Neural Synchronization of Music Large-Scale Form

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Abstract

Music large-scale form, the structure of musical units ranging over several bars, are studied using EEG measurements of 25 participants listened to the first four minutes of a piece of electronic dance music (EDM). Grand-averages of event-related potentials (ERPs) calculated for all electrodes show dynamics in phase synchronization between different brain regions. Here local maxima of the perceptual parameters correspond to strong synchronization, which culminate at time points, where musical large-scale form boundaries were perceptually expected. Significant differences between local maxima and minima were found, using a Paired Samples t-test, showing global neural synchronization between different brain regions most strongly in the gamma-band EEG frequency range. Such synchronization increases before musical large-scale form boundaries, and decreases afterwards, therefore representing musical large-scale form perception.

I Introduction

A Music Large-scale form

Music large-scale form as investigated in this paper is meant to be the overall structure of a piece of music. The verse and chorus concatenation in a song, the sonata form of classical music, or the continuous night-long tension built-up and decay in Techno, House, or Electronic Dance Music (EDM) are all examples of such large-scale forms. So in the hierarchical structuring of music form is the perceptual highest level of grouping.

Although this paper is investigating large-scale forms of EDM, all forms are closely related to the creation and release of perceived tension and expectations. In terms of music theory this was prominently been discussed already by Hugo Riemann in 1895 when suggesting a cadence to consist of functions, therefore introducing functional harmony. There he used the Hegel terms of thetic-antithetic-synthetic (These-Antithese-Synthese) for the chord progression I-IV-I-V-I, finding the V to have a maximum tension, demanding the tension release in the following I

While listening to music, the incoming flow of auditory information is perceptually segregated and organized onto different levels by the principles of Gestalt psychology. These principles apply to the formation of primitive auditory objects like pitches or chords, as well as to the organization of phrases and greater passages in pieces of music. These structural aspects on the highest level of musical organization ranging over several bars as a combination of all elements that constitute a piece of music, like pitch, rhythm and timbre, are here referred to as musical form.

In the early 1930s, music theory was much influenced by energetics (Energetiker). In 1931 the music theory of Ernst Kurth described music as an interplay of potential and kinetic energy, where tension is characterized by high potential energy that will be converted into kinetic energy, therefore lowering the potential energy. According to Rothfarb this idea was supported by Arnold Schering, for whom the essence of music was alternating phases of tension and release. More modern theories like the Generative Theory of Tonal Music (GTTM) incorporate tension as well, namely between strong metrical events. In general, Schönberg characterized the musical form by the contrasts of its subsidiary parts, or in his own words: Larger forms develop through the generating power of contrasts. p. 178. Due to this contrasting elements in different form parts, the use of letters as formal representation of the different form parts has been established, like ABA, ABA or ABAC, where A denotes the first part, B a second part and A a variation of the first part.

B Music form in ’no-score’ music

As most theories have been investigating form extracting a musical score. These theories are not applicable to modern dance music like House, Techno, or EDM in a straightforward way, as these musical styles most often have no scores at all. Still such music has form, an overall structure, and like most musical styles this form follows a certain typical schema. This schema is based on the metrical structure of a piece in such a way that instrumentation and looped parts or grooves change only at metrically strong positions, namely after a multiple of 16 or 32 bars. These highest-level musical events are constitutive for the musical form, since they determine the
boundaries of the different form parts.

C Musical schema cause expectations

Perceptually, these schema or normative archetypes give rise to schematic or high-level structural expectations. Since House, Techno, or EDM music rely on repeated or looped parts or grooves, based on a 16- or 32-bar schema, the time points of high-level musical part boundaries are predictable, and so expectations and tension emerge while listening. When the predicted event occurs, and so expectation is fulfilled, tension releases. In the context to Dance music, and with respect to Ernst Kurth’s alternating potential tension releases. Expectations are often found to emerge from learning processes, and in particular from statistical learning. Since musical events happen on different time-scales, from milliseconds to life-time spans, also expectations built-up for musical events on different time-scales.

Zanto showed gamma-band synchronization in response to perturbed auditory pulse sequences in an EGG-study with eight subjects. Evoked gamma-band activity (phase-locked to stimulus) was measured at metrical positions where an auditory pulse actually appeared, and induced gamma-band activity (time-locked to stimulus) was measured at the sites where an auditory pulse should have occurred, but actually was not presented physically.

In a more complex context Jones et al. investigated the influence of the precise temporal placement of a target tone on the judgments of a pitch-comparison task. It was shown that the judgments were more accurate the more precise the target tone was placed on a metrical strong position. The authors interpreted the results in that way that attention is not equally distributed over time, and in general support the idea of Seashore that attention may be periodic.

Krumhansl et al. were able to show culturally influenced learning and expectations in a probe-tone experiment with tone-scales. Subjects were asked to judge how good a certain probe-tone fits to a previously heard tone-scale from the pool of all 24 major and minor scales and tones. The analysis of the presented intervals for major and minor scales, the so-called tone-profiles, show that octave, fifth, and major or minor third, are rated highest. These results support the hypothesis of cultural learning of tonal relations within a certain tonal system, and as such was also modeled using an artificial neural network.

D Timing representation in the brain

Less empirical research was performed on how music large-scale form is processed by the human brain. However, there are expectation models independent of musical interpretations, such as the pacemaker-accumulator model or the synchronization model by.

Time perception, like music, is organized on different time-scales: the circadian timing, the interval timing, and the millisecond timing. The circadian timing is linked to the 24h sleep-wake cycle and appetite, and its corresponding neural timer is located in the suprachiasmatic nucleus of the hypothalamus. Millisecond timing is crucial for motor control and speech generation, and is discussed to be neurally represented in the cerebellum.

Yet the third time-span is in a seconds-to-minutes range, and referred to as interval timing. Interval timing is found to be cognitively controlled, and involved in decision-making and conscious time estimation. Interval timing is characterized by the scalar property that has been found in several timing reproduction task in a wide variety of animals species. By asking subjects to reproduce a given duration, the responses are normally distributed around that duration, and the distribution is proportional to the duration. A model of timing therefore has to reproduce this scalar property.

The traditional explanation of the scalar property is the pacemaker-accumulator model as a scalar expectancy theory. Here, the internal clock is represented by a pacemaker that sends pulses to an accumulator which stores the pulses until a certain feedback or reward occurs. The number of stored pulses represents the time-span, and is stored in a reference memory. When reproducing the time-span, the current number of pulses is compared to the number in the reference memory. The scalar property is explained by the proportionality between the accumulation error and the criterion duration.

Buhusi postulated a neural model based on a review of literature on neural mechanisms, where interval timing is described by a coincidence-detection model. Cortical oscillations modulate neural activity in the striatum, which acts as a coincidence detector of the phases of these cortical oscillations. As more and more cortical oscillations synchronize, striatal neurons monitor this by an increasing activity and dopamine release, thereby having the scalar property.

E Neural synchronization

Concerning perception, the brain is considered as a Helmholtz machine, a self-organizing system that actively constructs predictions and or explanations for sensory input using internal or generative models. In that context, synchronization is seen as a far-ranging principle used by neurons or neural ensembles to code and process information. While a total synchronization of all neurons is associated with an epileptic seizure, partly synchronization of different neurons or neural ensembles, locally or globally distributed over different brain regions, is associated with cognitive and perceptual processes.

Especially large-scale synchronization of cortical neurons are interesting, since they are associated with a bunch of cortical and perceptual processes like gestalt perception, timing and expectation, attention, and working memory.
In the context of music perception, neural synchronization in various frequency bands and domains has been found in various perceptual and cognitive tasks. An early approach of studying communication between different brain regions in relation to music perception was proposed by [58]. In their paper The EEG: An Adequate Method to Concretize Brain Processes Elicited by Music in an experiment with 75 subjects they examined if several EEG parameters (location, power, frequency, and coherence) differ between groups of musicians and non-musicians with respect to different musical tasks. They emphasize that coherence in perceptual tasks reflects different degrees of functional coordination of two adjacent brain regions or the two hemispheres [58] p. 133. In a following experiment Janata showed that neural coherence, and to a smaller extend neural amplitude, can predict if a musical context is completed, that is, if the context generated expectation is fulfilled or not [32].

Concerning synchronization in the gamma-band was realized by Zanto et al. [78]. In an EEG experiment they examined gamma-band activity in the averaged EEG activity of eight subjects as they listened to isochronous pure-tone sequences with embedded temporal perturbations. They found that induced (not phase-locked) gamma activity was enhanced at the occurrence of tone onsets, while evoked (phase-locked) gamma-band activity was observed after onset. At late perturbations, induced gamma-band activity, peaks precede tone onset, during early perturbations, induced activity following tone onset. The authors interfere that induced gamma-band activity represents metrical expectation and evoked gamma-band activity represents stimulus perception. Snyder et al. went a step further and examined metrical structures instead of pulse sequences [67]. They could confirm these results, and proposed that the power of evoked gamma-band activity reflects the loudness of the stimuli.

Besides experimental data, different models use mechanisms of neural synchronization to explain phenomena in music perception and physiology. In line with the results concerning the perception of pulse and meter above, Large et al. developed a model to explain beat perception in musical rhythms by synchronization of oscillations in self-organizing neural networks [42]. Concerning pitch perception in the auditory system, Bader used a coincidence detection model to explain the synchronization of the blurred spike output from the cochlear in the nucleus cochlearis and the trapezoid body found in cat auditory nerves [33, 37]. It shows that single neuron could detect pitches up to 300Hz by neural coincidence.

This paper therefore hypothesizes that when listening to a piece of music, the different hierarchical organized parts of the piece are perceptually integrated into a high-level Gestalt, so that musical form emerges over time. At the same time, expectations are formed towards the high-level

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**Table 10.23 Time scale of musical events (selection)**

| Time interval | Frequency | Event | Explanation/Remarks |
|---------------|-----------|-------|---------------------|
| Sound         | 62.5 - 50\,μs | 16 - 20 kHz | upper hearing threshold | orthotony of basilar membrane |
|               | ~ 250 μs | ~ 4 kHz | upper pitch threshold | tonotopy of interlocked nerve cells |
|               | 2 - 5 ms | 200 - 500 Hz | lower threshold above simple 'pitch' perception | ear lower limit filter constant |
|               | 625 - 500 ms | 10 - 20 Hz | lower pitch threshold, sound event separation threshold | |
|               | ~ 80 ms | ~ 12.5 Hz | Lateral Energy Fraction (LEF) time | not yet understood |

| Rhythm | 100 - 120 ms | 10 - 8 Hz | Upper rhythm production speed threshold | thalamo-cerebellar-motor cortical circuit frequency |
|        | ~ 500 ms | ~ 5 Hz | Upper thalamo-cerebellar-motor cortical circuit frequency | |
|        | ~ 500 ms | 2 Hz | Walking/movement speed peak | |
|        | 1 8 - 2 s | ~ 0.5 Hz | Fastest beat performance tempo | |

| Pattern | 2 - 5 s | Groove pattern, melodic unit time | Short term memory | |
| Form | 3 min | Optimum popular song duration | Musical form |
|      | 5 s ~ 60 min | Pacemaker-accumulator model, striatal beat-frequency model | Long term memory |

| Culture | 1 week | Club rotation speed, musical frequency | |
|         | 1 year | Musical style formation, instrument building | |
|         | ~ 15 000 years | Oldest musical instrument (flute), Halle lady (Schehelische Alt) | Cultural development |

| Evolution | ~ 100 000 years | Development of ear and auditory cortex | Evolutionary development |

Figure 1: Time scale of musical events (selection). [21] p. 324. Reprinted with permission.
musical events or cue point that determine the boarders of
the individual parts. Since both processes are represented
by dynamics of neural synchronization, we hypothesis that
large-scale neural synchronization increases before a musi-
cal event occurs and decrease afterwards, with a maximum
synchronization at the time of the musical event.

With EDM music the raise and fall of perceived ten-
sion is a major element in each performance. During a DJ
set lasting maybe a whole night, over and over again ten-
sion is increased most often by an increase of instrumen-
tation density, brightness, or amplitude raise, which then
is released when the bass drum comes in, in a so-called
four-to-the-floor beat, meaning the bass drum is played
at each quarter note. Therefore EDM music is used in
this investigation.

II Method

In order to test the hypothesis whether the synchroniza-
at the time of the musical events is higher than at
previous synchronization minima, we conducted an EEG
experiment with 25 participants listening to a piece of
EDM music. Then the synchronization between different
electrodes of the averaged brain activity of the test person
was calculated in successive time intervals. Subsequently,
the differences between the strength of synchronization at
the time of the musical events and the preceding local syn-
cchronization minima were tested with a paired sample t
test.

The stimulus (the musical piece) was selected accord-
ing to various criteria. The piece should follow a clear
structure, contain predictable musical events, so elicit ex-
pectations, and be accessible to the listener familiar with
the genre. These elements are prerequisites in modern
dance music, since genres such as Techno or House follow
clear compositional structures\textsuperscript{66,67}. Also from a prac-
tical point of view it is easier to find test persons for these
genres than for more complex structured music.

We chose the piece ’Classical Symphony’ by Shemian
in the remix of Alle Farben because it meets these re-
quirements\textsuperscript{1}. We took the first 128 bars from the piece.
It follows a 16-bar structure with a 4/4-time signature,
where parts with bassline and parts without bassline al-
ternate. The piece has a tempo of 125 beats per minute
(bpm). Fig. 2 shows the amplitude of the stimulus over
time. The differences between parts with low and high
amplitude are clearly visible. Fig. 3 shows the spectral
centroid calculated for subsequent time windows of one
second. The short peaks in Fig. 3 show fast changes in the
spectral midpoint, which are indicators of the important
musical events separating the musical form into different
parts. Following this reasoning the musical events occur
at the 58th, 93rd, 139th, 185th, 215th, and 246th second.
The solid vertical lines represent the boarders between the
form parts, following a typical Tech-House style sixteen-
bars schema. A few extra lines were added to clarify the
structure of the stimulus.

A Subjects

Twenty-five subjects, nine women and sixteen men aged
between 20 and 32 with a mean of 26.8 participated in this
study. During the experiment participants sat half lying
half sitting on a recliner in front of a white wall. They were
instructed to avoid, but explicitly not to suppress body
movements. The eyes were opened and eye movements
were not forbidden in order to avoid a behavioral concen-
tration to that goal. After the setup and instructions, the
stimulus was presented three times to each subject via a
pair of headphones (Sennheiser HD203, frequency range:
18-18.000Hz) at a medium listening volume.

B Procedure and recordings

Electroencephalographic (EEG) signals were recorded
from 32 electrodes (Electrode-cap Wave-guard 32, ANT-
Neuro). All impedances were kept below 10 kOhm. The
electrodes were positioned following the 10-20 method of placement\textsuperscript{33}, and were referred to the average of all ele-
trodes with a middle forehead ground. The EEG signal

\textsuperscript{1}https://www.youtube.com/watch?v=YauWD68O2RE
was processed by an amplifier (Refa-32, ANT-Neuro) with a sampling frequency of 500Hz. The recorded data were transferred to a computer, where the EEG processing software ASA (V. 4.7.3, ANT-Neuro) was used for recording and pre-processing.

C Data analysis

The data analysis consisted of three parts: the pre-processing, the calculation of the synchronization, and the hypothesis testing, whether the strength of the global synchronization differs between the time points of the minima before a musical event and the time points of the musical events.

1 Pre-processing

The recorded data consisted of 75 datasets, 25 subjects × 3 trials, containing the EEG signal of the 32 electrodes over stimulus length of 4:22 min. The time series of each electrode represented the measured voltage fluctuations over time in µV. The pre-processing consisted of three steps:

1. Artefacts: In a recorded EEG signal all potential fluctuations that are not induced by brain activity are regarded as artefacts. The most common artefacts are induced by eye-blinks, body movements, or transpiration. Eye-blinks were corrected using the ASA Artefact correction feature, which is based on a principle components analysis of the whole signal to separate artefacts from stimulus correlated brain activity.\(^{41}\) Body movements cause muscle artefacts, which can be found in the EEG raw data by visual inspection. Since these artefacts are strongly not-linear, and so hard to correct, we replaced the affected sections by zeros. Transpiration increases the conductivity of the skin and so impedances becomes better. This leads to a better measurement of brain activity over longer periods, and thus could skew them. To flatten these long-term changes in electrode impedances, the signal was high-pass filtered with a cut-off frequency of 0.5 Hz. All steps of artefact correction have been applied to all 75 individual data sets.

2. Grand-averaging or ERP calculation: The brain activity measured with an EEG is caused only to a small extent by the stimulus. A larger part is spontaneous activity and of a random nature. To enhance the signal to noise ratio (SNR), and thereby reveal the evoked event-related potentials (ERPs) across subjects, grand-averages for each electrode have been calculated by averaging the datasets of all subjects and trials.\(^{31}\) This averaged data set was used to calculate synchronization between different electrodes and therefore between different brain regions.

3. Frequency filter: The recorded EEG data was decomposed into common frequency bands: delta (0.5Hz - 3.5Hz), theta (3.5Hz - 7.5Hz), alpha (7.5Hz - 12.5Hz), beta (12.5Hz - 30Hz), and gamma (30Hz - 80Hz) using the finite impulse response (FIR) filter integrated into Matlab’s EELab toolbox (v. 13.2.2b) resulting in 5 individual datasets.

2 Calculation of the synchronization

Basically, synchronization between a pair of electrodes, and so between different brain regions, has been calculated for one second time windows by calculating the Pearsons correlation coefficient \(r\), the covariance between the neural activity of the one second time window of two electrodes, divided by the product of their standard deviations. This gives a value of \(1 \geq r \geq -1\). For a completely in-phase synchronization of the signals \(r = 1\), for a completely anti-phase synchronization of the signals \(r = -1\), and for no synchronization \(r = 0\).

By calculating the correlation coefficient for the successive time-windows over stimulus length, a course of synchronization between a pair of electrodes over time is obtained. This calculation was performed for all electrode pairs (32 × 31/2 = 496). In order to determine the global synchronization of all brain regions represented by the individual electrodes, the curves of all electrode-pairs were averaged. This procedure was performed for all 5 filtered datasets.

Of particular interest is whether the local synchronization maxima match the times of the musical events. In order to determine the time points of the maxima, the areas in which the local maxima are searched for must first be defined. These are defined as the time of the musical events ± eight bars, shown in Tab. 1. Eight bars correspond to a stimulus length of 15.36 sec (one beat = 60 sec / 125 bpm = 0.48 sec × 4 beats per bar × 8 bars = 15.36 sec). Since the time windows for synchronization is 1 sec, we will round time spans to 16 sec for calculation.

In addition to the maxima, the minima preceding the maxima are also interesting as comparison events, to see whether the strength of the global synchronization differs between the time points of the minima before a musical event and the time points of the musical event. In this way it can be determined whether the global synchronization has increased at the time point of a musical event. The time points of the minima are taken as in between the time points of the musical events.

3 Statistical analysis of differences between local synchronization minima and musical events synchronzation

With a Paired Samples t Test the hypothesis can be tested, whether the synchronization strength at time points of musical events differ significantly from the synchronization strength at times points of local minima. The synchronization strength or values of all electrode pairs at the corresponding time points are used as synchronization values. In order to assess the meaning of a result, effect strengths are calculated. The effect strengths of the mean differences between groups can be determined by calculating a correlation coefficient \(r\) using the t value and the...
degrees of freedom. According to [10], \( r = 0.1 \) corresponds to a weak effect, \( r = 0.30 \) corresponds to a medium effect, and \( r = 0.50 \) corresponds to a strong effect.

### III Results

#### A Synchronization analysis

In Fig. 4, the time series of synchronization of all filtered datasets are shown. The solid vertical lines represent the borders between the form parts of the song, as discussed in the stimulus section.

It can clearly be seen that local synchronization maxima in the gamma-band synchronization time series correspond to the musical events in a way that synchronization increases before a musical event occurs and decreases afterwards, while synchronization time series in all other filtered bands do not show any dynamics. The following results therefore refer to the averaged synchronization time series of all electrode pairs in the gamma-band. The local maxima are preluded by a rise and followed by a steeper decline in correlation. Tab. 1 shows the exact time points of the local synchronization maxima in the gamma-band synchronization time series corresponding to the musical events. The local synchronization maxima are very close to the time points of the musical events, but do not fit exactly.

| Musical event / in sec | Local maxima time span / in sec | Local synchronization maxima / in sec |
|-----------------------|---------------------------------|--------------------------------------|
| 58                    | 042 - 074                       | 57                                   |
| 93                    | 077 - 109                       | 95                                   |
| 139                   | 123 - 155                       | 135                                  |
| 185                   | 169 - 201                       | 176                                  |
| 215                   | 199 - 231                       | 228                                  |
| 246                   | 230 - 262                       | 255                                  |

Table 1: Time points of local synchronization maxima in the gamma-band filtered EEG signal.

Besides the time points of local maxima, local minima are interesting too, to compare the magnitude of synchronization between maxima and minima. Tab. 2 shows the exact time points of local synchronization minima in the gamma-band, preceding a corresponding musical event.

| Musical event / in sec | Local minima time span / in sec | Local synchronization minima / in sec |
|-----------------------|---------------------------------|--------------------------------------|
| 58                    | 001 - 057                       | 17                                   |
| 93                    | 058 - 138                       | 70                                   |
| 139                   | 130 - 184                       | 109                                  |
| 185                   | 185 - 214                       | 153                                  |
| 215                   | 215 - 246                       | 207                                  |
| 246                   | 246 - 262                       | 238                                  |

Table 2: Time points of local synchronization minima in the gamma-band filtered EEG signal.

#### B Statistical analysis of differences between local synchronization minima and musical events synchronization

To test if local synchronization maxima corresponding to the musical events and preceding local minima differ significantly, a Paired Samples t-Test between the synchro-
nization values of all electrode pairs at these time points were performed, using IBM SPSS Statistics 24, as shown in Tab. 8.

It can be shown that the mean differences between local synchronization maxima corresponding to the musical events and local synchronization minima preceding musical events are significant for all tested groups. The local synchronization maxima corresponding to the first three musical events (seconds 58, 93 and 139) differ with a very high effect, according to Cohens correlation coefficient, the lowest effect can be observed at the musical event at second 215.

In case of varying the 16-bars metrical structure, local maxima the 185th second is particularly noteworthy, since in the musical piece the drop of the bass sets in too late at this 185th second, in contrast to the 16-bars metrical structure the piece is composed of throughout. Relative to the expected beginning of the next musical form part, the bass starts too late. However, the curve showing the correlation reaches its local maximum after 16 bars, remaining at the same level until the drop starts, and does not decline until after.

IV Discussion

The results show that global neural synchronization between different brain regions in the gamma-band range increases before musical high-level events occur, and decreases afterwards. Paired Samples t-Test analysis shows significant differences between synchronization maxima corresponding to the defined musical events and preceding synchronization minima, with a strong effect for 5 of 6 tests.

Since the perception of the musical form is related to a multiple of cortical processes, including timing and expectation as well as Gestalt formation and structured attention, it is hard to determine exactly what modulates large-scale synchronized neural activity while listening to a piece of music.

Since synchronization analysis is performed with a dataset grand-averaged over 25 subjects and 75 recordings in total, the synchronized neural activity must be phase-locked to the stimulus, and must be the same in all subjects. The shown synchronization can therefore be seen as a perceptual process and not as an individual experience of the subjects.

Table 3: Results of paired t-test between local synchronization maxima and preceding local minima.

| ME time | Local maxima | Local minima | Paired Samples Test |
|---------|--------------|--------------|---------------------|
| Time    | Mean SD      | Time Mean SD | t df Sig. 2-tailed r according to Cohen |
| 58      | 57 0.01 0.33 | 17 0.55 0.32 | -37.93 1023 p<.001 0.76 |
| 93      | 95 0.08 0.41 | 70 0.63 0.28 | -36.42 1023 p<.001 0.75 |
| 139     | 135 0.02 0.41 | 109 0.59 0.33 | -35.28 1023 p<.001 0.74 |
| 185     | 176 0.00 0.01 | 153 0.46 0.02 | -27.81 1023 p<.001 0.66 |
| 215     | 228 -0.01 0.01 | 207 0.10 0.01 | -10.24 1023 p<.001 0.30 |
| 246     | 255 -0.00 0.36 | 238 0.32 0.39 | -21.70 1023 p<.001 0.56 |

Since all subjects have experience with Tech-House music, and have therefore implicit knowledge about the structure of the genre44, expectations about the high-level structure of the piece, the musical form, are generated by listening to a piece belonging to the genre. Since the form of this genre is pretty straightforward (16-bar structure), the time points of the musical events are predictable. By counting bars it would be possible for a trained listener to predict the occurrence of a musical event very exactly. Since the task for subjects was just to listen, predictions made were probably not that exact, and by this it can be explained why local maxima differ slightly from time points calculated by the spectral centroid, but were at a maximum level around these time points.

On a neural level, the cognitive processes underlying the perception of musical form, expectation, and feature integration or Gestalt perception, are associated with large-scale neural synchronization. Besides that, attention modulates neural activity independent of the specific task. Several authors formulated a Dynamic Attending Theory that attention related to music is not equally distributed, but rather periodic. In that context it is reasonable that attention is channeled towards the predictable musical events on the level of musical form, and therefore supports the cognitive and perceptual processes underlying the perception of musical form by stronger modulation of synchronized neural activity.

References

[1] B. J. Baars. Global workspace theory of consciousness: toward a cognitive neuroscience of human experience. In S. Laureys, editor, The Boundaries of Consciousness, volume 150 of Progress in Brain Research, pages 45–53. Elsevier professional, s.l., 2006.
[2] R. Bader. Nonlinearities and Synchronization in Musical Acoustics and Music Psychology. Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.
[3] R. Bader. Cochlear spike synchronization and neuron coincidence detection model. Chaos (Woodbury, N.Y.), 28(2):023105, 2018.
[4] R. Bader, M.-K. Dietz, P. Elvers, M. Elias, and N. Tolkien. Foundation of a syllogistic music the-
ory. In R. Bader, editor, *Musical Acoustics, Neurocognition and Psychology of Music / Musikalische Akustik, Neurokognition and Musikpsychologie*, Hamburger Jahrbuch für Musikwissenschaft, pages 177–196, 2009.

[5] J. Bhattacharya, H. Petsche, and E. Pereda. Long-range synchrony in the gamma band: Role in music perception. *The Journal of Neuroscience*, 21(16):6329–6337, 2001.

[6] A. S. Bregman. *Auditory scene analysis: the perceptual organization of sound*. MIT Press, Cambridge and Mass. [u.a.], 1990.

[7] C. V. Buhusi and W. H. Meck. What makes us tick? functional and neural mechanisms of interval timing. *Nature reviews. Neuroscience*, 6(10):755–765, 2005.

[8] C. V. Buhusi and W. H. Meck. Relativity theory and time perception: single or multiple clocks? *PloS one*, 4(7):e6268, 2009.

[9] S. Burnham. Form. In T. S. Christensen, editor, *The Cambridge history of Western music theory*, pages 880–906. Cambridge Univ. Press, Cambridge, 2006.

[10] J. Cohen. A power primer. *Psychological bulletin*, 112(1):155–159, 1992.

[11] L. Davidova, S. Újvári, and Z. Nédá. Sync or antisync – dynamical pattern selection in coupled self-sustained oscillator systems. *Journal of Physics: Conference Series*, 510:012009, 2014.

[12] P. Dayan, G. E. Hinton, R. M. Neal, and R. S. Zemel. The helmholtz machine. *Neural Computation*, 7(5):889–904, 1995.

[13] S. Dehaene, J.-P. Changeux, and L. Naccache. The global neuronal workspace model of conscious access: From neuronal architectures to clinical applications. In S. Dehaene and Y. Christen, editors, *Characterizing Consciousness: From Cognition to the Clinic?*, Research and Perspectives in Neurosciences, pages 55–84. Springer-Verlag Berlin Heidelberg, Berlin, Heidelberg, 2011.

[14] I. Deliège and M. Mélen. Cue abstraction in the representation musical form. In I. Deliège and J. A. Sloboda, editors, *Perception and cognition of music*, pages 387–412. Psychology Press, Hove, 2014.

[15] D. Deutsch. *The psychology of music*. Academic Press series in cognition and perception. Academic, Oxford, 3rd ed. edition, 2013.

[16] A. K. Engel, P. Fries, and W. Singer. Dynamic predictions: oscillations and synchrony in top-down processing. *Nature reviews. Neuroscience*, 2(10):704–716, 2001.

[17] A. K. Engel and W. Singer. Temporal binding and the neural correlates of sensory awareness. *Trends in Cognitive Sciences*, 5(1):16–25, 2001.

[18] W. J. Freeman. Mechanism and significance of global coherence in scalp eeg. *Current Opinion in Neurobiology*, 31:199–205, 2015.

[19] W. J. Freeman and R. Quiño Quiroga. Imaging brain function with EEG: Advanced temporal and spatial analysis of electroencephalographic signals. Springer, New York, 2013.

[20] P. Fries. Neuronal gamma-band synchronization as a fundamental process in cortical computation. *Annual review of neuroscience*, 32:209–224, 2009.

[21] K. Friston and Friston Dimonic A. A free energy formulation of music generation and perception: Helmholtz revisited. In R. Bader, editor, *Sound - perception - performance*, Current Research in Systematic Musicology, pages 43–69. Springer, Cham [u.a.], 2013.

[22] K. Friston, J. Kilner, and L. Harrison. A free energy principle for the brain. *Journal of physiology, Paris*, 100(1–3):70–87, 2006.

[23] K. J. Friston and K. E. Stephan. Free-energy and the brain. *Synthese*, 159(3):417–458, 2007.

[24] J. Gibbon. Scalar expectancy theory and weber’s law in animal timing. *Psychological Review*, 84(3):279–325, 1977.

[25] J. Gibbon, R. M. Church, and W. H. Meck. Scalar timing in memory. *Annals of the New York Academy of Sciences*, 423:52–77, 1984.

[26] C. M. Gray and W. Singer. Stimulus-specific neuronal oscillations in orientation columns of cat visual cortex. *Proceedings of the National Academy of Sciences of the United States of America*, 86(5):1698–1702, 1989.

[27] R. Guevara Erra, J. L. Perez Velazquez, and M. Rosenblum. Neural synchronization from the perspective of non-linear dynamics. *Frontiers in computational neuroscience*, 11:98, 2017.

[28] R. Holson, J. F. Bowyer, P. Clausing, and B. Gough. Methamphetamine-stimulated striatal dopamine release declines rapidly over time following microdialysis probe insertion. *Brain Research*, 739(1–2):301–307, 1996.

[29] D. Huron. *Sweet anticipation: Music and the psychology of expectation*. A Bradford book. MIT Press, Cambridge, Mass., 2006.

[30] D. Huron and E. H. Margulis. Musical expectancy and thrills. In P. N. Juslin and J. Sloboda, editors, *Handbook of music and emotion*, Series in affective science, pages 575–604. Oxford University Press, Oxford, 2012.
[31] N. Ille, P. Berg, and M. Scherg. Artifact correction of the ongoing eeg using spatial filters based on artifact and brain signal topographies. *Journal of clinical neurophysiology: official publication of the American Electroencephalographic Society*, 19(2):113–124, 2002.

[32] P. Janata and H. Petsche. Spectral analysis of the eeg as a tool for evaluating expectancy violations of musical contexts. *Music Perception: An Interdisciplinary Journal*, 10(3):281–304, 1993.

[33] H. H. Jasper. The ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology*, 10:371–375, 1958.

[34] P. Jiruska, M. de Curtis, J. G. R. Jefferys, C. A. Schevon, S. J. Schiff, and K. Schindler. Synchronization and desynchronization in epilepsy: controversies and hypotheses. *The Journal of physiology*, 591(4):787–797, 2013.

[35] M. R. Jones, H. Moynihan, N. MacKenzie, and J. Puente. Temporal aspects of stimulus-driven attenting in dynamic arrays. *Psychological Science*, 13(4):313–319, 2002.

[36] P. X. Joris, L. H. Carney, P. H. Smith, and T. C. Yin. Enhancement of neural synchronization in the anteroventral cochlear nucleus. i. responses to tones at the characteristic frequency. *Journal of neurophysiology*, 71(3):1022–1036, 1994.

[37] P. X. Joris, P. H. Smith, and T. C. Yin. Enhancement of neural synchronization in the anteroventral cochlear nucleus. ii. responses in the tuning curve tail. *Journal of neurophysiology*, 71(3):1037–1051, 1994.

[38] J. A. S. Kelso. *Dynamic patterns: The self-organization of brain and behavior*. A Bradford book. MIT Press, Cambridge, Mass., paperback ed. edition, 1997.

[39] S. Koelsch, M. Rohrmeier, R. Torrecuso, and S. Jentschke. Processing of hierarchical syntactic structure in music. *Proceedings of the National Academy of Sciences of the United States of America*, 110(38):15443–15448, 2013.

[40] C. L. Krumhansl and R. N. Shepard. Quantification of the hierarchy of tonal functions within a diatonic context. *Journal of Experimental Psychology: Human Perception and Performance*, 5(4):579–594, 1979.

[41] E. Kurth. *Musikpsychologie*. Hesse, Berlin, 1931.

[42] E. W. Large, J. A. Herrera, and M. J. Velasco. Neural networks for beat perception in musical rhythm. *Frontiers in systems neuroscience*, 9:159, 2015.

[43] M. Leman. *Music and schema theory : cognitive foundations of systematic musicology ; with 101 figures*. Springer series in information sciences. Springer, Berlin [u.a.], 1995.

[44] F. Lerdahl and R. Jackendoff. *A generative theory of tonal music*. The MIT Press series on cognitive theory and mental representation. MIT Press, Cambridge, Mass., 4. print edition, 1990.

[45] S. J. Luck. *An introduction to the event-related potential technique*. MIT Press, 2014.

[46] L. Melloni, C. Molina, M. Pena, D. Torres, W. Singer, and E. Rodriguez. Synchronization of neural activity across cortical areas correlates with conscious perception. *Journal of Neuroscience*, 27(11):2858–2865, 2007.

[47] L. B. Meyer. *Emotion and meaning in music*. Univ. of Chicago Press, Chicago, 1956.

[48] T. Mima, T. Oluwatimilehin, T. Hiraoka, and M. Hallet. Transient interhemispheric neuronal synchrony correlates with object recognition. *The Journal of Neuroscience*, 21(11):3942–3948, 2001.

[49] P. S. Nazemi and Y. Jamali. On the influence of structural connectivity on the correlation patterns and network synchronization. *Frontiers in computational neuroscience*, 12:105, 2018.

[50] C. Neuhaus. Processing musical form: Behavioural and neurocognitive approaches. *Musicae Scientiae*, 17(1):109–127, 2013.

[51] D. Nikolić, P. Fries, and W. Singer. Gamma oscillations: precise temporal coordination without a metronome. *Trends in Cognitive Sciences*, 17(2):54–55, 2013.

[52] A. Nowak, R. R. Vallacher, M. Zochowski, and A. Rychwalska. Functional synchronization: The emergence of coordinated activity in human systems. *Frontiers in psychology*, 8:945, 2017.

[53] M. Owen and M. P. Guta. Physically sufficient neural mechanisms of consciousness. *Frontiers in systems neuroscience*, 13:24, 2019.

[54] E. R. Palacios, T. Isomura, T. Parr, and K. Friston. The emergence of synchrony in networks of mutually inferring neurons. *Scientific reports*, 9(1):6412, 2019.

[55] J. Pastor, R. G. de Sola, and G. J. Hyper-synchronization, de-synchronization, synchronization and seizures. In D. Stevanovic, editor, *Automated Non-Invasive Identification and Localization of Focal Epileptic Activity by Exploiting Information Derived from Surface EEG Recordings*. INTECH Open Access Publisher, 2012.

[56] M. T. Pearce and G. A. Wiggins. Auditory expectations: the information dynamics of music perception and cognition. *Topics in cognitive science*, 4(4):625–652, 2012.
A. Pérez, M. Carreiras, and J. A. Duñabeitia. Brain-to-brain entrainment: EEG interbrain synchronization while speaking and listening. *Scientific reports*, 7(1):4190, 2017.

H. Petsche, K. Linder, P. Rappelsberger, and G. Gruber. The EEG: An adequate method to concretize brain processes elicited by music. *Music Perception: An Interdisciplinary Journal*, 6(2):133–159, 1988.

S. M. Reppert and D. R. Weaver. Coordination of circadian timing in mammals. *Nature*, 418(6901):935–941, 2002.

H. Riemann. *Präludien und Studien gesammelte Aufsätze zur Aesthetik, Theorie und Geschichte der Musik*. Musikalische Studien. Kraus, Nendeln, reprint [d. ausg. 1895 u. 1900] edition, 1976.

E. Rodriguez, N. George, J. P. Lachaux, J. Martinierie, B. Renault, and F. J. Varela. Perception’s shadow: long-distance synchronization of human brain activity. *Nature*, 397(6718):430–433, 1999.

L. Rothfarb. Energetics. In T. S. Christensen, editor, *The Cambridge history of Western music theory*, pages 927–955. Cambridge Univ. Press, Cambridge, 2006.

E. Salinas and T. J. Sejnowski. Correlated neuronal activity and the flow of neural information. *Nature reviews. Neuroscience*, 2(8):539–550, 2001.

A. Schoenberg, editor. *Fundamentals of musical composition*. Faber Faber, London, 1967.

C. E. Seashore. *Psychology of music*. McGraw-Hill, New York, London, 1938.

R. Snoman. *Dance music manual: Tools, toys and techniques. - Previous ed.: 2004. - Accompanying CD-ROM includes audio examples in mp3 form. - Includes index*. Focal, Amsterdam, 2nd ed. edition, 2009.

J. S. Snyder and E. W. Large. Gamma-band activity reflects the metric structure of rhythmic tone sequences. *Brain research. Cognitive brain research*, 24(1):117–126, 2005.

C. Tallon, O. Bertrand, P. Bouchet, and J. Pernier. Gamma-range activity evoked by coherent visual stimuli in humans. *European Journal of Neuroscience*, 7(6):1285–1291, 1995.