event density* & Madison et al., 2011) and rhythmic salience (MIR *pulse clarity* & Madison et al., 2011). Since musicians use short notes to induce groove (Madison & Sioros, 2014), we additionally extracted the attack characteristics of the music stimuli, expecting that fast attack times would be associated with higher groove ratings. To differentiate the associations of the previously described features and groove ratings from more global characteristics of the audio signal, we further investigated the effects of loudness and root-mean-square (RMS) energy of the audio signal on groove ratings.

In Studies 2 and 3, we manipulated audio features that were identified as being correlated with groove ratings in Study 1 in order to determine their role in shaping groove ratings. To disentangle possible confounds between *event density*, RMS measures, and loudness variables in predictions of perceived groove, we first examined the effects of manipulating a subset of low, mid, and high groove stimuli from Janata et al. (2012) across three loudness intensity levels on perceived groove ratings. Finally, in Study 3 we obtained groove ratings and finger-tapping data in an experiment that used novel music clips composed to manipulate low frequency flux and attack times, two audio-feature correlates of perceived groove identified in Study 1.

Study 1

We investigated the relationship between subjective groove ratings and a number of audio features for 80 song clips that had been rated previously for perceived groove (Janata et al., 2012). The features were selected based on the results of previous studies that examined relations between acoustic descriptors and subjective ratings (Madison et al., 2011; Stupacher et al., 2013), and relations between acoustic descriptors and music-induced movement (Burger et al., 2012;

van Dyck et al., 2013). We selected the following audio features from the MIR Toolbox (Lartillot & Toiviainen, 2007) that were identified as related to music-induced movement or groove in previous studies: *Spectral flux*, *sub-band flux* (Alluri & Toiviainen, 2009; Burger et al., 2012; Stupacher et al., 2013), measures of rhythmic clarity (*pulse clarity* in Burger et al., 2012; *beat salience* in Madison et al., 2011), *event density* (Madison et al., 2011), *RMS energy* (Janata & Tomic, unpublished data), along with a derived measure of the variance in RMS energy. Given the common assumption that RMS is primarily a measure of loudness, we also computed a measure of loudness following the model of Glasberg and Moore (2002). Finally, we computed *beat salience* and *event density* estimates using the method of Madison et al. (2011).

Methods

Groove ratings. Groove ratings for the analyzed music clips were obtained from the Appendix of Janata et al. (2012). In that study, 19 undergraduates from the University of California, Davis rated groove using a slider quantized on a 128-point scale, anchored by "music doesn't 'groove' at all" at the slider extreme closest to the participant and "music imparts a very strong feeling of 'groove'" at the slider extreme farthest from the participant. Average groove ratings ranged from 29.3 (lowest groove rating) to 108.7 (highest groove rating).

Music clips. We coded the instrumentation of 128 music clips that were previously rated on groove in Study 1 of Janata et al. (2012). The genres included folk, jazz, rock, and soul/R&B. The 20 MIDI drum loops from that study were not included here. The music clips consisted of the first 20 s taken from the 30 s previews available on the iTunes Music Store.

~ Table 1 ~

We analyzed the audio features of only the 80 music clips that include a full drum set (Appendix), because usually no other instrument covers such a large frequency spectrum and songs with a full drum set are most commonly associated with groove. However, one must note that music without a drum set can also be perceived to have groove and induce an experience of being in the groove. Table 1 shows the drum instrumentation of the 128 music clips. Only 3 of the 80 drum set tracks contained no audible bass instrument, but did include a bass drum. Groove ratings of the 80 drum set music clips ($M = 74.76$) were higher than groove ratings of the remaining 48 music clips without a drum set ($M = 49.98$), $t(126) = 8.15$, $p < .001$. Audio features (described below) were calculated using the MIR Toolbox except as noted otherwise. Every MIR toolbox audio feature differed between drum-set and no-drum-set music clips with higher values for music clips containing a drum set (ps < .001).

Since the measures of *event density* and *beat salience* based on Madison et al. (2011) require knowing the locations of beats at the tactus level of a musical piece, we created a subset of music clips for which we could extract this information from available tapping data. Janata et al. (2012, Study 2) obtained tapping data for 38 of the 128 musical stimuli considered for this study, and of those, 22 were part of the final set of 80 stimuli that were produced with a full drum kit and subjected to the analyses described here (see Appendix).

RMS and loudness measures. A common measure of the intensity of a signal is the root-mean-square (RMS) energy. The RMS of each clip was extracted using the MIR toolbox function, *mirrms*. We also computed the standard deviation of the RMS curve returned by the *mirrms* function using the 'Frame' option. The RMS curve consists of RMS values in 50 ms windows (50% overlap between successive windows). We refer to this measure of variability as *RMS SD*. The loudness estimate for each music clip was based on Glasberg and Moore's (2002) loudness model, as implemented in the Genesis Loudness toolbox for MATLAB (Genesis, Aix en Provence, France). We computed the mean value of the overall loudness curve. Loudness describes a subjective sensation, and calculations were based on the equal loudness curve corresponding to 70 dB SPL at 1 kHz.

Spectral flux measures. Another form of variability in the musical signal can be quantified by *spectral flux*, i.e. changes in the spectrum of an audio signal between successive frames. We used the *mirflux* function of the MIR Toolbox (window duration: 50 ms; 50% window overlap) to estimate *spectral flux* in the overall signal. In the MIR Toolbox this measure of *spectral flux* is called *mirflux* when applied to the global signal, and *sub-band flux* when applied to different frequency bands. We analyzed *spectral flux* across the full-bandwidth and *sub-band flux* in 10 frequency bands: 0 – 50 Hz, 50 – 100 Hz, 100 – 200 Hz, 200 – 400 Hz, 400 – 800 Hz, 800 – 1600 Hz, 1600 – 3200 Hz, 3200 – 6400 Hz, 6400 – 12800 Hz, and 12800 – 22050 Hz, as previously established by Alluri and Toiviainen (2010).

Pulse clarity, attack, and beat salience measures. In contrast to the measures above, which operate on the audio signal without regard for the timing of musical events, other measures, particularly those related to the musical beat, are calculated based on representations of event onsets within the audio signal. Most MIR tools that perform beat estimation and extraction operate on a pre-processed audio signal, sometimes referred to as a *driving function* (McKinney, Moelants, Davies, & Klapuri, 2007), that commonly represents event onsets (Klapuri, Eronen, & Astola, 2006; Lartillot, Toiviainen, & Eerola, 2008, Madison et al., 2011; Scheirer, 1998; Tomic & Janata, 2008). Here, we refer to the driving function as the onset curve, from which *pulse clarity*, *attack*, *beat salience*, and *event density* measures are obtained.

The implementations for calculations of onset curves differ slightly between the MIR Toolbox and the functions used by Madison et al. (2011), but the principles behind the different steps are the same. Given the flowchart depiction available in the MIR Toolbox documentation, only the Madison algorithm is summarized here. The onset curve for estimates of *beat salience* and *event density* is obtained in several stages: (1) the audio signal is bandpass filtered into six sub-bands, (2) the signal in each sub-band is half-wave rectified, (3) Weber law compression (normalization) is applied within each sub-band, (4) the first-order difference is calculated (using the diff function in MATLAB), (5) half-wave rectified, and (6) summed across the sub-bands.

Pulse clarity is a measure that captures how easily “listeners can perceive the underlying rhythmic or metrical pulsation” of music (Lartillot, Eerola, Toiviainen, Fornari, 2008). We calculated *pulse clarity* with the function *mirpulseclarity* using ‘MaxAutocor’ and ‘Attack’ options. *Pulse clarity* calculated using the ‘MaxAutocor’ option (hereafter referred to as *pulse clarity*) is related to the rhythmic periodicity of an audio signal and corresponds to the maximum value of the autocorrelation function calculated on the onset curve. It is comparable to *beat salience*, which also describes the self-similarity of an onset curve signal (Madison et al., 2011), and which we also calculated. ‘Attack’ *pulse clarity* (hereafter referred to as *attack*) computes the mean attack slope of all onsets in an audio signal. Audio events with steeper slopes reach their maximum amplitude in less time, have a fast attack, and larger attack values.

Event density measures. In the literature, the concept of *event density* has been defined in two different ways. Perhaps most straightforward is a definition in terms of the number of events per unit time, without regard for any potential variability in those events (e.g., Goebl & Dixon, 2001; Balkwill, Thompson, & Matsunaga, 2004). In other words, each event is defined as a unitary impulse, and the number of these impulses per meaningful timespan (e.g., beat, measure, or available excerpt) is the estimate of *event density*. This is the implementation within the MIR Toolbox’s mireventdensity function, and is referred to here as *MIRtbx event density*.

However, *event density* can also be defined in terms of the amount of variance per unit time of a signal that represents the onsets in an audio signal (as in Madison et al., 2011). Given the onset curve, *event density* estimates are obtained by, (1) calculating the variance in the onset curve between beats (beat-to-beat variance), and (2) calculating the mean of the beat-to-beat variance estimates. We refer to this as *variance event density*. The *variance event density* calculation requires ground-truth knowledge of beat locations at the tactus level of the piece's metric structure. In the case of Madison et al. (2011), the ground-truth estimate was obtained by asking a single listener to tap along with the musical excerpts followed by visual alignment of the tap markers to the audio signal. In recognition of the fact that different listeners may perceive the tactus at different metric levels (Martens, 2011; McKinney & Moelants, 2006; Tomic & Janata, 2008), we obtained beat location estimates using the tapping data from 34 participants in the isochronous tapping condition of Study 2 from Janata et al. (2012).

We estimated beat locations for each stimulus using the following algorithm:

(1) Tap onsets from which MIDI velocity information had been removed were quantized into a vector of 10 ms bins (100 Hz sampling rate).

(2) Tap onset vectors were averaged across participants.

(3) The average vector was convolved with a Gaussian envelope (100 ms full width at half of the maximum amplitude) to accommodate slight inter-participant variation in the timing of taps corresponding to the same events.

(4) Peaks with an amplitude greater than 20% of the maximum amplitude were marked.

(5) A histogram of peak amplitudes was calculated to determine whether different metric levels were considered the tactus level by different sub-sets of participants. For example, if half the participants perceived the tactus at a metric level double the period of the tactus perceived by

the other participants, two peaks would be present in the peak-amplitude histogram. If more than one peak was present in the histogram, the largest peak was considered to be the tactus level of interest (which necessarily corresponded to the slower metric level).

(6) Inter-peak-intervals (IPI) and their distribution were calculated for events at the tactus level of interest.

(7) The best IPI was defined as the IPI associated with the peak of the IPI distribution.

(8) A final step verified that marked peaks aligned with a temporal grid based on the intervals matching the best IPI. Beat locations were inferred when taps were missing (most commonly during the initial 4 – 6 s of an excerpt).

The vector of beat locations, along with the onset curve obtained as described above were used to obtain the *variance event density* measure for each excerpt.

Results

~ Table 2 ~

We examined correlations between subjective groove ratings and the extracted audio features. Correlations between groove ratings and extracted full-bandwidth audio features are shown in Table 2. For the full complement of 80 music clips, positive correlations were found between groove ratings and *RMS energy*, variance of the RMS curve (*RMS SD*), mean attack slope of onsets, and *spectral flux*. However, the correlations of groove ratings with *pulse clarity* (Figure 1B) and *MIRtbx event density* (Figure 2B) were not statistically significant.

~ Figure 1 ~

~ Figure 2 ~

For a subset of 22 stimuli we were able to compare MIR Toolbox and Madison et al. (2011) measures that are related conceptually, specifically *MIRtbx event density* and *variance event* *density*, and MIR Toolbox *pulse clarity* and *beat salience*. In this model, with a reduced number of exemplars, *RMS energy* and *spectral flux* were no longer significant. The correlation between groove ratings and *MIRtbx event density* remained nonsignificant (Figure 2A, left panel), however, the correlation between groove ratings and *variance event density* was significant (Figure 2A, right panel). Similarly, the correlation between groove ratings and *pulse clarity* was not significant (Figure 1A, left panel), though the correlation between groove ratings and *beat salience* was (Figure 1A, right panel). We address these discrepancies further in the discussion.

Correlations between groove ratings and *sub-band flux* in all 10 frequency bands are shown in Figure 3. The strongest positive correlations, rs = .29, were observed in sub-bands 1 [0 – 50 Hz], and 2 [50 – 100 Hz]. Low to moderate positive correlations, rs = .23 – .24, were observed in sub-bands 3 [100 – 200 Hz], 5 [400 – 800 Hz], and 6 [800 – 1600 Hz]. All other correlations were positive, but not significant.

~ Figure 3 ~

To examine the relationships between *RMS energy*, groove, and loudness, we computed a measure of loudness using the loudness model of Glasberg and Moore (2002). Unlike mean *RMS energy*, the mean loudness did not correlate significantly with groove ratings.

Discussion

Using a validated library of excerpts of real music that vary in perceived groove, Study 1 revealed several audio features that were predictive of groove ratings. The two most general features to predict groove were *RMS energy* (especially *RMS SD*, a measure of the variability in the time-varying RMS values) and mean *spectral flux* (across all frequency bands). These measures estimate the average amount of variability in an audio signal's envelope (*RMS SD*) and spectrogram (*spectral flux*), and cannot easily be related to specific musical characteristics. *RMS*

SD and *spectral flux* also correlated strongly with each other (r = .69). Their significant correlations with groove ratings suggest that perceived groove increases with increased variability in the audio signal. Overall, these findings corroborate results of previous studies of subjective states that found that increased *spectral flux* leads to increased arousal (Gingras, Marin, & Fitch, 2013) or perceived musical activity (Alluri & Toiviainen, 2009).

To better contextualize the global *RMS energy* and *spectral flux* results, it is useful to consider the energy within different spectral sub-bands. Across the different sub-bands, variability in the amount of energy in the two sub-bands below 100 Hz was most predictive of groove. Correlations between full *spectral flux* and each of *sub-band flux* measures were strong (all rs ≥ .64), but strongest for the 0 – 50 Hz, 50 – 100 Hz, and 100 – 200 Hz sub-bands (rs = .80, .88, and .81, respectively). In addition, *RMS SD* correlated more strongly with *sub-band flux* in the 50 – 100 Hz band (r = .71) than with any other variable (aside from global *RMS energy*, r = .77). Together, these observations further support the notion that low frequency instruments contributed strongly to the *spectral flux* measure, to perceived groove, and by extension to the translation of an urge to move into actual entrained movement (van Dyck et al., 2013). We explicitly tested these ideas in Study 3.

Whereas measures such as *RMS energy* or full-bandwidth *spectral flux* reflect general properties of the audio signal, other measures are related more directly to audio features with clearer musical or psychological relevance. Of particular interest to studies of groove are measures that reflect the temporal structure of the music, such as the perceived beat or timing characteristics of event onsets that can support processes of sensorimotor entrainment (Madison et al, 2011; Davies et al., 2013). As music increases in groove, the likelihood that it will trigger spontaneous movement also increases (Janata et al., 2012; Hurley et al., 2014), and the ease with which a person is able to synchronize with music during a tapping task predicts the degree to which s/he will feel in the groove (Janata et al., 2012). Here we examined the ability of average attack slope (*attack*), *pulse clarity*, *beat salience*, and two different *event density* measures to predict perceived groove.

We observed that as the average slope of attack of the identified event onsets increased, so did the groove ratings. Steep onset slopes are characteristic for percussive sounds and were mostly found in music clips with high groove ratings. The steepness of onset slopes represents the rise time that an acoustic onset needs to reach its maximum amplitude. Auditory stimulus rise time affects sensorimotor synchronization accuracy while tapping to an isochronous metronome, with higher accuracy for faster rise times (Vos, Mates, & van Kruysbergen, 1995). Additionally, high percussiveness of music (i.e. steep onset slopes) was recently shown to induce movement (Burger et al., 2012; Burger, Thompson, Luck, Saarikallio, & Toiviainen, 2013).

Previous studies found that rhythmic regularity correlates with temporal movement regularity (Burger et al., 2012), and that groove ratings can be predicted by *beat salience* (Madison et al., 2011). We therefore expected *pulse clarity* and *beat salience* to predict groove ratings also. However, calculated across the sample of 80 music clips, we found no significant correlation between groove ratings and *pulse clarity* (Figure 1B). When restricted to the 22 music clips for which we could also calculate *beat salience* and *event density* measures, *pulse clarity* increased considerably (to r = .41) though it did not reach significance (Figure 1 A, left panel). In contrast, the closely related measure of *beat salience* correlated positively with groove ratings (r = .49; Figure 1A, right panel).

Heterogeneous results were also found across different measures of *event density* (Figure 2). The *event density* estimate calculated using the MIR Toolbox as the number of event onsets per second was unable to explain groove ratings, whereas an *event density* estimate based on the variance in the onset curve between beats, averaged across beats, as in Madison et al. (2011) was a strong predictor of groove ratings (Figure 2A). A visual comparison of the distributions of *event density* values for mid-groove clips highlights the difference between the two *event density* calculations and suggests that in the MIRtbx calculation, greater perceptual influence is being attributed to weaker onset events than may be warranted.

Study 2

The relationship between the RMS of musical audio signals and perceived groove, as illustrated in Study 1, raises the possibility that perceived groove is trivially a function of how loudly a piece of music is played. Heterogeneity in groove ratings may reflect nothing more than variability in the way that pieces of music have been normalized for loudness, given that normalization to RMS-related measures is common practice. Moreover, common wisdom among devotees of rock and electronic dance music genres stipulates that music at concerts and dance clubs has a certain acoustic intensity, particularly in low frequencies, to engender movement and groove – a position that has received empirical support (van Dyck et al., 2013; Todd & Cody, 2000). Although the failure of loudness estimates to predict groove ratings in Study 1 speaks against an interpretation of dependence of loudness on perceived groove, direct empirical manipulation of overall *RMS energy* (and loudness) is nonetheless warranted. Study 2 addressed this issue.

Method

Participants. Ratings were collected from 11 participants (19 – 26 years of age; mean ± *SD* = 20.6 ± 2.1 y; 5 female), who participated for partial course credit after providing informed consent according to a protocol approved by the UC Davis Institutional Review Board. All of the participants spoke English.

Stimuli. The 48 music excerpts (16 each from high-, mid-, and low-groove categories) used in Study 2 of Janata et al. (2012) were used as the parent sound files (22 of these excerpts were used in Study 1 of this paper). Sound files were stored and manipulated in WAV format. The amplitude of each was normalized relative to the peak amplitude in the audio to create three different intensity categories: high (0 dB), mid (-6 dB), and low (-12 dB).

Procedure. Each participant was seated in a sound-attenuating room in front of a computer monitor. Audio files were played from an Apple G5 Macintosh computer via a MOTU 828mkII interface, amplified with a Crown XLS 202 amplifier, and played from Tannoy Reveal 6 speakers situated approximately 45 inches away at 40 degrees to the left and right of the participant. Music clips in the high intensity category were at peak volumes of ~83 dB.

A 3 x 3 factorial design was employed with factors Groove (Low, Mid, High) and Intensity (Low, Mid, High). Each participant rated every music exemplar, but heard only one intensity version of the exemplar in order to minimize confounding of groove ratings with multiple exposures to the same music over the course of the experiment. The intensity level at which each exemplar was heard was varied randomly across participants. The order of exemplars was also randomized across participants. Ensemble (Tomic & Janata, 2007) controlled the presentation of stimuli and recording of responses.

Prior to listening to the music, participants were asked if they had heard the term groove as applied to music. Three of the 11 participants had not, and were provided with the definition: "'The groove' is the aspect of music that compels the body to move." The others provided their own definitions, which were largely consistent with the definition we provided[1].

Upon listening to each 30 s excerpt, participants answered the following questions on 7-point scales:

To what extent did you feel that the musical excerpt grooved (1 = least groove; 7 = most groove)?

To what extent did you feel "in the groove" while listening to the excerpt (1 = least groove; 7 = most groove)?

How much did you enjoy what was just played (1 = not at all; 7 = very much)?

Are you familiar with the excerpt that just played? (Yes, No)

How much would you have liked to continue performing the task (1 = not at all; 7 = very much)?

Statistical analyses. Of primary interest were responses to the question of perceived groove in the music. Because of the sparse sampling method in the 3 x 3 design, the responses were analyzed using the mixed-model approach implemented in the function, PROC MIXED, in SAS statistical software (SAS Institute, Inc.) with Restricted Maximum Likelihood as the estimation method, a Variance Components covariance structure, and the Between-Within method of degrees-of-freedom calculation. The dependent variable – the perceived degree of groove in the musical excerpt – was modeled as a function *groove* and *intensity* main effects and their interaction. To accommodate individual differences in use of the rating scale, participants were treated as a random variable, meaning that the model contained an intercept fitted for each participant.

Results

In response to the question, “to what extent did you feel that the musical excerpt grooved,” there was a significant main effect of groove, $F(2,20) = 65.27$, $p < .001$, but no main effect of intensity, $F(2,20) = 1.08$, p =0.36, and no interaction between groove and intensity, $F(4,40) = 0.32$, n.s.. Corroborating previous ratings (Janata et al., 2012), exemplars from the high-groove category received higher ratings than exemplars from the mid-groove category, (1.25 ± .15, difference ± *SEM*), $t(20) = 8.08$, $p < .001$, which, in turn, received higher ratings than song clips from the low-groove category, (.46 ± .15), $t(20) = 2.96$, $p = .008$.

To exclude the possibility that familiarity influenced groove ratings or their interaction with intensity, familiarity ratings were added into the model as a covariate. The main results remained unchanged: there was a main effect of groove, $F(2,20) = 32.10$, $p < .001$, but no main effect of intensity, $F(2,20) = 1.16$, $p = 0.33$, and no interaction between intensity and groove, $F(2,40) = 0.39$, n.s..

Discussion

The results of Study 2 indicate clearly that, across a range of normal listening intensities, the perceived groove in a piece of music is not a function of how loud the music is played. This is corroborated both by the self reflections of 149 participants asked to endorse the statement, “The groove depends on the overall loudness of the music,” who on average expressed slight but significant disagreement with that statement (Figure 1 in Janata et al., 2012), and by the analysis of the Glasberg and Moore loudness estimates presented here in Study 1.

The results also highlight that care should be exercised if RMS-based measures are used to normalize the amplitudes of stimulus materials used in studies of groove. Though the relationship between *RMS energy* and sound intensity is reasonably straightforward when considering brief sounds consisting of a small number of steady-state components, the matter is complicated considerably when considering extended passages of real music.

The positive relationship between groove ratings and the variability in global RMS values within a set of similarly normalized musical pieces, or averages of local RMS values, such as the Madison et al. (2011) *event density* measure, nonetheless points toward the importance of the variability in a musical signal for determining the amount of perceived groove.

Study 3

The purpose of Study 3 was to manipulate different potential determinants of perceived groove: the amount of energy in low frequency sub-bands that are characteristic of the bass, as well as the attack characteristics of the events. These variables correlated significantly with groove ratings in Study 1. We created novel audio clips that directly manipulated the audio features *bass frequency* (low vs. high) and *attack time* (long vs. short), thus excluding the possibility that groove ratings could be driven by variability in instrumentation, songwriting, or mastering, present in Study 1. Groove ratings were collected to examine the subjective aspects of groove. Additionally, tapping data were recorded to examine sensorimotor aspects of groove.

Methods

Participants. Groove ratings and finger-tapping data were collected from 36 German-speaking undergraduates (20 females) from the University of Graz, Austria. The mean age was 25.4 years (*SD* = 4.6). Nineteen participants were amateur musicians with musical performance experience of *M* = 9.2 years (*SD* = 5.1). The remaining 17 participants had no music training. Participants were paid 5 Euros for taking part in the study.

Musical stimuli. Musical stimuli were short audio clips consisting of drums, bass, and keyboards (see supplementary material). The clips were created by a professional drummer and a professional pianist using MIDI instruments (Yamaha DTXtreme e-drum set, and a Nord Wave keyboard for bass and organ sounds). They were instructed to play repetitive and groovy rhythms at 5 different tempi (90, 100, 110, 120, and 135 bpm). The tempo was established by a metronome count-in with a length of one measure (4/4 time). Audio clips were recorded and reviewed by author JS. Each instrument (bass, organ, bass drum, snare, and hi-hat) was quantized on a 16th note level and adjusted to a fixed MIDI velocity with the software Ableton Live 8 (Ableton AG, Berlin, Germany). The clips were looped (one or two measures) and lasted 16 beats per clip (4 measures of 4/4 time).

The experimental manipulation consisted of altering the bass-frequency range of bass drum and bass and the *attack time* of all instruments. The audio tracks were manipulated using Ableton Live 8. The *bass frequency* manipulation had two levels (low bass and high bass), which altered the frequency of the bass line by one octave and the peak frequency of the bass drum by approximately 100 Hz (40 Hz in low frequency bass vs. 140 Hz in high frequency bass stimuli). The *attack time* manipulation lengthened the onset rise time of bass drum, snare and hi-hat by approximately 15 ms, and the onset rise time of bass and organ by approximately 50 ms. Table 3 shows the means of the two *bass frequency* and the two *attack time* levels for *spectral flux* in the three lowest frequency bands (0–50 Hz, 50–100 Hz, 100–200 Hz) and mean attack slope values (extracted with the 'attack' feature of the *mirpulseclarity* function in the MIR Toolbox). In sum, there were 20 different audio clips resulting from the combination of tempo (90, 100, 110, 120, and 135 BPM), *bass frequency* (low and high bass), and *attack time* (short and long attack). The loudness of audio clips was adjusted to subjective equal levels in a pre-study with 6 participants. The clips were presented over AKG K601 headphones (AKG, Vienna, Austria) connected to an ART HeadAmp 4 headphone amplifier (Art Pro Audio, Niagara Falls, NY). The overall loudness during the experiment was adjusted to be comfortably loud and clear and stayed at the same level for each participant. Ratings of overall loudness after the experiment indicated that the settings were perfectly centered (*M* = 50.15, *SD* = 4.77), on a continuous 100 mm scale ranging from 0 (way too soft) to 100 (way too loud).

~ Table 3 ~

Procedure. MAX/MSP 5 (Cycling ’74, San Francisco, CA) software was used to present the audio clips and to record groove ratings and tapping performances. Ratings of groove (defined as a musical quality that initiates movements, e.g., head bobs or foot taps) were given on a mouse-controlled horizontal slider ranging from 0 on the left (“sehr schwacher groove” [very weak groove]) to 100 on the right (“sehr starker groove” [very strong groove]), but participants could not see these numbers. Audio clips were presented in two randomized blocks, resulting in a total number of 40 rating trials (approximately 10 min).

Tapping performances were recorded with an Akai LPD8 tapping pad (Akai, Tokyo, Japan) with LED light feedback turned off. At the beginning of the tapping portion, three to eight practice trials were presented and monitored by author JS to ensure that participants understood the task. Participants were instructed to tap on each beat (i.e. quarter note) as synchronously as possible with the beat. Trials started without any delay by pressing the space key. Audio clips were presented in three randomized blocks, resulting in 60 total trials (approximately 15 min).

Half of the participants started with the rating portion, and half started with the tapping portion of the study. To examine potential effects of counterbalancing, we included the *task order* (rating first vs. tapping first) as a between-subject factor in the following ANOVAs.

Data analysis. Outlier ratings that were more than two standard deviations from the mean rating of each audio file were removed from further analysis (3.3% of all ratings). For the tapping data, inter-tap intervals (ITIs) were computed by subtracting the absolute time of a tap *n* from the absolute time of the following tap *n*+1. Doubled or missing taps (defined as ITIs more than twothirds longer or shorter than the target inter-onset interval) and outlier ITIs that were more than 2.5 standard deviations from the mean ITI for each participant and trial were excluded (5.7%). Tap-to-beat asynchronies were calculated as the difference between tap times and the quarter-note onset times of the acoustic stimuli. After removing off-beat taps (i.e., taps with unsigned asynchronies greater than 25% of the inter-beat interval), outliers that were more than 2.5 standard deviations from the mean asynchrony for each participant and trial were excluded (in sum 5.6%). While the SD of ITIs represents a person's ability to tap consistently at a steady rate, the SD of tap-to-beat asynchronies provides information about the accuracy with which a person taps with the beat. We also analyzed the velocity of taps (i.e., how hard a person tapped). Since the used tapping pad had a maximum velocity value and participants often tapped at the maximum velocity or stronger, we split the tapping data. The total number of maximum velocity taps (i.e., MIDI value 127; 29.6%) was analyzed in a nonparametric test, while the velocity values of the remaining taps (MIDI values between 1 and 126) were arcsine transformed to better meet the assumptions of normality. Velocities that were more than two standard deviations from the mean velocity for each participant and trial were excluded (4.0%). Tapping performances of three participants could not be analyzed due to a technical failure of the tapping pad (fewer than 70 taps were recorded for each of the three participants compared to an average of 918.2 taps (*SD* = 76.7) for the other participants).

Results

Groove ratings. Mean groove ratings are shown in Figure 4A. An ANOVA with the within-subjects factors *bass frequency* and *attack time* and the between-subject factor *task order* on the groove ratings revealed a trend in the main effect of *bass frequency*, $F(1,34) = 3.50$, $p = .070$, in which groove ratings were higher for low frequency bass clips ($M = 60.63$, *SD* = 9.79) compared to high frequency bass clips (*M* = 59.37, *SD* = 10.02). No main effect of *attack time*, no main effect of *task order*, and no interactions were found (all *p*s > .15)

~ Figure 4 ~

Tapping variability. Figure 4C shows the participants' ability to tap at a steady rate with the beat (indicated by the SD of ITIs) for the manipulated *bass frequency* and *attack time* levels. An ANOVA with the within-subjects factors *bass frequency* and *attack time* and the between-subject factor *task order* on the SDs of ITIs revealed a trend in the main effect of *attack time*, *F*(1,31) = 4.09, *p* = .052, such that tapping variability was smaller with long attack clips (*M* = 32.17, *SD* = 11.05) compared to short attack clips (*M* = 33.86, *SD* = 13.38). No interaction between *attack time* and *bass frequency* or *task order* was found (both *p*s > .27). We found no main effect of *bass frequency* or *task order* (both *p*s > .16). However, since *bass frequency* interacted with *task order*, *F*(1,31) = 5.85, *p* = .022, we computed two individual ANOVAs to follow up this interaction. Participants who completed the rating before the tapping task tapped at a more steady rate with low bass frequency clips (*M* = 30.90, *SD* = 11.08) compared to high bass frequency clips (*M* = 33.47, *SD* = 12.82), *F*(1,14) = 5.55, *p* = .034, whereas no main effect of *bass frequency* was found in participants who first tapped and then rated (*p* > .42). Both ANOVAs revealed no main effect of *attack time* and no interactions (all *p*s > .15).

The analysis of the SDs of tap-to-beat asynchronies (Figure 4D) with the within-subject factors *bass frequency* and *attack time* and the between-subject factor *task order* showed no significant main effects or interactions (all *p*s > .07).

Tapping velocity. Mean tapping velocities are shown in Figure 4B. An ANOVA with the within-subjects factors *bass frequency* and *attack time* and the between-subject factor *task order* on taps with MIDI velocity values between 1 and 126 revealed that participants tapped harder with low bass frequency clips ($M = 1.94$, $SD = .59$) compared to high bass frequency clips ($M = 1.91$, $SD = .58$), $F(1,28) = 7.23$, $p = .012$. No main effects of *attack time* and *task order*, and no interactions were found (all ps > .18). A sign test on the remaining numbers of taps with maximum velocity (i.e. MIDI values of 127) showed no difference between low and high bass frequency, $Z = -.72$, $p = .440$, and long and short attack, $Z = -1.39$, $p = .165$.

Correlation between groove ratings and tapping performances. The relationships between the participants' mean values of groove ratings and tapping performance measures were investigated with a correlation analysis (Table 4). The two tapping variability measures (SD of ITIs and SD of tap-to-beat asynchronies) were positively correlated with each other, $r = .78$, $p < .001$, and negatively correlated with tapping velocity (both ps < .05), indicating that harder taps were associated with lower tapping variability. The relation between groove ratings and tapping variability measures was negative (lower tapping variability with higher groove ratings) but not significant (both ps > .34).

Additionally, separate correlations between groove ratings and tapping variability (SD of ITIs and tap-to-beat asynchronies) were computed for each participant across the 20 audio clips s/he heard. A one sample t-test of the resulting Fisher-z-transformed Pearson's correlation coefficients revealed a tendency that on individual level, tracks with higher groove ratings were associated with more synchronized tapping performances, as indicated by the SD of tap-to-beat asynchronies, $t(32) = -1.78$, $p = .085$. However, no significant effect was found for SD of ITIs, $t(32) = -.67$, $p = .506$.

~ Table 4 ~

Discussion

In Study 3 we manipulated the *bass frequency* and the *attack time* of newly created audio clips. Clips in which the bass and bass drum were played in a lower frequency range tended to be rated higher in groove than when the pitch of those instruments was in a higher frequency range. Consistent with this result, participants tapped harder with low bass frequency clips than with high bass frequency clips, potentially reflecting motivational effects. Additionally, participants who first completed the rating part of the experiment, later tapped at a steadier rate with low bass frequency clips. This effect of *task order* might be a result of familiarization with the audio clips. In sum, these findings offer some corroboration of the results from Study 1, in which perceived groove was correlated with the amount of energy in low frequency bands. They are further consistent with previous studies that showed that low frequencies are especially important for entrainment (Burger et al., 2012; Hove, Keller, & Krumhansl, 2007; van Dyck et al., 2013) and rhythm perception (Hove, Marie, Bruce, & Trainor, 2014).

For the variability of ITIs, a trend in the effect of *attack time* was found, with lower variability for audio clips with longer attack times. Longer attack times of low frequency notes might result in a stronger perceived presence of low frequency instruments like bass drum and bass and could therefore increase tapping stability. Additionally, it is possible that, similar to the rhythmic feature of syncopation, the relation between *attack time* and sensorimotor aspects of groove can be described by an inverted U-shaped function (cf. Witek et al., 2014). Testing this interpretation would require manipulating *attack time* with at least three different rise times.

Although tapping and rating trials were completed at separate times, individual correlations for each participant indicated that the variability of tap-to-beat asynchronies tended to be lower with audio clips that were rated higher on groove. This observation supports previous suggestions that the ease of sensorimotor coupling with musical stimuli underlies perceived and experienced groove (Fairhurst, Janata, & Keller, 2013; Janata et al., 2012; Stupacher et al., 2013).

In sum, we found some evidence that low bass frequencies can positively affect groove ratings and tapping performances, but these effects are probably not independent from more general musical aspects like instrumentation, songwriting, genre, or mixing and mastering.

General discussion

The concept of groove in music can be treated as a multifaceted musical, psychological, and neural phenomenon that encompasses pleasurable entrainment and movement in musical situations (Janata et al., 2012). Of considerable interest are acoustic and musical determinants of groove in the musical stimuli themselves, as well as the way in which specific features support entrainment and shape rhythmic movements as a person moves to music. The present work contributes to a growing number of theoretical and empirical studies illuminating various facets of the broad groove phenomenon.

In our analyses of music clips that had been previously rated for groove (samples of 80 music clips, and a subset of 22 music clips that had tapping data available to compute *beat salience* and *variance event density*), we found that measures of variability (RMS-related measures and *spectral flux*), particularly in low frequencies, together with the average attack characteristics of event onsets were predictive of perceived groove in the music clips. We performed an experiment that dissociated the effects of RMS predictors (global *RMS energy* and variability of the RMS curve) of groove and loudness, illustrating that RMS measures must be thought of as carrying more psychologically relevant information than loudness alone. In doing so, we also highlighted divergent operational conceptions of *event density* (Larillot & Toiviainen, 2007; Madison et al., 2011), and showed that the measure of *event density* based on variance of event onsets (Madison et al., 2011) is a better predictor of groove. Finally, we performed an experiment that deliberately manipulated energy in low frequency instruments and attack characteristics and showed that subjective ratings of groove tended to be higher for stimuli with lower bass frequencies. Furthermore, tapping at a steady rate along with the beat was best in association with stimuli in which lower bass frequencies were present. However, this effect was quite small and was only found when participants completed the rating part of the experiment first and then tapped to the stimuli. We now place these findings in the context of earlier studies of groove and music-induced movement.

Not surprisingly, temporal aspects of music have received the most attention as the musical factors underlying groove. Earlier theoretical considerations emphasized the roles of subtle timing deviations (microtiming; participatory discrepancies) between players/instruments (Keil & Feld, 1994; Iyer, 2002; Pressing, 2002), but recent studies failed to find a positive correlation between microtiming and perceived groove (Madison et al., 2011; Davies et al., 2013; Frühauf et al., 2013). In fact, as timing deviations increase, perceived groove decreases, particularly among musically trained individuals (Davies et al., 2013). While deviations from strict metronomic timing are inevitable in real music performances, it appears that adaptive timing deviations that serve to decrease asynchronies among individuals stand the best chance of reducing activity in brain areas associated with cognitive control and increasing activity in brain areas associated with socio-emotional processes, reward, and the feeling of being in the groove (Fairhurst et al., 2013; Kokal, Engel, Kirschner, & Keysers, 2011). Thus the question becomes what musical characteristics, as reflected in MIR analyses, support timing and entrainment.

Low frequencies

From a musicological point of view, low frequency onsets (e.g., bass drum onsets) often mark important metrical locations (e.g., Large, 2000). Strong metrical accents facilitate the perceptual grouping of complex rhythmic structures into beat and meter (London, 2004). On a behavioral level it has been shown that people move more actively and are more entrained with louder bass drum levels in dance music (van Dyck et al., 2013). Similarly, frequencies below 200 Hz positively affect temporal movement regularity (Burger et al., 2012). At a neural level, the acoustic cues provided by low frequency instruments support greater sensitivity to timing variations than higher frequency instruments (Hove et al., 2014), perhaps as a consequence of differences in cochlear stimulation patterns when low frequency tones lead high frequency tones by tens of milliseconds (Hove et al., 2014; Zilany, Bruce, Nelson, & Carney, 2009). Our findings of positive correlations of energy in bass frequencies with groove ratings (in both a collection of commercially available music samples and controlled music loops) alongside decreased tapping variability (SD of ITIs) with the audio clips containing low bass frequencies further highlight the importance of low frequency instruments in supporting perceptual and sensorimotor components of groove.

Accentuated bass frequencies are thought to increase arousal during sport exercises (Karageorghis, Terry, Lane, Bishop, & Priest 2012), perhaps pointing to movement-induction effects of low frequency instruments on experienced groove that may be dissociated from potential timing mechanisms. Falling along the lines of arousal are suggestions that loud music, and in particular the low frequency aspects thereof, may activate the vestibular system thus creating more extensive sensory stimulation at periodicities corresponding to the underlying beat, and promoting entrainment (Todd & Cody, 2000; van Dyck et al., 2013). Though louder bass parts may induce more movement and a stronger experience of groove, louder music per se is not perceived as having more groove, as shown here in Study 2.

Pulse clarity, beat salience, and attack

Above, we suggested that low frequency instruments contribute to perceived groove, perhaps, in part, through mechanisms that more clearly define the beat and timing relationships. Indeed, a clear pulsating beat of a loud bass drum is an unambiguous signal with which to synchronize at a dance club, and so it can be expected that the clarity or salience of a beat, along with sharp onsets would aid in sensorimotor synchronization.

Our results in this regard were mixed. When considering the sample of 80 music clips, *pulse clarity* was significantly correlated with predictors of groove: *attack* ($r = .51$, $p < .001$), *RMS SD* ($r = .39$, $p < 0.01$), and *sub-band flux* in low frequencies (< 200 Hz, mean $r = .35$, $p < .01$) but no other spectral bands other than between 12800 – 22050 Hz ($r = .51$, $p < .001$). However, *pulse clarity* did not predict groove itself. In contrast, when considering a more restricted sample of 22 clips for which beat locations at the tactus level of a musical piece were available, *beat salience*, an alternative measure of rhythmic periodicity (Madison et al., 2011), was positively correlated with groove ratings. These results point to algorithmic differences underlying closely related concepts.

Our results regarding average onset attack characteristics were also mixed. Though we found significant positive correlations between groove ratings and the steepness of attack slopes in both samples of music clips, an explicit manipulation of *attack time* did not result in higher groove ratings for shorter attack times. A possible explanation for this result is that onset manipulations in Study 3 were applied to all of the instruments, whereas in the music clips of Study 1, the attack estimates may have been driven by a subset of instruments.

Variability

Until now, we have considered MIR measures that primarily reflect the overall presence of low frequency instruments or more clearly perceived aspects of a musical signal. However, we also found that measures of full-bandwidth audio variability (*RMS SD* and *variance event density*) were strong predictors of groove. Taking into account the results that groove ratings did not depend on loudness (Study 2), these results support previous findings, which showed that the common, “louder is better” perspective of the music industry that maximizes loudness at the cost of dynamic variability is misleading in the context of subjective groove ratings (cf. Croghan, Arehart, & Kates, 2012; Vickers, 2010). The reduction of dynamic variability (e.g., through heavy compression of an audio signal) is thought to lead to listening fatigue (Vickers, 2010), whereas sudden changes in loudness within a musical piece are connected to the experience of chills (Grewe, Nagel, Kopiez, & Altenmüller, 2005). In line with these findings, our results demonstrate that music with lower dynamic variability is associated with the perception of less groove.

The positive correlations between groove ratings and measures of audio variability also turn us to a different determinant of groove: syncopation. Syncopation, the omission of events at strong metric locations and the sounding of events at weak metric locations, inherently plays with our temporal expectations and has been postulated to underlie our affective responses to music (Fitch & Rosenfeld, 2007; Huron, 2006), as has been recently shown (Keller & Schubert, 2011; Witek et al., 2014). Without explicit examination, it is impossible to know how measures of variability in the audio signal (e.g., *variance event density* and *RMS SD*) would map onto syncopation; but *variance event density* would be of particular interest because it is explicitly tied to the event structure that underlies syncopation calculations. The model of metric salience used by Witek et al. (2014) for computing syncopation values incorporates different weights for events that would fall between tactus level beats, thus capturing a similar principle of variability that the *variance event density* measure is sensitive to, raising the possibility that the *variance event density* audio descriptor might be explicitly tied to the musical phenomenon of syncopation.

Conclusions

We examined audio and musical correlates of perceived groove, identifying and experimentally manipulating low frequency cues provided by the bass and bass drum to show that energy in low frequency bands tends to positively affect ratings of groove, influences a participant's ability to tap at a steady rate along with the beat, and can enhance finger-tapping velocity. These results are consistent with previous findings of the role of low frequencies in shaping movement to music. Additionally, we showed that measures of variability of the audio signal are effective predictors of perceived groove, highlighting the fact that musical dynamics and less salient events need to be represented appropriately. While the precise relationships among the extracted audio features and their musical interpretation are in need of further study, a picture of groove as a multifaceted phenomenon continues to emerge.

Footnotes

[1] Although this approach of specifying the groove construct that participants are asked to rate is associated with greater variability, than if all participants were given the same definition, it accommodates the reality that the groove construct is complex and may not be adequately defined with only a single sentence. Any significant differences in ratings of perceived groove between stimulus categories thus reflect a certain degree of robustness of the construct, given the individual differences in the conception of the multifaceted groove construct.

References

Alluri, V., & Toiviainen, P. (2009). In Search of Perceptual and Acoustical Correlates of Polyphonic Timbre. In *Proceedings of the 7th Triennial Conference of European Society for the Cognitive Sciences of Music* (pp. 5–10).

Alluri, V., & Toiviainen, P. (2010). Exploring perceptual and acoustical correlates of polyphonic timbre. *Music Perception*, *27*, 223–241.

Balkwill, L. L., Thompson, W. F., & Matsunaga, R. (2004). Recognition of emotion in Japanese, Western, and Hindustani music by Japanese listeners. *Japanese Psychological Research*, *46*, 337–349.

Burger, B., Thompson, M. R., Luck, G., Saarikallio, S., & Toiviainen, P. (2012). Music moves us: Beat-related musical features influence regularity of music-induced movement. In *Proceedings of the 12th International Conference in Music Perception and Cognition and the 8th Triennial Conference of the European Society for the Cognitive Sciences for Music* (pp. 183–187).

Burger, B., Thompson, M. R., Luck, G., Saarikallio, S., & Toiviainen, P. (2013). Influences of rhythm- and timbre-related musical features on characteristics of music-induced movement. *Frontiers in Psychology*, *4*, 183.

Butler, M. J. (2006). *Unlocking the groove: Rhythm, meter, and musical design in electronic dance music.* Georgetown University Press.

Butterfield, M. (2010). Participatory discrepancies and the perception of beats in jazz. *Music Perception*, *27*, 157–176.

Collins, T., Tillmann, B., Barrett, F. S., Delbé, C., & Janata, P. (2014). A combined model of sensory and cognitive representations underlying tonal expectations in music: From audio signals to behavior. *Psychological Review, 121*, 33–65.

Croghan, N. B., Arehart, K. H., & Kates, J. M. (2012). Quality and loudness judgments for music subjected to compression limiting. *Journal of the Acoustical Society of America*, *132*, 1177–1188.

Davies, M., Madison, G., Silva, P., & Gouyon, F. (2013). The effect of microtiming deviations on the perception of groove in short rhythms. *Music Perception*, *30*, 497–510.

Fairhurst, M. T., Janata, P., & Keller, P. E. (2013). Being and Feeling in Sync with an Adaptive Virtual Partner: Brain Mechanisms Underlying Dynamic Cooperativity. *Cerebral Cortex, 23*, 2592–2600.

Fitch, W. T., & Rosenfeld, A. J. (2007). Perception and production of syncopated rhythms. *Music Perception, 25*, 43–58.

Frühauf, J., Kopiez, R., & Platz, F. (2013). Music on the timing grid: The influence of microtiming on the perceived groove quality of a simple drum pattern performance. *Musicae Scientiae*, *17*, 246–260.

Gingras, B., Marin, M. M., & Fitch, W. T. (2014). Beyond intensity: Spectral features effectively predict music-induced subjective arousal. *Quarterly Journal of Experimental Psychology, 67,* 1428–1446.

Glasberg, B. R., & Moore, B. C. J. (2002). A model of loudness applicable to time-varying sounds. *Journal Audio Engineering Society*, *50*, 331–342.

Goebl, W., & Dixon, S. (2001). Analysis of tempo classes in performances of Mozart sonatas. In *Proceedings of VII International Symposium on Systematic and Comparative Musicology and III International Conference on Cognitive Musicology* (pp. 65–76).

Grewe, O., Nagel, F., Kopiez, R., & Altenmüller, E. (2005). How Does Music Arouse "Chills"? *Annals of the New York Academy of Sciences*, *1060*, 446–449.

Hove, M. J., Keller, P. E., & Krumhansl, C. L. (2007). Sensorimotor synchronization with chords containing tone-onset asynchronies. *Attention, Perception, & Psychophysics, 69,* 699-708.

Hove, M. J., Marie, C., Bruce, I. C., & Trainor, L. J. (2014). Superior time perception for lower musical pitch explains why bass-ranged instruments lay down musical rhythms. *Proceedings of the National Academy of Sciences*, *111*, 10383–10388.

Hurley, B.K., Martens, P. A., & Janata, P. (2014). Spontaneous sensorimotor coupling with multipart music. *Journal of Experimental Psychology: Human Perception and Performance, 40*, 1679–1696.

Huron, D. (2006). *Sweet Anticipation: Music and the Psychology of Expectation.* MIT Press.

Iyer, V. (2002). Embodied mind, situated cognition, and expressive microtiming in African-American music. *Music Perception*, *19*, 387–414.

Janata, P., Tomic, S. T., & Haberman, J. M. (2012). Sensorimotor coupling in music and the psychology of the groove. *Journal of Experimental Psychology. General*, *141*, 54–75.

Karageorghis, C. I., Terry, P. C., Lane, A. M., Bishop, D. T., & Priest, D. (2012). The BASES Expert Statement on use of music in exercise. *Journal of Sports Sciences*, *30*, 953–956.

Keil, C. (1995). The theory of participatory discrepancies: A progress report. *Ethnomusicology*, *39*, 1–19.

Keil, C., & Feld, S. (1994). *Music grooves*. Chicago: University of Chicago Press.

Keller, P. E., & Schubert, E. (2011). Cognitive and affective judgements of syncopated musical themes. *Advances in Cognitive Psychology, 7*, 142-156.

Klapuri, A. P., Eronen, A. J., & Astola, J. T. (2006). Analysis of the meter of acoustic musical signals. *IEEE Transactions on Audio Speech and Language Processing, 14*, 342–355.

Kokal, I., Engel, A., Kirschner, S., & Keysers, C. (2011). Synchronized Drumming Enhances Activity in the Caudate and Facilitates Prosocial Commitment - If the Rhythm Comes Easily. *Plos One, 6*, e27272.

Lartillot, O., Eerola, T., Toiviainen, P., & Fornari, J. (2008). Multi-Feature Modeling of Pulse Clarity: Design, Validation and Optimization. In *ISMIR* (pp. 521–526).

Lartillot, O., & Toiviainen, P. (2007). A Matlab toolbox for musical feature extraction from audio. In *International Conference on Digital Audio Effects* (pp. 237–244).

Lartillot, O., Toiviainen, P., & Eerola, T. (2008). A Matlab toolbox for music information retrieval. In C. Preisach, H. Burkhardt, L. Schmidt-Thieme & R. Decker (Eds.), *Data Analysis, Machine Learning, and Applications* (pp. 261–268). Berlin: Springer.

Large, E. W. (2000). On synchronizing movements to music. *Human Movement Science*, *19*, 527–566.

London, J. (2004). *Hearing in Time: Psychological Aspects of Musical Meter*. New York: Oxford University Press.

MacDougall, H. G., & Moore, S. T. (2005). Marching to the beat of the same drummer: The spontaneous tempo of human locomotion. *Journal of Applied Physiology*, *99*, 1164–1173.

Madison, G. (2006). Experiencing groove induced by music: Consistency and phenomenology. *Music Perception*, *24*, 201–208.

Madison, G., Gouyon, F., Ullén, F., & Hörnström, K. (2011). Modeling the tendency for music to induce movement in humans: first correlations with low-level audio descriptors across music genres. *Journal of Experimental Psychology: Human Perception and Performance*, *37*, 1578–94.

Madison, G., & Sioros, G. (2014). What musicians do to induce the sensation of groove in simple and complex melodies, and how listeners perceive it. *Frontiers in Psychology*, *5*, 894.

Martens, Peter A. (2011). The Ambiguous Tactus: Tempo, Subdivision Benefit, And Three Listener Strategies. *Music Perception, 28*, 433–448.

McKinney, M. F., & Moelants, D. (2006). Ambiguity in tempo perception: What draws listeners to different metrical levels? *Music Perception, 24*, 155–165.

McKinney, M. F., Moelants, D., Davies, M. E. P., & Klapuri, A. (2007). Evaluation of audio beat tracking and music tempo extraction algorithms. *Journal of New Music Research, 36*, 1–16.

Merker, B. (2014). Groove or swing as distributed rhythmic consonance: Introducing the groove matrix. *Frontiers in Human Neuroscience*, *8*, 454.

Pressing, J. (2002). Black Atlantic rhythm: Its computational and transcultural foundations. *Music Perception*, *19*, 285–310.

Prögler, J. A. (1995). Searching for swing: Participatory discrepancies in the jazz rhythm section. *Ethnomusicology, 39*, 21–54.

Sioros, G., Miron, M., Davies, M., Gouyon, F., & Madison, G. (2014). Syncopation creates the sensation of groove in synthesized music examples. *Frontiers in Psychology, 5*,1036.

Scheirer, E. D. (1998). Tempo and beat analysis of acoustic musical signals. *Journal of the Acoustical Society of America, 103*, 588–601.

Stupacher, J., Hove, M. J., Novembre, G., Schütz-Bosbach, S., & Keller, P. E. (2013). Musical groove modulates motor cortex excitability: a TMS investigation. *Brain and Cognition*, *82*, 127–136.

Todd, N. P. M., & Cody, F. W. (2000). Vestibular responses to loud dance music: a physiological basis of the "rock and roll threshold"? *Journal of the Acoustical Society of America, 107*, 496–500.

Tomic, S.T., & Janata, P. (2007). Ensemble: A web-based system for psychology survey and experiment management. *Behavior Research Methods, 39*, 635–650.

Tomic, S.T., & Janata, P. (2008). Beyond the beat: modeling metric structure in music and performance. *Journal of the Acoustical Society of America, 124*, 4024–4041.

Van Dyck, E., Moelants, D., Demey, M., Deweppe, A., Coussement, P., & Leman, M. (2013). The impact of the bass drum on human dance movement. *Music Perception*, *30*, 349–359.

Vickers, E. (2010). The loudness war: Background, speculation, and recommendations. In *Audio Engineering Society Convention 129*.

Vos, P. G., Mates, J., & van Kruysbergen, N. W. (1995). The Perceptual Centre of a Stimulus as the Cue for Synchronization to a Metronome: Evidence from Asynchronies. *The Quarterly Journal of Experimental Psychology*, *48*, 1024–1040.

Witek, M. A., Clarke, E. F., Wallentin, M., Kringelbach, M. L., & Vuust, P. (2014). Syncopation, Body-Movement and Pleasure in Groove Music. *Plos One*, *9*, e94446.

Zilany M. S., Bruce I. C., Nelson P. C., & Carney L. H. (2009). A phenomenological model of the synapse between the inner hair cell and auditory nerve: Long-term adaptation with power-law dynamics. *Journal of the Acoustical Society of America, 126*, 2390–2412.

Appendix

Song name	Artist	Groove rating*	Used in Study 1 N = 80	N = 22
Superstition	Stevie Wonder	108.7	yes	yes
It's A Wrap	FH1 (Funky Hobo #1)	105.9	yes	yes
Flash Light	Parliament	105.1	yes	yes
Lady Marmalade	La Belle	102.5	yes	yes
Up for the Downstroke	The Clinton Administration	102.4	yes	yes
Mama Cita	Funk Squad	101.6	yes	yes
Music	Leela James	101.1	yes	yes
If I Ain't Got You	Alicia Keys	98.7	yes	yes
Sing, Sing, Sing	Benny Goodman and His Orchestra	97.4	yes	yes
In the Mood	Glenn Miller and His Orchestra	96.9	yes	yes
Sco-Mule (DJ Logic Remix)	Bernie Worrell, Chris Wood, Gov't Mule, and John Scofield	93.9	yes	yes
Look-Ka Py Py	The Meters	92.5	yes	yes
Goodies	Ciara feat. Petey Pablo	92.3	yes	yes
Dip It Low	Christina Milan	91.5	yes	yes
Outa-Space	Billy Preston	90.9	yes	yes
Bring the Funk	Ben Harper	89.9	yes	no
Yeah!	Usher	89.7	yes	yes
I Used to Love Someone	Anthony Hamilton	88.7	yes	no
Bring Me BBQ Baby	Joe Krown Organ Combo	88.4	yes	no
Flurries	Soulive	87.8	yes	no
Naughty Girl	Beyoncé	87.0	yes	no
Lose My Breath	Destiny's Child	86.4	yes	no
Sabrosa	Beasty Boys	86.3	yes	no
Bad Tune	Earth, Wind, and Fire	86.2	yes	no
Fast Soul Music	London Elektricity	86.2	yes	no
Come Fly With Me	John Stevens	86.0	yes	no
Word Up	Cameo	85.9	yes	no
Cheek to Cheek	Frank Sinatra	85.7	no	no
What You Waiting For?	Gwen Stefani	85.7	yes	no
Be-Bop	Arturo Sandoval	85.1	yes	no
Soul Ecstasy	Soul Ecstasy	84.8	yes	no
Dreaming of You	Selena	84.3	yes	no
Please	Toni Braxton	83.8	yes	no
Angela	Bob James	82.9	yes	no
The Eternal Triangle	Dizzy Gillespie, Sonny Rollins, and Sonny Stitt	81.2	yes	no
Dot's Groovy	Chet Baker	80.0	yes	no
Lay Down the Law	G. Love and Special Sauce	79.8	yes	no
Baby It's You	JoJo	79.7	yes	no
Jungle Blues	The Dirty Dozen Brass Band	79.1	yes	no
The Look of Love	Diana Krall	79.1	no	no
Funk That	Armani and Ghost	79.0	yes	no
Straight From the Gate	The Headhunters	78.2	yes	no
N.E.S.T.A.	Antibalas Afrobeat Orchestra	77.4	yes	no
Reflector	Medeski, Martin, and Wood	76.6	yes	no
Take Five	The Dave Brubeck Quartett	75.4	yes	no
Two Franks	Count Basie, Frank B. Foster, and Frank Wess	75.4	yes	no
Hell	Squirrel Nut Zippers	73.8	yes	no

Low Gravy	The Chenille Sisters	73.4	no	no
Too Much	Dave Mathews Band	73.1	yes	no
We Are More	Erin McKeown	73.1	yes	no
Kiss From a Rose	Seal	73.0	yes	no
The Stripper	David Rose	72.7	yes	no
Don’t Stop Me Now	Queen	72.5	yes	no
Somebody to Love	Jefferson Airplane	71.3	yes	no
Start Me Up	The Rolling Stones	71.0	yes	no
Recipe for Love	Harry Connick, Jr.	70.8	no	no
The Illustrated Band	Vida Blue	68.1	yes	no
Summertime	Ella Fitzgerald and Louis Armstrong	67.9	no	no
TFS	Herbie Hancock	67.8	yes	no
Soulshine	Gov't Mule	67.3	no	no
What a Wonderful World	Louis Armstrong	66.4	yes	yes
My One and Only Love	John Coltrane and Johnny Hartman	66.3	no	no
In a Sentimental Mood	John Coltrane and Duke Ellington	66.1	no	no
How High the Moon	Ella Fitzgerald	65.2	no	no
Walk on the Wild Side	Jimmy Smith	65.1	yes	no
Party at Your Mama’s House	Widespread Panic	64.1	yes	no
Squeeze	Robert Randolph and the Family Band	63.4	yes	yes
The Child Is Gone	Fiona Apple	62.3	yes	yes
Must Be Dreaming	Frou Frou	60.9	yes	no
Run	Beth Hart	60.8	yes	yes
Freedom of the Road	Martin Sexton	59.7	yes	yes
Lookout 31	Derek Trucks	59.6	yes	no
Can’t Let Go	Lucinda Williams	58.9	no	no
Uphill Both Ways	Reeves Gabrels	58.0	yes	no
Lois Ann	Railroad Earth	57.8	no	no
Please Don’t Dog Me	Lawrence Lebo	57.8	no	no
Down With Love	Blossom Dearie	57.0	yes	yes
The Girl From Ipanema	Astrud Gilberto, Joao Gilberto, and Stan Getz	57.0	no	no
New Jazz Fiddle	Asylum Street Spankers	56.9	no	no
Blue in Green	Miles Davis	56.1	no	no
Stomping Grounds	Bela Fleck and the Flecktones	54.6	yes	no
Roses and Hips	Keren Ann	54.2	yes	no
Tell It to Me	Old Crow Medicine Show	54.1	no	no
Running Wild	Peppino D'Agostino	53.3	no	no
Gold Rush	The Tony Rice Unit	53.1	no	no
What’s New	Clifford Brown and Helen Merrill	52.2	no	no
Some Other Time	Monica Zetterlund and the Bill Evans Trio	51.1	no	no
Mud	Greg Brown	50.5	no	no
Till There Was You	Etta Jones	50.2	no	no
I Remember When	The Disco Biscuits	49.9	yes	no
Orange Sky	Alexi Murdoch	49.8	no	no
Children of December	The Slip	49.5	no	no
Carolinain My Mind	James Taylor	49.0	yes	no
Cheeseburger in Paradise	Jimmy Buffett	48.6	yes	no
Orion’s Belt	The String Cheese Incident	47.9	no	no
Time in a Bottle	Glen Campbell	47.9	no	no
Octoroon	Laura Love	47.6	yes	no
Raise a Ruckus	Jesse Fuller	46.5	no	no
Aural Oasis	Wynton Marsalis	46.1	no	no
Spanish Gold	Michael Houser	45.6	no	no
Sarba Miracinae	Klezmer Conservatory Band	45.3	yes	no

Just to Be Near You	Laurie Macallister	45.0	no	no
The Nashua Rose	The Slip	44.7	no	no
Fire in the Brain	Club d'Elf, Dave Tronzo, Erik Kerr, Mat Maneri, and Mike Rivard	44.3	yes	no
All Things Reconsidered	Phish	44.0	yes	no
Stupid, Stupid Rain	Shawn Persinger	43.9	no	no
Taxman	Nickel Greek	43.9	no	no
Bottle of Hope	Tony Furtado and the American Gypsies	43.4	yes	no
If I Had Known	Greg Brown	43.3	yes	no
Comfortably Numb	Pink Floyd	42.3	yes	no
Ghost	Indigo Girls	42.1	no	no
Strong, Strong Wind	Heart	41.8	yes	no
Bryter Layter	Nick Drake	40.4	yes	no
Yes I Am	Melissa Etheridge	40.2	yes	no
I Get The Blues When It Rains	Kate MacKenzie	40.0	no	no
Better Man	Pearl Jam	39.8	no	no
Master Crowley's/The Jug of Punch	The Bothy Band	39.3	no	no
Space Oddity	David Bowie	38.7	no	no
Ray Dawn Balloon	Trey Anastatio	38.5	no	no
Druid Fluid	Yo-Yo Ma, Mark O'Connor, and Edgar Meyer	38.1	no	no
Flandyke Shore	The Albion Band	36.5	no	no
Citi Na GCumman	William Coulter and Friends	35.2	no	no
Dawn Star	Dean Magraw	34.8	no	no
Fortuna	Kaki King	32.6	no	no
Beauty of the Sea	The Gabe Dixon Band	32.1	no	no
Sweet Thing	Alison Brown	30.9	no	no
Hymn for Jaco	Adrian Legg	29.3	no	no
Thugamar Fin an Samhradh Linn	Barry Phillips	29.3	no	no

* Janata et al. (2012)

Table 1

Summary of drum set instrument coding of all 128 song clips used in Janata et al., (2012)

Number of song clips	Presence of drum set instruments		
	Bass drum	Snare	Hi-hat/cymbals/ percussion
80	yes	yes	yes
20	no	no	no
18	no	no	yes
6	no	yes	yes
2	yes	no	yes
1	yes	no	no
1	no	yes	no

Table 2

Correlations between groove ratings and full-bandwidth audio features.

	MIR Toolbox						Madison et al. (2011)	
	RMS energy	Spectral flux	Attack	Pulse clarity	MIRtbx event density	RMS SD	Beat salience	Variance event density
Groove rating (N = 80)	.37***	.34**	.37***	.18	-.05	.57***	NA	NA
(N = 22)	.21	.23	.57**	.41	-.05	.55**	.49*	.51*

* *p* < .05; ** *p* < .01; *** *p* < .001; NA: not available

Table 3

Mean values (and standard deviation) for some audio features for the two bass frequency and two attack levels.

	Low bass frequency, N = 10	High bass frequency, N = 10	Long attack, N = 10	Short attack, N = 10
Spectral flux [0-50 Hz]	27.83 (7.00)	7.84 (1.16)	19.51 (12.58)	16.16 (10.38)
Spectral flux [50-100 Hz]	41.39 (10.43)	22.48 (4.32)	30.89 (10.52)	32.98 (14.59)
Spectral flux [100-200 Hz]	24.85 (5.63)	27.32 (5.58)	23.85 (5.72)	28.33 (4.74)
Attack (*mir*pulseclarity 'attack')	4.35 (.74)	4.28 (1.06)	3.81 (.62)	4.83 (.85)

Table 4

Correlations between groove ratings and tapping performance measures in Study 3.

	SD of ITIs	SD of tap-beat asynchronies	Velocity (MIDI values 1-126)
Groove rating	-.17	-.16	.25
SD of ITIs		.78***	-.37*
SD of tap-beat asynchronies			-.56***

* $p < .05$; *** $p < .001$

Figure Captions

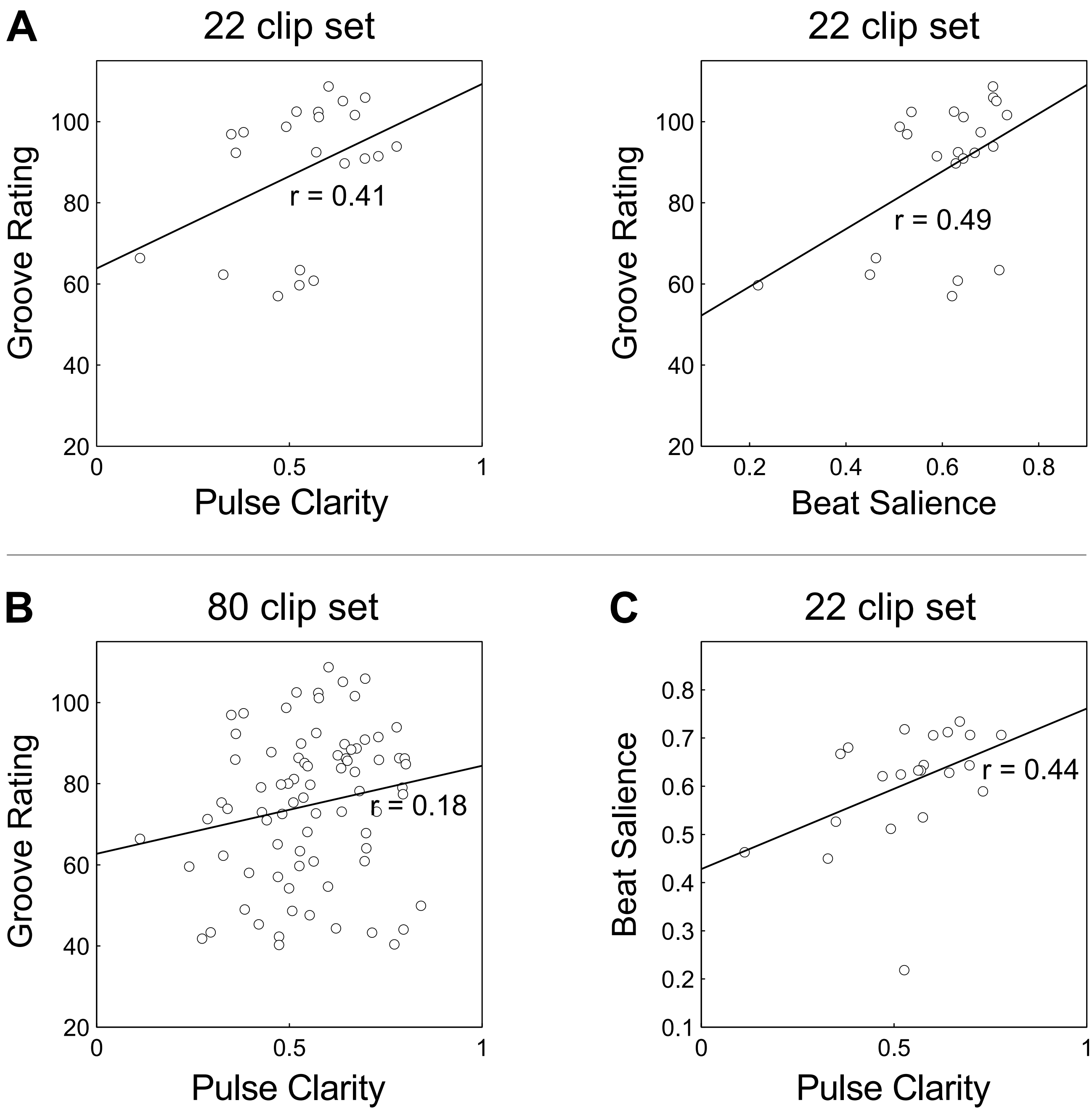
Figure 1: A comparison of pulse clarity and beat salience measures in the perception of groove across two samples of music stimuli drawn from Study 1 of Janata et al. (2012). Pulse clarity was calculated using the MIR Toolbox (Lartillot & Toiviainen, 2007). Beat salience was calculated using the method of Madison et al. (2011). (A) A subset of 22 clips for which both measures could be calculated. (B) The set of 80 clips containing bass and a full drum kit, for which only pulse clarity could be computed. (C) A direct comparison of pulse clarity and beat salience for the subset of 22 clips.

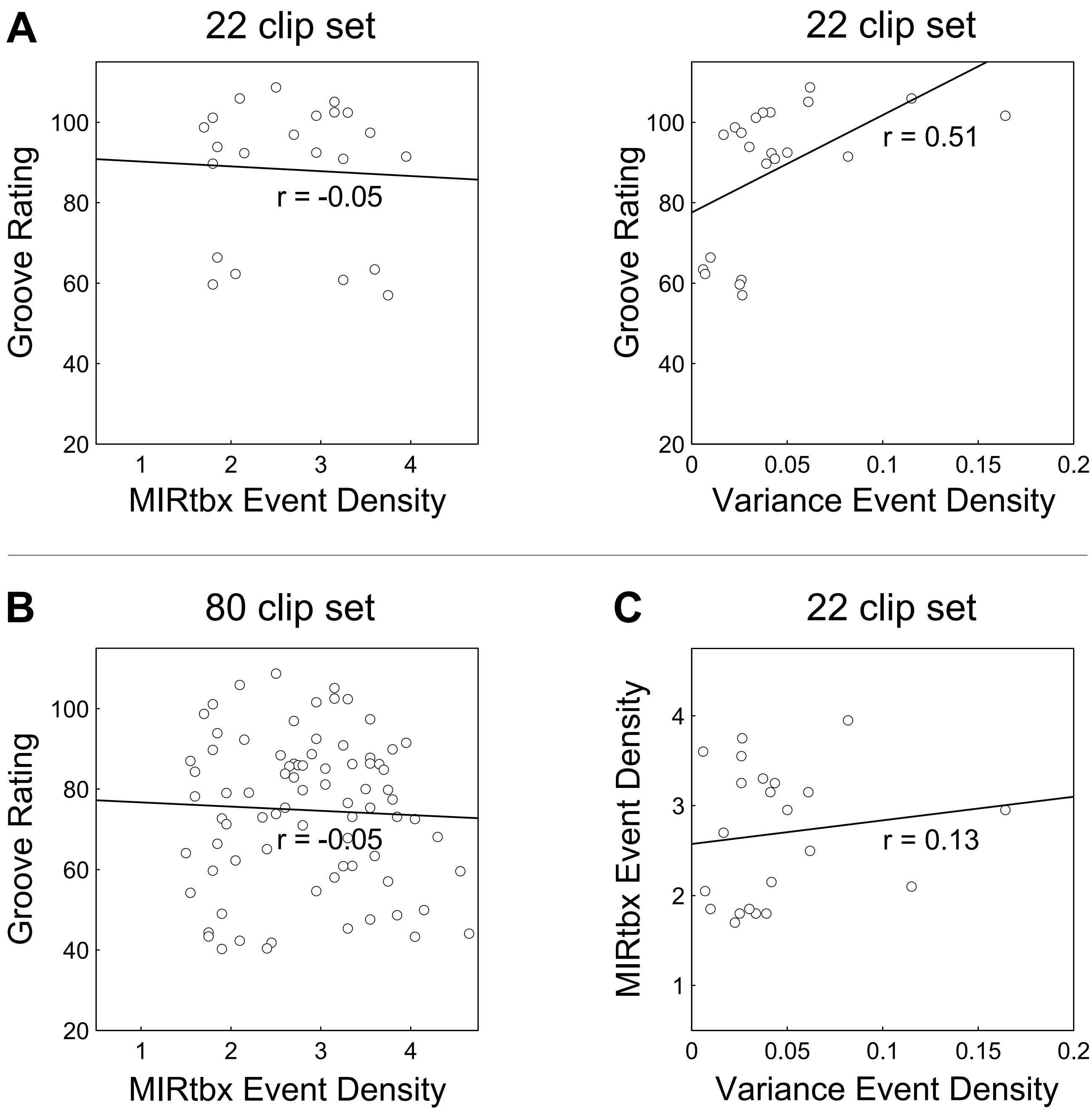
Figure 2: A comparison of event density measures in the perception of groove across two samples of music stimuli drawn from Study 1 of Janata et al. (2012). MIRtbx event density was calculated using the MIR Toolbox (Lartillot & Toiviainen, 2007). Variance event density was calculated using the method of Madison et al. (2011). (A) A subset of 22 clips for which both measures could be calculated. (B) The set of 80 clips containing bass and a full drum kit, for which only MIRtbx event density could be computed. (C) A direct comparison of the two density measures for the subset of 22 clips.

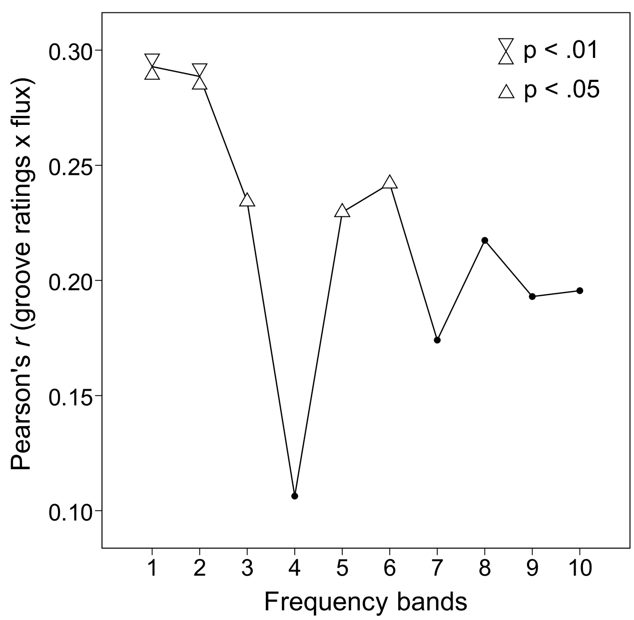
Figure 3: Pearson correlation coefficients for correlations between groove ratings and spectral flux in sub-bands 1 [0 – 50 Hz], 2 [50 – 100 Hz], 3 [100 – 200 Hz], 4 [200 – 400 Hz], 5 [400 – 800 Hz], 6 [800 – 1600 Hz], 7 [1600 – 3200 Hz], 8 [3200 – 6400 Hz], 9 [6400 – 12800 Hz], and 10 [12800 – 22050 Hz]. Significant correlations are notated by triangular markers.

Figure 4: Summary of the results of Study 3 with novel audio clips that manipulated *bass frequency* (low vs. high) and *attack time* (long vs. short). (A) Means of groove ratings. (B) Means of arcsine transformed tapping velocities of MIDI values between 1 and 126. (C)

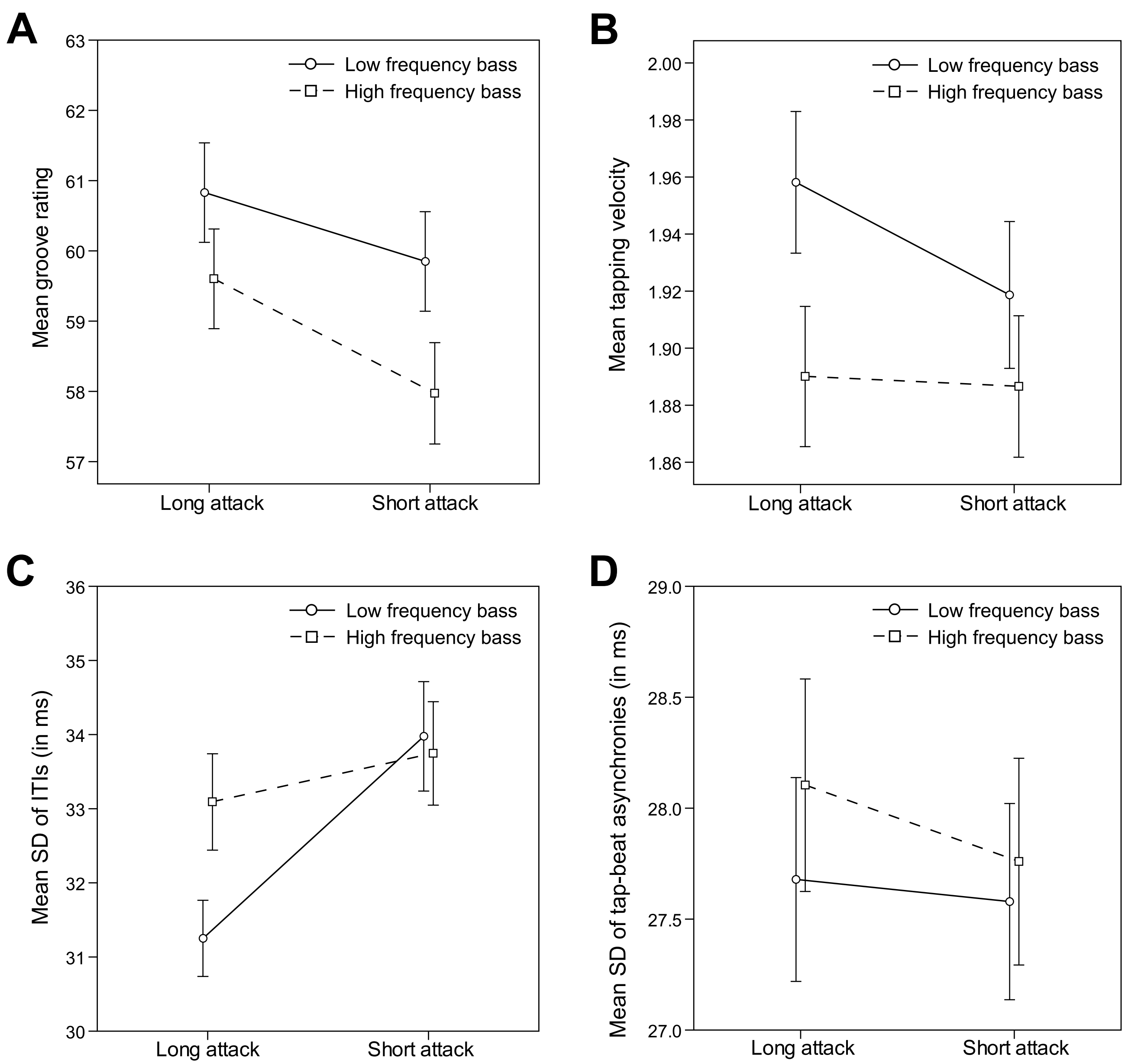
Means of tapping variability indicated by the SD of ITIs in milliseconds. (D) Means of tapping variability indicated by the SD of tap-to-beat asynchronies in milliseconds. All error bars represent +/- .5 *SE*.


A
22 clip set
Groove Rating
Pulse Clarity
r = 0.41
22 clip set
Groove Rating
Beat Salience
r = 0.49
B
80 clip set
Groove Rating
Pulse Clarity
r = 0.18
C
22 clip set
Beat Salience
Pulse Clarity
r = 0.44


A
22 clip set
Groove Rating
MIRtbx Event Density
r = -0.05
22 clip set
Groove Rating
Variance Event Density
r = 0.51
B
80 clip set
Groove Rating
MIRtbx Event Density
r = -0.05
C
22 clip set
MIRtbx Event Density
Variance Event Density
r = 0.13



0.30
0.25
0.20
0.15
0.10
Pearson's r (groove ratings x flux)
1
2
3
4
5
6
7
8
9
10
Frequency bands
p < .01
p < .05


A
Mean groove rating
63
62
61
60
59
58
57
Low frequency bass
High frequency bass
Long attack
Short attack
B
Mean tapping velocity
2.00
1.98
1.96
1.94
1.92
1.90
1.88
1.86
Low frequency bass
High frequency bass
Long attack
Short attack
C
Mean SD of ITIs (in ms)
36
35
34
33
32
31
30
Low frequency bass
High frequency bass
Long attack
Short attack
D
Mean SD of tap-beat asynchronies (in ms)
29.0
28.5
28.0
27.5
27.0
Low frequency bass
High frequency bass
Long attack
Short attack