

Exploring Melodic Contour: A Clustering Approach

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Abstract

Previous studies investigating common melodic contour shapes have relied on methodologies that require prior assumptions regarding the expected contour patterns. Here, a new approach for examining contour using dimensionality reduction and unsupervised machine-learning clustering methods is presented. This new methodology was tested across four sets of data — two sets of European folksongs, a mixed-style, curated dataset of Western music, and a set of Chinese folksongs. In general, the results indicate four broad common contour shapes across all four datasets: convex, concave, descending, and ascending. In addition, the analysis revealed some micro-contour tendencies, such as pitch stability at the beginning of phrases and descending pitch at phrase endings. These results are in line with previous studies of melodic contour and provide new insights regarding the prevalent contour characteristics in Western music.

Key Words: melodic contour, cross-cultural, machine-learning, clustering, datasets

Introduction

Contour is an overall outline that represents a shape — an ordering of values in one dimension relative to the ordering of values in another dimension. In music, these dimensions are usually the relative pitch height in relation to sequential temporal ordering (Bor, 2009). In other words, musical contour represents the shape of a melody, describing how pitch changes and unfolds in a series of rising and falling patterns over time, and constitutes one of the central parameters of a musical stimulus (Cohen, Trehub, & Thorpe, 1989; Lee, Janata, Frost, Hanke, & Granger, 2011; Patel, 2003; Tierney, Russo, & Patel, 2011).

Exploration of contours over multiple datasets of Western music has shown that melodies tend to be governed by various conventions, such as (1) the pervasiveness of small steps, especially for descending intervals; (2) a tendency of the notes at the end of phrases to be relatively long; and (3) a predominance of arch-shape and descending contours (Cohen et al., 1989; Huron, 2006; Tierney et al., 2011). Moreover, arch-shaped and descending contours are known to be common cross-culturally, suggesting that this is a common musical feature (Savage, Brown, Sakai, & Currie, 2015).

Melodic information is encoded as a combination of contour and tonality (Dowling, 1978; Schmuckler, 2016) and thus contour plays an important role in the organization and construction of melodic information and in the cognitive organization of melodic pitch streams (Schubert & Stevens, 2006). What defines a melody is not the absolute pitch of the notes, but the relationships, distances, and directionality between the notes. The intervals allow for the emergence of specific scale structures, tonality, and harmonic structure, while the contour determines the general shape of the melody (Patel, 2003; Trainor, McDonald, & Alain, 2002).

Accordingly, melodic contour affects how we learn and perceive music. Sensitivity to contour emerges early in infancy, and both infants and musically untrained individuals can easily detect contour

changes (Patel, 2003; Trainor et al., 2002). For example, young children can reproduce the contour of a melody before they are able to reproduce the exact intervals (Dowling, 1982). An electroencephalography (EEG) study by Trainor et al. (2002) indicated that contour processing appears to be automatic and independent of musical training. The results of their study indicate a mismatch negativity (MMN) response to contour changes in musical stimuli in non-musicians, in both attentive and inattentive conditions. There also appears to be a neural substrate dedicated to information about the directionality of successive notes. This was discovered in patients with lesions in the right superior temporal lobe, who were able to distinguish whether notes were the same or different but could not tell whether notes were higher or lower than each other (Lee et al., 2011).

In addition, contour also affects similarity perception between different melodies (Dowling & Fujitani, 1971). For example, melodies with similar up-and-down patterns tend to be confused even if the notes differ (Levitin, 1999). Furthermore, in an experiment where melodies were encapsulated as the Fourier transform of their contour, perceived similarity by the listeners was predicted from the degree of overlap between the extracted analyses (Schmuckler, 2016).

Contours can determine not only perceived similarity but also short-term memory for melodies, and there is evidence that memory for contours is separate from memory of exact interval sizes. An experiment by Dowling (1978) showed that the contours of short atonal melodies can be retrieved from short-term memory, even when the exact intervals were not remembered correctly. Specifically, this effect is evident mostly in implicit, but not necessarily explicit, memory retrieval (Schmuckler, 2016). Moreover, melodic contour plays a major role in the long-term memory and recognition of melodies (Schubert & Stevens, 2006). For example, distorted familiar melodies were recognized more frequently if the distortion preserved the contour (White, 1960).

Given the importance of contour in the context of music, it is crucial to develop methodologies that allow for its characterization. One way to study musical contour is through the examination of melodic datasets. For instance, a study by Huron (1996) tested the hypothesis that a disproportionate number of Western phrases exhibit an arch-shaped contour. Huron utilized the Essen database, which is a large corpus of annotated folksongs from different, mostly European, regions (more than 6000 pieces; Schaffrath, 1995; Selfridge-Field, 1995). The Essen database includes annotations of key, pitch, meter, bar lines, rests, and segmentation to phrases. Phrases are defined here as a musical unit that is marked by metrical quality, musical rests, and musical syntax. In this database, shorter phrases were chosen over longer ones in ambiguous cases (Schaffrath, 1987).

Capitalizing on this database, Huron examined the frequency of different contour shapes in the dataset by representing each phrase as a three-note pattern, each composed of the first and last notes and the average of all notes in between. His analysis shows that convex, arch-shape contour is the most common in the dataset, followed by descending, ascending, and concave contour shapes. Furthermore, even across phrases, complete short melodies also tend to present a general arch-shape, regardless of the shapes of the individual phrases of which the melody is composed.

Another study that used the Essen database also demonstrated the prevalence of arch-shaped and descending contours in melodies from the Essen database (Tierney et al., 2011), which were reduced using the same three-note method as used by Huron (1996). In this study, they also investigated bird songs, and showed that convex and descending contours are common even outside of human music (Tierney et al., 2011). In a follow up study, Savage, Tierney, & Patel (2017) examined melodies from additional datasets, but instead of reducing each phrase to a three-note pattern, each contour was tested on whether it was significantly descending or arch-shaped by fitting it to a linear and

quadratic model. This analysis yielded similar findings to previous ones by Huron (1996) and Tierney et al. (2011).

Overall, these studies indicate the predominance of convex and descending contours. However, they did not examine the contours directly but simplified the contours into three-note patterns. This simplification, although useful, precludes other, more complex contour shapes from being considered. Similarly, fitting specific models to the contours does not enable an unbiased examination of the melodic contours that exist in the dataset. With this in mind, the current series of experiments aim to explore contour shapes and their relative frequency without prior assumptions regarding their shape. In order to do that, we based our analysis on a dimension-reduction methodology followed by a k-means analysis — a machine-learning based clustering approach. In Experiments 1 and 2 we explore the Essen database, focusing on contours of individual phrases in Experiment 1 and complete, short folk songs in Experiment 2. In Experiment 3 we examine contours of individual phrases in a curated dataset that includes a variety of Western musical styles. In Experiment 4, we use the same methodology to assess a set of Chinese folksongs from the Essen database.

Experiment 1

Method

The goals and the dataset used in the first experiment were the same as those in Huron's 1996 study: to explore the shape and relative prevalence of contours in the Essen database. Here we incorporate an automated analysis with a procedure that does not require any prior assumptions regarding the shapes of the contours that are expected to be found. Our method is based on a clustering analysis that explores the distribution of contour shapes in a dataset.

Materials. The dataset for the first experiment consisted of 35,793 phrases from the Essen Folksong Database. In order to maintain maximum similarity to Huron's original analysis and provide interpretability of the output, only European phrases were included in the current analysis. The phrases were extracted at a tempo of 80 bpm which resulted in a mean phrase duration of 5.26 seconds. The mean pitch register within a phrase was 167.60 Hertz.

Data pre-processing. The Essen database annotations were imported using custom-written code in Python. All the analysis scripts are available at: <https://github.com/MichalGoldstein/ContourAnalysis>. Phrase segmentation, pitch, and duration information from the Essen dataset were used to create individual audio files for each phrase. All phrases were adjusted to a length of 10 seconds using the *time_stretch* function from the Librosa package (McFee et al., 2015) and exported at a sampling rate of 22050 Hz. The phrases were exported as audio files, as we were aiming for a methodology that could be applied to all musical styles and tuning systems, here and in future applications. This also enabled to ensure that the data processing method was uniform across the three experiments, as some of the data for Experiment 3 consists of audio wav files without available annotations.

All audio files were imported back to Python and the pitch information was estimated using the Librosa *pyin* algorithm. If there were non-pitched values in the excerpt, they were replaced with the last pitched frequency value to create a continuous contour. The pitch and time axes for each contour were normalized to a scale between 0 and 1 and sampled at a frame length of 2048 with a sampling rate of 22050 Hz, resulting in 431 equally spaced points for each audio file that each represents 0.023 seconds of the audio. Finally, the pitch values were converted from Hertz to log scale using the formula $12 \cdot \log_2(f_0 / \text{mean}(f_0))$, where f_0 is the frequency of the note in Hertz, in order to represent the pitch in a continuous semitone scale (Savage et al., 2017).

Principal component analysis (PCA) was used to determine the number of clusters that would subsequently be used in the clustering analysis. Principal component and clustering analysis were also implemented in *Python*. The data were normalized and centered to a mean of 0 and a variance of 1 before applying the PCA. Following the PCA, a permutation test, using 1000 independent permutations without replacement of each of the 431 columns of the dataset, was used in order to determine the significance of each component. Specifically, we compared the explained variance of the original dataset to the permuted, randomized version.

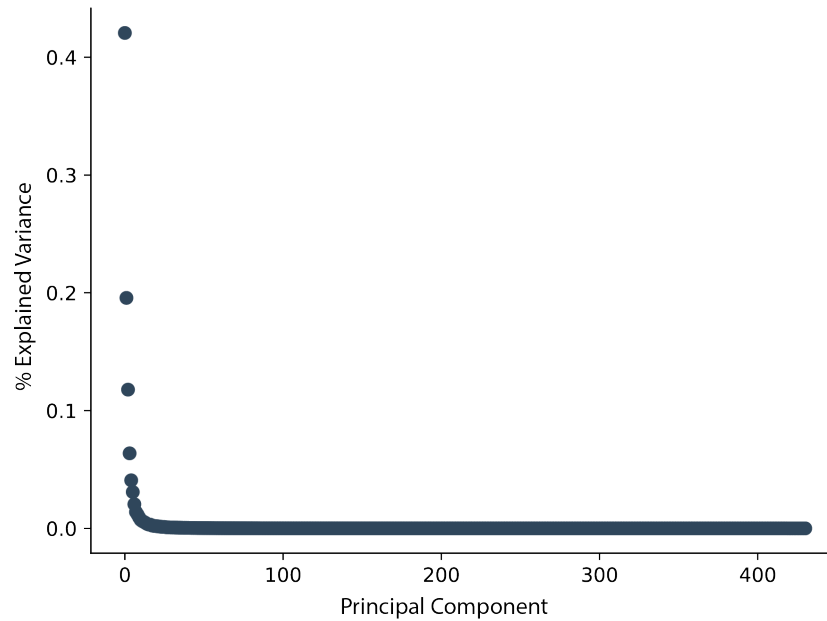
The PCA was followed by a k-means clustering analysis. For each cluster, we averaged and visualized the phrases to determine the average shape of the contour of each cluster. Finally, pairwise and post-hoc Pearson's chi-square tests were used to test the significance of the difference between cluster sizes.

Results

The permutation analysis indicated that the first 17 components in this analysis were significant—that is, the explained variance of these components was greater than their explained variance in the permuted, randomized sets. We chose to proceed with four components (explaining 79.78% of the variance in the data: 42.06%, 19.57%, 11.78%, and 6.37%) because, as can be seen in Figure 1, the remaining components following the first four explain a minimal part of the variance in the data (see Supplementary Fig. 1A for a visualization of the first 8 components).

Figure 1

Experiment 1. Explained variance by principal component of the Essen phrases dataset.



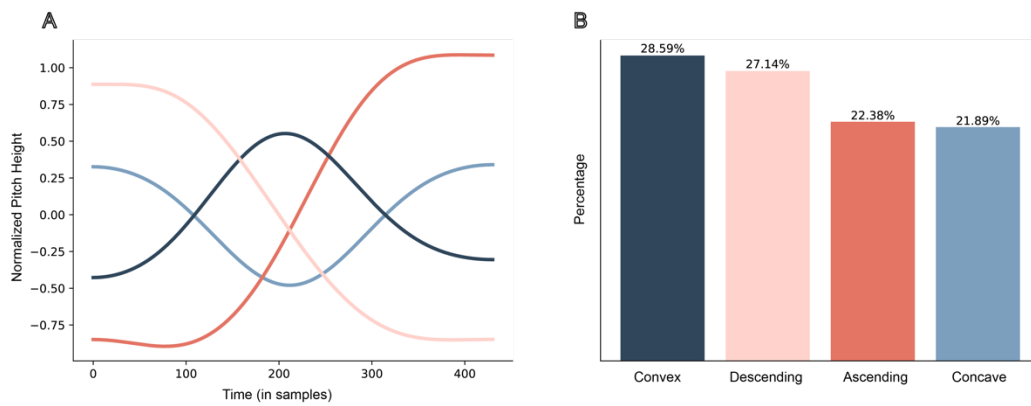
To examine the four main contour clusters in our dataset, we applied a k-means clustering analysis on the centered and normalized data with $k = 4$. The components of each cluster were averaged and smoothed using a two-dimensional Gaussian filter for visual clarity (smoothing kernel standard deviation = 50). Results indicate that the clusters correspond to descending, ascending, convex, and concave contour shapes (see Figure 2), which also correspond to Huron's (1996) results.

To examine whether the percentage of phrases assigned to each cluster differed significantly from each other, Pearson's chi-square tests were applied. Out of a total of 35,793 phrases, 10,233 phrases (28.59%) were classified as convex; 9714 phrases (27.14%) were classified as descending; 8012 phrases (22.38%) were classified as ascending; and 7834 phrases (21.89%) were classified as concave.

Overall, the percentage of phrases that were classified to each cluster was found to be significantly different, $\chi^2(3) = 486.70, p < .001$.

Figure 2

Experiment 1. Clusters' means for the phrases of the Essen dataset.



Note. **A.** Average shape of the four main musical contours plotted over time. **B.** Percentage of phrases in the dataset corresponding to each musical contour. Convex (dark blue), Descending (pink), Ascending (orange), Concave (light blue).

Post-hoc Pearson's chi-square tests with Bonferroni correction for multiple comparisons were performed to compare the significance of the difference in the number of phrases between each pair of clusters (six tests computed). All the differences between each pair of clusters were found to be significant, $p < .001$, except for the difference in cluster size between the convex and descending clusters ($p < .05$) and the ascending and concave clusters (no significant difference; see Table 1).

Table 1

Experiment 1. Post-hoc chi square testing.

Clusters	χ^2	p-value
Convex * Descending	13.50	< 0.05
Convex * Ascending	270.37	< 0.001
Convex * Concave	318.55	< 0.001
Descending * Ascending	163.42	< 0.001
Descending * Concave	201.42	< 0.001
Ascending * Concave	2.00	0.94

Note. P-values are corrected for multiple comparisons.

Discussion

Using a fully automatic, data-driven approach without the need of a priori assumptions, we showed that the dataset contains four main classes of contour shapes. Visualizations of smoothed averages of each cluster correspond to convex, concave, descending, and ascending patterns. The frequencies of each contour shape in this dataset varied, with the cluster corresponding to the convex contour the largest, followed by descending, concave, and ascending contours (no significant difference in size between the latter two).

These results replicate those of the analogous experiment by Huron (1996), who also found the same four main contour shapes, with the convex and descending ones being the most common in his analysis (although in Huron's analysis the difference in percentage between contours was larger). This replication is of particular significance given that we did not have any prior assumptions, and we did not limit the possible contours in our analysis to those that can be represented by a maximum of three notes.

Since our analysis method enables the exploration of more complex shapes, it can also reveal finer contour details. For example, visual examination of the averaged contour shapes suggests that there is generally some level of pitch stability in the beginning of the and end of phrases. From a musical standpoint, this may represent the use of long notes and pitch stability in order to mark phrase boundaries within a melody (Schulkind, Posner, & Rubin, 2003).

Experiment 2

Following his original (1996) analysis of phrase contours, Huron examined the contours of complete short melodies in the Essen database in order to establish whether the prevalence of the arch-shape contour was maintained beyond the single-phrase level. Huron conducted this analysis by averaging the pitch of each phrase separately into a single value and subsequently examining the

contour of this concise melodic version. He indeed found that the average pitch height of phrases towards the middle of the melody tended to be higher than the average pitch of phrases in the beginning and the end of the melodies. Yet in his analysis, the next-common contour was that of an ascending shape, and the descending and concave contours were the least frequent. In Experiment 2 we also examined full-length melodies in the Essen database to assess whether our data-driven, fully automated analysis with no a priori assumptions revealed similar results.

Method

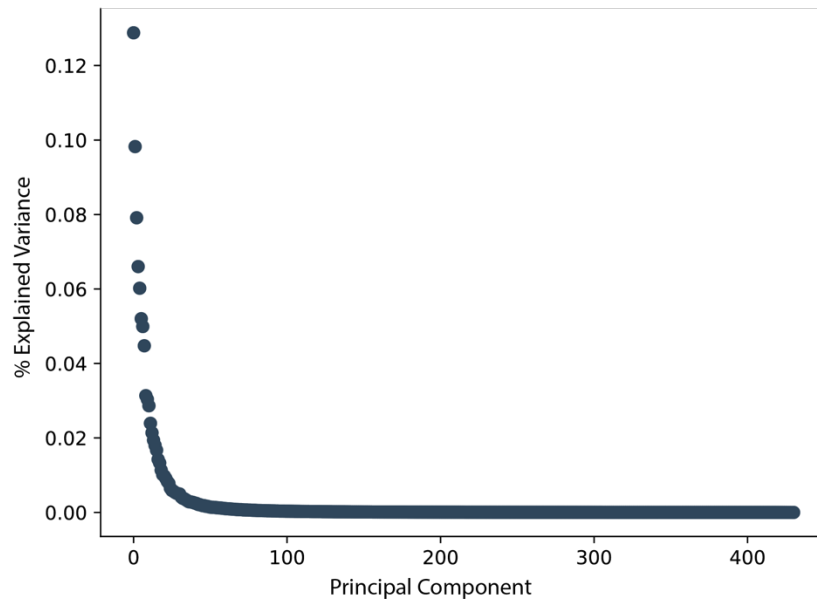
The dataset for the second experiment consisted of 6183 European folk melodies from the Essen Folksong Database. The mean length of a melody in the database was 31.98 seconds, with a mean pitch register of 299.17 Hertz within a melody. In Huron's experiments, different data pre-processing methods had to be applied when analyzing single phrases and complete melodies: single phrases were summarized into three-notes patterns, while complete melodies were summed up by averaging each phrase into a single note. In contrast, our methodology offered a high degree of flexibility with regard to stimulus length, which enabled us to use the exact same method to study both single phrases and complete melodies, and thus allowed more direct comparability. Hence, data pre-processing and analysis methods were identical to those of Experiment 1.

Results

As in Experiment 1, a permutation test was conducted to determine the significance of each component of the PCA of the complete-melody analysis. This test indicated that the first 35 components were significant. For establishing comparability to Experiment 1 and to Huron's (1996) study, we again chose the first four components, explaining 37.21% of the variance in the data (12.88%, 9.82%, 7.91% and 6.60%; see Supplementary Fig. 1B for the average contours of the first eight components).

Figure 3

Experiment 2. Explained variance by principal component of the Essen full melodies dataset.

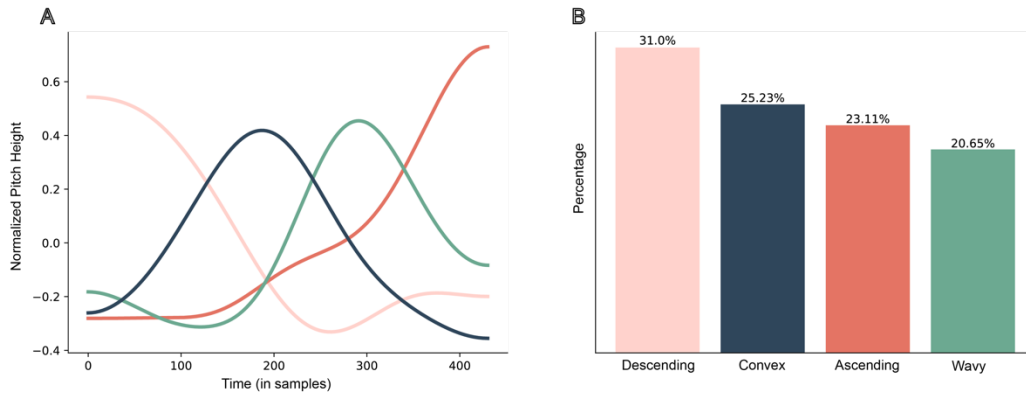


The k-means clustering analysis on the centered and normalized data with four clusters was applied on this dataset as well. Unlike the results of Experiment 1, the results of the cluster averaging and smoothing showed that they corresponded to ascending, descending, convex, and a wavy contour with a pitch descent in the first half and a convex with a peak in the second half (see Figure 4).

Out of a total of 6183 melodies, 1917 melodies (31.00%) were classified as descending; 1560 melodies (25.23%) were classified as convex; 1429 melodies (23.11%) were classified as ascending; and 1277 melodies (20.65%) were classified as wavy. Overall, the percentage of phrases that were classified for each cluster was found to be significantly different, $\chi^2(3) = 144.84$, $p < .001$ (Pearson's chi-square tests).

Figure 4

Experiment 2. Clusters' means for the complete melodies of the Essen dataset.



Note. **A.** Average shape of the four main musical contours plotted over time. **B.** Percentage of phrases in the dataset corresponding to each musical contour. Descending (pink), Convex (dark blue), Ascending (orange), Wavy (green).

Post-hoc Pearson's chi-square tests with Bonferroni corrections, examining the differences between each pair of clusters, indicated that the differences between the ascending and wavy clusters were significant with $p < .05$, and the differences between the sizes of the rest of the clusters significant with $p < .001$, except for the difference between the sizes of the ascending and convex clusters, which was not significant (see Table 2).

Table 2*Experiment 2. Post-hoc chi square testing.*

Clusters	χ^2	p-value
Convex * Descending	36.65	< 0.001
Convex * Ascending	5.74	0.10
Convex * Wavy	28.23	< 0.001
Descending * Ascending	71.17	< 0.001
Descending * Wavy	128.24	< 0.001
Ascending * Wavy	8.54	< 0.05

Note. P-values are corrected for multiple comparisons.

Discussion

The analysis of complete melodies from the folksong dataset showed that the most prevalent contours were descending, convex, ascending, and wavy (descending followed by convex) contour shapes. This analysis highlights the strengths of the current analysis methods, as it was able to reveal an unexpected contour shape that cannot be represented by merely three notes.

In addition, our findings differed somewhat from Huron's complete-melody results. In his analysis, compared to individual phrases, the descending contour was not particularly common, while the ascending contour was relatively prevalent. Our analysis, on the other hand, showed that the descending and convex contour clusters were larger than the other clusters. This discrepancy might stem from the difference in the pre-processing methods between the current experiment and Huron's, as our analysis did not require averaging the pitch of each melody.

Compared to the analysis of individual phrases, the current analysis indicates that the tendencies for pitch stability in melodies is more contour specific, with the pitch stability at the beginning of the melody apparent mainly in the ascending contour, and pitch stability at the end of the melody mainly at the descending contour.

Experiment 3

The results of Experiments 1 and 2 were somewhat similar to the findings of Huron (1996). However, all of these experiments were conducted using the same dataset. While the Essen dataset has the advantage of being very large and richly annotated — containing phrase segmentation in addition to pitch and duration, making it ideal for contour examination — the question arises as to whether these converging results will also extend to more varied music collections that include genres beyond folk songs. For this reason, we curated and assessed a new dataset containing more diverse genres for Experiment 3.

Method

The sources for this dataset include the Orchset dataset (Bosch, Marxer, & Gómez, 2016) of monophonic symphonic music in WAVE audio format, as well as MIDI sources that are available for free online (IMSLP.org, freemidi.org, piano-midi.de, romwell.com, midiworld.com). For the MIDI files, we first extracted the main melodic line using GarageBand (version 10.4.6; Apple inc.).

The final curated dataset included 37 phrases from Orchset and 195 phrases from online MIDI sources. The genres included in the dataset are classical (117 phrases), folk (59 phrases), soundtracks and Disney (20 phrases), pop (17 phrases), and rock (20 phrases). A full description of the curated dataset is available in Supplementary Table 1. MIDI files were converted to WAVE format, and individual

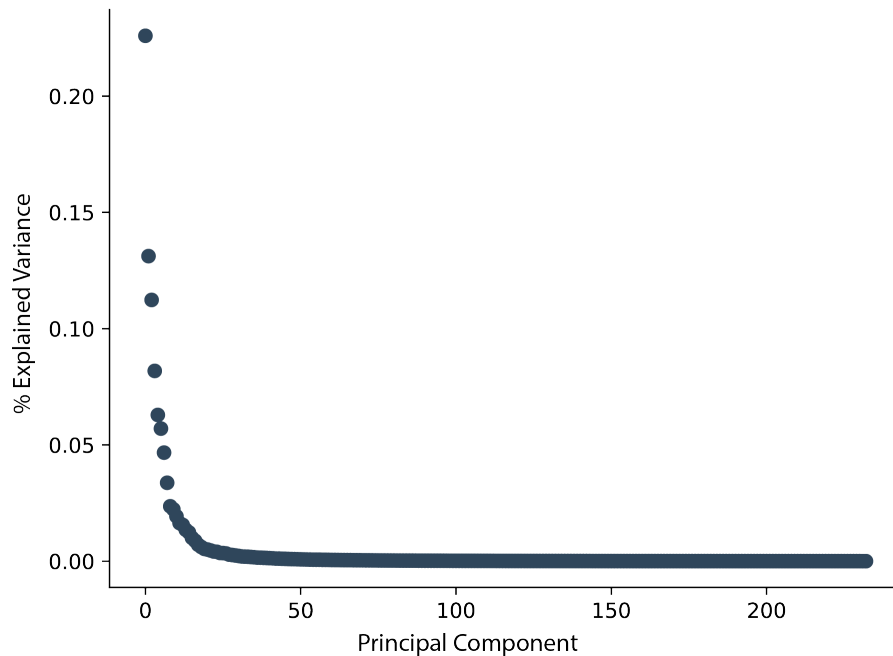
phrases were manually extracted from them using custom-written code in Python, with a limit of one phrase for each piece or Orchset excerpt. These phrases were chosen based on judgments of coherence and completeness of the phrase. The pre-processing and analysis steps applied were the same as in Experiments 1 and 2.

Results

Similar to the previous experiments, we first conducted a PCA with a permutation significance test. The permutation test showed that the first 13 components were significant. Similarly to Experiments 1 and 2, the first four components, explaining 55.12% of the variance in the data (22.56%, 13.13%, 11.24% and 8.19%), were chosen for the clustering analysis. see Supplementary Fig. 1C for the average contours of the first 8 components.

Figure 5

Experiment 2. Explained variance by principal component of the Essen full melodies dataset.

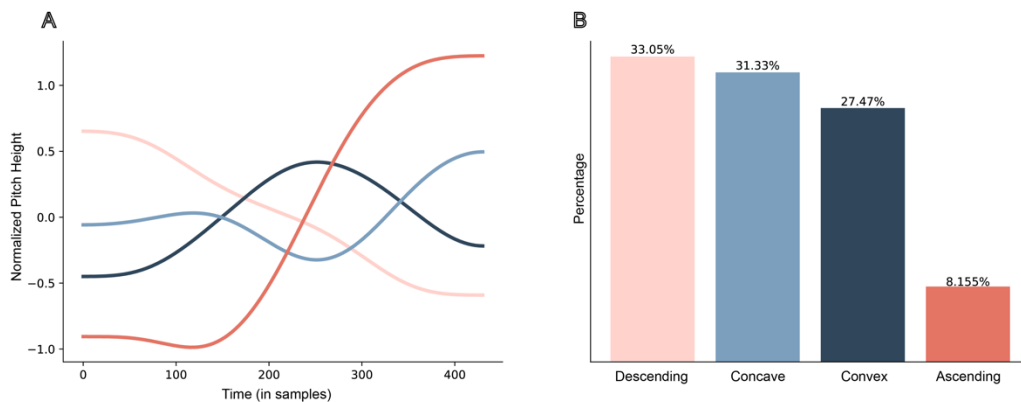


The results of averaging the four clusters show that, similar to findings of Experiments 1 and 2 and Huron's original results, the clusters corresponded to descending, ascending, convex, and concave contour shapes (see Figure 6). However, probably due to the much smaller size of the dataset, the contour shapes were less defined.

Out of a total of 233 melodies, 77 phrases (33.05%) were classified as descending; 73 melodies (31.33%) were classified as concave; 64 melodies (27.47%) were classified as convex; and 19 melodies (8.15%) were classified as ascending. Overall, the percentage of phrases that were classified in each cluster was significantly different, $\chi^2(3) = 34.00$, $p < .001$ (Pearson's chi-square test).

Figure 6

Experiment 3. Clusters' means for the complete melodies of the Essen dataset.



Note. **A.** Average shape of the four main musical contours plotted over time. **B.** Percentage of phrases in the dataset corresponding to each musical contour. Descending (pink), Convex (dark blue), Concave (light blue), Ascending (orange).

Post-hoc Pearson's chi-square tests with Bonferroni corrections for multiple comparisons show that the differences between the ascending cluster and each of the other clusters were significant $p < .001$, while the rest of the pairwise comparisons were not significant (see Table 3).

Table 3

Experiment 3. Post-hoc chi square testing.

Clusters	χ^2	p-value
Convex * Descending	1.20	1.00
Convex * Ascending	24.40	< 0.001
Convex * Concave	0.59	1.00
Descending * Ascending	34.04	< 0.001
Descending * Concave	0.11	1.00
Ascending * Concave	31.70	< 0.001

Note. P-values are corrected for multiple comparisons.

Discussion

Clustering analysis of the mixed-style phrase dataset resulted in contours with shapes similar to the phrases from the Essen database. In addition, the average contours indicated the tendency for pitch stability in the beginning and end of phrases and pitch descent towards the end of phrases, similar to the findings of Experiments 1 and 2. These results are also indicative of the strength and consistency of our findings, as they also appear in a much smaller and varied dataset.

Experiment 4

The Essen dataset also includes a subset of Chinese folksongs, and we were interested in examining whether a similar pattern of common contour shapes would be found in a non-European dataset. However, we found this subset somewhat problematic, as it also includes non-Chinese songs and repetitions of some songs. For these reasons, we did not analyze the entire set but a subset that included 1042 Chinese folksongs. The mean phrase duration was 5.42 seconds, with a mean pitch register within a phrase of 297.68 Hertz.

Method

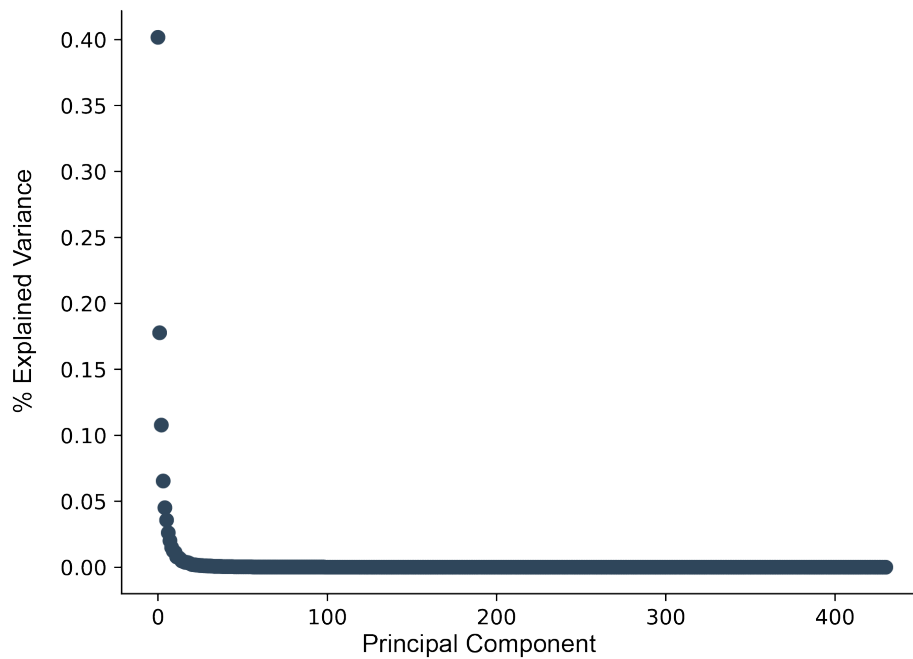
The methodology for Experiment 4 was identical to that of Experiment 1. The annotations were imported and individual audio files were created for each phrase and adjusted to be of equal length. Pitch information was estimated and the pitch and time axes were normalized and sampled and transformed to a log scale. Principal component analysis (PCA) and clustering analysis were conducted and for each cluster we averaged and visualized the phrases as well as performed a pairwise and post-hoc Pearson's chi-square tests.

Results

A PCA with a permutation significance test revealed that the first 14 components were significant. Similarly to Experiment 1, the first four components appeared to explain the vast majority of the variance in the data (40.17%, 17.77%, 10.78% and 6.54%, adding up to 75.26%). See Supplementary Fig. 1D for the average contours of the first eight components.

Figure 7

Experiment 4. Explained variance by principal component for the Chinese folksongs dataset.

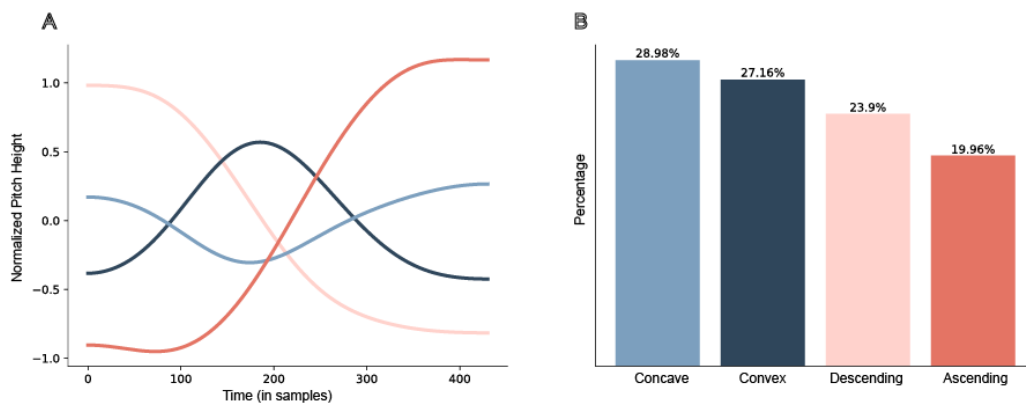


The results of averaging the four clusters show that, similar to the findings in Experiment 1, the clusters for the contours of Chinese folk songs in our dataset corresponded to descending, ascending, convex, and concave contour shapes (see Figure 8).

Out of a total of 1042 melodies, 302 phrases (28.98%) were classified as concave; 283 melodies (27.16%) were classified as convex; 249 melodies (23.90%) were classified as descending; and 208 melodies (19.96%) were classified as ascending. Overall, the percentage of phrases that were classified in each cluster was significantly different, $\chi^2(3) = 19.64$, $p < .001$ (Pearson's chi-square test).

Figure 8

Experiment 4. Clusters' means for the phrases of the Chinese folksongs dataset.



Note. **A.** Average shape of the four main musical contours plotted over time. **B.** Percentage of phrases in the dataset corresponding to each musical contour. Descending (pink), Convex (dark blue), Concave (light blue), Ascending (orange).

Post-hoc Pearson's chi-square tests with Bonferroni corrections for multiple comparisons show that the only significant differences in cluster sizes were those between the ascending and concave clusters ($p < .001$), and between the ascending and convex clusters ($p < .05$). The rest of the pairwise comparisons were not significant (see Table 4).

Table 3

Experiment 4. Post-hoc chi square testing.

Clusters	χ^2	p-value
Convex * Descending	2.17	0.84
Convex * Ascending	11.46	< 0.05
Convex * Concave	0.62	1.00
Descending * Ascending	3.68	0.33
Descending * Concave	5.10	0.14
Ascending * Concave	1.33	< 0.001

Note. P-values are corrected for multiple comparisons.

Discussion

Capitalizing on the Chinese folk songs subset of the Essen dataset, we were able to examine whether the same contours that were found to be common in the European section of the dataset would also be common here. The results indeed showed that the same four contours that accounted for the majority of the variance in the Western data were similar to the contours that were prevalent in the Chinese data. However, no significant difference was found between the three largest contour clusters - - convex, concave, and descending. In addition, pitch stability at the beginning and end of phrases appeared to different degrees in all four clusters.

General Discussion

This study sought to investigate the shape and prevalence of common contours in Western and non-Western music. More specifically, we used an objective, automated, and machine-learning based methodology in order to examine contours without the need to assume any priors regarding the expected shapes of the contours.

Using our unbiased method, we were able to confirm that across different datasets and musical cultures, the common contour shapes for phrases roughly corresponded to convex, concave, descending, and ascending. For complete melodies, the common contour shapes were similar but also included a “wavy” contour — descending and then convex. These findings were not highly affected by the size of the dataset or by whether we examined Western folksongs, Chinese folksongs, or a variety of Western musical styles. In Experiments 1 and 2, we found a significant effect for the relative prevalence of the descending and arch-shape contours compared to other contours shapes.

Our novel methodology for studying contour offers some insights not only on the question of which contour profiles are common across musical genres and cultures, but also on micro-contour

characteristics. For example, taking a closer look at the shapes of the averages of the clusters revealed a trend for descending pitch at the end of the phrases or melodies. Another micro-contour tendency that we found was for general pitch stability at the beginning and end of phrases, which is in line with the musical trend for longer notes at phrase boundaries (Boltz, 1999). Figure 7 presents two examples of phrases from Western folksongs that exhibit all of these micro-contours trends: pitch stability or long notes at the beginning and closing of the phrase and pitch descent towards the end of the phrase. These are merely exemplar prototypes, and our findings refer to a tendency of the average across many instances.

Figure 9

Examples of phrases that exhibit common micro-contour tendencies.



Note. Top: Jingles Bells, **Bottom:** God save the Queen.

Future studies should utilize our methodology to examine contour in other non-Western datasets. In the current paper we explored one such dataset, yet there is a lot more to be studied regarding non-Western music. While these examinations are beyond the scope of this paper, it would be interesting to examine whether the effects and trends found in the current study would be replicated in other diverse datasets, and whether there are contour shapes that are specific to music of different regions around the world.

It would also be interesting to explore whether some of the contours that were found to be common in musical datasets will also be found when examining datasets of speech audio. Studies of speech melody and intonation have shown a tendency for descending and arch-shape contours in speech (Chow & Brown, 2018). Tierney et al., (2011) explain the prevalence of descending contours as a hypothesized effect of motor constraints, as it is easier to produce a higher pitch when the air pressure underneath the vocal folds is high near the beginning of the utterance and lower pitched towards the end of the utterance. If this indeed explains (even partially) the prevalence of descending and/or convex contours, or if there are other common explanations underlying the contours in both speech and music, we could expect to find similarities in the common contours between music and speech.

In addition to the main findings, this work presents a new approach for studying contour by utilizing an unsupervised machine-learning based methodology. We believe that such an approach can be used to achieve a greater understanding of auditory contours across musical and auditory traditions, styles, and domains.

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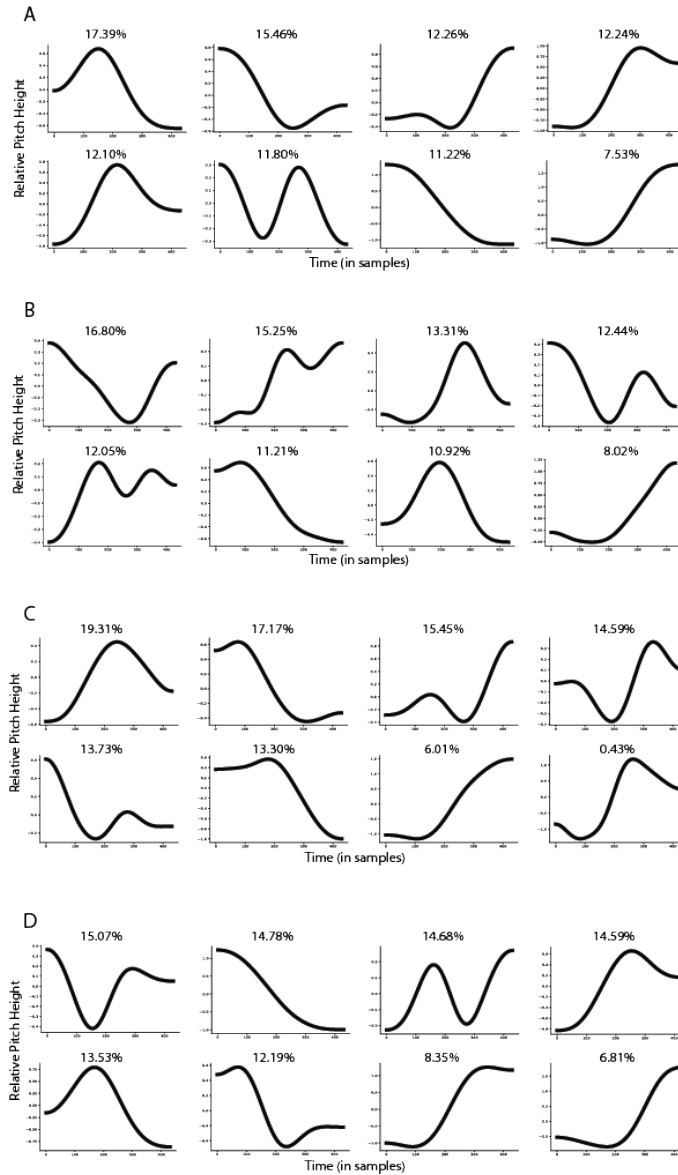
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Supplementary Materials

Supplementary Figure 1.

Clusters' means for the first eight components of each dataset, and relative cluster size as percentage from the dataset



Note. **A.** Average shape of the eight main musical contours of Experiment 1 (Essen dataset phrases) plotted over time. **B.** Average shape of the eight main musical contours of Experiment 2 (Essen dataset full melodies) plotted over time. **C.** Average shape of the eight main musical contours of Experiment 3 (mixed--style dataset phrases) plotted over time. **D.** Average shape of the eight main musical contours of Experiment 4 (Chinese dataset phrases) plotted over time.

Note that the prevalence and order of contours is affected by the number of clusters, as phrases or melodies that were included in the same cluster in the analysis with four clusters could be separated between multiple smaller clusters here.

Supplementary Table 1.*Detailed description of the songs and pieces included in the dataset for Experiment 3.*

Genre	Artist/Composer/Subgenre	Title	Source
Classic	Bach	Air in G	freemidi.org
Classic	Beethoven	Opus 2 Number 3	IMSLP
Classic	Beethoven	Opus 57	IMSLP
Classic	Beethoven	Rondo a Capriccio	freemidi.org
Classic	Beethoven	Symphony 3 movement 1, excerpt 1	Orchset
Classic	Beethoven	Symphony 3 movement 1, excerpt 2	Orchset
Classic	Beethoven	Symphony 3 movement 1, excerpt 5	Orchset
Classic	Beethoven	Symphony 3 movement 1, excerpt 6	Orchset
Classic	Beethoven	Symphony 5 movement 2, excerpt 1	Orchset
Classic	Beethoven	Symphony 5 movement 2, excerpt 3	Orchset
Classic	Beethoven	Symphony 9 movement 2, excerpt 2	Orchset
Classic	Beethoven	Fur Elise	piano-midi.de
Classic	Beethoven	Pathetique no. 3	piano-midi.de
Classic	Bizet	Carmen, interlude	freemidi.org
Classic	Brahms	Hungarian Dance Number 5	freemidi.org
Classic	Chopin	op. 7 no. 1	piano-midi.de
Classic	Chopin	op. 7 no. 2	piano-midi.de
Classic	Chopin	op. 28 no. 4	piano-midi.de
Classic	Chopin	op. 33 no. 4	piano-midi.de
Classic	Clementi	Opus 36 Number 2	IMSLP
Classic	Clementi	Opus 36 Number 5	IMSLP
Classic	Clementi	Op. 36 no. 1 mov. 1	piano-midi.de
Classic	Clementi	Op. 36 no. 1 mov. 2	piano-midi.de
Classic	Clementi	Op. 36 no. 1 mov. 3	piano-midi.de
Classic	Clementi	Op. 36 no. 3 mov. 3	piano-midi.de
Classic	Clementi	Op. 36 no. 6 mov. 1	piano-midi.de
Classic	Dvorak	Symphony 9, movement 4, excerpt 1	Orchset
Classic	Dvorak	Symphony 9, movement 4, excerpt 3	Orchset
Classic	Dvorak	Symphony 9, movement 4, excerpt 4	Orchset

Classic	Grieg	Peer Gynt, Hall of the Mountain King, excerpt 1	Orchset
Classic	Grieg	Peer Gynt, Morning Mood, excerpt 1	Orchset
Classic	Haydn	Piano Sonata number 13	IMSLP
Classic	Haydn	Piano Sonata number 16	IMSLP
Classic	Haydn	Piano Sonata number 33	IMSLP
Classic	Haydn	Piano Sonata number 34	IMSLP
Classic	Haydn	Symphony 94, Andante, excerpt 2	Orchset
Classic	Haydn	Symphony 94, Menuet, excerpt 1	Orchset
Classic	Haydn	hob 35 no. 1	piano-midi.de
Classic	Haydn	hob 35 no. 2	piano-midi.de
Classic	Haydn	hob 35 no. 3	piano-midi.de
Classic	Haydn	hob 40 no. 2	piano-midi.de
Classic	Haydn	hob 43 no. 1	piano-midi.de
Classic	Haydn	hob 43 no. 2	piano-midi.de
Classic	Haydn	hob 43 no. 3	piano-midi.de
Classic	Haydn	op. 7 no. 2	piano-midi.de
Classic	Haydn	op. 8 no. 1	piano-midi.de
Classic	Haydn	op. 8 no. 2	piano-midi.de
Classic	Haydn	op. 8 no. 3	piano-midi.de
Classic	Haydn	op. 8 no. 4	piano-midi.de
Classic	Haydn	op. 9 no. 1	piano-midi.de
Classic	Haydn	op. 9 no. 2	piano-midi.de
Classic	Hoslt	The Planets, Jupiter, excerpt 1	Orchset
Classic	Hoslt	The Planets, Jupiter, excerpt 2	Orchset
Classic	Hoslt	The Planets, Jupiter, excerpt 3	Orchset
Classic	Mendelssohn	Wedding March	freemidi.org
Classic	Mendelssohn	op. 19 no. 1	piano-midi.de
Classic	Mendelssohn	op. 30 no. 1	piano-midi.de
Classic	Mozart	Symphony number 40	freemidi.org
Classic	Mozart	The Marriage of Figaro	freemidi.org
Classic	Mozart	Piano Sonata k279	IMSLP
Classic	Mozart	Piano Sonata k283	IMSLP
Classic	Mozart	Piano Sonata k330	IMSLP

Classic	Mozart	Piano Sonata k331	IMSLP
Classic	Mozart	Piano Sonata k576	IMSLP
Classic	Mozart	op. 330 no. 1	piano-midi.de
Classic	Mozart	op. 331 no. 2	piano-midi.de
Classic	Mozart	op. 332 no. 2	piano-midi.de
Classic	Mozart	op. 333 no. 3	piano-midi.de
Classic	Mozart	op. 545 no. 1	piano-midi.de
Classic	Mozart	op. 570 no. 1	piano-midi.de
Classic	Mozart	op. 385 no. 1	piano-midi.de
Classic	Mozart	op. 385 no. 2	piano-midi.de
Classic	Mozart	op. 385 no. 3	piano-midi.de
Classic	Mozart	op. 385 no. 4	piano-midi.de
Classic	Mozart	op. 504 no. 1	piano-midi.de
Classic	Mozart	op. 504 no. 2	piano-midi.de
Classic	Mozart	op. 504 no. 3	piano-midi.de
Classic	Mozart	op. 183 no. 1	piano-midi.de
Classic	Mozart	op. 183 no. 2	piano-midi.de
Classic	Mozart	op. 183 no. 3	piano-midi.de
Classic	Mozart	op. 183 no. 4	piano-midi.de
Classic	Mozart	op 425. no. 1	piano-midi.de
Classic	Mozart	op 425. no. 2	piano-midi.de
Classic	Mozart	op 425. no. 3	piano-midi.de
Classic	Mozart	op 425. no. 4	piano-midi.de
Classic	Mozart	op. 543 no. 1	piano-midi.de
Classic	Mozart	op. 543 no. 2	piano-midi.de
Classic	Mozart	op. 543 no. 3	piano-midi.de
Classic	Mozart	op. 543 no. 4	piano-midi.de
Classic	Mozart	op. 550 no. 1	piano-midi.de
Classic	Musorgski	Pictures at the Exhibition, excerpt 5	Orchset
Classic	Musorgski	Pictures at the Exhibition, excerpt 6	Orchset
Classic	Musorgski	Pictures at the Exhibition, excerpt 7	Orchset
Classic	Musorgski	Pictures at the Exhibition, excerpt 8	Orchset
Classic	Musorgski	Pictures at the Exhibition, excerpt 10	Orchset

Classic	Musorgski	Pictures at the Exhibition, excerpt 11	Orchset
Classic	Musorgski	Pictures at the Exhibition, Promenade, excerpt 1	Orchset
Classic	Musorgski	Pictures at the Exhibition, Promenade, excerpt 2	Orchset
Classic	Prokofiev	Romeo and Juliet, Dance Knights, excerpt 1	Orchset
Classic	Ravel	Bolero, excerpt 1	Orchset
Classic	Rimski-Korsakov	Scheherazade, Kalender, excerpt 1	Orchset
Classic	Rimski-Korsakov	Scheherazade, Sea-SinbadShip, excerpt 2	Orchset
Classic	Rimski-Korsakov	Scheherazade, Sea-SinbadShip, excerpt 5	Orchset
Classic	Rimski-Korsakov	Scheherazade, Young Prince Princess, excerpt 1	Orchset
Classic	Rimski-Korsakov	Scheherazade, Young Prince Princess, excerpt 3	Orchset
Classic	Rimski-Korsakov	Scheherazade, Kalender, excerpt 4	Orchset
Classic	Rossini	William Tell Overture	freemidi.org
Classic	Schubert	Ave Maria	freemidi.org
Classic	Schubert	Impromptu Opus 142 Number 2	IMSLP
Classic	Schubert	Impromptu Opus 142 Number 4	IMSLP
Classic	Schubert	D. 935 no. 4	piano-midi.de
Classic	Schumann	op. 15 no. 1	piano-midi.de
Classic	Smetana	Ma Vlast, Vltava, excerpt 1	Orchset
Classic	Strauss	Blue Danube, excerpt 3	Orchset
Classic	Tchikovsky	Swan Lake, excerpt 2	Orchset
Classic	Tchikovsky	op. 73a no. 4	piano-midi.de
Classic	Wagner	Tannhauser, act 2, excerpt 2	Orchset
Folk	Christmas	A Christmas Tradition	freemidi.org
Folk	Christmas	All I Want For Christmas is You	freemidi.org
Folk	Christmas	Away In a Manger	freemidi.org
Folk	Christmas	Chipmunk Christmas	freemidi.org
Folk	Christmas	Christmas Song	freemidi.org
Folk	Christmas	Christmas Tree	freemidi.org
Folk	Christmas	Grandma Got Ran Over By a Reindeer	freemidi.org
Folk	Christmas	Here Comes Santa Clause	freemidi.org
Folk	Christmas	In Old Judea	freemidi.org
Folk	Christmas	Its Beginning To Look a Lot Like Christmas	freemidi.org
Folk	Christmas	Jingle Bell Rock	freemidi.org

Folk	Christmas	Leroy	freemidi.org
Folk	Christmas	Little Saint Nick	freemidi.org
Folk	Christmas	My Favorite Things	freemidi.org
Folk	Christmas	Of the Cardle	freemidi.org
Folk	Christmas	Rudolph the Red Nosed Reindeer	freemidi.org
Folk	Christmas	Santa Claus Is Coming To Town	freemidi.org
Folk	Christmas	Silent Night	freemidi.org
Folk	Christmas	Sleigh Ride	freemidi.org
Folk	Christmas	That Beautiful Start	freemidi.org
Folk	Christmas	Through The Night	freemidi.org
Folk	Christmas	Toyland	freemidi.org
Folk	Christmas	We Wish You a Merry Christmas	freemidi.org
Folk	Christmas	What Child is This	freemidi.org
Folk	Christmas	12 Day of Christmas	freemidi.org
Folk	American Folk	USA National Anthem	freemidi.org
Folk	American Folk	America Patrol	freemidi.org
Folk	American Folk	America the Beautiful	freemidi.org
Folk	American Folk	Buffalo Gals	freemidi.org
Folk	American Folk	Camptown Races	freemidi.org
Folk	American Folk	Dixie	freemidi.org
Folk	American Folk	God Bless America	freemidi.org
Folk	American Folk	God Save the Queen	freemidi.org
Folk	American Folk	Hail to the Chief	freemidi.org
Folk	American Folk	Liberty Bell March	freemidi.org
Folk	American Folk	Off We Go Into the Wild Blue Yonder	freemidi.org
Folk	American Folk	Polly Wolly Doodle	freemidi.org
Folk	American Folk	Semper Paratus	freemidi.org
Folk	American Folk	The Caissons Go Rolling Along	freemidi.org
Folk	American Folk	The Star Spangled Banner	freemidi.org
Folk	American Folk	Yankee Doodle	freemidi.org
Folk	American Folk	You are a Grand Ole Flag	freemidi.org
Folk	Nursery Rhythm	A Tisket A Tasket	Romwell.com
Folk	Nursery Rhythm	Are You Sleeping Frere Jacques	Romwell.com

Folk	Nursery Rhythm	Bicycle Built for Two	Romwell.com
Folk	Nursery Rhythm	BINGO	Romwell.com
Folk	Nursery Rhythm	Farmer in the Dell	Romwell.com
Folk	Nursery Rhythm	Happy and You Know It	Romwell.com
Folk	Nursery Rhythm	Hush Little Baby	Romwell.com
Folk	Nursery Rhythm	Little Raindrops	Romwell.com
Folk	Nursery Rhythm	Little Boy Blue	Romwell.com
Folk	Nursery Rhythm	London Bridge	Romwell.com
Folk	Nursery Rhythm	Mulberry Bridge	Romwell.com
Folk	Nursery Rhythm	Paw Paw Patch	Romwell.com
Folk	Nursery Rhythm	Pretty Little Horses	Romwell.com
Folk	Nursery Rhythm	The Animal Fair	Romwell.com
Folk	Nursery Rhythm	The More We Get Together	Romwell.com
Folk	Nursery Rhythm	There is a hole in the Sea	Romwell.com
Folk	Nursery Rhythm	Twinkle Little Star	Romwell.com
Pop	ABBA	The winner takes it all	midiworld.com
Pop	Adele	Set fire to the rain	freemidi.org
Pop	Aretha Franklin	You make me feel like a natural woman	midiworld.com
Pop	Barry Manilow	Copacabana	midiworld.com
Pop	Bill Withers	Aint No Sunshine	midiworld.com
Pop	Bruno Mars	Marry You	midiworld.com
Pop	Bruno Mars	Just The Way You Are	freemidi.org
Pop	Cat Stevens	Moonshadow	midiworld.com
Pop	Cat Stevens	Morning Has Broken	midiworld.com
Pop	Cyndi Lauper	Time After Time	midiworld.com
Pop	Helen Reddy	Delta Dawn	midiworld.com
Pop	Katy Perry	Firework	freemidi.org
Pop	Leonard Cohen	Halleluja	freemidi.org
Pop	Mamas and Papas	Dream a Little Dream of Me	midiworld.com
Pop	Sonny and Cher	I Got You Babe	midiworld.com
Pop	Stevie Wonder	For Once in My Life	midiworld.com
Pop	The Carpenters	Close To You	midiworld.com
Pop	The Carpenters	Rainy Days	midiworld.com

Pop	Stevie Wonder	I Just Called to Say I Love You	midiworld.com
Rock	Beatles	Hey Jude	freemidi.org
Rock	Beatles	Let It Be	freemidi.org
Rock	Beatles	A Little Help From My Friends	freemidi.org
Rock	Beatles	Another Girl	freemidi.org
Rock	Billy Joel	Piano Man	midiworld.com
Rock	Billy Joel	River of Dreams	midiworld.com
Rock	Billy Joel	She's Always a Woman to Me	midiworld.com
Rock	Billy Joel	The Longest Time	midiworld.com
Rock	Clearance Cleerwater Revival	Bad Moon Rising	freemidi.org
Rock	Clearance Cleerwater Revival	Down on the Corner	freemidi.org
Rock	Eagles	Hotel California	freemidi.org
Rock	Eric Calpton	Tears in Heaven	freemidi.org
Rock	Paul Simon	Kodachrome	midiworld.com
Rock	Paul Simon	Slip Sliding Away	midiworld.com
Rock	Simon and Garfunkel	Cecilia	midiworld.com
Rock	Van Morrison	Moondance	midiworld.com
Rock	The Monkees	Last Train to Clarksville	midiworld.com
Sound Tracks	Disney	Can You See The Love Tonight	freemidi.org
Sound Tracks	Disney	Colors of the Wind	freemidi.org
Sound Tracks	Disney	Chim Chim Cheree	freemidi.org
Sound Tracks	Disney	Gravity Falls Theme	freemidi.org
Sound Tracks	Disney	It's a Small World	freemidi.org
Sound Tracks	Disney	Jolly Holiday	freemidi.org
Sound Tracks	Disney	Duck Tales	freemidi.org
Sound Tracks	Disney	Can You Feel the Love Tonight	freemidi.org
Sound Tracks	Disney	Feed the Birds	freemidi.org
Sound Tracks	Disney	Haunted Mansion	freemidi.org
Sound Tracks	Disney	Main Street Electrical parade	freemidi.org
Sound Tracks	Disney	Winnie the Pooh	freemidi.org
Sound Tracks	Disney	March of the Gladiators	freemidi.org
Sound Tracks	Disney	Supercalifragilisticexpialidocious	freemidi.org
Sound Tracks	Disney	The Bear Necessities	freemidi.org

Sound Tracks	Disney	Tiki Room	freemidi.org
Sound Tracks	Movie Theme	Harry Potter	freemidi.org
Sound Tracks	Movie Theme	Pink Panther	freemidi.org
Sound Tracks	Movie Theme	Rocky	freemidi.org
Sound Tracks	Movie Theme	The Godfather	freemidi.org
