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Complexity judgments as a measure of event salience in musical rhythms

Olivia Ladinig & Henkjan Honing

Music Cognition Group

Institute for Logic, Language, and Computation

University of Amsterdam

Contact info:

Olivia Ladinig

School of Music

1866 College Road

Ohio State University

Columbus, OH 43210 USA

E: [olivia.ladinig@gmail.com](mailto:olivia.ladinig@gmail.com)

I: [www.olivialadinig.com](http://www.olivialadinig.com)

### **Abstract**

This study investigates potential differences between musicians and non-musicians in their perception of meter. Listeners with a variety of musical backgrounds were asked to judge the complexity of rhythms with 4/4 time signature in a Web-based perception experiment ( $N = 101$ ). The complexity judgments were used to derive salience values for each position in the rhythms. Both groups showed very similar judgments regarding the influence of the levels of metrical (hierarchical) processing. Further, both groups displayed an influence of the absolute position of an event in a bar (serial position effect). Listeners in both groups perceived a rhythm as more complex when syncopation occurred on an early beat of a bar than when syncopation occurred on the last beat (primacy effect). This primacy effect could be observed on the subbeat level as well, and additionally, a rise in salience for events at the end of a bar was found (recency effect). We propose to update the Longuet-Higgins model of syncopation with these empirically derived values.

## Complexity judgments as a measure of event salience in musical rhythms

Listener's expectations influence their perception, and in the case of musical rhythm, expectations exist about *when* an event will occur. The expectations are not the same for every event, and some events will be more and others less expected. Some events are expected very strongly, and this expectation is seen as being the basis for *beat induction* - a process in which a regular isochronous pattern (the beat) is activated internally while listening to music (for a recent overview see Patel, 2008). The *beat* (also termed *pulse* or *tactus*) is essential for time-keeping in music performance and affects the processing, coding, and appreciation of temporal patterns. Beats are positions in a rhythm that often coincide with spontaneous rhythmic behavior, like clapping hands or stomping while dancing (London, 2004; Parncutt, 1994), and there is a preference for beats to occur at intervals of about 600 msec. The induced beat underlies the perception of tempo and is the basis of temporal coding in music. Furthermore, it determines the relative importance of notes in the melodic and harmonic structure of music (Desain & Honing, 1999; Repp, 1992). Events between beats are subordinate to them, and are perceived as the weak events of a rhythm, in this paper referred to as *subbeats*. In most common Western rhythms, subbeats divide inter-beat intervals into parts whose durations form simple ratios such as 1:1, 2:1, or 3:1.

When at least two levels of metric structure are active during perception one speaks of *metric processing* (London, 2004; Yeston, 1976). The *event salience*, or sometimes termed metric salience, of a position within a pattern refers to the structural level the position is assigned to, which is an indicator of its importance relative to other positions within a certain metrical unit (e.g., bar). The tendency to creating a structure with different levels of salience can be observed even with very simple rhythms, such as the ticking of a clock or metronome, where every other event (more rarely, every third or

fourth) often receives a metric accent (Bolton, 1894; Brochard, Abecasis, Potter, Ragot, & Drake, 2003). This phenomenon is termed *subjective rhythmisation* (Fraisse, 1963; Bolton, 1894; Szelag, Kowalska, Rymarczyk, & Pöppel, 1998; Szelag, von Steinbüchel, Reiser, Gilles de Langen, & Pöppel, 1996), or more recently *subjective metricisation* (London, 2004). In general, events in positions that are perceived as salient are memorized and recalled easier, attract primary attention, are more expected to occur, and, when they are absent, lead to the impression of rhythmic complexity (Fitch & Rosenfeld, 2007; Pressing, 2002). Different theoretical models of meter perception make alternative predictions about the structure and the depth of the metric hierarchy of a rhythmic pattern.

#### *Musicians vs non-musicians*

There exist several conflicting theories about the influence of formal musical training on the perception of metric structure. Palmer and Krumhansl (1990) and Jongsma, Desain, and Honing (2004) reported differences between musicians and non-musicians. Palmer and Krumhansl analyzed goodness-of-fit judgments for single events presented in 16 positions within a 4/4 metric context; Jongsma et al. collected ERP as well as goodness-of-fit data for single events presented in seven positions within a duple and a triple metrical context. Musical training seemed to enhance depth of processing, allowing for the perception of more than two metrical levels at the same time. Palmer and Krumhansl found periodicities in the responses of non-musicians only for those positions that constitute the beat level, whereas musicians showed periodicities in their responses on lower metrical levels as well, displayed in a hierarchical structure of the positions between two beats. Results of Jongsma and colleagues are in line with those findings, but further suggest that non-musicians process temporal patterns in a more serial (as opposed to hierarchical) fashion, with a higher expectation for events to occur at the beginning of a bar.

Recently, several studies have indicated that non-musicians are more musically competent than previously thought. For example, Bigand and Poulin-Charronnat (2006), and Honing and Ladinig (2009) found evidence that if tasks and modes of responding do not require specialized training, differences between musicians and non-musicians tend to disappear.

### *Rhythmic complexity and syncopation*

Several researchers have attempted to define and formalize rhythmic complexity (Essens, 1995; Pressing, 2002; Shmulevich & Povel, 2000; for an overview see Streich, 2007), but there has been little empirical validation of their models and little agreement regarding definitions of crucial concepts. In this study, perceived rhythmic complexity is thought of as being approximated by the concept of *syncopation*. Syncopation is the music-theoretical term for a moment in the music where there is a strong metric expectation that is not confirmed with a note onset. Some authors refer to this as a *loud rest* (London, 1993). A formalization of syncopation was proposed by Longuet-Higgins and Lee (1984), and is referred to as the *L-model* here. It recursively breaks down a rhythmic pattern of specific length into equal subparts, and assigns to every event a weight relating to its metrical level, assuming a metric hierarchy of maximal depth (see description of model A in the following section). For example, for a typical bar in Western music, with a 4/4 time signature and the smallest note being a 16th note, this would imply five distinct levels of event salience (e.g., Lerdahl & Jackendoff, 1983; Longuet-Higgins & Lee, 1984). The L-model assumes that syncopation occurs if a rest or a tied note is at a higher metrical level than the immediately preceding sounding note, with the strength of the syncopation being the difference between the metrical levels of the note and the rest.

There exist two data-sets of rhythmic complexity judgments in the literature. Shmulevich and Povel (2000) collected judgments of musicians, whereas Essens (1995)

collected judgments of both musicians and non-musicians. The L-model accounted fairly well for the Shmulevich and Povel data, as shown by Smith and Honing (2006). For the data collected by Essens, such correlations with model predictions have not yet been reported.

The current paper first describes testable hypotheses derived from four models that differ in their assumptions regarding the salience values they assign to each metric position of a bar. Subsequently we describe test results that enabled us to derive empirically based event salience values for the average listener as well as for musicians and non-musicians separately, consisting of a metrical component and of a new component reflecting the serial position of events. We obtained these data by collecting complexity judgments about regular and syncopated rhythms.

By substituting our empirically derived salience values for the salience values assigned by the standard L-model, we generated two variants of the L-model, one for musicians and one for non-musicians. Since the new salience values are based on judgments of complexity rather than of syncopation (unlike the L-model), the resulting model variants may be suitable for specifying the complexity of a rhythm, which is here seen as superordinate to the syncopatedness of a rhythm.

### **Theoretical models**

In this section we present four theoretical models that will enable us to construct hypotheses. The models, some of which are derived from the literature, vary in their degree of explicitness regarding the level of formalization. We also describe an empirical method for testing the relevant hypotheses. A visual representation of the four models can be found in Figure 1. The numbers on the vertical axis represent the specified metrical levels; the asterisk indicates which metrical level constitutes the tactus level.

*Model A*

Model A is the L-Model, explained in the previous section. This model assumes that listeners impose as many metrical levels as possible on a rhythm. Empirical evidence for this model as representing the event salience values perceived by musicians comes from Palmer and Krumhansl (1990) and Jongsma et al. (2004). Additionally, Palmer and Krumhansl calculated frequency distributions of event onsets from a corpus of notated Western classical music, and the high correlation of those values with the event salience values perceived by musicians supports the model.

*Model B*

The same two studies (Jongsma et al., 2004; Palmer & Krumhansl, 1990), which support model A with data gathered from musicians, suggest a limited model of metric structure and event salience for non-musicians, which we call model B. As in model A, the values of event salience differ between the beat and the subbeat level, and also above the beat level (i.e., it assumes perception of a most important beat, the downbeat), but all events below the tactus belong to the same metric level and consequently have the same event salience.

*Model C*

Another model suggesting limited perception of metrical levels compared to model A is model C. This model again reflects the differentiation between beats and subbeats, but neglects the hierarchical structure of beats (no most salient beat, i.e., downbeat). Events below the beat level, however, are structured hierarchically and derived by recursive subdivision as in model A. A related formalization has recently been suggested by Gomez, Melvin, Rapaport, and Toussaint (2005), but so far has not been empirically validated.

*Model D*

A fourth model is introduced for the sake of completeness. It depicts a possible representation of the most basic metrical structure (Yeston, 1976), which contains only two different metric levels to which events are assigned: the beat and the subbeat level.

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Insert Figure 1 about here

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### Hypotheses

We restricted this study to duple meter and a constant tempo (600 ms inter-beat interval), and kept the number of notes constant. We used rhythms commonly expressed in a 4/4 time signature, with 16 equally spaced positions of possible event onsets. We will refer to positions 1, 5, 9, and 13 as *beats*, and to all remaining positions as *subbeats*. All subbeats between two beats are considered as belonging to the same *subbeat cluster*.

To evaluate the four models of event salience, we tested the following hypotheses regarding perceived event salience:

**Beat differentiation hypothesis:** This hypothesis (based on models A and B) predicts differences in perceived event salience among the events that constitute the beat, showing a weak-strong-weak pattern following an initial downbeat. The corresponding null hypothesis (based on models C and D) predicts no differences in salience judgments given to beat events.

**Subbeat differentiation hypothesis:** This hypothesis (based on models A and C) predicts differences in perceived event salience among the events in each subbeat cluster, showing a weak-strong-weak pattern. The corresponding null hypothesis (based on models B and D) predicts no differences in the salience judgments for subbeats within a cluster.

**Subbeat cluster differentiation hypothesis:** This hypothesis is not based on any of

the introduced models, but derives from an empirical finding by Jongsma et al. (2004), which predicts differences in salience judgments due to the position of the subbeat cluster within the bar (serial position effect). Events at the beginning of a bar may be perceived as more salient than events in the remainder of a bar. The corresponding null hypothesis (based on models A to D) predicts no such differences.

Beat/Subbeat relation hypothesis: This hypothesis (based on all models) predicts differences in perceived event salience between the beat and the subbeat level, with the beat positions receiving higher salience than the subbeat positions. The corresponding null hypothesis (not expressed in any of the introduced models) predicts no differences, and respective results would not only converse models of meter induction, but also models of beat induction.

Expertise hypothesis: Musicians are predicted to have an elaborate metrical hierarchy (cf. model A), leading to differentiation of beats as well as subbeats. Non-musicians are predicted to show a less developed metrical structure in their salience judgments (cf. models B, C, or D).

## Methods

The purpose of the experiment was to collect relative complexity judgments about regular and syncopated rhythms. An online Web-based setup was used because of its advantages of versatility and ecological validity of the results. Web-based experiments can potentially reach a much larger, more varied and intrinsically motivated participant pool. While Web-based experiments may interfere in ways that are different from a lab-based setup, the key problems of how to control for attention and how to make sure that participants act as instructed, is not essentially different from experiments that are performed in a laboratory. Furthermore, it is important to stress that if an effect is found, despite the limited control in Web-based experiments over the home environment and the

technological variance caused by the Internet, then the argument for that effect and its generalizability is even stronger (see Honing & Ladinig, 2008; Honing & Reips, 2008, for an elaborate discussion on Web-based versus lab-based experiments).

### *Participants*

Invitations were sent to various mailing lists, online forums, and universities, to reach a wide variety of respondents. From the 200 initial respondents, we excluded 29% because they did not finish the experiment or did it too quickly. The remaining participants ( $N = 142$ ) were between 17 and 63 years old ( $Mode = 20$ ,  $M = 32.7$ ,  $SD = 11.73$ ) and had various musical backgrounds, ranging from no musical training up to 30 years of training. After excluding participants who could not clearly be classified as either being a musician or a non-musician (see below for the criteria), 101 participants remained in the sample, which were between 17 and 63 years old ( $Modes = 20$  and  $30$ ,  $M = 34.2$ ,  $SD = 12.25$ ) and had a range of years of musical training from zero up to 30 years.

### *Equipment*

Rhythmic stimuli were constructed using custom software and converted to MPEG-4 file format to guarantee consistent sound quality on different computer platforms and to minimize download time. The sounds were drum samples (“bongos”) taken from the EZdrummer EZX Latin Percussion sample set (“Toontrack”).

### *Stimuli*

Sixteen rhythms, either syncopated or regular according to the definition by Longuet-Higgins and Lee (1984), were constructed (S01 - S16) and combined into seven stimulus sets, each consisting of two to four stimuli (see Figure 2). Note that one and the same rhythm can be used in multiple stimulus sets. The stimuli can be found on <http://www.musiccognition.nl/e4-stimuli>.

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Insert Figure 2 about here

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Small sets of stimuli were used for two reasons: First, to get clear indications of the differences in perceived complexity for a stimulus relative to certain other stimuli, as opposed to using judgments relative to the whole range of rhythms tested. And second, to employ scales that are being less prone to ceiling or floor effects. Each rhythm was repeated four times without a break. Two different sounds were used in alternation for the repetitions. The inter-onset interval (IOI) of consecutive 16th notes was 125 ms. The two sounds were drum sounds from the same instrument (i.e., low and high bongo) with a steep attack (30 ms) and a tail of up to 300 ms. The reason for changing the sounds between repetitions is to preserve the duration of the pattern in a natural and musical way. The two drum sounds are chosen to be from the same instrument. The reason was that the average listener attributes such stimuli to the same instrument (McAdams, 1999), allowing for a more realistic and ecologically valid listening experience. The first position in each rhythm was marked with a louder sound to prevent listeners from perceiving it as an upbeat.

Stimulus sets 1-4 tested the structure of event salience on the subbeat level, according to the subbeat differentiation hypothesis, for subbeat clusters 1, 2, 3, and 4, respectively. Each set contained three rhythms. They had events on every beat and on two of the three subbeats within one inter-beat interval. Listeners had to compare the three stimuli within each set with regard to their perceived complexity.

Stimulus set 5 tested whether or not there are differences in event salience on the beat level, according to the beat differentiation hypothesis. Three stimuli were constructed that had events in only every other metrical position (i.e., a beat with simple subdivisions). One of the three beat events following the initial downbeat was omitted.

Listeners were asked to compare the rhythms according to their perceived complexity. Stimulus set 6 was intended to shed light on whether the serial position of an invariant subbeat cluster within the rhythm affected perceived complexity, according to the subbeat cluster differentiation hypothesis. Listeners compared four stimuli, in which the same rhythmic pattern constructed of subbeats within one cluster (second and third subbeats only) occurred after beat 1, 2, 3, and 4, respectively.

Finally, stimulus set 7 provided a direct comparison of syncopation at the beat and subbeat levels. Both patterns in this set had events in the 1st, 2nd and 4th beat positions, and in the second and third subbeat position of subbeat cluster 3. The difference was that one pattern had an event on the third beat, and none on the first position of subbeat cluster 3 (subbeat syncopation), and the other pattern had no event on the third beat, but one on the first position of subbeat cluster 3 (beat syncopation).

### *Procedure*

Participants were invited to visit a Web page of the experiment. They were instructed by a short screen-cast, showing examples of the experiment while the instructions were narrated, with an option to access written instructions as well. The instructions were as follows:

In this experiment we are interested in your judgments on rhythmic complexity.

We will present you seven boxes containing 2 to 4 rhythms each, and we ask you to make a judgment on the complexity of the rhythms in relation to the other rhythms within the same box (referred to as ‘comparisons’).

Rhythmic complexity can be understood as a feeling of rhythmical tension, the violation of your expectation, a deviation of a regular rhythmic pattern, or non-predictability of events.

For each of the seven sets of comparisons we ask you to listen through the

whole sound samples, and, according to your perception, either 1) mark all rhythms in a box to be of equal complexity, or 2) rate their complexity on a 2 to 4 point scale (depending on the number of rhythms) where a low number indicates low complexity and a high number high complexity.

Every rhythm is repeated four times with the percussion sounds varying for every repetition. All rhythms are played in the same tempo. You can listen to the rhythms as often as you like before making the judgment.

N.B. There is no right or wrong answer; we are simply interested in your subjective, personal judgments.

The participants made their complexity judgments on a rating scale that had as many increments as there were rhythms to compare in a set. The sets as well as the rhythms within each set were shown on the screen in random order. At the end of the test we asked for information about musical experience and age. We left some space for comments and feedback. The whole task typically took about 10 minutes to complete. We recorded the total time from the moment the subject started the experiment until the response form was sent, to ensure that the subject listened to all stimuli.

### **Data analysis**

The responses were tabulated for further analysis with POCO (Honing, 1990), music software for symbolic and numerical analyses, and SPSS (Version 11) for statistical analyses.

#### *Grouping by musical experience*

We constructed two categories, musicians and non-musicians, and assigned participants to either of those groups. The category of musicians ( $N = 57$ ) consisted of subjects that had between eight and 30 years of musical training ( $M = 15.9$  years) that

had started when they were between three and eight years old ( $M = 6.5$  years). The non-musicians ( $N = 44$ ) had either no formal musical training at all or had started after the age of eight ( $M = 17.2$  years) and received training for a maximum of four years ( $M = 2.6$ ). The remaining participants were excluded from the analyses.

## Results

We performed separate repeated measure ANOVAs for each of our four hypotheses: beat differentiation hypothesis, the subbeat differentiation hypothesis, the subbeat cluster differentiation hypothesis, and the beat/subbeat relation hypothesis. Mean values and standard deviations for all stimuli are reported in Table 1.

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Insert Table 1 about here

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### *Beat differentiation hypothesis*

To test the beat differentiation hypothesis, judgments given to the stimuli of set 5 were compared. The hypothesis predicts a weak-strong-weak pattern of the three beats, with differences between the second and the third and the third and the fourth beat, but no differences between the second and the fourth beat. In other words, S14 was predicted to be judged as more complex than S13 and S15. The null hypothesis predicts no differences in judgments regarding the three stimuli. A 3 x 2 repeated measures ANOVA with position as the within-subject variable and expertise as the between-subject variable showed a significant effect of position,  $F(2, 198) = 14.853$ ,  $p < .001$ , but no interaction of position and expertise. Repeated-measures t-tests (with a modified Bonferroni procedure for error correction) showed that S15 had significantly lower values than both S13 and S14,  $t(100) = 4.728$ ,  $p < .001$  and  $t(100) = 3.983$ ,  $p < .001$ , respectively, with no

difference between S13 and S14. These results indicate a strong-strong-weak pattern, and support none of the introduced theoretical models (see Figure 3).

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Insert Figure 3 about here

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### *Subbeat differentiation hypothesis*

The subbeat differentiation hypothesis suggests a weak-strong-weak pattern, regardless of the position of the subbeat cluster within the rhythm. That is, in stimulus sets 1-4, each central stimulus was expected to receive higher ratings of complexity than the two corresponding outer stimuli. In order to test this hypothesis, a 3x4x2 repeated measures ANOVA was conducted, with event (i.e., position among a subbeat cluster) and cluster (i.e., position of the subbeat-cluster among the whole pattern) as the within-subject variables, and expertise as between-subject variable. The hypothesis predicts a weak-strong-weak pattern for every subbeat cluster. No differences among subbeat cluster were expected. A main effect was found for event,  $F(2, 198) = 74.904$ ,  $p < .001$ . Repeated-measures t-tests (with a modified Bonferroni procedure for error correction) showed that in general, both outer positions received significantly lower values than the central positions,  $t(100) = 10.509$ ,  $p < .001$ , and  $t(100) = 10.080$ ,  $p < .001$ , respectively, with no difference between the outer positions. This result is consistent with the prediction that subbeats within each cluster show a weak-strong-weak pattern.

A main effect was also found for cluster,  $F(3, 297) = 5.705$ ,  $p < .001$ . Repeated-measures t-tests (with a modified Bonferroni procedure for error correction) showed that in general, clusters two and three received lower events than cluster four,  $t(100) = 3.128$ ,  $p = .002$ , and  $t(100) = 3.982$ ,  $p < .001$ , respectively, with no differences with regard to cluster one. This result points to a serial position effect, which we will look at in more detail below.

However, both main effects were qualified by an interaction,  $F(6, 594) = 2.542$ ,  $p = .019$ , showing that the weak-strong-weak pattern was only present in clusters two, three, and four, but that the pattern was more differentiated in the first cluster, showing a weak-strong-medium pattern. This interaction suggests further that there was no effect of cluster when we compare the outer events of each cluster (i.e., the weak events) across clusters, but only when we compare the central events (i.e., the strong events) across clusters. The central event of cluster four received significantly higher values than the central events of clusters two and three,  $p < .001$  and  $.005$ , respectively. The main effect of event was also qualified by an interaction with expertise,  $F(2, 198) = 3.201$ ,  $p = .043$ . Repeated-measures t-tests showed that, in general, the observed weak-strong-weak pattern holds for non-musicians only, and that musicians tend to display a weak-strong-medium pattern. However, after the Bonferroni correction, this effect failed to reach significance (see Figure 4).

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Insert Figure 4 about here

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#### *Subbeat cluster differentiation hypothesis*

The subbeat cluster differentiation hypothesis makes predictions about a serial position effect among the subbeat clusters, with stimuli having omissions at the beginning of a bar being judged as more complex than stimuli with omissions at the end of a bar. This issue was already touched in the analyses about the subbeat differentiation hypothesis above. However, here additional data is presented, coming from judgments to set 6 (S01, S04, S07, and S10). A 4x2 repeated measures ANOVA, with position as within-subject variable and expertise as between-subject variable, showed a significant main effect of position,  $F(3, 297) = 5.116$ ,  $p = .002$ . Repeated-measures t-tests (with a

modified Bonferroni procedure for error correction) showed that position three was judged significantly lower than all other positions (see Figure 5). No differences according to musical expertise were found.

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Insert Figure 5 about here

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### *Beat/Subbeat relation hypothesis*

The beat/subbeat relation hypothesis suggests that an omission in a beat position would lead to higher complexity judgments than an omission in a subbeat position. In stimulus set 7, S16 was predicted to be judged as more complex than S07. This hypothesis was confirmed, with  $F(1, 99) = 1024.714$ ,  $p < .001$ , with no effect of expertise.

### *Conversion of complexity judgments into values of event salience*

Participants had judged perceived complexity of rhythmic stimuli relative to one, two, or three other stimuli within the same stimulus set (see Figure 2). Those ratings were used for the statistical hypothesis testing reported above. To use the data as event salience values for each position in a rhythm (i.e., as values for variants of the L-model), conversions are necessary. Since we did not find significant differences for musicians and non-musicians, we create one set of values that hold for both listener groups. The rhythms in each set can be regarded as differing in the position in which an event is omitted. Consequently, complexity judgments about a rhythmic stimulus are seen here as related to the event salience of the position of the omission. The average judgments of complexity for stimuli 01-12 in the context of stimulus sets 1-4 were taken directly as salience values for each subbeat position in a bar (see Figure 6, Step 1). The judgments given to stimuli in set 6 (where the same subbeat pattern occurred in different positions between beats) were added to each subbeat of the subbeat cluster represented in the stimulus (see Figure

6, Steps 2 and 3). They were treated as weights of each subbeat cluster within the whole measure, but leave the internal structure of each subbeat cluster intact. The resulting values were rescaled to values between 0 and 1. This was done because the judgments of stimulus set 7 indicated that participants perceived a violation of regularity on the beat level as more complex than a violation on the subbeat level. To account for this, the lowest beat position values had to be made higher than the highest subbeat position value (see Figure 6, Step 3). The average judgments to stimuli 13-15 were taken directly as salience values for each beat position (see Figure 6, Step 4). In a last step, subbeats and beats were combined (see Figure 6, Step 5). The resulting values per position (excluding the downbeat) are 2-0.78; 3-0.96; 4-0.83; 5-1.86; 6-0.77; 7-0.92; 8-0.8; 9-1.69; 10-0.68; 11-0.83; 12-0.70; 13-1.33; 14-0.79; 15-1; 16-0.79.

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Insert Figure 6 about here

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## Discussion and Conclusion

In this study we assessed event salience estimates derived from complexity judgments. Contrary to what has been found in some previous studies (Jongsma et al., 2004; Palmer & Krumhansl, 1990), we found musicians and non-musicians to behave similarly in terms of hierarchical processing (see section ‘Metric processing’ below). Additionally, we found substantial serial processing of events (see section ‘Serial processing’ below), again with no differences between musicians and non-musicians. By using musically plausible stimulus patterns rather than probe-tones, and small sets of rhythms to compare, we gave non-musicians a chance to respond in a more natural setting. Skills that are typically very developed in musicians, like the precise subdivision of silent intervals, that can lead to good performance in temporal probe-tone tasks, were not required or in any way helpful in the current experiment.

This is in accordance with a growing body of literature that shows that the performance in these types of listening experiments is not simply a result of formal musical training, but is enhanced, and sometimes even solely influenced, by listening experience (cf. Honing & Ladinig, 2009). For instance, Bigand and Poulin-Charronnat (2006) found musically untrained listeners (i.e. ‘nonmusicians’) to be highly correlated with those of musically trained listeners in their judgements of harmony, suggesting a musical capacity or skill that is acquired through mere exposure to music, without the help of explicit training. Also in the temporal domain several studies support the idea of similar levels of musical skill for both listener groups, such as expressive timing (Honing & Ladinig, 2009) and meter perception (Ladinig, Honing, Háden, & Winkler, 2009) using both behavioral and electrophysiological measurements in an lab-based setting.

Listeners discriminated between subbeats belonging to one subbeat cluster in a hierarchical weak - strong - weak fashion, and showed some metric structuring on the beat level, although not in line with the predictions of any of the models we considered. While the two last beats, positions nine and thirteen, showed the expected strong-weak pattern, the second beat, position five, had a higher salience than expected, and thus has to be considered as a strong beat as well. We assume that a primacy effect comes into play here, which makes it more important for a rhythmic pattern to have events on earlier beats of a bar than on later beats, in order to establish a framework for meter. We consider the results for the beat level as consistent with hierarchical processing of the beat level, since the distribution shows significant differences regarding beat position four, and thus the distribution of beat saliences is clearly not flat (excluding the first beat, which was strongest by definition).

Concerning the variation between subbeat clusters, we found declining salience later in the bar compared to the beginning of the bar (*primacy effect*), and again a strong rise in salience at the end of the bar (*recency effect*). Events at the beginning and the end of a

pattern seemed more important than events in the middle. This effect was shown on the subbeat level, but a primacy effect was also visible on the beat level. Interestingly, these results are in line with results from Jongasma et al. (2004) and (Palmer & Krumhansl, 1990), that showed some serial position effect being active, at least in non-musicians.

In order to construct a model of metrical perception it seems to be appropriate to keep a fully metrical model (see Figure 1, Model A) and add a serial component on top that consists of a primacy effect on the beat as well as the subbeat level, and a recency effect on the subbeat level. These results tempt us to speculate about the nature of processing of temporal information in general. Since we used rhythms that were arguably familiar to our participants, in 4/4 time-signature at a moderate tempo, probably not much cognitive effort had to be expended to relate the stimuli to known musical materials. Thereby, simple heuristic mechanisms could have come into play. Serial processing of temporal information can be seen as a quick way of grasping the structure of a rhythm, without detailed analytical, hierarchical processing.

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## References

- Bigand, E., & Poulin-Charronnat, B. (2006). Are we "experienced listeners"? A review of the musical capacities that do not depend on formal musical training. *Cognition*, *100*, 100-130.
- Bolton, T. (1894). Rhythm. *The American Journal of Psychology*, *6*, 145-238.
- Brochard, R., Abecasis, D., Potter, D., Ragot, R., & Drake, C. (2003). The 'ticktock' of our internal clock: Direct brain evidence of subjective accents in isochronous sequences. *Psychological Science*, *14*, 362-366.
- Desain, P., & Honing, H. (1999). Computational models of beat induction: The rule-based approach. *Journal of New Music Research*, *28*, 29-42.
- Essens, P. (1995). Structuring temporal sequences: Comparison of models and factors of complexity. *Perception and Psychophysics*, *57*, 519-532.
- Fitch, W. T., & Rosenfeld, A. J. (2007). Perception and production of syncopated rhythms. *Music Perception*, *25*, 43-58.
- Fraisse, P. (1963). *The psychology of time*. New York: Harper and Row.
- Gomez, F., Melvin, A., Rapaport, D., & Toussaint, G. T. (2005). Mathematical measures of syncopation. In *Proceedings of BRIDGES: Mathematical connections in art, music, and science* (p. 47-56). Alberta, Canada: Bridges.
- Honing, H. (1990). Poco: An environment for analysing, modifying, and generating expression in music. In *Proceedings of the 1990 International Computer Music Conference* (p. 364-368). San Francisco: Computer Music Association.
- Honing, H., & Ladinig, O. (2008). The potential of the internet for music perception research: A comment on lab-based versus web-based studies. *Empirical Musicology Research*, *3*, 4-7.
- Honing, H., & Ladinig, O. (2009). Exposure influences timing judgments in music. *Journal of Experimental Psychology: Human Perception and Performance*, *35*, 281-288.

- Honing, H., & Reips, U. (2008). Web-based versus lab-based studies: A response to Kendall. *Empirical Musicology Review*, *3*, 73-77.
- Jongsma, M. L. A., Desain, P., & Honing, H. (2004). Rhythmic context influences the auditory evoked potentials of musicians and nonmusicians. *Biological Psychology*, *66*, 129-152.
- Ladinig, O., Honing, H., Háden, G., & Winkler, I. (2009). Probing attentive and pre-attentive emergent meter in adult listeners with no extensive music training. *Music Perception*, *26*, 377-386.
- Lerdahl, F., & Jackendoff, R. (1983). *A generative theory of tonal music*. Cambridge, Mass.: MIT Press.
- London, J. (1993). Loud rests and other strange metric phenomena (or, meter as heard). *Music Theory Online*, *0*.
- London, J. (2004). *Hearing in time: Psychological aspects of musical meter*. New York: Oxford University Press.
- Longuet-Higgins, H. C., & Lee, C. S. (1984). The rhythmic interpretation of monophonic music. *Music Perception*, *1*, 424-441.
- McAdams, S. (1999). Perspectives on the contribution of timbre to musical structure. *Computer Music Journal*, *23*, 85-102.
- Palmer, C., & Krumhansl, C. L. (1990). Mental representations for musical meter. *Journal of Experimental Psychology: Human Perception and Performance*, *16*, 728-741.
- Parncutt, R. (1994). A perceptual model of pulse salience and metrical accent in musical rhythms. *Music Perception*, *11*, 409-464.
- Patel, A. (2008). *Music, language, and the brain*. New York: Oxford University Press.
- Pressing, J. (2002). *Cognitive complexity and the structure of musical patterns*.
- Repp, B. H. (1992). Probing the cognitive representation of musical time: Structural constraints on the perception of timing perturbations. *Cognition*, *44*, 241-81.

- Shmulevich, I., & Povel, D. J. (2000). Measures of temporal pattern complexity. *Journal of New Music Research*, 29, 61–69.
- Smith, L., & Honing, H. (2006). *Evaluating and extending computational models of rhythmic syncopation in music*. New Orleans, LA: International Computer Music Association.
- Streich, S. (2007). *Music complexity: a multi-faceted description of audio content*. Unpublished doctoral dissertation.
- Szelag, E., Kowalska, J., Rymarczyk, K., & Pöppel, E. (1998). Temporal integration in a subjective accentuation task as a function of child cognitive development. *Neuroscience Letters*, 257, 69–72.
- Szelag, E., von Steinbüchel, N., Reiser, M., Gilles de Langen, E., & Pöppel, E. (1996). Temporal constraints in processing of nonverbal rhythmic patterns. *Acta Neurobiologiae Experimentalis*, 56, 215–225.
- Yeston, M. (1976). *The stratification of musical rhythm*. New Haven, Conn.: Yale University Press.

Stimulus	Musicians	Non-musicians	Combined
S01 (SBC1)	1.28 (.526)	1.43 (.625)	1.35 (.573)
S02 (SBC1)	2.12 (.908)	2.07 (.873)	2.10 (.889)
S03 (SBC1)	1.46 (.657)	1.68 (.708)	1.55 (.685)
S04 (SBC2)	1.26 (.518)	1.52 (.698)	1.38 (.614)
S05 (SBC2)	2.07 (.863)	1.84 (.861)	1.97 (.866)
S06 (SBC2)	1.44 (.655)	1.55 (.703)	1.49 (.687)
S07 (SBC3)	1.23 (.464)	1.43 (.661)	1.32 (.564)
S08 (SBC3)	1.95 (.915)	1.91 (.910)	1.93 (.908)
S09 (SBC3)	1.39 (.620)	1.43 (.587)	1.41 (.603)
S10 (SBC4)	1.30 (.566)	1.66 (.745)	1.46 (.671)
S11 (SBC4)	2.26 (.877)	2.34 (.834)	2.30 (.855)
S12 (SBC4)	1.49 (.571)	1.43 (.545)	1.47 (.558)
S13 (B)	1.72 (.840)	2.05 (.914)	1.86 (.884)
S14 (B)	1.65 (.719)	1.75 (.751)	1.69 (.731)
S15 (B)	1.28 (.648)	1.39 (.579)	1.33 (.618)
S01 (BSBC)	1.61 (1.065)	2.02 (1.131)	1.79 (1.107)
S04 (BSBC)	1.51 (.889)	2.02 (.976)	1.73 (.958)
S07 (BSBC)	1.33 (.664)	1.55 (.848)	1.43 (.753)
S10 (BSBC)	1.46 (.927)	2.07 (1.169)	1.72 (1.078)
S16 (BSBR)	1.88 (.331)	1.95 (.211)	1.91 (.286)
S07 (BSBR)	1.00 (.000)	1.00 (.000)	1.00 (.000)

Table 1

*Mean values and standard deviations for the judgments to each stimulus are given for musicians and non-musicians. Abbreviations used for stimuli are taken from Figure 2.*

### Figure Captions

*Figure 1.* Four hypothetical metrical salience profiles. The length of the vertical lines indicate the relative saliences (longer is more salient) of an event in that position within the bar (in 16 grid-points). Metrical levels marked with an asterisk constitute the tactus level.

*Figure 2.* Stimuli. The x-axis indicates the grid position, ‘—’ marks a note/sound, ‘.’ marks a rest/silence

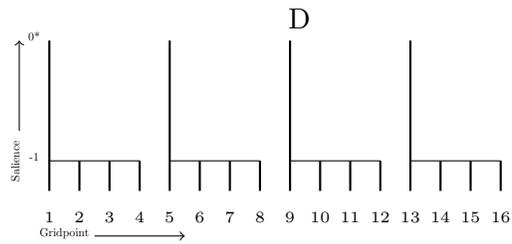
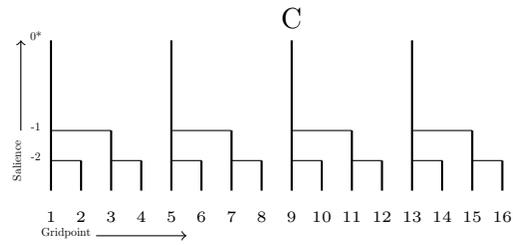
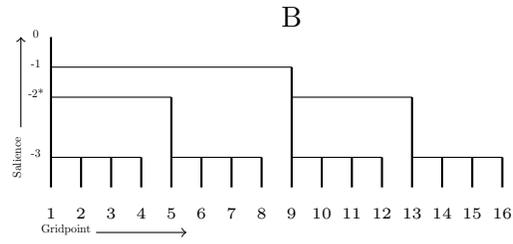
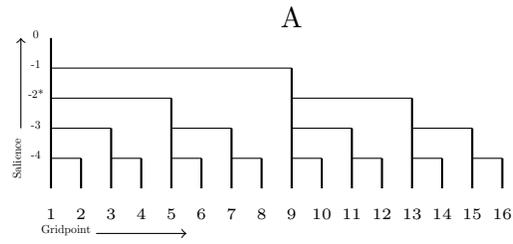
*Figure 3.* Judgments of stimulus set 5. The results suggest an effect of position, but no effect of musical expertise.

*Figure 4.* Judgments of stimulus sets 1-4, for musicians and non-musicians separately.

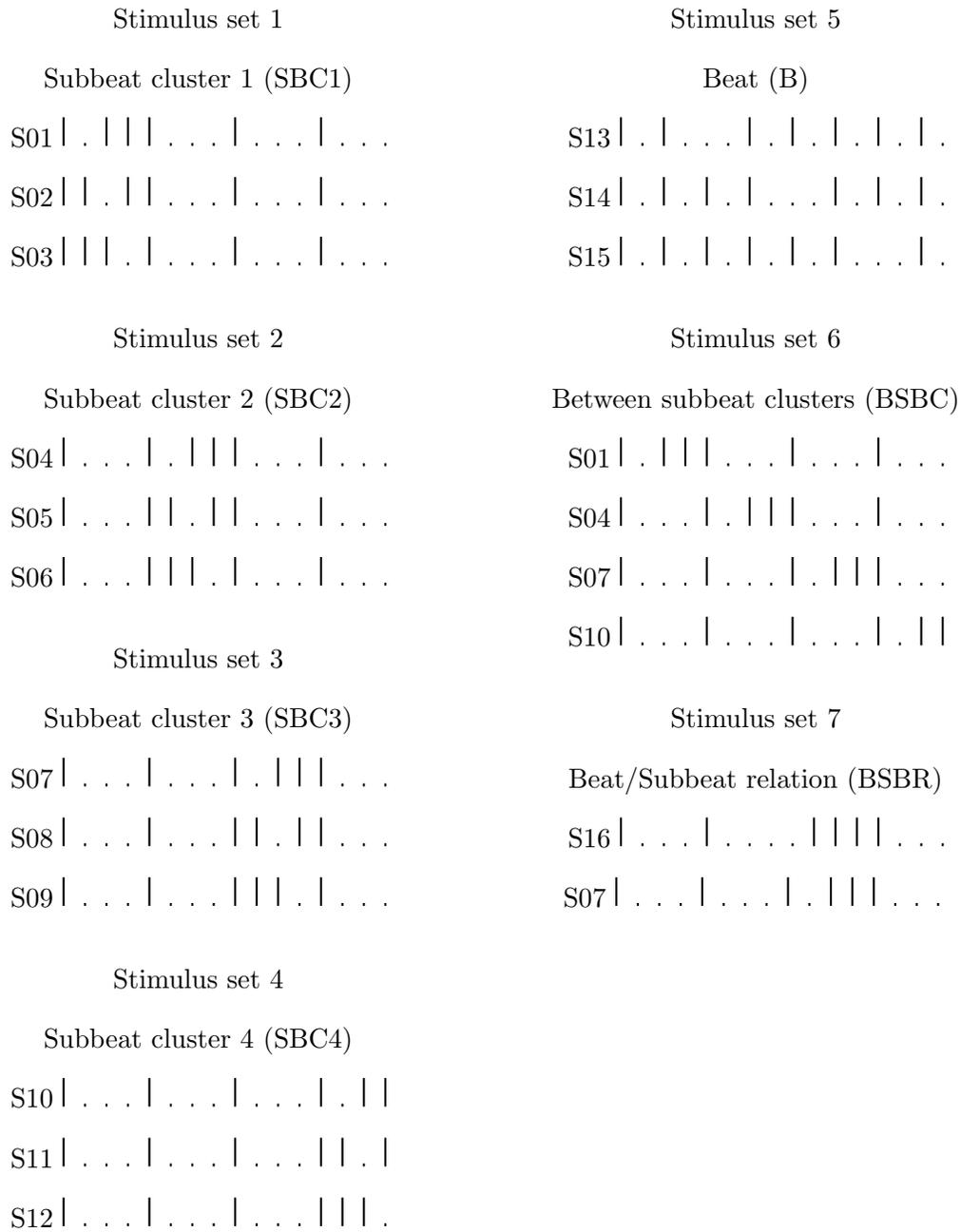
*Figure 5.* Judgments of stimulus set 6, for musicians and non-musicians. Results show lower values for position three compared to all other positions, with no significant differences according to musical expertise.

*Figure 6.* Conversion of complexity judgments into event salience values

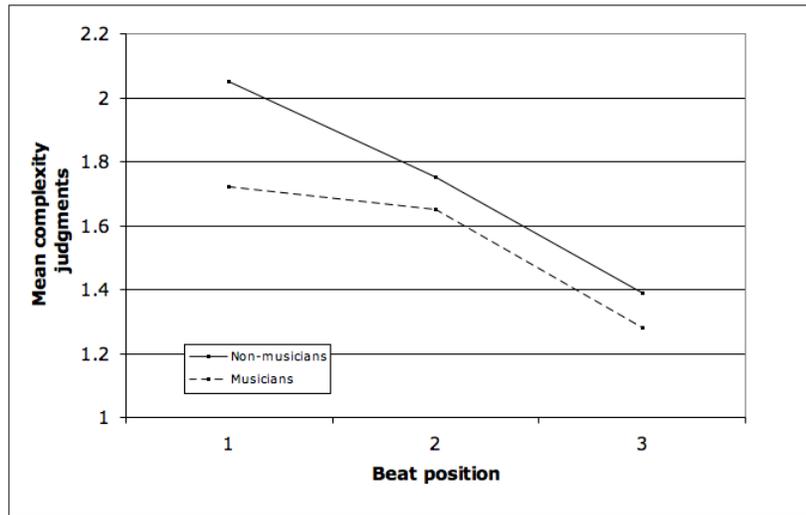
Complexity judgments as a measure of event salience, Figure 1



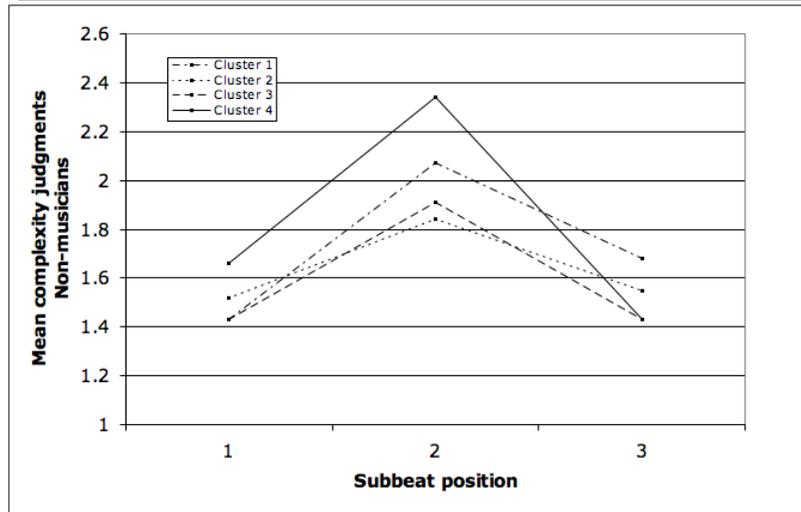
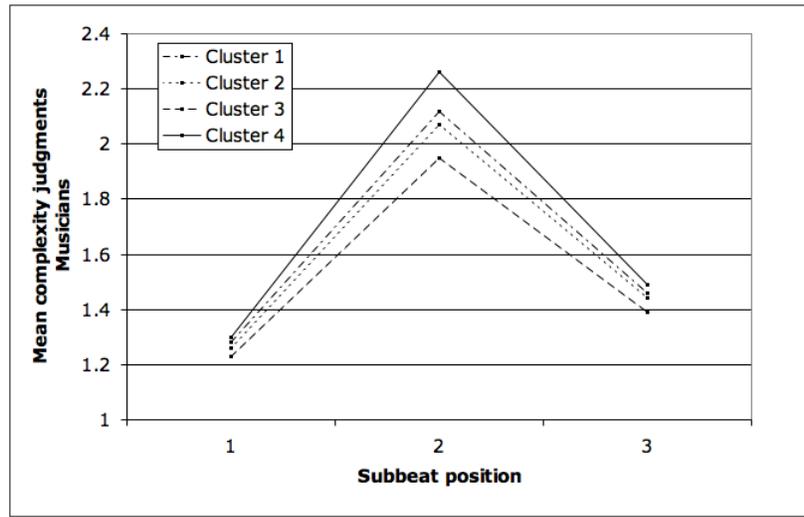
Complexity judgments as a measure of event salience, Figure 2



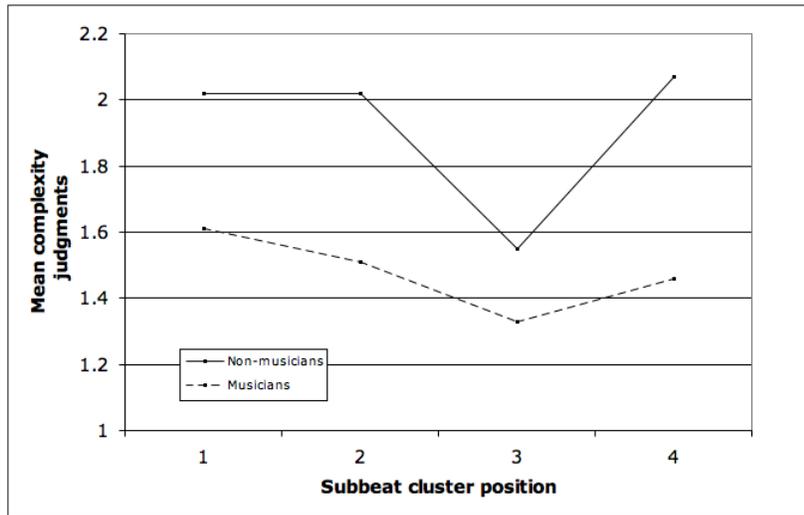
Complexity judgments as a measure of event salience, Figure 3



Complexity judgments as a measure of event salience, Figure 4

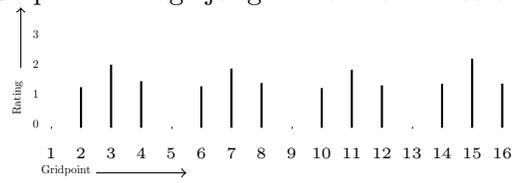


Complexity judgments as a measure of event salience, Figure 5

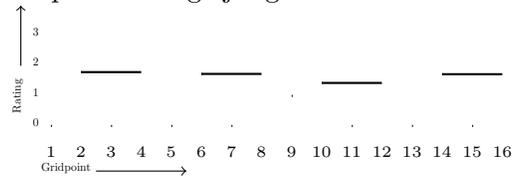


# Complexity judgments as a measure of event salience, Figure 6

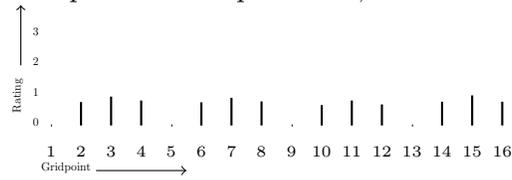
Step 1: Average judgments of stimulus sets 1-4



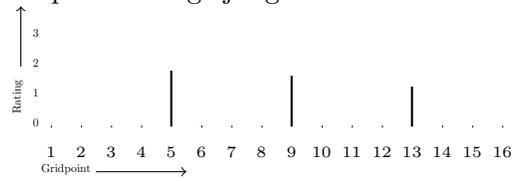
Step 2: Average judgments of stimulus set 6



Step 3: Sum Step 1 and 2, and normalize



Step 4: Average judgments of stimulus set 5



Step 5: Combine Step 3 and 4

