Syncopation and Groove in Polyphonic Music: Patterns Matter

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Music often evokes a regular beat and a pleasurable sensation of wanting to move to that beat called groove. Recent studies show that a rhythmic pattern's ability to evoke groove increases at moderate levels of syncopation, essentially, when some notes occur earlier than expected. We present two studies that investigate that effect of syncopation in more realistic polyphonic music examples. First, listeners rated their urge to move to music excerpts transcribed from funk and rock songs, and to algorithmically transformed versions of these excerpts: 1) with the original syncopation removed, and 2) with various levels of pseudorandom syncopation introduced. While the original excerpts were rated higher than the de-syncopated, the algorithmic syncopation was not as successful in evoking groove. Consequently, a moderate level of syncopation increases groove, but only for certain syncopation patterns. The second study provides detailed comparisons of the original and transformed rhythmic structures that revealed key differences between them in: 1) the distribution of syncopation across instruments and metrical positions, 2) the counter-meter figures formed by the syncopating notes, and 3) the number of pickup notes. On this basis, we form four concrete hypotheses about the function of syncopation in groove, to be tested in future experiments.

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Music with a regular pulse often urges us to move, for instance by bobbing our head or tapping our foot,[1] a phenomenon termed "groove" in the music psychology literature (Janata et al., 2012; Madison, 2006). Apparently, there is something about the musical structure, the way it is played, and the properties of the sound signal that accounts for this effect (Câmara & Danielsen, 2020), and several candidates have been proposed (for a review, see Madison et al., 2011). A strong candidate seems to be syncopation, as we review below. To further explore its function, this paper investigates the effect of generalized, pseudorandom syncopation on groove.

Syncopation is a pervasive rhythmic phenomenon found in many musical styles and cultures. It is defined as a certain class of violation of a learned schema that describes our temporal expectation (Huron, 2006, p. 297; Randel, 1986). The term meter is used to refer to such temporal schemata in music cognition, which was adopted from music theory where it is understood as a hierarchical structure (London, 2012). Among the core formal aspects of meter is the alternation of strong and weak pulses seen as the alternation of high and low expectation of musical events (Danielsen, 2018; Palmer & Krumhansl, 1990; Parncutt, 1987, 1994). An event in a weak pulse increases our expectation of an event in the following strong pulse. Syncopation breaks the expected weak-strong bond when an event in a weak pulse is not followed by an event in a strong pulse (Huron, 2006, p. 295). Longuet-Higgins and Lee (1984) formalized and quantified the strength of a syncopation by attributing weights to the levels of a metrical hierarchy similar to that of the Generative Theory of Tonal Music of Lerdahl and Jackendoff (1983) or that of consonant rhythmic strata of Yeston (1976). Accordingly, a syncopation occurs when a note in a fast metrical level—weak pulse—is followed by a rest at the next position of a slower level—stronger pulse; its strength is the difference of the metrical weights of the two levels. Despite this quantification, Longuet-Higgins and Lee approached the metrical interpretation of a rhythmic

[1] This phenomenon may have evolutionary significance, as has been elaborated by many scholars (Bryant & Hagen, 2003; Huron, 2003; Merker, 2000; Merker et al., 2009; Ravignani et al., 2014; Ravignani & Madison, 2017).

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pattern as a categorical one: either as syncopated or not. They also claimed that the listener will favor a non-syncopated interpretation of a given pattern, when such an interpretation is possible.[2] In this paper, we follow an equivalent definition of syncopation by Sioros and colleagues (Sioros & Guedes, 2014; Sioros et al., 2018) that describes it as the displacement of a note from its non-syncopating position to an earlier position in a faster metrical level (Tan et al., 2019; Temperley, 1999, 2001, Chapter 9), creating in this way an event in a weak pulse not bound to an event in the following strong pulse.

The above definitions of syncopation approach it as a local phenomenon, either as a sensation that arises at a certain moment in time or a quality attributed to a certain note. In contrast, many scholars and researchers have operationalized syncopation as a quantity that characterizes the entire rhythmic pattern; that is, as a level of complexity that could be compared across patterns (Fitch & Rosenfeld, 2007; Gómez et al., 2005; Keith, 1991; Pressing, 1997; Sioros & Guedes, 2011; Smith & Honing, 2006; Thul & Toussaint, 2008; Witek, Clarke, Wallentin, et al., 2014). They argue that if the effect of a single instance of syncopation is quantifiable, for instance through the metrical weights proposed by Longuet-Higgins and Lee (1984), then an overall degree of syncopation may be calculated as the accumulated effect of single instances of syncopation. However, the general validity of such approaches is questionable. As we review in more detail in the section On Measuring Syncopation, the combined effect of syncopation on higher-level perceptual features such as complexity and groove is not captured by a simple accumulating scalar quantity.

Syncopation has been associated with groove, understood as the pleasurable propensity to move along with the music. Madison and colleagues (2011) attempted to track the temporal properties of the musical signal that correlate with the tendency of listeners to experience groove. Although syncopation was not explicitly tested nor directly identified as a predictor for groove in their exploratory approach, groove was strongly correlated with low level rhythmic descriptors closely related to syncopation, such as beat salience and the presence of faster metrical levels. These findings were corroborated in subsequent studies showing a correlation between groove and various forms of syncopation (Madison & Sioros, 2014; Sioros et al., 2014; Witek, Clarke, Wallentin, et al., 2014). Witek et al. (2014) suggested an inverted U-shape relation between the degree of syncopation and groove, where a moderate amount of syncopation should lead to the highest level of groove, which was partly supported in an experiment using commercially available drum breaks and quantifying the degree of syncopation as a weighted sum of the Longuet-Higgins and Lee (1984) scores. The above studies were focused on the rhythmic properties of the music alone. A different study (Matthews et al., 2019), in which the rhythmic patterns were articulated by chords of various degrees of harmonic complexity, showed that the effect of syncopation on groove is modulated by harmonic context. With regards to physiological evidence, both syncopation and groove have been shown to a have stimulating effect reflected in stronger pupil dilation (Bowling et al., 2019). Furthermore, moderately complex rhythms, which were rated higher in groove compared to higher complexity rhythms, also evoked increased activity in motor and reward networks of the brain (Matthews et al., 2020).

Recently the U-shape relation between syncopation and groove has been explained in the predictive coding (PC) framework (Koelsch et al., 2019; Vuust & Witek, 2014; Vuust et al., 2018). The idea is that the sensory input is being compared to a continuously updated predictive model in the listener's mind, which, in the case of rhythm perception, consists primarily of the inferred metrical structure. When a mismatch occurs, the corresponding error updates the model for future predictions. However, the precision of the prediction attenuates the errors, so that low precision predictions would lead to small precision-weighted errors even when the mismatch between the model and the sensory input is large. Our body movement is then an expression of our efforts to supress the detected errors and emphasize the beat, that is, the model. The explanation (Koelsch et al., 2019; Vuust et al., 2018) for why high syncopation entails low groove is that higher levels of syncopation weaken the neural representation of the meter and therefore lower the precision of the model. In essence, in the high syncopation condition our brain treats the music signal as noise. Conversely, no syncopation leads to no errors and requires no strengthening of the metric model (through body motion). A moderate amount of syncopation thus hits the sweet spot, where moderately complex rhythms evoke and maintain a stable predictive model, while they still generate a small amount of predictive errors.

Madison, Sioros, and colleagues explored the relation between syncopation and groove in a production experiment. They asked musicians to minimize and maximize groove by playing prescribed melodies that were either syncopated or not (Madison & Sioros, 2014). They found that musicians employed, among other

[2] Although Lee (1985) later questioned the model and the strict requirement of avoidance of syncopation.

devices, syncopation to create groove, and deadpan timing and the destruction of the regular pulse for reducing groove. In a second experiment following a generative approach (Sioros et al., 2014), the groove of algorithmically generated variations of simple piano melodies—such as children's songs and lullabies that contained no syncopation in their original form—was rated by listeners. The generated variations that contained syncopation received significantly higher groove ratings than the original versions or non-syncopating variations. The moderate syncopation received the highest ratings, in line with the inverted U relation. The highest degree of syncopation was achieved by interlacing the notes of the melodies with a metronome, so that one of them may be thought as articulating the meter, either the metronome or the melody, while the other syncopates in off-beat positions throughout the music example. This highly syncopated pattern does not weaken the perceived meter and, therefore, this result only partly corroborates the PC mechanism for groove. Furthermore, a direct comparison between the variations of each melody showed that syncopations that occurred in certain "key" moments at phrase boundaries contributed more to the sensation of groove than syncopation that is uniformly distributed throughout each melody. Sioros et al. concluded that the relation between groove and syncopation is complex and depends on other structural factors as well as those who create syncopation. This finding was part of the motivation for the present study.

Here we present two studies that investigate the relation between groove and syncopation in more complex music examples representative of real music, involving several different voices/instruments. The first study is a listening experiment that extends the generative approach of Sioros et al. (2014) to multi-voiced music examples. The second study offers a detailed music theoretical analysis of the rhythmic patterns used in the listening experiment.

The first study aims at investigating the extent to which the amount of syncopation itself affects the sensation of groove in realistic multi-voice music examples. To this end we produced algorithmic variations that differed in the number of syncopation instances and randomized their metrical positions. Using transcriptions of funk and rock songs, we produced short music examples (ME) containing drums, bass, and guitar or keyboards. Starting from the transcriptions of the original excerpts, we algorithmically first de-syncopated them and then introduced different amount of random syncopation using a variant of the syncopation transformations of Sioros and Guedes (2014). All algorithmic variations and the transcriptions of the original music excerpts were then rendered into audio music examples using professionally sampled instruments, so that the only difference between the transformed and the original examples is the duration patterns created by our algorithm. We hypothesized that: 1) the original, syncopated versions would be rated higher than their de-syncopated variations, and 2) the variations with a moderate amount of algorithmically generated syncopation would receive higher ratings than the ones with no or excessive syncopation. In other words, the groove ratings should follow an inverted U shape relative to the number of syncopations independently of the specific combinations of syncopations found in the original performances or the ones randomly generated from the de-syncopated versions.

The second study addresses the limitations of measuring the accumulating effect of syncopation with a scalar quantity and aims instead at providing a detailed comparison of the syncopation in the algorithmic variations and in the original versions. It is focused on identifying key differences on the distribution of syncopation between instruments and metrical positions, as well as in the patterns that the syncopations form. Finally, in the General Discussion, we consider the two studies together and propose potential cognitive mechanisms that may explain the groove ratings of the listening experiment in light of the analysis of the music examples.

Study 1: Listening Experiment

METHOD

Participants

Thirty-five participants (9 female, 26 male, age $M = 32.4$ years, $SD = 6.7$ years) were recruited via email and did not receive any remuneration for their participation.

Stimuli

Ten short excerpts of two or four bars were created for the purpose of this experiment. We aimed at a high ecological validity of the MEs, while at the same time focusing on syncopation by eliminating other expressive factors typical of a musical performance. To this end, we based the MEs on publicly available songs that were transcribed. The MEs were based on six music excerpts taken from commercial popular songs and four from the RWC Music Genre dataset (Goto et al., 2003; "RWC Music Genre Database," n.d.), all in the funk or rock music genre. The original excerpts included several instruments; however, the MEs were created from MIDI versions that were adapted for only three instruments—bass, drums, and guitar or keyboards. Each short excerpt was repeated three or four times in a continuous loop to form longer MEs. They were all presented at 100 BPM regardless of their original tempo to eliminate the effect of tempo on the ratings. The original tempi of the excerpts ranged from 88 BPM the slowest to 125 BPM the fastest. A set of transformations was then applied to the original excerpts resulting in five different versions described in more detail below. Unless otherwise specified, "excerpt" refers to the original music structure of a song, upon which the MEs were based, and "song" refers to the MEs created from the same original music, including the original version and the generated variations.

The MEs were created and generated in Ableton Live, and the transformations were automatically applied by a device developed in Max for Live. MIDI files were generated for all five versions of each excerpt and rendered into 16-bit wave files using high quality instrument voice samples. The first and last bar of each ME were faded in and out respectively. The rhythmic structures of the MEs are shown in the Appendix.

As the original music excerpts were already syncopated, an algorithm was employed to remove the existing syncopation (Sioros & Guedes, 2014) and another to generate new pseudorandom syncopation. The de-syncopation algorithm automatically identifies any syncopated notes and delays them to the following metrical position of a slower metrical level. It reiterates until no syncopated notes are found. The syncopation algorithm was developed for the specific needs of the experiment and is described in detail in the following subsection. The original syncopation could also be generated by the same algorithm since the de-syncopation algorithm is shown to be fully reversible (Sioros & Guedes, 2014). The transformations were applied separately and independently to each instrument. The drums were split into two streams treated as different instruments, namely hi-hats/cymbals and kick/snare drums. Figure 1 exemplifies in notation one transcript and its transformations. This process resulted in a total of five versions of each excerpt:

a) **Original:** Transcribed from original music excerpt with all syncopation intact (limited to three instruments: bass, drums, and guitar or keyboards). The fastest metrical level in the excerpts was the sixteenth note level except in one music excerpt which contained six thirty-second notes that were also syncopated.
b) **Deadpan:** Fully de-syncopated version of the original transcription (0% syncopation)
c) **25%:** ~25% of total possible syncopations randomly generated (see Syncopation Transformations)
d) **50%:** ~50% of total possible syncopations randomly generated (see Syncopation Transformations)
e) **70%:** ~70% of total possible syncopations randomly generated (see Syncopation Transformations)

Syncopation Transformations

The syncopation generation algorithm is an adaptation of that described in (Sioros & Guedes, 2014) that aims at randomizing the distribution of syncopations across the notes of a non-syncopating pattern. It automatically identifies possible syncopations from their metrical position in the deadpan version, taking a standard MIDI file as input. The present version of the algorithm anticipates a desired proportion of these notes to earlier positions of a faster metrical level (e.g., a quarter note in the deadpan version is shifted to the previous eighth note). The formalization of the transformations ensures that the order of notes is always preserved.

The algorithm begins by counting the number of possible syncopation shifts, which is equal to the number of notes that do not belong to the fastest metrical level; that is, all notes that belong in the eighth note level or slower. Then a certain predefined percentage (25%, 50%, or 70%) of these notes is selected at random to be syncopated. The three syncopation transformations of different amounts are all applied upon the deadpan version, randomly and independently of each other. The selection of notes to be syncopated is therefore different for each of the 25%, 50%, and 70% transformations. The selected notes are shifted to the preceding metrical position belonging to the immediately faster level available. For instance, a note at the second quarter note position in the bar is shifted to the previous eighth-note position. However, to preserve the original note order, if another note is already articulated in that position or any in-between positions, a faster metrical level is chosen. For example, in Figure 2a, the eighth-note position is already occupied and the quarter-note is shifted to the in between sixteenth-note position instead. The fastest metrical level allowed is the sixteenth-note level. In cases where the transformation is blocked by a note articulated in the preceding sixteenth-note position, these two notes are shifted together as a group (Figure 2b and Figure 1, the circled guitar rhythmic figure in the beginning of the second bar). Finally, if the sixteenth note cannot be shifted due to an existing note in the immediately preceding position, that sixteen note is deleted to give space for the syncopation to occur (Figure 2c). For instance, in the kick/snare in Figure 1, the first kick was shifted to the last sixteenth note

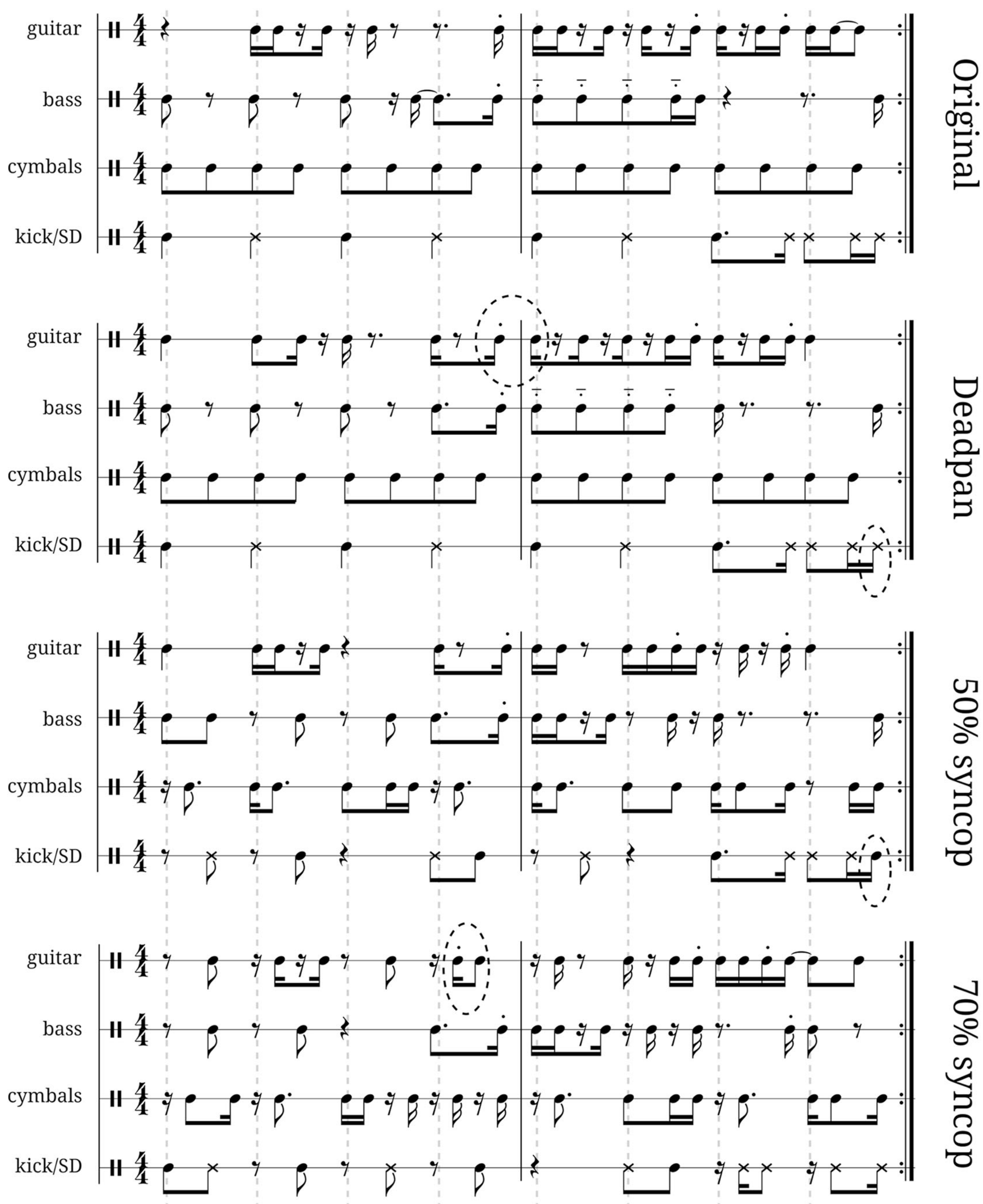

FIGURE 1. Rhythmic part of music excerpt 10 and the transformations applied. The 25% syncopation transformation was omitted for simplicity. Notes in circle indicate two special cases of syncopation shifts, which are explained in the text.

position in the 50% syncopation, where a snare event originally existed. The snare could not be shifted together with the kick because of another snare preceding it and was therefore deleted instead. However, such cases were rare. The difference in the number of notes between the 25%, 50%, and 70% transformation is 4%, 6%, and 4.4% of the original number of notes respectively.

The above algorithm enables us to shift at random any note of the deadpan version from a relatively slow

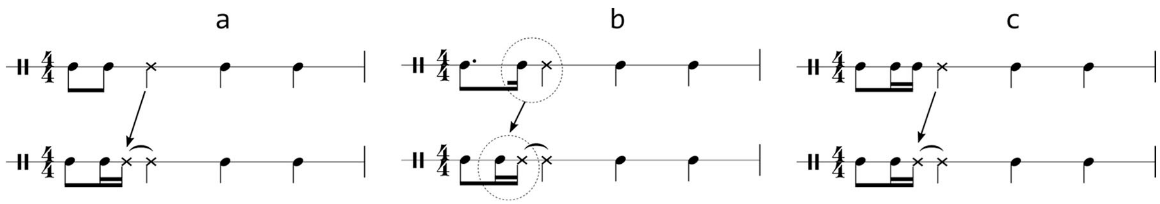

FIGURE 2. Examples of syncopation shifts. In the top row, the non-syncopating patterns are shown. The arrows represent the shifts of notes from slow metrical levels to faster ones. In (a) the sixteenth-note level is available. In (b) and (c) the shift to the fastest metrical level is blocked by another note in the preceding sixteenth position. In (b) the two notes are shifted as a group. In (c) the preceding sixteenth note is deleted for the syncopation shift to take place.

metrical level and generate syncopations that are better distributed throughout the duration of the ME, as well as to provide better control of the number of syncopations generated. If we were to limit the generated syncopations to only notes in strong metrical positions not preceded by a sixteenth note, the positions of the syncopations would be unevenly distributed depending on the rhythmic structure of each phrase. Although the algorithm gives relatively precise control of the amount of syncopation, it allows for shifts that could "mask" an existing syncopation. For example, consider two consecutive notes, the first belonging in an eighth note metrical position and second in the following quarter note position. If the eighth note is syncopated, it would be shifted to the previous sixteen position, leaving the eighth note position free. If the quarter note is also syncopated and shifted to the eighth note position, the previous syncopation would be masked, and the two shifts would result in only one syncopation instead of two. As the amount of random syncopation increases, this is more likely to happen, especially in dense passages with longer sequences of eighth notes.

In the above algorithm, once a position for a syncopation is randomly selected, the syncopation shift to an earlier pulse is not random but fully determined by the preceding notes. In this way, interactions between instruments that may introduce additional factors of complexity are minimized. When the same strong metrical position is syncopated in more than one instrument, the syncopating notes are not necessarily shifted to the same weak metrical position. Fully randomized syncopations are more likely to generate shifts to different positions, but in the original excerpts, such cases are rare. As we show in Study 2 (*Interaction across Instruments*), our algorithm keeps such interactions at similar levels as in the original excerpts, while still distributing the syncopation randomly across each ME.

The MIDI note durations in the transformed variations were kept the same as in the transcriptions of the original songs; that is, the "offset" of notes was shifted together with their respective "onset." However, in certain cases, the note shifts may break the legato to the following or previous note, which may affect qualities of the rhythm beyond syncopation. To avoid this effect, such cases were identified by inspecting the automatically generated MIDI files and the durations of the notes were adjusted manually inline with the original character of each ME.

Rating Scales

While the study was focused on groove, participants were told that the purpose was to study "rhythm perception" to minimize possible response bias. The experiment included three additional rating scales, namely familiarity, preference, and naturalness. Preference is closely related to the experience of groove (Janata et al., 2012) as well as familiarity (Senn et al., 2019) and were therefore expected to correlate with the groove scale. The purpose of the fourth scale was to distract from the focus on the movement-inducing effect of syncopation.

All four scales were framed by the global question "How well do the following words describe your experience of the music?" followed by each of the terms: "Familiar," "Like it," "Natural," and "Movement inducing." The last term was defined in the instructions as "the sensation of wanting to move some part of your body in relation to some aspect of the music," which is the definition of groove adopted in this study. The ratings ranged from 0 (*not at all*) to 10 (*entirely*) in unit increments. Ratings were input through a separate horizontal slider for each scale, initially positioned at 5. The four scales were presented in the same order throughout the experiment.

Design

The dependent variable was the rating of groove, and the independent variables were: 1) the type of transform (5 levels including 1 deadpan, 1 original, and 3 syncopation), 2) the 10 music excerpts themselves. A within-participants design was employed in which each

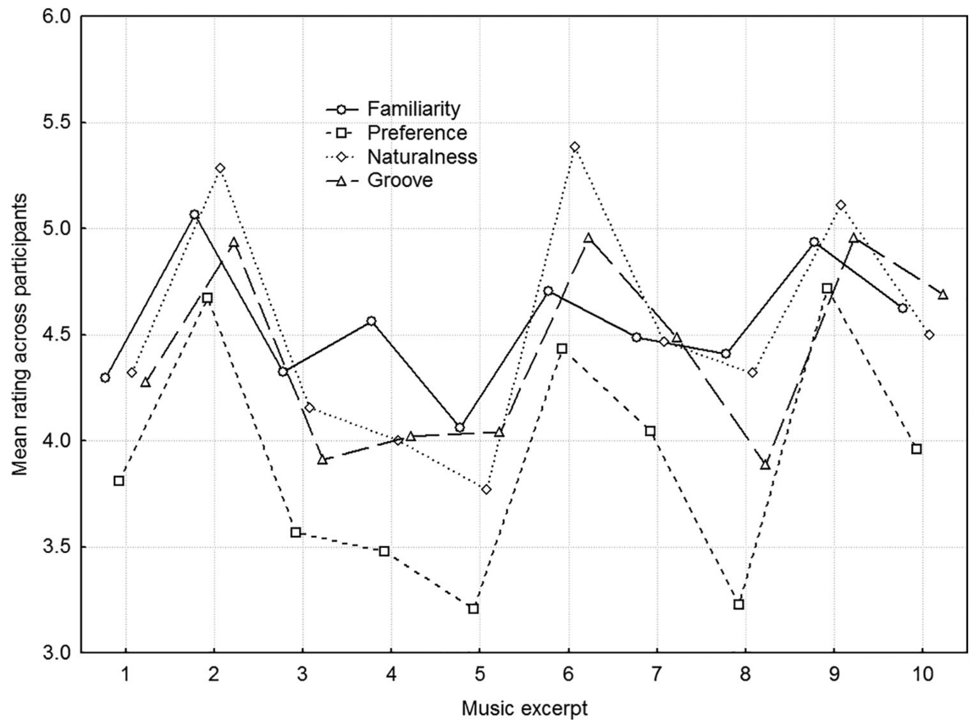

FIGURE 3. Mean values of all four rating scales across music examples, and participants for the 25% transformation music examples.

participant rated all 50 conditions (5 transforms x 10 MEs), which were presented in a different random order to each participant. Randomization and other functionality was built into a custom-made presentation and response recording software developed for a previous study (Davies et al., 2013).

Procedure

The experiment was conducted online using a web-based interface (Davies et al., 2013) that instructed the participants to complete the experiment in one session in a quiet listening environment, using high quality headphones or loudspeakers. After the instructions were presented, participants had the options to either withdraw from further participation or consent to take part in the experiment and submit personal information including their sex and age.

The experiment proper was preceded by three training trials, in which the participants were familiarized with the type of stimuli and the interface and were encouraged to adjust the playback volume to a comfortable level. The training MEs were not included in the experiment proper. The whole procedure took about 40 minutes, after which participants were given the opportunity to offer feedback and comments.

TABLE 1. *Correlations Between Rating Scales for the 25% Transformation MEs*

	Preference	Naturalness	Groove
Familiarity	.70	.49	.72
Preference	-	.76	.82
Naturalness		-	.72

Note: Correlations are significant at $p < .05$.

Results

Both transform and music excerpt (the original melodic and rhythmic structure) had substantial effects on all four rating scales. There was a general tendency for all scales to correlate across MEs, such that MEs rated as more familiar were also rated as more preferred, natural, and having more groove. Figure 3 and Table 1 show this tendency for the MEs of the 25% variations. Similar correlations were observed for the other variations.

Two-way repeated-measures ANOVAs were applied to assess the independent contributions from music excerpt and transforms. They revealed strong main effects for all scales except familiarity, for which there were only moderate main effects of transform and music excerpt. The main effects are summarized in Table 2.

TABLE 2. *Summary of ANOVA Results for all Scales*

Rating scale	Variable	*df*	*F*	*p*
Groove	Intercept	1, 34	177.73	< .000001
	Transform	4, 136	10.97	< .000001
	Music excerpt	9, 306	5.12	< .000001
Familiarity	Intercept	1, 34	120.56	< .000001
	Transform	4, 136	4.49	< .005
	Music excerpt	9, 306	2.96	< .005
Naturalness	Intercept	1, 34	217.40	< .000001
	Transform	4, 136	8.07	< .000001
	Music excerpt	9, 306	4.28	< .00005
Preference	Intercept	1, 34	135.07	< .000001
	Transform	4, 136	7.08	< .00005
	Music excerpt	9, 306	5.84	< .000001

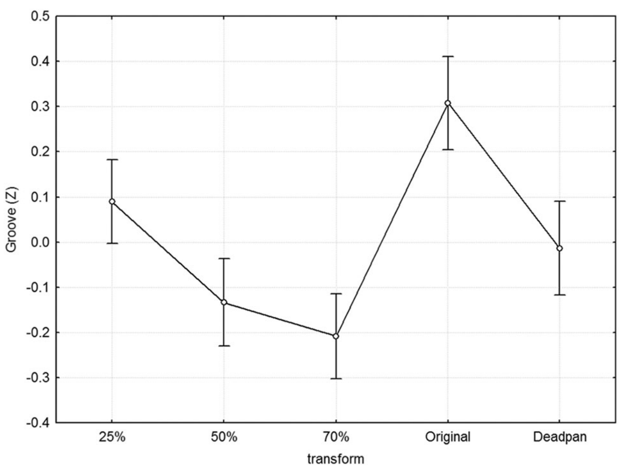

FIGURE 4. Mean values and confidence intervals (95%) of the Z-transformed groove ratings for transformation, across music examples and participants.

The main effect of transform is depicted in Figure 4, showing the mean standardized (z-score) across participants and ME. The z-scores were computed within each participant in order to exclude artifacts from differences in rating scale use, such as using all or part of the scale or only the lower or middle range, for example. The original recordings were rated highest in groove, followed by the 25% transformation, the deadpan (0%), 50, and 70%. Effect sizes and their confidence intervals were computed according to Hedges and Olkin (1985, p. 86), and degrees of freedom (*df*) computed according to the Welch-Satterthwaite equation (Welch, 1947). The contrast of interest for Hypothesis 1 is that between original and deadpan, corresponding to d = 0.315 with confidence interval (CI) 0.166 and 0.464, and *df* = 698.0. This effect is statistically significant, as the CI does not include zero. For Hypothesis 2 we examine the contrasts between original and 25% syncopation (d = 0.224, CI = 0.075 and 0.372, *df* = 689.3), 25% and deadpan (d = 0.109, CI = -0.039 and 0.257, *df* = 689.4), 25% and 50% (d = 0.259, CI = 0.110 and 0.408, *df* = 696.4), and 50% and 70% (d = 0.099, CI = -0.049 and 0.247, *df* = 696.0). For comparison, the largest difference between original and 70% was d = 0.571 (CI = 0.420 and 0.722, *df* = 688.2).

Discussion

The study aimed at investigating the effect of the amount of syncopation to the sensation of groove. In contrast to the experiments in Sioros et al. (2014), where the focus was on simple monophonic melodies or in Witek, Clarke, Wallentin, et al. (2014), where the focus was on drum loops, the experiment presented here focused on more complex polyphonic rhythmic MEs containing multiple instruments. Such highly complex and realistic MEs may introduce expressive factors other than syncopation. The algorithmic generation of MEs with various degrees of syncopation from a single music excerpt that was employed in the design of the stimuli helps to control for such factors and reveal the effect of syncopation.

Our hypothesis was twofold. First, we hypothesized that removing the syncopation of the original songs would decrease the groove ratings. Second, based on the results of Witek et al. (2014), we hypothesized that the algorithmically generated syncopation would result in higher groove ratings than the deadpan versions, at least for moderate amounts of syncopation.

Our first hypothesis was confirmed, as the results of the experiment show a significant decrease of the groove ratings when the syncopation is algorithmically removed from the original song. Our second hypothesis was falsified, as there was no statistically significant increase in groove for any level of random syncopation introduced to a deadpan non-syncopated ME. Rather, groove was rated significantly lower for the 25% syncopation than for the original syncopation, and higher amounts of syncopation (50% or 70%) led to even lower groove ratings. In other words, only the original syncopation of the MEs had a positive and significant effect on groove, relative to the deadpan.

Study 2: Rhythmical Analysis of Music Examples

The results of the first study raise the question of how the original syncopation is different from the automatic transformations. The second study was designed to help answer this question through post hoc analyses of the

MEs. The general experience ratings of the first study provide little insight into what the participants actually perceive and react to. We therefore analyzed some qualitative and quantitative aspects of the algorithmically generated MEs and compared those to the original ones. The analysis avoids the direct quantification of the degree of syncopation. As we argue in the following subsection On Measuring Syncopation, calculations of the degree of syncopation can lead to misleading generalizations, especially in a polyphonic context. Instead, we focus on how syncopation is structured. We examine the distribution of syncopation at different metrical positions in the bar for the different instrument groups, potential interactions between syncopations across the instruments, patterns that the syncopated notes are creating, and how the syncopation transformations affected the pickups existing in the original music excerpts. Our comparisons focus on the original excerpts and the 25% algorithmic variations since they have similar numbers of syncopations.

ON MEASURING SYNCOPATION

Music theoretical and cognitive definitions of syncopation describe it as a local phenomenon resulting from the displacement of an accent to an off-beat position (Huron, 2006; Longuet-Higgins & Lee, 1984). Although these definitions capture the essence of syncopation, they do not offer a systematic method for assessing and comparing effects of syncopated patterns. Hence, many scholars broadened the concept of syncopation to an overall quality of the rhythmic pattern related to complexity. They operationalized it as a scalar quantity that expresses the accumulating effect of local syncopation instances. Keith (1991), in his work on music combinatorics, defined the degree of syncopation as the sum of local syncopations that were identified and weighted through pattern matching. Smith and Honing (2006) measured the overall syncopation as the sum of the syncopation strengths of the Longuet-Higgins and Lee (1984) model. They found a moderate correlation ($r = .75$) of this sum with human judgments of complexity previously reported by Shmulevich and Povel (2000). Fitch and Rosenfeld (2007), independently from Smith and Honig, used the same syncopation metric based on the Longuet-Higgins and Lee (1984) model to index the complexity of rhythmic patterns of a rhythm perception task, and found that it was significantly harder for participants to tap along with highly syncopated rhythms. Besides a lower accuracy of the participants' tapping the metronome beat along with moderately syncopated rhythms, participants had a strong tendency to "reset" their internal metrical framework for higher levels of syncopation and tap to an alternative pulse which corresponded to a less syncopated interpretation of the patterns, in accordance with the Longuet-Higgins and Lee (1984) hypothesis.

Although an overall degree of syncopation derived from the sum of local instances seems intuitively compelling, there is as yet little evidence for its general validity. First, a comparison of the amount of syncopation of fundamentally different patterns—for instance, patterns with different number of notes or of substantially different durations or tempi—is probably not meaningful. Second, a scalar quantity does not necessarily capture the overall syncopation feel or the effect it has on higher level qualities such as complexity or groove. The rhythmic patterns used in the study of Smith and Honing (2006), for example, were irregular by design, as they were constructed by permuting four different durations (Shmulevich & Povel, 2000), and did therefore not include simple but highly syncopated patterns. Fitch and Rosenfeld (2007) also note that some more general aspect of complexity other than syncopation could have contributed to the difficulty the participants met when tapping to the beat and playing the patterns in their study.

Despite having a wide range of levels of the amount of syncopation, the patterns used in the studies above do not cover syncopation patterns that commonly occur in many musical genres, such as cross-rhythmic or phase-shifted metrical patterns (off-beat pulse). In both these types of patterns, syncopation results from counter-rhythmic figures that momentarily articulate a competing pulse to the established meter without challenging it (Câmara & Danielsen, 2020; Danielsen, 2006). Cross-rhythm may be defined as the overlap of two rhythms whose periodicities are non-integer multiples (London, 2012, p. 66) such as 2:3 or 4:3, and is typically associated with West-African drumming traditions (Nketia, 1974, p. 134). Shorter stretches of cross-rhythm are, however, common in many African-diasporic musicals traditions. A classic example from the African-American tradition is the distinction between primary and secondary rag in ragtime. In contrast to primary rag (a singular syncopation), secondary rag was described early on by Knowlton (1926) as "the superimposition of one, two, three upon the basic one, two, three, four." This pattern forms "a tendency towards cross-rhythm" (Danielsen, 2006, p. 62) and is commonly used in many highly groove-inducing musical styles, such as salsa (Boehler, 2016; Stover, 2009), funk, R&B and soul (Danielsen, 2006, 2010, 2012, 2015), and electronic dance music (Butler, 2006; Zeiner-Henriksen, 2010). Also phase-shifted metrical patterns that form shorter counter-rhythmic figures on the off-beat pulse are typical of groove-based music (Butler, 2006; Danielsen, 2006; Zeiner-Henriksen, 2010), and have been referred to as spacing (Nketia, 1974) or off-beat phrasing (Waterman, 1948). Both forms of counter-rhythms—cross-rhythmic tendencies and phase-shifted patterns—contribute to making every layer in the rhythmic fabric audible and promote a texture of complementary rhythms. Syncopation is thus not only a matter of magnitude but can be strongly dependent on the particular *patterns* formed by the counter-meter rhythmic events.

METHOD

We were interested in identifying the key rhythmic characteristics of the syncopated variations of the MEs. To this end, we employed the generative model of Sioros et al. (2018), which codifies a rhythmic pattern in a given meter as a unique combination of three distinct elements occurring at specific metrical locations, namely syncopations, pickups, and density.

Syncopations follow the definition of Huron (Huron, 2006, p. 295; London, 2012, p. 107): a note occurring in a weak metrical position that is not properly bound to a note in the following stronger metrical position. Similarly, pickups and "density" notes are defined as notes in weak metrical positions that are properly bound to following notes in stronger metrical positions. While density notes are preceded by notes on stronger metrical positions creating an isochronous pulse at the corresponding metrical level, pickups are found at the beginning of rhythmic groups initiating a rhythmic figure together with the following note on a stronger metrical position. Pick up notes function as cues for the following on-the-beat note, increasing our expectations for that note and emphasizing in this way the beat. As the transformations did not substantially alter the number of notes or their distribution, our analysis focuses on the syncopation and pickups identified by the model. According to Huron (2006, p. 201), syncopation is experienced at the silent strong beat and is retrospectively attributed to the preceding sounding event. In the generative model of Sioros et al. (2018) that is used in this study, the syncopations are assigned to the silent strong beat in which a syncopation is experienced. Similarly, pickups are assigned to the strong beat of their weak-strong pair.

The half bar was chosen to be the slowest metrical level in the 4/4 meter. The characterization algorithm was implemented in max/MSP and further analysis was performed in Matlab.

RESULTS AND DISCUSSION

Distribution of Syncopation

To examine the distribution of syncopation between metrical positions and across instruments, we summed the number of syncopation instances across all MEs in the original version and the three algorithmically generated variations. We present the results in Figure 5 and Figure 6. In Figure 5, the calculation was performed for each metrical position independently, while in Figure 6 we additionally distinguished between the instruments. The drums were split in two separate streams, one for the kick/snare combination and one for the cymbals, that were treated as independent instruments.

As expected, the overall amount of syncopations in the algorithmic variations increases almost linearly with the percentage of notes shifted. Additionally, the analysis shows that the original versions contain a similar number of syncopations to the 25% variations. The slight differences in the distribution across metrical positions between the two versions, observed mainly on beats 3 and 4, are driven primarily by three songs, and therefore, it is unlikely that they can account for the differences in the ratings.

In contrast to the distribution between metrical positions shown in Figure 5, the distribution across instruments shown in Figure 6 reveal stark differences between the original version and the algorithmic variations. While the generated syncopation is rather evenly distributed between instruments, the original versions have close to no syncopation in the hi-hat cymbals, except for the one instance, and increasingly more syncopation in the kick/snare drum, bass and guitar/keyboard instruments. Noticeable are also the differences in the distribution between metrical positions in the drums, where metrical positions 2 and 4 (the backbeat) are syncopated only once in the ten original MEs. In addition to the comparison shown in Figure 6, we report the total syncopations in the four instruments in the different variations in Table 3.

We must note that the distribution of syncopation in the generated transformations is restricted by the distribution of events in the deadpan versions, which in turn depends on the original versions. After all, for an event to syncopate, it must first exist. The weak eighth-note positions are less populated than the beat positions, resulting in the alternating high-low syncopation patterns of Figure 5, characteristic especially of the generated variations. As can be seen in Figure 6 (bottom panels) this alternating pattern is due mainly to the distribution of notes in the bass and guitar parts. In contrast, the hi-hat cymbal contains a rather constant density of events in the original versions which results

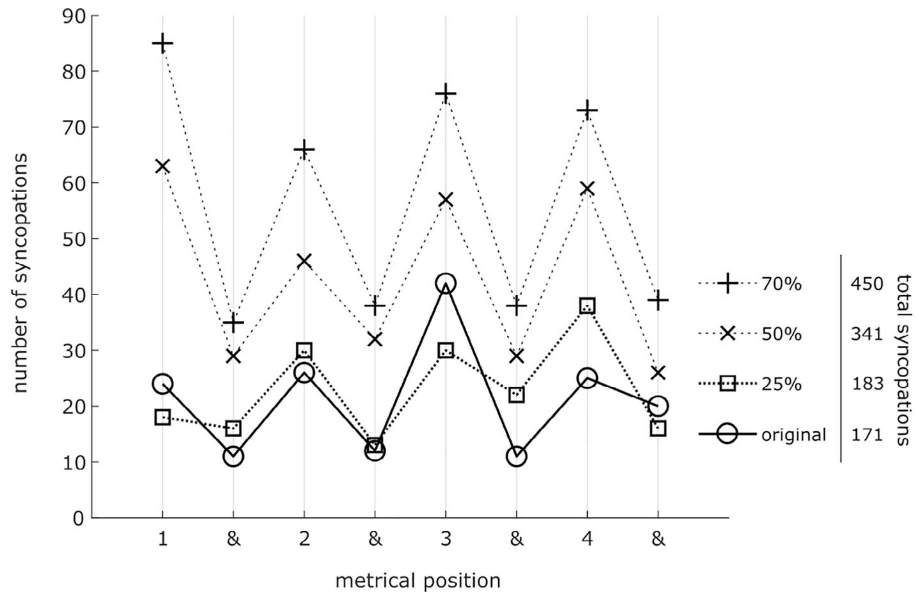

FIGURE 5. Total number of syncopation instances found across all music examples at different metrical positions for the original and algorithmic variations. On the right panel the total number of syncopations across all music examples in each variation is shown.

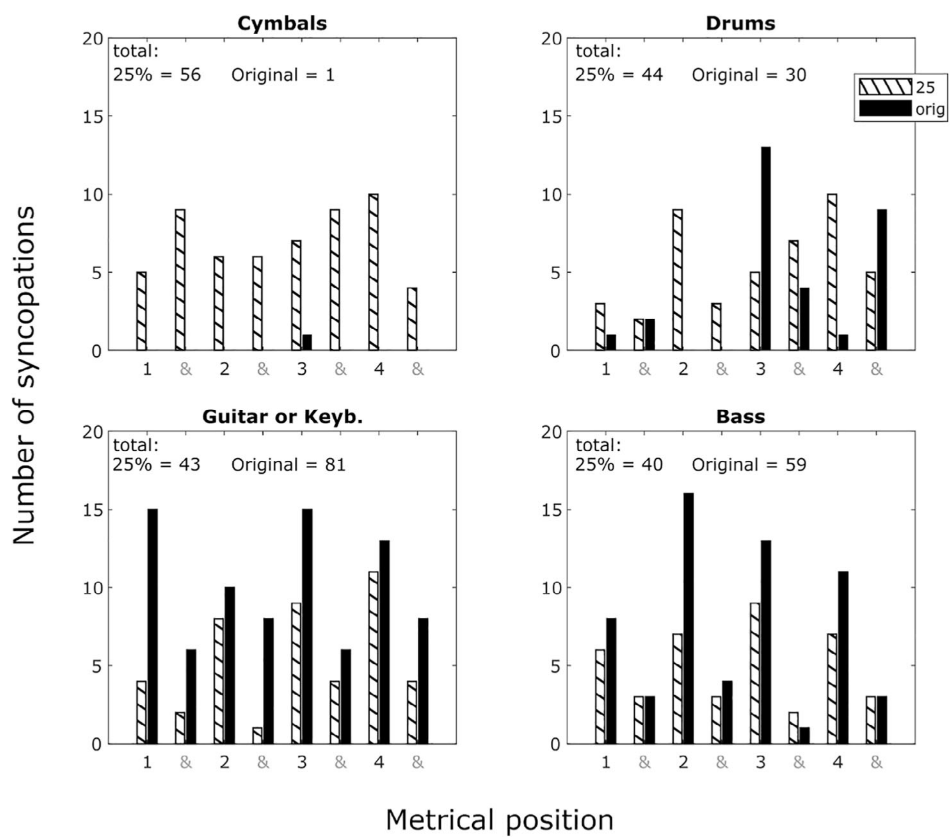

FIGURE 6. Total number of syncopation instances across all music examples at different metrical positions for each instrument separately. In each panel the total number of syncopations is shown for the two versions.

TABLE 3. *Total Number of Syncopations Split by Instrument*

Transformation	Cymbals	Drums (snare/kick)	Guitar or Keyb.	Bass
25%	56	44	43	40
50%	104	84	78	75
70%	132	109	109	100
Original	1	30	81	59

in the generation of more evenly distributed random syncopation (Figure 6 top left panel).

In summary, the above analysis shows that the amount of the original syncopation and its distribution across metrical positions is similar to that of the 25% algorithmic variation. However, these syncopations are distributed differently in the original versions and the algorithmic variations. While the algorithmic syncopation is distributed evenly between the instruments, in the original versions the bass and guitar instrumental layers carry most of the syncopation, while syncopation in the drums is significantly more rare and the hi-hat cymbals are never syncopated.

Interaction Across Instruments

The non-uniform distribution of syncopation between the instruments in the original excerpts presented in the previous subsection brings attention to the potential weakening of the metrical feel because of the "vertical" interaction of random syncopations, that is, because of interactions between instruments. Such interactions could take three forms:

1. Syncopations that occur simultaneously in more than one instrument.
2. Syncopations that occur simultaneously in more than one instrument and introduce different metrical levels, for instance, when in one instrument a note at the sixteenth-note level and in another instrument a note at the eighth-note level syncopate the same beat position.
3. Syncopations of strong beats that are not articulated by any other instrument.

Each of the above cases has the potential to weaken the metrical feel and therefore could affect the experience of groove. We counted the number of syncopations belonging to these three different classes above. The results are shown in Table 4. The original versions and the 25% variation show almost no differences. In fact, the number of simultaneous syncopations is slightly greater in the original versions. The last column of the table reflects the fact that the hi-hat cymbals are never syncopated in the original versions and therefore all

TABLE 4. *Total Number of Syncopations in the Music Examples with Three Different Relations to the Other Instruments*

Variation	Simultaneous syncopations	Simultaneous syncopations Different metrical levels	Syncopations with no articulation of beat
25%	38	19	2
50%	104	47	3
70%	148	69	16
original	42	21	0

FIGURE 7. Example of a cross-rhythmic pattern. Five notes form an isochronous pulse (*) of a dotted eighth note pulse duration, three of which syncopate. The quarter note pulse is marked with vertical lines. The length of the pattern is three quarter note beats.

beat positions are articulated. However, although the 25% variations have considerable syncopation in the hi-hat cymbals, there were only two instances in all songs where syncopations coincided with a silent beat.

In summary, the interaction between syncopation across instruments shows no notable differences between the original versions and the 25% variations.

Cross-rhythmic and Phase-shifted Syncopation Patterns

In addition to the "vertical" interaction between simultaneous syncopations, we examined the "horizontal" interactions of syncopations; that is, the rhythmic patterns that syncopating notes create. In particular, we examined the existence of cross-rhythmic and phase-shifted patterns. Cross-rhythmic patterns form isochronous pulses of non-integer relations to the beat; for instance, a series of dotted eighth note durations in a 4/4 meter (Figure 7). Phase-shifted patterns form isochronous and syncopating pulses of integer relations to the beat; for instance, a series of off-beat quarter-note or eighth-note durations that are not aligned to the established 4/4 metrical grid. Both the above patterns can be summarized under a single operational definition: patterns articulating an isochronous pulse in which at least one of the notes is syncopating. This definition captures that such patterns, given sufficient duration, suggest an alternative pulse to the one of the established meter. A notable exception to the above definition is an isochronous sequence of eighth note durations that ends with

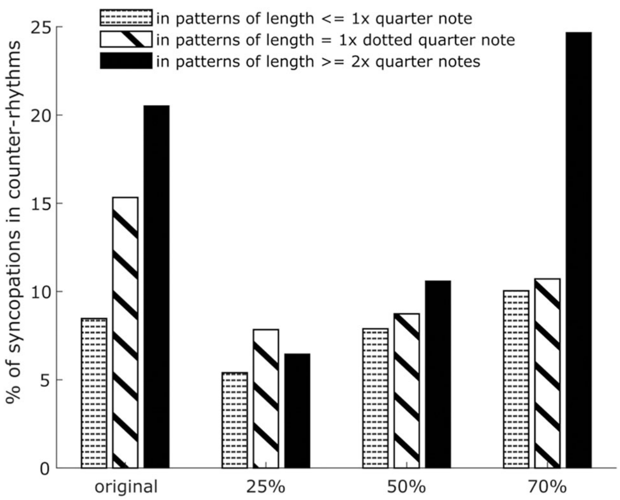

FIGURE 8. Average of the ratio of number of syncopations belonging in a counter-rhythmic pattern to the number of total syncopations in the respective music example, across all music examples, split according to the length of the counter-rhythm.

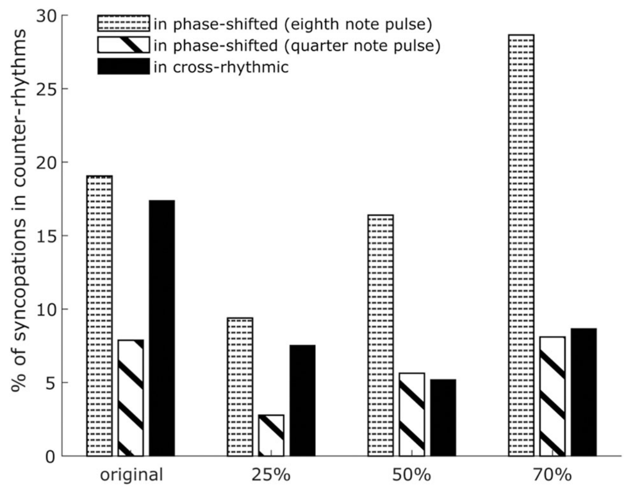

FIGURE 9. Average of the ratio of number of syncopations belonging in a cross-rhythmic or phase-shifted pattern to the number of total syncopations in the respective music example, across all music examples. The pulse of the phase-shifted patterns had a duration of either an eighth note or a quarter note. Cross-rhythmic patterns are not split according to the duration of the pulse. We report that the pulse of the cross-rhythmic patterns had most often a duration of a dotted eight note, less often of a dotted quarter note, and rarely, only in the 50% and 70% variations, of 5x sixteenth notes.

a single syncopated note. Such patterns are excluded from this analysis.

We first identified patterns that belong to the above operational definition for each variation and instrument of each song and counted the syncopating notes in each of them. We then calculated the ratio of syncopating notes belonging in such patterns to the total number of syncopating notes for each ME. Finally, we averaged the ratios across all songs for each variation. In Figure 8, we present the results split into three groups based on the length of the counter-rhythmic pattern (phase-shifted and cross-rhythmic patterns are collapsed). The original syncopations belong to counter-rhythmic patterns more than twice as often compared to the 25% variations. Moreover, they form twice as often patterns that have a length of dotted-quarter-note and three times more often patterns of half a bar length or longer.

In Figure 9, we present the results for phase-shifted and cross-rhythmic patterns separately (pattern durations are collapsed). The percentage of syncopations in phase-shifted patterns gradually increases for the 25%, 50%, and 70% variations respectively. This reflects the fact that the larger the number of syncopating notes in a certain instrument the more the likelihood that they will form an isochronous pulse. For instance, if every note articulated on the beat is shifted to the previous eighth note metrical position a phase-shifted pattern will be formed. The likelihood of such "serial" syncopations thus becomes greater as the amount of syncopation increases.

The original syncopation in the guitar and bass has similar levels to that of the 50% variation (see Table 3). It is therefore more likely to form phase shifted patterns than the syncopation in the 25% variation. However, the syncopation ratio in phase-shifted patterns in the original versions is slightly greater than in the 50% variations. Especially for the slower, quarter-note, phase-shifted pulses it corresponds to that of the 70% variation. Thus, only part of the original slow phase-shifted patterns is the result of chance.

Although phase-shifted patterns could be formed by chance, cross-rhythmic patterns undoubtedly are not, as can be seen from the corresponding low ratios of the algorithmic variations in Figure 9 that do not depend on the amount of syncopation. Cross-rhythmic patterns are formed by a specific combination of syncopating and non-syncopating notes that is less likely to occur by chance. Most noticeably, syncopation in the original music excerpts forms twice as often cross-rhythmic patterns compared to any of the algorithmic variations. This is also reflected in Figure 8: the syncopation ratio that forms cross-rhythmic and phase-shifted patterns of any duration in the original versions (44.3%) is considerably higher to that in the 25% (19.7%) or the 50% variation (27.2%) and only comparable to the 70% variation (45.5%).

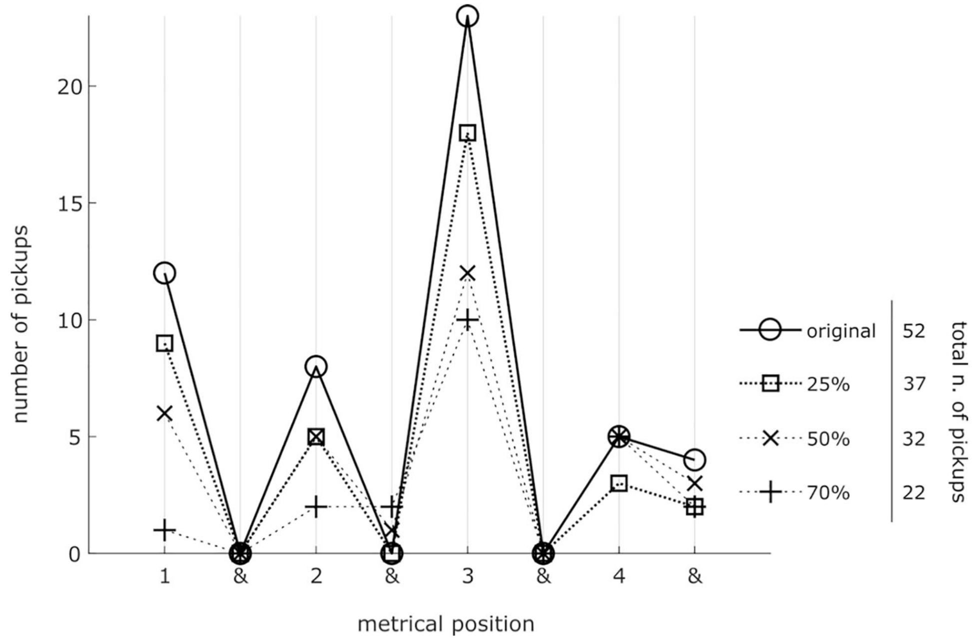

FIGURE 10. Total number of pickups across all music examples at different metrical positions for the original and algorithmic variations.

In summary, more and longer counter-rhythmic patterns are found in the original versions than in the algorithmically generated variations.

Distribution of Pickups

As a result of the syncopation algorithm, the number of pickups in the algorithmically syncopated variations was uniformly reduced. After all, by their definitions, syncopation and pickups depend on the same bonds between notes on weak metrical positions and the following stronger ones, and therefore in many cases they are mutually exclusive. To ensure that our transformation algorithm would introduce syncopation in as random as possible metrical positions, it was not restricted by the pickups in the original versions which were "shifted" together with the syncopating notes as described earlier. Although the rhythmic figures were maintained after the shift, they might not anymore constitute pickups because of their relation to the beat. Figure 10 presents the distribution of pickups across metrical positions in a similar graph to the one presented for syncopation earlier.

In summary, the algorithmic generation of syncopation results in a proportional decrease of the number of pickups. In particular, the average ratio of the number of pickups between the original and the respective 25% variation across all songs is 0.72.

DISCUSSION

The most obvious difference between the algorithmic syncopation applied in this experiment and its original music excerpts, or the drum loops of Witek et al. (2014), and the algorithms of the experiments of Sioros et al. (2014), is the stochastic nature of the former. Syncopation was introduced indiscriminately in each voice and in any position without considering the patterns formed by the syncopating notes, nor the rhythmic or other structure of each excerpt. Having in mind that the de-syncopation algorithm is also an automatic transformation that is completely reversible, and therefore the original syncopation could also be automatically generated, the following question arises: are there certain patterns of syncopation that create groove, such as the syncopation patterns of the original music excerpts of this experiment, while others do not? Can one determine the characteristics of successful syncopations in a systematic way?

Our analysis of the differences between the original music excerpts and the algorithmic variations point to some possible answers. Three main differences were identified between the algorithmic variations and the original syncopations: 1) the distribution of syncopation between the instruments, which in the generated variations was even, while in the original consists in different number of syncopations in each instrument, with the hi-hat cymbals having no syncopation, the kick-snare patterns having no displacements of the snare on 2 and 4, and finally the bass and guitar with the highest number of syncopations, 2) the counter-rhythmic (cross-rhythmic or phase-shifted) patterns that the syncopation creates in the original excerpts and that are reduced in number and duration in the algorithmic variations, and 3) the reduced number of pickups in the algorithmic variations.

These findings suggest specific improvements that can be integrated into the generative algorithm presented earlier, as well as more generally in rhythm generation algorithms to produce rhythmic variations that better suit the funk and rock styles, as in the original excerpts. The implications of these findings for meter perception and the sensation of groove are discussed in detail in the following section.

GENERAL DISCUSSION

In what follows, we consider the implications of the findings of the rhythmic analysis of Study 2 about the differences between the algorithmic and original syncopation for the perception of pulse and the sensation of groove, which is reflected in the ratings of the listening experiment of Study 1.

In the original music excerpts of the experiment, the syncopation was not uniformly distributed between the instruments: certain instruments were heavily syncopated while others were not syncopated at all. In a previous study, Sioros et al. (2012) observed a similar distribution of syncopation among the instruments in songs taken from the RWC Music genre dataset (Goto et al., 2003). A tapping study (Witek, Clarke, Kringelbach, et al., 2014) showed that when a syncopated rhythmic stream is combined with one or two non-syncopated streams the perceived stability of the rhythm is increased. These observations are related to a more general assumption that a stable rhythmic layer is needed to establish a metrical framework against which the syncopation is felt. The randomness introduced by our algorithm in the vertical dimension (across instruments) might have weakened the metrical feel and introduced ambiguity in the perception of the basic pulse. This ambiguity increases with the number of random syncopation shifts introduced, which is in agreement with the results showing that the 25% variations did not negatively affect the sensation of groove but rather had a small positive effect compared to the dead-pan version.

As seen in Table 4, the beat succeeding the syncopation was articulated by one of the instruments for almost all syncopations of the 25% variations and no other interactions between simultaneous syncopations in different instruments were fundamentally different from the original excerpts. Therefore, the *combination* of all instruments provides in fact a clearly articulated beat. However, each instrumental layer of the 25% variations provides only a partially articulated beat. If random distribution of syncopation between instruments leads to a weakened metric framework because all layers become unstable, this implies that each rhythmic stream is at some level processed in the mind independently and that cues for pulse and meter are extracted for each stream before combined into a single coherent framework.

Furthermore, familiarity with the rhythmic patterns as well as style bias have been shown to have a positive effect on groove ratings (Senn et al., 2018, 2019). The stochastic manipulation altered the familiar patterns characteristic of the music style of the original excerpts, such as the steady pulse provided by the non-syncopating hi-hat cymbals or the back-beat "metrical anchor" of the snare drum. Such clear instrument roles, which may, among other, assist the listeners in inferring a more steady meter, are absent in the algorithmically generated variations, resulting in the sense of pulse and meter as well as groove being weakened.

Our second finding—that the original syncopation forms more counter-rhythmic patterns and that these patterns have often longer durations than in the algorithmically generated variations—is open to a similar interpretation. Counter-rhythmic patterns form an alternative isochronous pulse, which does not coincide with the basic pulse of the established meter. One can argue that such patterns suggest the possibility of an alternative beat that is processed in the mind in parallel to the primary meter; the longer the duration of the pattern, the more probable is an alternative metrical interpretation of the rhythm.

The above findings and hypotheses agree with the recent predictive coding interpretation of incongruent rhythms (Koelsch et al., 2019; Vuust et al., 2018). The predictive coding explanation essentially formalizes Huron's definition of syncopation as a certain class of violation of metrical expectations that challenge but do not annihilate the established meter (2006, p. 303). According to the model, syncopation is felt stronger when the prediction error arising from a syncopating note is larger. The prediction error is weighted by the certainty, that is, the precision, of the prediction, so that a weak pulse sensation leads to a weak prediction which in turn leads to a smaller error and a weak syncopation feel. In a polyphonic context some rhythmic streams will create strong predictions, while other rhythmic streams challenge them and produce predictive errors. In all automatically generated MEs of this experiment, the streams in combination articulate fully the beat and one would expect that, when heard in combination, a strong feel of pulse should emerge. Our results suggest, however, that this interaction between pulse-establishing and pulse-challenging events is significantly weakened when the separate rhythmic streams do not have distinct roles. When syncopation is evenly distributed across streams, each rhythmic stream only partly articulates a regular pulse, which is frequently interrupted. This might not be as effective in creating the steady sense of pulse needed for syncopations to have a groove-inducing effect.

The widespread use of cross-rhythmic and phase-shifted patterns in the original excerpts further supports this as isochronous patterns that do not align with the established beat might create relatively strong and independent but complementary pulse layers. Such a sense of an independent isochronous pulse entails the independent processing of the corresponding rhythmic stream. One reasonable hypothesis, then, is that streams related to the main and alternative pulses, respectively, are first processed separately and that an overall predictive model is inferred after this initial processing. Several scholars of Western music theory have argued against such a possibility; that is, of parallel processing of different meters or polymeters in the mind (see London, 2012, Chapter 6 discussion on metric dissonance). Scholars of West-African instrumental music, have, on the other hand, indirectly opened up for this option. Jones (1954), for example, in his classic ethnomusicological research into cross-rhythmic musical textures in West-African drumming traditions, states that "the cardinal principle of African music is the clash and conflict of rhythms" (p. 27). Pantaleoni (1972) agrees with Jones in complementary patterns being metrically constitutive of these musical traditions but claims that the basic bell pattern is primary in the interaction with the cross pattern. Agawu (1986) opens up for both metric dissonance being a fundamental level of structure and a metric situation characterized via concepts of foreground, middle ground, and background. As to experimental research, the study by Poudrier and Repp (2013) concludes that musicians can track the beats of two simultaneous rhythms in a cross-rhythmic relationship, albeit not perfectly. Stupacher et al. (2017) found that neural oscillations entrain simultaneously to both parts of 4:3 polyrhythms, for both musicians and nonmusicians. The authors conclude that in the case of the simple polyrhythms of that study, the neural oscillations corresponding to the two parts are eventually integrated into a common rhythmic framework, although more complex polyrhythms could employ more complex mechanisms or independent timekeepers. All these accounts suggest that a combination of two different rhythmic streams may underlie instances of extensive syncopation in music. In the present context, however, the overarching question emerging from these studies that remains unanswered is whether we tend to experience a hierarchical relationship between these two rhythmic streams/predictive models or not.

Our third finding concerns the relation between pickups and groove, which has been largely overlooked in the music cognition literature. To our knowledge there is no report of a systematic study of it. In the past experiment of Sioros et al. (2014), the combination of pickups in the beginning of monophonic melodic phrases and a syncopating note at the end resulted in increased groove ratings. It was proposed that the pickups create a strong metrical framework that enhances the effect of syncopation at the end of each phrase. Our findings point to pick-ups supporting the pulse and hence syncopation also in the polyphonic structures examined here. One explanation is that pickup notes function as cues for the following on-the-beat note, increasing our expectations for that note and emphasizing the corresponding metrical position. However, one cannot exclude an effect of pickups on groove that is independent from syncopation. As pickups introduce faster metrical levels, both the above explanations would be consistent with previous findings that faster metrical levels are associated with groove (Madison & Sioros, 2014; Madison et al., 2011). The current knowledge does not point to any one explanation being more likely.

In conclusion, we found that the original syncopation does create the sense of groove, in contrast to the randomly generated syncopation for the same music excerpts. The original degree of syncopation is quite high (close to 50% of the onsets in relatively strong metrical positions for bass and guitar riffs) and it often forms short isochronous patterns that suggest an alternative pulse. Nevertheless, the meter is not challenged. A timekeeper rhythmic layer articulated by the hi-hat cymbals and style-specific anchors like the unsyncopated second and fourth quarter note "back-beat" positions balance the overall syncopation and create a strong feel of pulse and meter. The pulse is further enhanced by pickups. In contrast, the stochastic nature of our algorithm creates a uniformly distributed syncopation both in time and across instruments, which lacks the necessary synergies present in the original music for an increased sensation of groove to emerge.

The above analysis of the MEs does not provide definite answers but points to four concrete hypotheses that can be tested in further experiments. First, the sensation of groove in a polyphonic context is increased when certain rhythmic streams can evoke a strong sensation of pulse and meter that is challenged by syncopation in other streams. Examples of such rhythmic streams are a close-to-isochronous timekeeper, or culturally familiar and learned patterns, such as the backbeat pattern on the snare. In contrast, the absence of such distinct roles weakens the sensation of groove. Second, syncopation that forms patterns that suggest an alternative beat, such as cross-rhythmic or phase-shifted patterns, is more effective in creating groove than other repetitive forms of syncopation. Third, syncopation is more effective in creating groove when combined with pickups. This hypothesis is twofold: 1) pickups alone increase the sensation of groove, and 2) pickups strengthen the metrical feel which in turn enhances the syncopation feel and the sensation of groove. Finally, a fourth hypothesis comes about from the combination of the first two. The groovy feel of patterns such as the original music excerpts used in this study might be the result of interacting metric models that can be processed in parallel. While congruent meters lead to one dominant meter, competing meters can lead to rhythmic phenomena such as the sensation of groove.

Conclusion

The purpose of the two studies presented in this paper was to examine the effect of syncopation on the perception of groove independently of other expressive features of music performances and to investigate the role of the amount of syncopation in this effect.

The first study confirmed that syncopation creates groove in realistic and complex polyphonic music in agreement with previous research on simpler music examples (Sioros et al., 2014; Witek, Clarke, Wallentin, et al., 2014). However, it also showed that not all syncopation patterns have the same potential to induce the pleasurable movement associated with groove. While the original syncopation, "created" by musicians was successful, a similar amount of algorithmically generated syncopation did not have the same effect. Therefore, the inverted U-shaped relation between the amount of syncopation and groove that was previously presented by Witek et al. (2014) and was subsequently the basis for the predictive coding explanation of the relation between groove and syncopation (Koelsch et al., 2019) was not fully replicated.

While the first study showed that the degree of syncopation alone is not a good predictor of groove ratings, the second study challenges the general validity of the theoretical foundation of syncopation as an overall scalar quantity. It offers instead a comprehensive rhythm analysis that takes into account interactions between syncopating patterns, either articulated simultaneously by different instruments or serially by a single instrument. This type of analysis proved successful in identifying certain key structural differences between music examples with similar degrees of syncopation, but which differed in the groove ratings they received. The analysis provided insights into the listeners' response to the algorithmic variations contrasted with the original excerpts. Taken together, the two studies helped us formulate four concrete hypotheses about specific rhythmic properties of the music examples that induce groove, which will be tested in follow-up laboratory experiments.

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References

Agawu, V. K. (1986). "'Gi Dunu,' 'Nyekpadudo,' and the Study of West African Rhythm." *Ethnomusicology*, *30*(1), 64–83.

Boehler, K. K. (2016). "Somos la mezcla perfecta, la combinación más pura, cubanos, la más grande creación": Grooves, Pleasures, and Politics in Today's Cuba. *Latin American Music Review*, *37*(2), 165–207.

Bowling, D. L., Ancochea, P. G., Hove, M. J., & Tecumseh Fitch, W. (2019). Pupillometry of groove: Evidence for noradrenergic arousal in the link between music and movement. *Frontiers in Neuroscience*, *13*(JAN), 1–12.

Bryant, G. A., & Hagen, E. H. (2003). Music and dance as a coalition signaling system. *Human Nature*, *14*(1), 21–51.

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

Câmara, G. S., & Danielsen, A. (2020). Groove. In A. Rehding & S. Rings (Eds.), *The Oxford handbook of critical concepts in music theory* (Vol. 1, pp. 270–294). Oxford University Press.

Danielsen, A. (2006). *Presence and pleasure: The funk grooves of James Brown and Parliament*. Wesleyan University Press.

Danielsen, A. (2010). Here, there and everywhere: Three accounts of pulse in D'Angelo's "left and right." In A. Danielsen (Ed.), *Musical rhythm in the age of digital reproduction* (pp. 19–36). Ashgate/Routledge.

Danielsen, A. (2012). The sound of crossover: Micro-rhythm and sonic pleasure in Michael Jackson's "Don't Stop 'Til You Get Enough." *Popular Music and Society*, *35*(2), 151–168.

Danielsen, A. (2015). Metrical ambiguity or microrhythmic flexibility? Analysing groove in 'Nasty Girl' by Destiny's Child. In A. Doehring, D. Helms, & A. F. Moore (Eds.), *Song interpretation in 21st-century pop music* (pp. 53–72). Ashgate.

Danielsen, A. (2018). Pulse as dynamic attending: Analysing beat bin metre in neo soul grooves. In C. Scotto, K. M. Smith, & J. Brackett (Eds.), *The Routledge companion to popular music analysis: Expanding approaches.* (pp. 179–189). Routledge.

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*(5), 497–510.

Fitch, W. T., & Rosenfeld, A. J. (2007). Perception and production of syncopated rhythms. *Music Perception*, *25*(1), 43–58.

Gómez, F., Melvin, A., Rappaport, D., & Toussaint, G. T. (2005). Mathematical measures of syncopation. In *Proceedings of BRIDGES: Mathematical Connections in Art, Music and Science* (pp. 73–84). Citeseer.

Goto, M., Hashiguchi, H., Nishimura, T., & Oka, R. (2003). RWC Music Database: Music Genre Database and Musical Instrument Sound Database Masataka. In *Proceedings of the 4th International Conference on Music Information Retrieval* (pp. 229–230) ISMIR.

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.

Huron, D. (2003). Is music an evolutionary adaptation? In I. Peretz & R. J. Zatorre (Eds.), *The cognitive neuroscience of music* (pp. 57–75). Oxford University Press.

Huron, D. (2006). *Sweet anticipation: Music and the psychology of expectation*. MIT Press.

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*(1), 54–75.

Jones, A. M. (1954). African rhythm. *Africa*, *24*(1), 26–47.

Keith, M. (1991). *From polychords to polya: Adventures in musical combinatorics*. Vinculum Press.

Knowlton, D. (1926). The anatomy of jazz. *Harper's*, *154*.

Koelsch, S., Vuust, P., & Friston, K. (2019). Predictive processes and the peculiar case of music. *Trends in Cognitive Sciences*, *23*(1), 63–77.

Lee, C. S. (1985). The rhythmic interpretation of simple musical sequences: Towards a perceptual model. In P. Howell, I. Cross, & R. West (Eds.), *Musical structure and cognition* (pp. 53–69). Academic Press.

Lerdahl, F., & Jackendoff, R. (1983). *A generative theory of tonal music*. MIT Press.

London, J. (2012). *Hearing in time: Psychological aspects of musical meter* (2nd ed.). Oxford University Press.

Longuet-Higgins, H. C., & Lee, C. S. (1984). The rhythmic interpretation of monophonic music. *Music Perception*, *1*(4), 424–441.

Madison, G. (2006). Experiencing groove induced by music: Consistency and phenomenology. *Music Perception*, *24*(2), 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*(5), 1578–1594.

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.

Matthews, T. E., Witek, M. A. G., Heggli, O. A., Penhune, V. B., & Vuust, P. (2019). The sensation of groove is affected by the interaction of rhythmic and harmonic complexity. *PLoS ONE*, *14*(1), 1–17.

Matthews, T. E., Witek, M. A. G., Lund, T., Vuust, P., & Penhune, V. B. (2020). The sensation of groove engages motor and reward networks. *NeuroImage*, *214* (November 2019), 116768.

Merker, B. (2000). Synchronous chorusing and human origins. In N. L. Wallin, B. Merker, & S. W. Brown (Eds.), *The origins of music* (pp. 315–327). MIT Press.

Merker, B. H., Madison, G. S., & Eckerdal, P. (2009). On the role and origin of isochrony in human rhythmic entrainment. *Cortex*, *45*(1), 4–17.

Nketia, J. H. K. (1974). *The music of Africa*. W. W. Norton & Company.

Palmer, C., & Krumhansl, C. L. (1990). Mental representations for musical meter. *Journal of Experimental Psychology. Human Perception and Performance*, *16*(4), 728–741.

Pantaleoni, H. (1972). Three principles of timing in Anlo dance drumming. *African Music*, *5*(2), 50–63.

Parncutt, R. (1987). The perception of pulse in musical rhythm. In A. Gabrielsson (Ed.), *Action and perception in rhythm and music* (pp. 127–138). Royal Swedish Academy of Music.

Parncutt, R. (1994). A perceptual model of pulse salience and metrical accent in musical rhythms. *Music Perception*, *11*(4), 409–464.

Poudrier, È., & Repp, B. H. (2013). Can musicians track two different beats simultaneously? *Music Perception*, *30*(4), 369–390.

Pressing, J. (1997). Cognitive complexity and the structure of musical patterns. In R. Heath, B. Hayes, A. Heathcote, & C. Hooker (Eds.), *Proceedings of the 4th Conference of the Australasian Cognitive Science Society.* Australia.

Randel, D. M. (1986). *The Harvard dictionary of music.* (D. M. Randel, Ed.) (4th ed.). Belknap Press of Harvard University Press.

Ravignani, A., Bowling, D. L., & Fitch, W. T. (2014). Chorusing, synchrony, and the evolutionary functions of rhythm. *Frontiers in Psychology*, *5*, 1118.

Ravignani, A., & Madison, G. (2017). The paradox of isochrony in the evolution of human rhythm. *Frontiers in Psychology*, *8*.

RWC Music Genre Database. (n.d.). Retrieved December 5, 2012, from http://staff.aist.go.jp/m.goto/RWC-MDB/

Senn, O., Bechtold, T. A., Hoesl, F., & Kilchenmann, L. (2019). Taste and familiarity affect the experience of groove in popular music. *Musicae Scientiae*, 102986491983917.

Senn, O., Kilchenmann, L., Bechtold, T., & Hoesl, F. (2018). Groove in drum patterns as a function of both rhythmic properties and listeners' attitudes. *PLoS ONE*, *13*.

Shmulevich, I., & Povel, D.-J. (2000). Measures of temporal pattern complexity. *Journal of New Music Research*, *29*(1), 61–69.

Sioros, G., Davies, M. E. P., & Guedes, C. (2018). A generative model for the characterization of musical rhythms. *Journal of New Music Research*, *47*(2), 114–128.

Sioros, G., & Guedes, C. (2011). Complexity driven recombination of MIDI loops. In *Proceedings of the 12th International Society for Music Information Retrieval Conference* (pp. 381–386) ISMIR.

Sioros, G., & Guedes, C. (2014). Syncopation as transformation. In M. Aramaki, O. Derrien, R. Kronland-Martinet, & S. Ystad (Eds.), *Sound, music, and motion* (Vol. 8905, pp. 635–658). Springer International Publishing.

Sioros, G., Holzapfel, A., & Guedes, C. (2012). On measuring syncopation to drive an interactive music system. In F. Gouyon, P. Herrera, L. G. Martins, & M. Mülle (Eds.), *Proceedings of the 13th International Society for Music Information Retrieval Conference* (pp. 283–288). FEUP Edições.

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.

Smith, L. M., & Honing, H. (2006). Evaluating and extending computational models of rhythmic syncopation in music. In *Proceedings of the International Computer Music Conference* (pp. 688–691). ICMC.

Stover, C. D. (2009). *A theory of flexible rhythmic spaces for diasporic African music*. University of Washington. Retrieved from https://www.utexaspressjournals.org/doi/10.7560/LAMR37202

Stupacher, J., Wood, G., & Witte, M. (2017). Neural entrainment to polyrhythms: A comparison of musicians and non-musicians. *Frontiers in Neuroscience*, *11*, 1–17.

Tan, I., Lustig, E., & Temperley, D. (2019). Anticipatory syncopation in rock: A corpus study. *Music Perception*, *36*(4), 353–370.

Temperley, D. (1999). Syncopation in rock: A perceptual perspective. *Popular Music*, *18*(01), 19–40.

Temperley, D. (2001). *The cognition of basic musical structures.* MIT Press.

Thul, E., & Toussaint, G. T. (2008). Rhythm complexity measures: A comparison of mathematical models of human perception and performance. In *Proceedings of the 9th International Conference on Music Information Retrieval* (pp. 663–668). ISMIR.

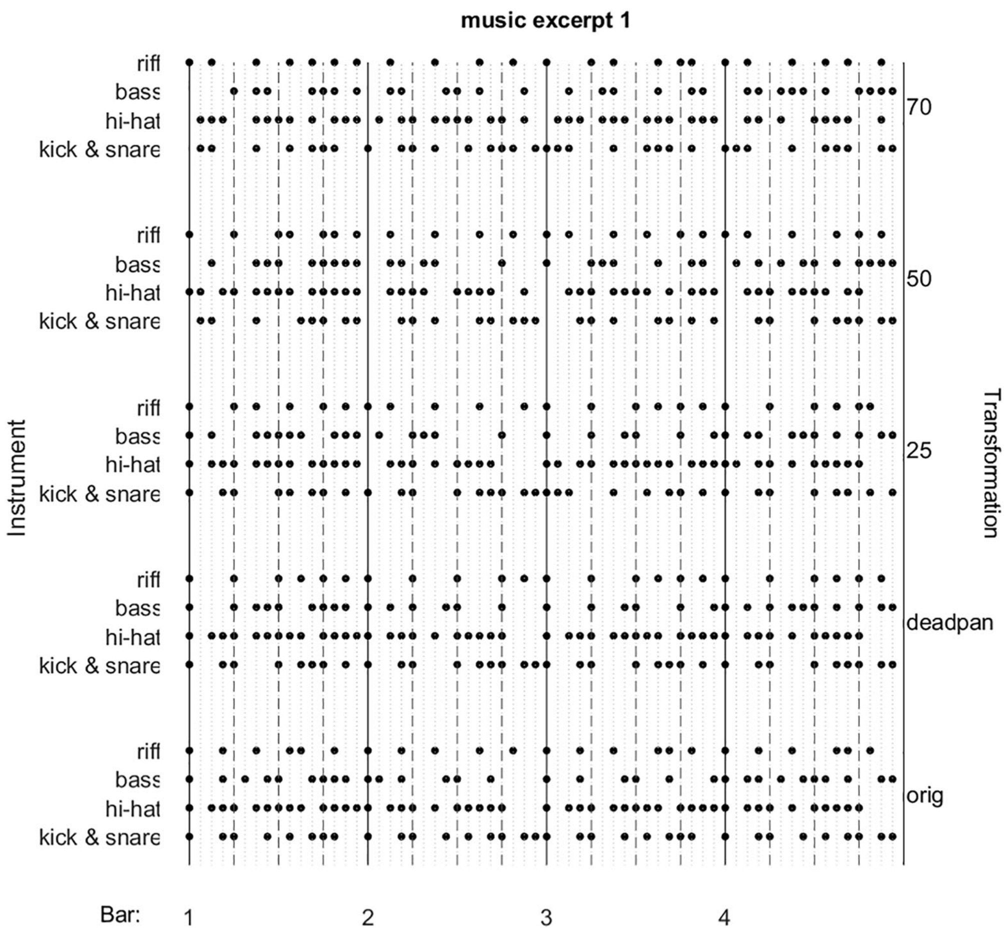
Vuust, P., Dietz, M. J., Witek, M. A. G., & Kringelbach, M. L. (2018). Now you hear it: A predictive coding model for understanding rhythmic incongruity. *Annals of the New York Academy of Sciences*, *1423*(1), 19–29.

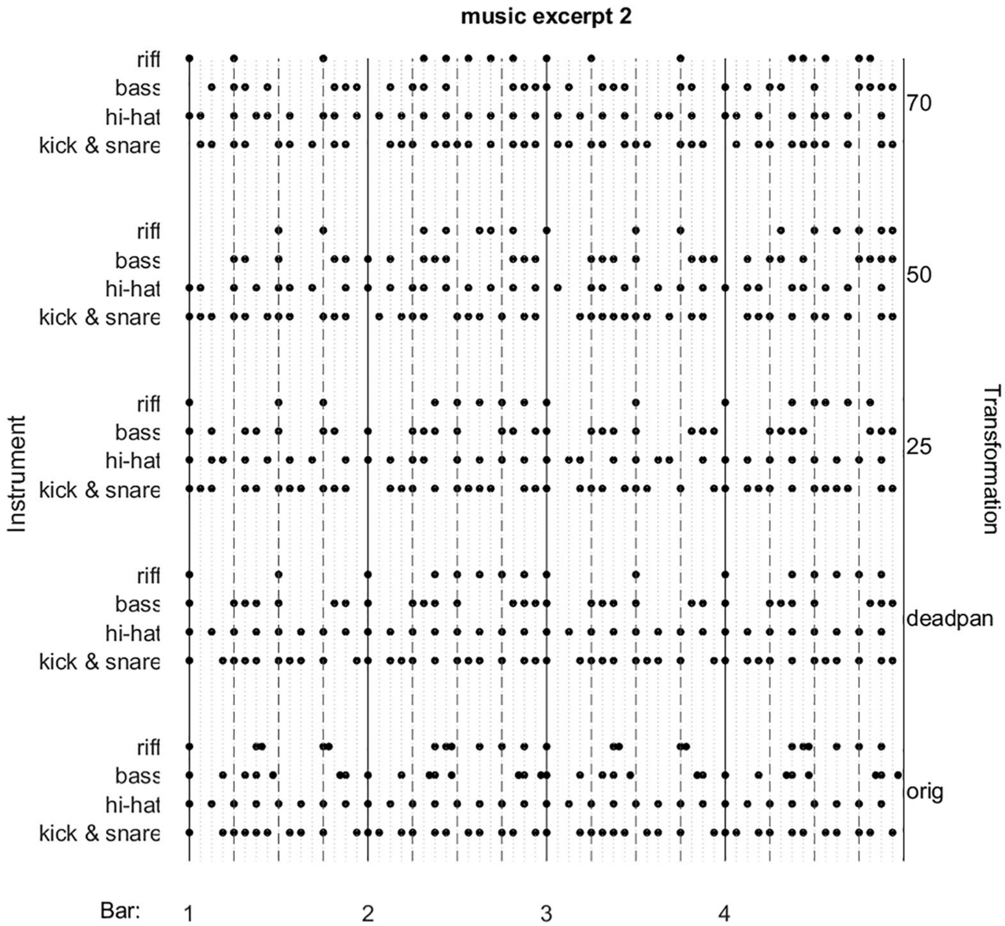
Vuust, P., & Witek, M. A. G. (2014). Rhythmic complexity and predictive coding: A novel approach to modeling rhythm and meter perception in music. *Frontiers in Psychology*, *5*.

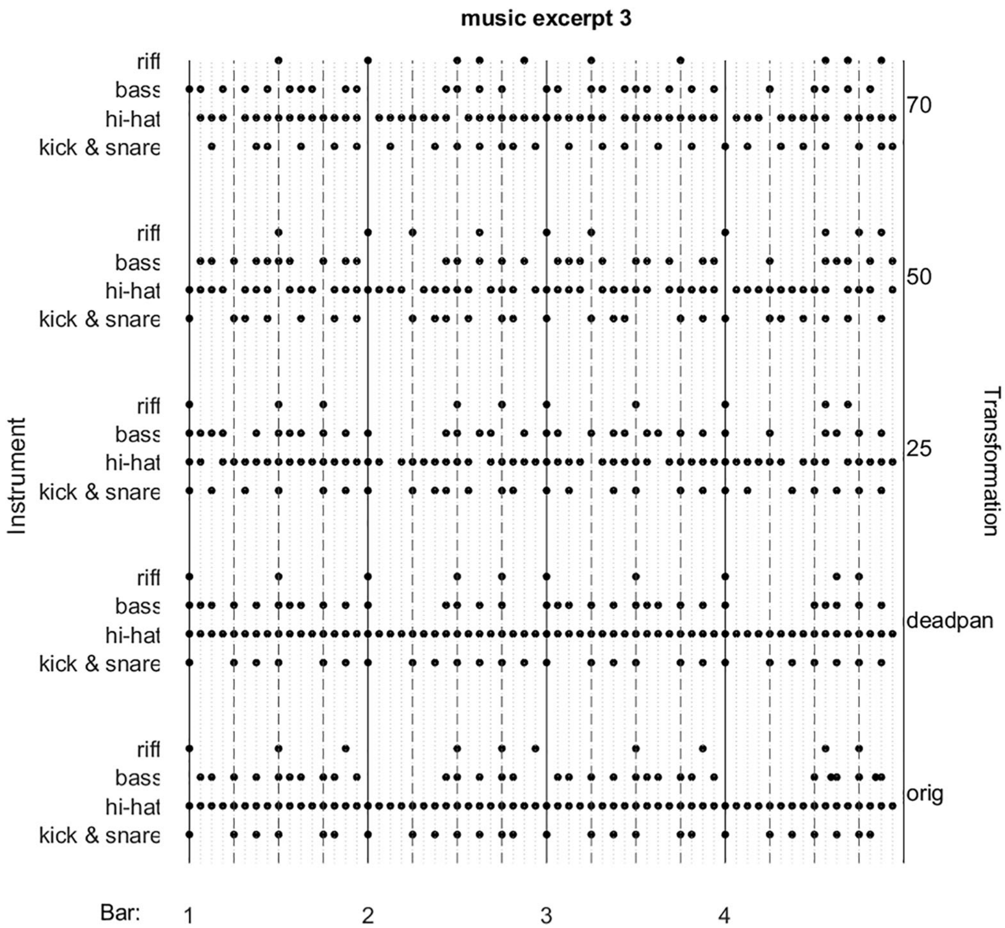
Waterman, R. A. (1948). "Hot" rhythm in Negro music. *Journal of the American Musicological Society, 1*(1), 24–37.
Welch, B. L. (1947). The generalization of "student's" problem when several different population variances are involved. *Biometrika, 34*, 28–35.
Witek, M. A. G., Clarke, E. F., Kringelbach, M. L., & Vuust, P. (2014). Effects of polyphonic context, instrumentation, and metrical location on syncopation in music. *Music Perception, 32*(2), 201–217.
Witek, M. A. G., Clarke, E. F., Wallentin, M., Kringelbach, M. L., & Vuust, P. (2014). Syncopation, body-movement and pleasure in groove music. *PLoS ONE, 9*(4), e94446.
Yeston, M. (1976). *The stratification of musical rhythm.* Yale University Press.
Zeiner-Henriksen, H. T. (2010). *The "poumtchak" pattern: Correspondences between rhythm, sound, and movements in electronic dance music* [Doctoral dissertation, University of Oslo, Oslo, Norway].

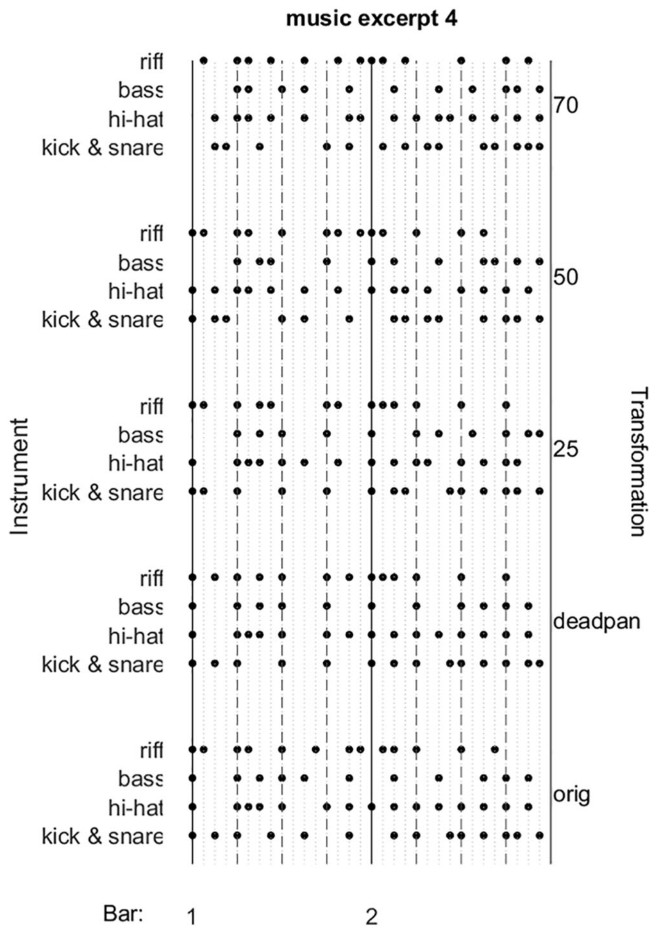
Appendix
Supporting Figures

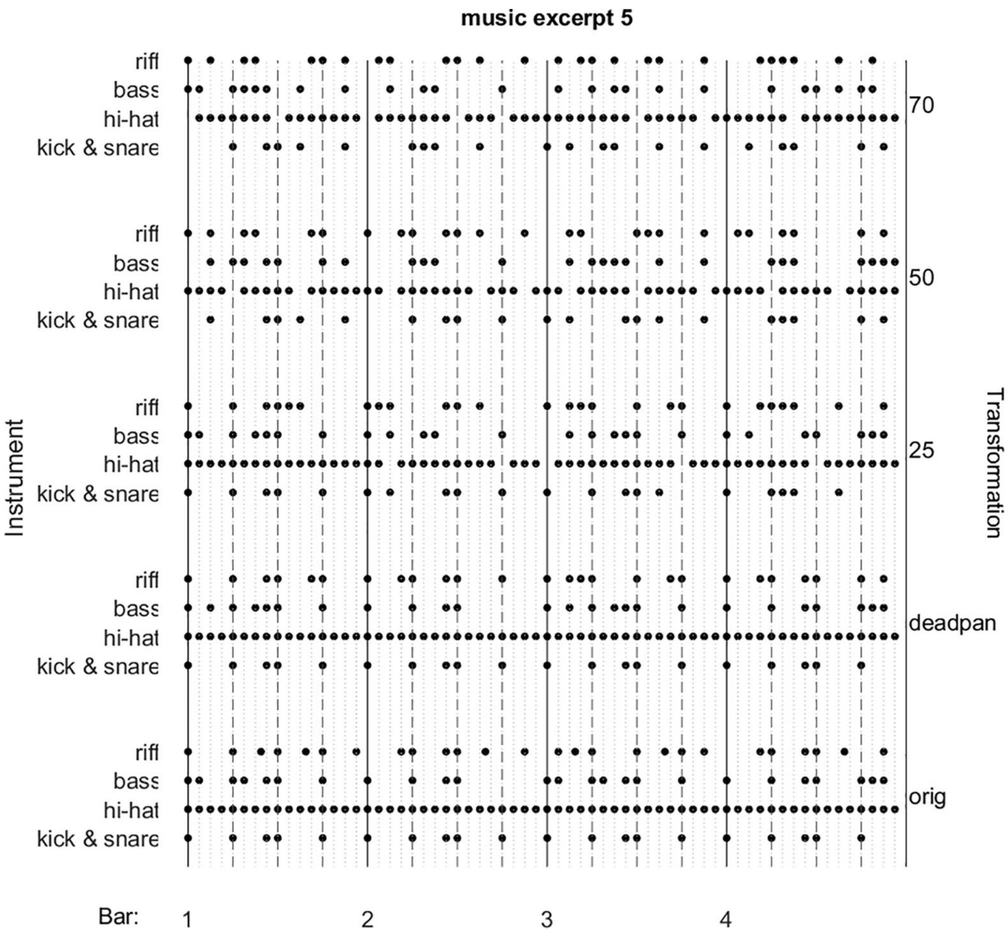
Reduced representation of the rhythmic structures of the ten transcriptions of the music excerpts and their algorithmic variations. Each figure corresponds to a music excerpt (1-10) and its algorithmic variations: deadpan (de-syncopated), 25%, 50%, and 70% syncopation. The horizontal axis represents time with the vertical grid lines corresponding to the metrical grid. Solid lines correspond to the beginning of the bars. Black dashed lines correspond to the quarter note level. Grey dashed lines correspond to the sixteenth note level. Each instrument in a variation is notated in a separate line, with the black dots corresponding to the positions of the note onsets.

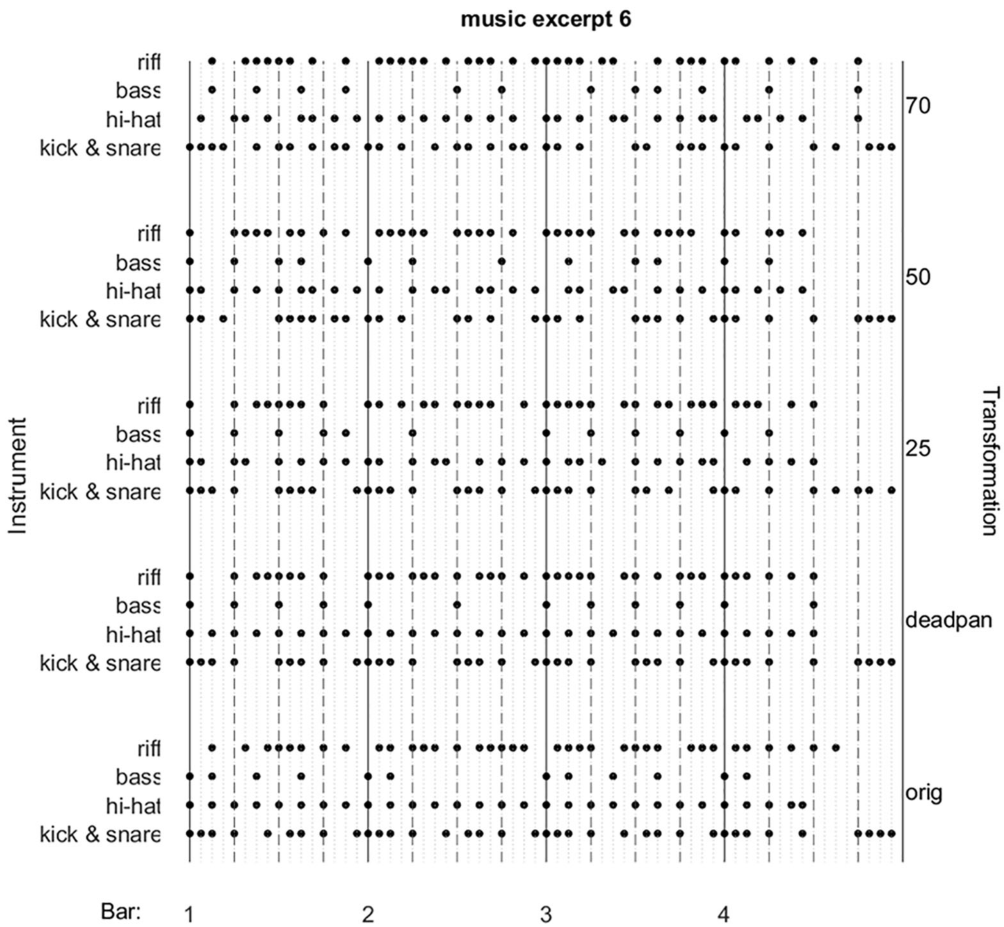


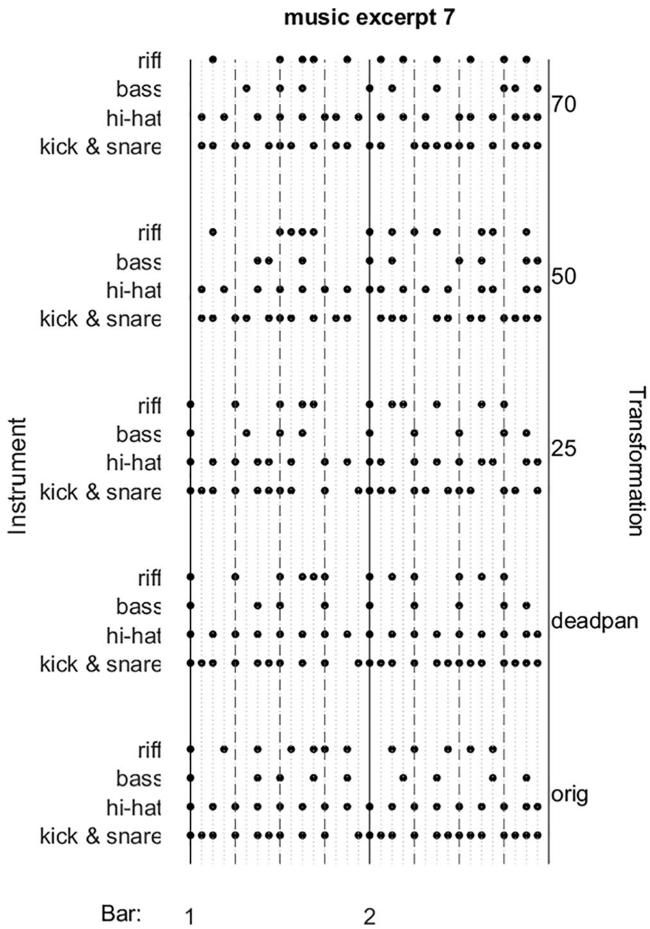

music excerpt 2
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2
3
4


music excerpt 3
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2
3
4

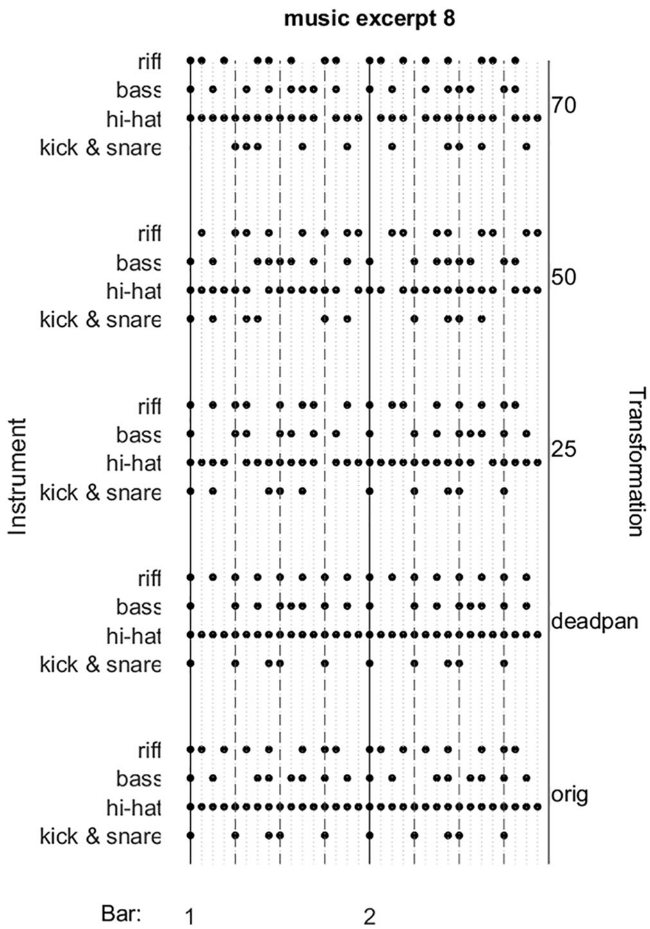

music excerpt 4
Instrument
riff
bass
hi-hat
kick & snare
70
50
25
deadpan
orig
Transformation
Bar:
1
2

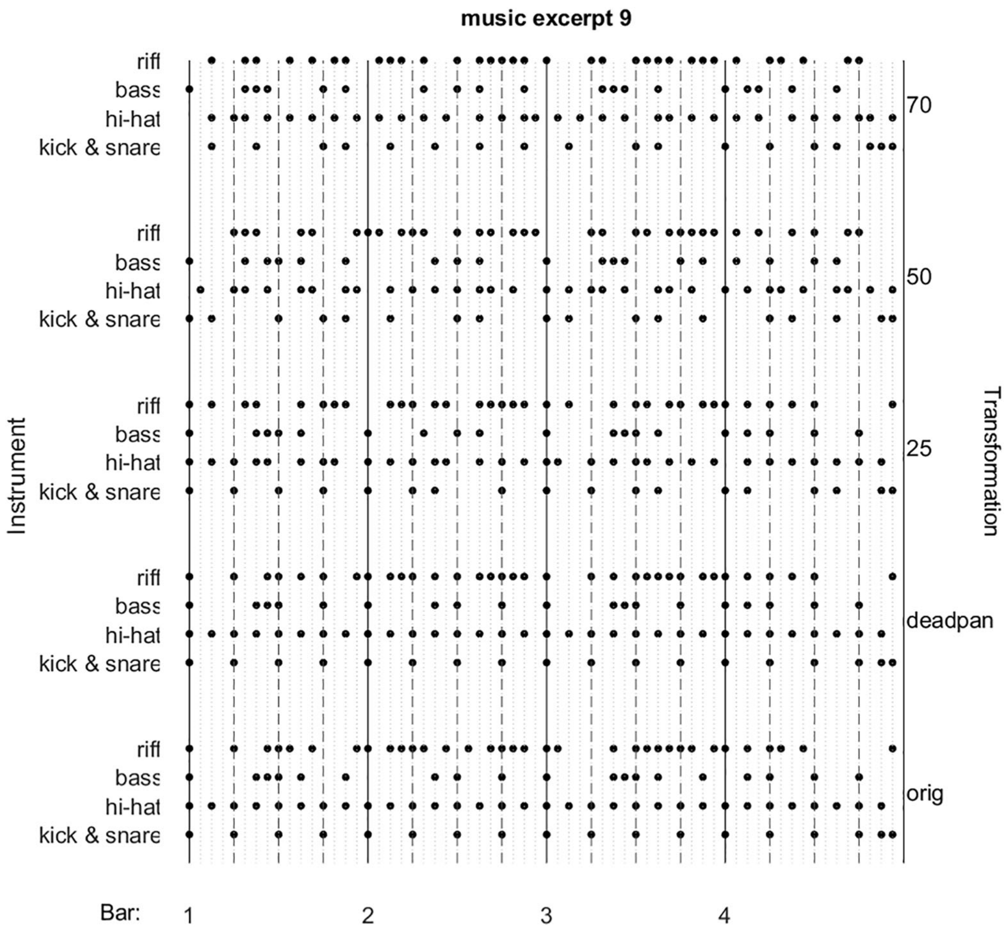

music excerpt 5
riff
bass
hi-hat
kick & snare
70
50
25
deadpan
orig
Instrument
Transformation
Bar:
1
2
3
4

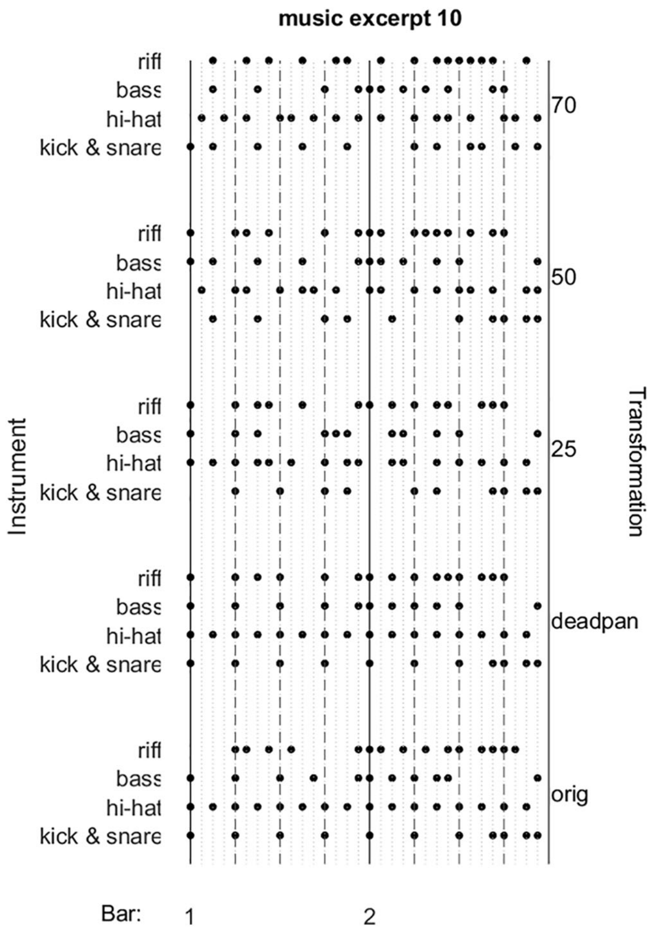

music excerpt 6
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2
3
4



music excerpt 7
riff
bass
hi-hat
kick & snare
70
50
25
deadpan
orig
Instrument
Transformation
Bar:
1
2


music excerpt 8
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2


music excerpt 9
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2
3
4



music excerpt 10
Instrument
riff
bass
hi-hat
kick & snare
Transformation
70
50
25
deadpan
orig
Bar:
1
2