

Title	Distance in Pitch Sensitive Time-span Tree
Author(s)	Matsubara, Masaki; Hirata, Keiji; Tojo, Satoshi
Citation	International Computer Music Conference (ICMC/SMC) 2014: 1-6
Issue Date	2014-09
Type	Conference Paper
Text version	publisher
URL	<a href="http://hdl.handle.net/10119/12339">http://hdl.handle.net/10119/12339</a>
Rights	(c) 2014 Masaki Matsubara et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 Unported License, which permits unre-stricted use, distribution, and reproduction in any medium, provided the original author and source are credited.
Description	

# Distance in Pitch Sensitive Time-span Tree

Masaki Matsubara

University of Tsukuba

masaki@slis.tsukuba.ac.jp

Keiji Hirata

Future University Hakodate

hirata@fun.ac.jp

Satoshi Tojo

JAIST

tojo@jaist.ac.jp

## ABSTRACT

The time-span tree of Jackendoff and Lerdahl’s Generative Theory of Tonal Music is one of the most promising representations of our human cognition of music. In order to show this, we compare the distance in trees and our psychological dissimilarity, using variations of *Ah vous dirais-je, maman* by Mozart. Since pitch and chord sequence also affect the time-spans, we first amend the time-span analysis to include pitch information. Then, we introduce the pitch distance based on Lerdahl’s theory, and renovate the tree distance. We compare the analyses with/without the pitch information, and show its efficacy.

## 1. INTRODUCTION

Cognitive similarity of music is one of the most important themes of music, both for practical applications such as music retrieval, classification, and recommendation [15, 5, 17], and for modeling the human cognitive process [2, 3]. Thus far, various viewpoints have been considered for us to evaluate the similarity, including melodic segmentation/parallelism, phonetic chromatography, and so on. In this paper, we consider the structural similarity. Schenkerian Theory in 1920’s [13] adopted the *reduction hypothesis*, that is, the importance of each pitch event is different in a piece of music, and hence, we can retrieve an intrinsic skeleton of music, picking up these important events.

Although the idea of reduction starts with Schenker, there have been various approaches for the reduction, such as Gestalt/grammatical/memory-based models [4, 1, 10]. Among which, the *time-span analysis* in Lerdahl and Jackendoff’s Generative Theory of Tonal Music (GTTM; hereafter) [11] gives us a more concrete process of reduction, based on rhythmic/harmonic stability, avoiding metaphysical issues. The theory assigns structural importance to each pitch events, derived by the *grouping analysis* and by the *metrical analysis*. As neighboring events can be compared by this structural importance, a branch from a less important event is absorbed into that from a more important event; as a result such a hierarchical structure forms a *time-span tree* in the bottom-up way (Figure 1.).

In the analysis in GTTM, as the preference rules are rather arbitrarily defined, contrary to the well-formedness rules,

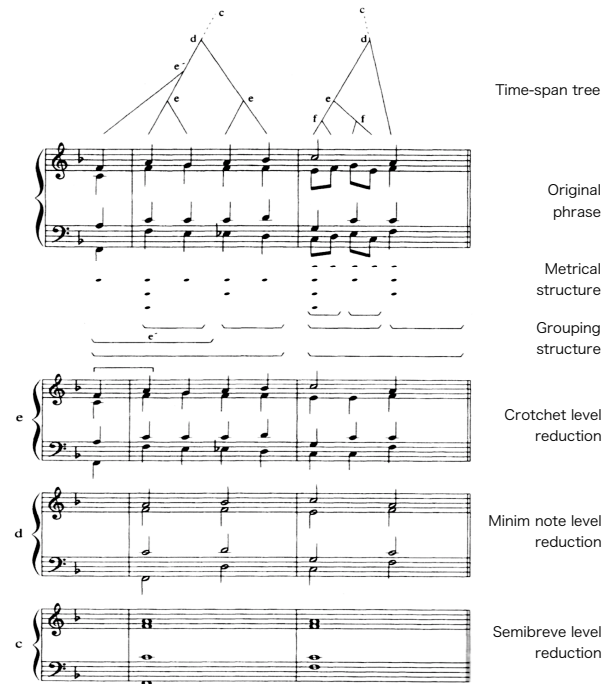


Figure 1. Time-span reduction for the first phrase of the BWV281 [12, pp.10–11].

they often conflict each other. Hamanaka et al. [6] have assigned parametric weights to each rule to control the process to avoid this problem, but the time-span tree still needs to be redressed by pitch and/or chordal information, which appear especially in half cadence or cadential retention.<sup>1</sup> In this paper, to amend the default of pitch information, we introduce a new preference rule, based on Tonal Pitch Space (TPS; hereafter) [12].

Thus far, we have defined the edit distance of time-span tree [19], and have measured the distance in variations of *Ah, vous dirais-je, maman* by Wolfgang Amadeus Mozart, K.265/300e [9], where the distance rather correctly reflected human intuition. One problem was that if one of two variations was in minor key the rhythmic resemblance did not match our psychological similarity. In this paper, we tackle the same set of variations, and show that the pitch information improves the situation.

This paper is organized as follows. In Section 2, we define the editing procedure of time-span tree together with the notion of maximal time-span. In the following Section 3, we show our revision; we formally define the distance

<sup>1</sup> The theory provides another tree, called *prolongation tree*, which should properly reflect harmonic structure

regarding the preorder of pitches and chords. In Section 4, we report the result of our distance calculation, compared with our human psychological similarity. In Section 5, we summarize our contribution and discuss the future work.

## 2. DISTANCE IN TREE WITHOUT PITCH INFORMATION

We hypothesize that if a branch with a single pitch event is removed from a time-span tree the amount of information proportional to the length of its time-span is lost. The *head* pitch event of a tree is the most salient event of the whole tree; then, we may regard its saliency is extended to the whole tree. The situation is the same as the head of each subtree. Thus, we consider that each pitch event has its maximal length of saliency, called *maximal time-span*.

Let  $\zeta(\sigma)$  be a set of pitch events in  $\sigma$ , and  $mts(e)$  be the maximal time-span of event  $e$ . For each reduction step, when event  $e$  on the reducible branch disappears, the length of its maximal time-span  $mts(e)$  becomes the distance of the step. Ditto for an addition of a branch. Therefore, the distance  $d$  of two time-span trees  $\sigma_A$  and  $\sigma_B$  is defined by

$$d(\sigma_A, \sigma_B) = \sum_{e \in |\zeta(\sigma_A) - \zeta(\sigma_B)|} mts(e).^2$$

Note that there is a latent order in the addition/reduction of branches though the distance is defined as a simple summation of maximal time-spans. Finally, we can easily show the triangle inequality [19]:

$$d(\sigma_A, \sigma_B) + d(\sigma_B, \sigma_C) \geq d(\sigma_A, \sigma_C).$$

## 3. DISTANCE WITH PITCH INFORMATION

In the time-span reduction, there are several preference rules concerning pitch and harmony in GTTM. Among which, we pay attention to TSRPR(Time-Span Reduction Preference Rule)<sup>2</sup> (Local Harmony).<sup>3</sup> We assume that relative consonance could be evaluated with root note and chord inversion type. Thus, we redefine TSRPR<sup>2'</sup> as follows:

### TSRPR<sup>2'</sup> (Local Harmony)

(a) prefer chord inversion as follows:

$$\mathbf{I} > \mathbf{I}^6 > \mathbf{I}_4^6.$$

(b) prefer a chord that relatively closely related to the local tonic as follows:

$$\mathbf{I} > \mathbf{V} > \mathbf{IV} > \mathbf{VII} > \mathbf{II} > \mathbf{III} > \mathbf{VI}.$$

There often appear dissonant notes<sup>4</sup> in the local harmony, and thus, we add a new preference rule, based on TPS[12].

### TSRPR<sup>10</sup> (New) (Local Pitch Consonance)

prefer pitch class in local harmony as follows:

$$\mathbf{0} > \mathbf{7} > \mathbf{4} > \{\mathbf{2}, \mathbf{5}, \mathbf{9}, \mathbf{11}\} > \{\mathbf{1}, \mathbf{3}, \mathbf{6}, \mathbf{8}, \mathbf{10}\},$$

<sup>2</sup>  $|A - B| \equiv A \cup B - A \cap B$ .

<sup>3</sup> "Of the possible choices for head of a time-span T, prefer a choice that is (a) relatively intrinsically consonant, (b) relatively closely related to the local tonic."

<sup>4</sup> as anticipation, neighbor tone, passing tone, etc.

where each number represents the pitch class in the local key, e.g., if in G major the numbers are interpreted as  $G > D > H$ , and so on. Note that there is no preference among pitch classes in a brace.

Now, we define the pitch-sensitive distance. The distance is basically the edit distance of *maximal time-span*, introduced in Section 2. Some algebraic features of the distance is mentioned in [19].

### Tree Distance with pitch information

Let  $\sigma_A, \sigma_B$  be trees; then the revised distance  $d^\pi(\sigma_A, \sigma_B)$  is defined as follows.

$$d^\pi(\sigma_A, \sigma_B) = \sum_{e_j \in |\zeta(\sigma_A) - \zeta(\sigma_B)|} (\delta_{e_i}(e_j) \times mts(e_j)),$$

where  $\delta_{e_i}(e_j)$  is the proximity from the pitch event on the parent branch  $e_i$  to that on the subordinate branch  $e_j$

We give the proximity based on TPS (Table 1)[12]. Let  $d^\pi(\sigma_A, \sigma_B) = 0$ , when  $\sigma_A$  and  $\sigma_B$  have only one pitch event, respectively, with different pitch classes of the same duration (shifting root).

For example, Figure 2. shows the calculation of distance between melody C-F-A and melody C-F#-A. The distance becomes the difference of F note which is to be removed from melody C-F-A (= 0.75), plus that of F# note to be added to melody C-A (= 0.625), which results in total 1.375. Figure 3. also shows the tree distance of root shifting when no common note exists between two trees.

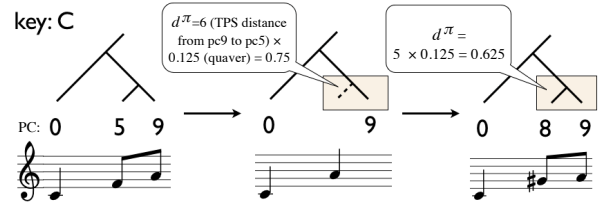


Figure 2. Pitch sensitive tree distance (1.375 in total)

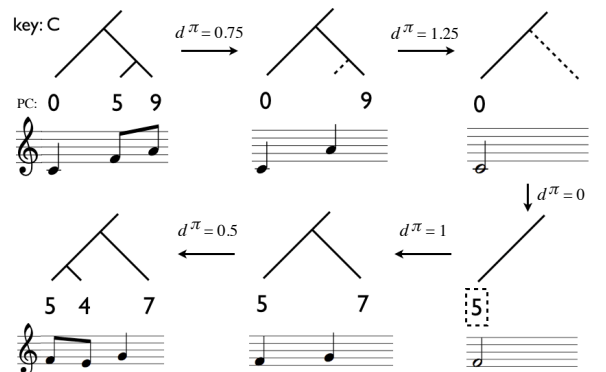


Figure 3. Distance including root shifting (3.5 in total)

**Table 1.** Pitch class proximity in TPS ([12, p. 49])

Pitch class (pc)	0	1	2	3	4	5	6	7	8	9	10	11
distance from pc0	0	5	4	6	3	5	7	2	6	5	6	4

**Table 2.** Tree Distance

	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	No. 9	No. 10	No. 11	No. 12
Theme	13.31	33.0	18.42	34.92	8.88	32.94	13.44	19.25	11.25	47.06	26.5	51.63
No. 1	–	44.81	31.23	47.73	20.94	45.75	25.75	32.06	24.06	59.88	39.31	64.44
No. 2	–	–	44.92	18.92	41.38	37.44	43.94	43.75	39.75	51.56	42.88	56.13
No. 3	–	–	–	45.17	26.79	44.85	29.35	37.17	25.17	58.98	40.33	63.54
No. 4	–	–	–	–	43.29	28.69	45.85	45.67	41.67	53.48	44.71	58.04
No. 5	–	–	–	–	–	41.31	21.81	27.63	19.63	55.44	34.88	60.0
No. 6	–	–	–	–	–	–	43.88	43.69	39.69	51.5	42.81	56.06
No. 7	–	–	–	–	–	–	–	32.19	24.19	58.0	39.44	62.56
No. 8	–	–	–	–	–	–	–	–	27.5	57.81	41.25	62.38
No. 9	–	–	–	–	–	–	–	–	–	53.81	33.25	58.38
No. 10	–	–	–	–	–	–	–	–	–	–	56.94	70.19
No. 11	–	–	–	–	–	–	–	–	–	–	–	61.5

## 4. EXPERIMENTAL RESULT

### 4.1 Material and Method

We have experimented the difference of distance on the same material as [9], that is, variations of *Ah, vous dirai-je, maman* by Wolfgang Amadeus Mozart K.265/300e as is shown in Figure 4. Although the original piece consists of two voices, we have extracted a more salient pitch event between the two, as well as a prominent note per each chord, and have arranged the piece into monophonic melody. In this process, we have disregarded the difference of octave so that the resultant melody is heard smoothly.

First, we have given time-span trees of the theme and its twelve variations by hand, and have cross-checked among the authors. We have given a chord sequence only on first eight-bars for each variation, with the help of a professional composer. The distance between two variations are calculated according to the definition in Section 3, including the new criteria of pitch difference. The number of comparison amounts to  $78 (= {}_{13}C_2)$  pairs.

Thereafter, we have investigated the cognitive similarity; the examinees consists of eleven university students, seven out of whom had experiences in playing music instruments. Examinees have listened to all the pairs  $\langle m_i, m_j \rangle$  in the random order without duplication, where  $m_{\{i,j\}}$  was either theme or variations No.1 to 12. To cancel the cold start bias, examinees have heard all through the theme and twelve variations (eight-bars long) without rating them. After then, each of them rated the intuitive similarity by five grades:  $\{-2, -1, 0, 1, 2\}$ . If one has rated a pair of  $\langle m_i, m_j \rangle$ , he/she must have tried the same pair later again in the reverse order as  $\langle m_j, m_i \rangle$  to avoid the order effect. Finally, the average ratings were normalized within all the examinees.

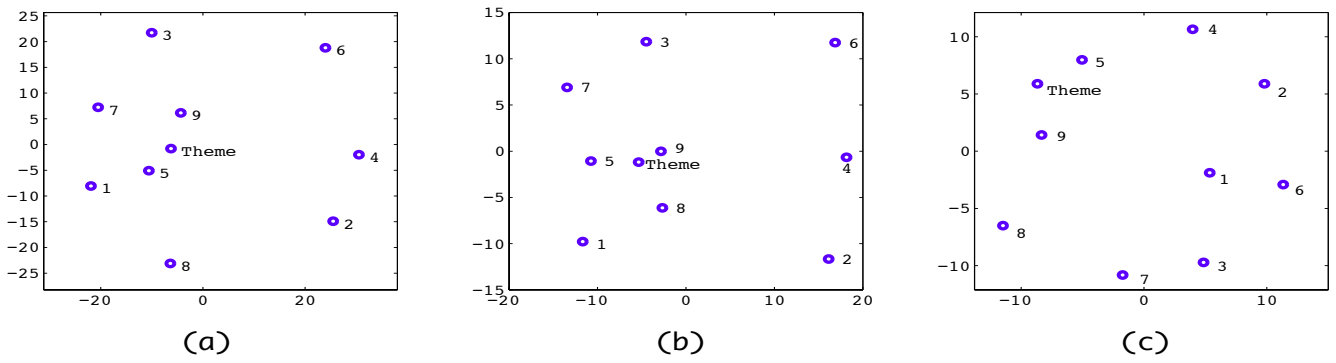
### 4.2 Result

The experimental results are shown in the distance-matrix in Table 2. Since the values of  $d^\pi(\sigma_{m_i}, \sigma_{m_j})$  and  $d^\pi(\sigma_{m_j}, \sigma_{m_i})$

**Figure 4.** Monophonic melodies arranged for experiment

are exactly the same, only the upper triangle is shown. The results of conventional study, which is psychological resemblance by examinees are shown in Table 3 in Appendix.

We have employed multidimensional scaling (MDS) [20] to visualize the comparison. MDS takes a distance matrix



**Figure 5.** Relative distances among melodies in multidimensional scaling: (a) pitch sensitive (b) only maximal time-span (c) human listeners

containing dissimilarity values or distances among items, identifies the axes to discriminate items most prominently, and plots items on the coordinate system with the axes. In short, the more similar items are, the closer they lie on the coordinate plane.

First, we used the MATLAB `mdscale` function which adopted Torgerson scaling of MDS to plot the proximity among the 13 melodies, however, it was still difficult to find a clear distinction. Therefore, we restricted the target melodies to the theme and variations No.1 to 9 as in Figure 5. Theme and No. $i$  in the figure correspond to those in Figure 5., respectively ( $i = 1, \dots, 9$ ). The contributions in MDS became as follows: (a) Tree distance with pitch information: first axis (horizontal) = 0.28, second = 0.20; (b) Tree distance without pitch information: first axis (horizontal) = 0.23, second = 0.21; (c) Human listeners: first axis (horizontal) = 0.33, second = 0.17.

### 4.3 Analysis

Here we summarize characteristic phenomena appeared in Figure 5.

**Theme, No. 5, and 9** In all (a), (b) and (c), we find that the theme, No.5, and No.9 make a clump; especially in (a) and (b), so No.2, No.4 and No.6 do. No.5 and No.9 are contrapuntal variations of the theme, and their rhythmic structure rather stay near. In our experiment, we have extracted salient pitch events according to the time-span analysis, so that these three trees resemble each other.

**No. 8** Although No.8 has similar rhythmic structure to the theme, No.8 is in c-minor. In our experiment in (b), No. 8 stayed near to the theme because of this reason. In the experiment (a), however, we could adequately distinguish the key by the pitch sensitivity.

**No. 2, 4, and 6** No.2, No.4, and No.6 include the salient pitch events in the bass voice, and thus, situate far from other variations. Those which consist of pitch events in the soprano voice tend to form a common tree, which reflects the original contour of the theme, and thus, form a macroscopic clump. On the contrary, the monophonic representation of No.2, No.4

and No.6 include arpeggio of the harmony, so that the consonant notes tend to remain significant.

**No. 3** No. 3 stays far from the clump of the theme as the chord progression is different.

**No. 10** As we have mentioned above, we excluded No. 10 to No. 12 from Figure 5. The monophonic representation of No.10 is the mixture of two voices, and also its grouping structure is quite different in bar 3 from the other variations;

**No. 12** No.12 is in the triple meter, so that the distance easily tend to be larger. If we do compare it with others in our settings, we need to normalize the meter.

## 5. CONCLUSION

In this research, we extended GTTM with a preference rule for the pitch difference, that is, the important note in the local key is salient. According to this new rule, we have revised the formula for the distance and have calculated the distance in variations of Mozart K.265/300e. We could show that the time-span tree with pitch information adequately reflected human cognitive reality music of music, as the tree distance had an expected correlation with psychological similarity.

Our framework suggests further the following issues. First, in general, variations are classified as follows [18]:

- decorative variation of melody with dissonant notes (No. 1, 3, and 7)
- rhythmic variation of melody (No. 1, 3, and 7)
- rhythmic variation of accompaniment (No. 2, 4, and 6)
- key changing (No. 8)
- harmonic variation (No. 2, 3, 4, 7, 10, and 11)
- contrapuntal variation (No. 5, 9, and 11)
- metrical variation (No. 12)
- exchanging melody and accompaniment (None in this piece)

It would be worth investigating if this normative classification correlates with the result of structural analysis.

Second, this time, the examinees may be rather much conscious of rhythmic structure (Figure 5 (c)). We need to verify if this result is biased by our examinees or general tendency, considering the deviation of examinees in musical experience.

Thirdly, this time we have put all the original pieces into monophonic representation. Since the pitch information strongly depends on the chord, we are now required to verify the adequacy of obtained chord sequence; this implies that if we claim the cognitive reality of the time-span tree we need to treat homophonic representation of music and this would be our future work.

### Acknowledgments

This work was supported by JSPS KAKENHI Grant Numbers 23500145 and 25330434. We thank K. Miyashita for help in harmonic analysis, K. Okada for help in statistical analysis.

### 6. REFERENCES

- [1] Bernabeu, J. F., Calera-Rubio, J., Iesta, J. M. and Rizo, D.: Melodic Identification Using Probabilistic Tree Automata, *Journal of New Music Research*, Vol. 40, Iss. 2, 2011.
- [2] ESCOM: 2007 Discussion Forum 4A. Similarity Perception in Listening to Music. *Musicae Scientiae*
- [3] ESCOM: 2009 Discussion Forum 4B. Musical Similarity. *Musicae Scientiae*
- [4] Gilbert, E. and Conklin, D.: A Probabilistic Context-Free Grammar for Melodic Reduction, *International Workshop on Artificial Intelligence and Music*, IJCAI-07, 2007.
- [5] Grachten, M., Arcos, J.-L. and de Mantaras, R.L.: Melody retrieval using the Implication/Realization model. 2005 MIREX. <http://www.music-ir.org/evaluation/mirexresults/articles/similarity/grachten.pdf>
- [6] Hamanaka, M., Hirata, K., Tojo, S.: Implementing “A Generative Theory of Tonal Music”. *Journal of New Music Research*, Vol. 35, Iss. 4, pp. 249–277 2007.
- [7] Hamanaka, M., Hirata, K. and Tojo, S.: Melody Morphing Method Based on GTTM, *Proceedings of ICMC 2008*, pp.155–158, 2008.
- [8] Hirata, K., Tojo, S. and Hamanaka, M.: Melodic Morphing Algorithm in Formalism, *LNAI6726*, Springer, pp. 338–341, 2011.
- [9] Hirata, K., Tojo, S. and Hamanaka, M.: Cognitive Similarity grounded by tree distance from the analysis of K.265/300e, *Proceedings of CMMR 2013*, pp. 415–430, 2013.
- [10] Kirilin., P. B.: *A Probabilistic Model of Hierarchical Music Analysis*, PhD thesis, University of Massachusetts Amherst, 2014.
- [11] F. Lerdahl and R. Jackendoff: *A Generative Theory of Tonal Music*, The MIT Press, Cambridge, 1983.
- [12] Lerdahl, F.: *Tonal Pitch Space*, Oxford University Press, 2001.
- [13] Schenker, H. (Oster, E. (trans.)) *Free Composition*, Longman, 1979. Original: *Der Freie Satz*, 1935.
- [14] Marsden, A.: Generative Structural Representation of Tonal Music, *Journal of New Music Research*, Vol. 34, Iss. 4, pp. 409–428, 2005.
- [15] Pampalk, E.: Computational Models of Music Similarity and their Application in Music Information Retrieval, PhD Thesis, Vienna University of Technology, 2006.
- [16] Rizo-Valero, D.: Symbolic Music Comparison with Tree Data Structure, Ph.D. Thesis, Universitat d’ Alacant, Departamento de Lenguajes y Sistemas Informáticos, 2010.
- [17] Schedl, M., Knees, P. and Böck, S.: Investigating the Similarity Space of Music Artists on the Micro-Blogosphere, *Proceedings of ISMIR 2011*, pp. 323–328, 2011.
- [18] Randel, D., M.: *The new Harvard dictionary of music*, Harvard University Press, 1986.
- [19] Tojo S., and Hirata, K.: Structural Similarity Based on Time-span Tree, *Proceedings of CMMR 2012*, pp. 645–660, 2012.
- [20] Torgerson, W. S.: *Theory & Methods of Scaling*, New York: Wiley, 1958.

### Appendix

Table 3. shows computationally calculated tree distance and psychological resemblance, which was shown in [9]. If an examinee, for instance, listen to Theme and variation No.1 in this order, the ranking made by an examinee is found at the first row, the second column cell (-0.73). The values in (b) are the averages over all the examinees.

**Table 3.** Computationally calculated tree distance and psychological resemblance (showed in [9])  
(a) Tree Distance without pitch information

	No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8	No.9	No.10	No.11	No.12
Theme	183	177	195	183	117	249	162	15	21	363	262.5	246
No.1	–	228	332	326	264	360	219	174	204	456	409.5	421
No.2	–	–	264	216	246	282	105	168	186	438	391.5	423
No.3	–	–	–	252	262	320	259	188	198	462	334.5	379
No.4	–	–	–	–	238	246	213	176	186	424	387.5	399
No.5	–	–	–	–	–	276	243	114	108	414	298.5	325
No.6	–	–	–	–	–	–	291	234	264	378	409.5	449
No.7	–	–	–	–	–	–	–	153	171	429	376.5	400
No.8	–	–	–	–	–	–	–	–	30	348	259.4	255
No.9	–	–	–	–	–	–	–	–	–	378	277.5	261
No.10	–	–	–	–	–	–	–	–	–	–	406.5	403
No.11	–	–	–	–	–	–	–	–	–	–	–	298.5

(b) Rankings by human listeners (listening in row→column order)

	Theme	No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8	No.9	No.10	No.11	No.12
Theme	–	-0.73	-0.91	-1.09	-0.82	1.18	-1.00	-1.45	-0.64	1.36	0.64	0.73	1.00
No.1	-1.00	–	-0.82	-0.73	-0.91	-0.64	0.36	-0.64	-1.45	-0.82	-0.82	-1.00	-0.64
No.2	-0.91	-0.36	–	-0.64	-0.27	-0.82	-0.45	-0.55	-1.55	-0.91	-0.09	-0.64	-0.91
No.3	-0.82	-0.45	-0.82	–	0	-0.91	-1.00	-0.36	-1.36	-0.73	-0.64	-0.73	-0.91
No.4	-1.00	-0.82	-0.73	0.18	–	-0.73	-0.82	-0.82	-1.73	-0.91	-0.45	-1.27	-1.00
No.5	1.27	-1.18	-0.91	-0.91	-0.64	–	-0.82	-1.09	-1.00	0.73	0.55	0.36	0.73
No.6	-1.18	0.27	-0.27	-0.45	-0.82	-0.64	–	-0.36	-1.64	-0.91	-0.55	-0.64	-0.91
No.7	-1.18	-0.64	-0.45	-0.18	-0.82	-0.73	-0.64	–	-1.18	-0.73	-0.36	-0.64	-0.73
No.8	-0.73	-1.27	-1.36	-1.55	-1.27	-0.73	-1.00	-1.36	–	-0.09	-1.09	-0.64	-0.91
No.9	1.27	-0.91	-0.91	-0.73	-1.09	0.91	-1.27	-0.82	-0.18	–	0.55	0.45	1.00
No.10	0.55	-0.82	-0.27	-0.64	-0.36	0.73	-0.45	-0.82	-1.00	0.73	–	0.18	0.45
No.11	0.64	-0.82	-0.91	-0.73	-0.91	0.55	-0.91	-1.09	-0.73	0.64	0.27	–	1.00
No.12	1.09	-1.18	-1.09	-1.00	-1.00	0.91	-1.00	-1.18	-0.91	1.09	0.36	0.82	–