Testing Models of Melodic Contour Similarity
Author(s): Mark A. Schmuckler
Source: *Music Perception: An Interdisciplinary Journal*, Vol. 16, No. 3 (Spring, 1999), pp. 295-326
Published by: University of California Press
Stable URL: http://www.jstor.org/stable/40285795
Accessed: 09/04/2013 20:36

Music Perception
Spring 1999, Vol. 16, No. 3, 295–326

Testing Models of Melodic Contour Similarity

MARK A. SCHMUCKLER
University of Toronto at Scarborough

In two experiments, descriptions of melodic contour structure and predictions of perceived similarity relations between pairs of contours produced by a number of different models are examined. Two of these models, based on the music-theoretic approaches of Friedmann (1985) and Marvin and Laprade (1987), characterize contours in terms of interval content or contour subset information. The remaining two approaches quantify the global shape of the contours, through the presence of cyclical information (assessed via Fourier analysis) and the amount of oscillation (e.g., reversals in direction, pitch deviations) in the contours. Theoretical predictions for contour similarity generated by these models were examined for 20th century, nontonal melodies (Experiment 1) and simplistic, tonal patterns (Experiment 2). These experiments demonstrated that similarity based on Fourier analysis procedures and oscillation measures predicted a derived measure of perceived similarity, with both variables contributing relatively independently; the music-theoretic models were inconsistent in their predictive power. These results suggest that listeners are sensitive to the presence of global shape information in melodic contour, with such information underlying the perception of contour structure and contour similarity.

Melodic contour (the pattern of rising and falling intervals within a melody) has long been recognized as a fundamental component of musical perception. Contour has traditionally been a concern in psychological (e.g., Deutsch, 1969; Dowling, 1978) and music-theoretic (e.g., Marvin, 1991, 1995; Morris, 1987, 1993; Narmour, 1990; Schoenberg, 1967; Toch, 1948/1977) analyses of musical structure and has given rise to extensive bodies of research on melody identification (e.g., Deutsch, 1972; Dowling, 1984; Dowling & Hollombe, 1977; Idson & Massaro, 1978; Massaro, Kallman, & Kelly, 1980), memory for musical passages (e.g., Bartlett & Dowling, 1980; Croonen, 1994, 1995; Croonen & Kop, 1989; DeWitt & Crowder, 1986; Dowling, 1978, 1982, 1991; Dowling & Bartlett, 1981; Dowling & Fujitani, 1971; Dowling & Harwood, 1986), and so on.

Address correspondence to Mark A. Schmuckler, Division of Life Sciences, University of Toronto at Scarborough, 1265 Military Trail, Scarborough, Ontario, Canada M1C 1A4. (e-mail: marksch@banks.scar.utoronto.ca)

Given that contour is so crucial to melodic processing, a quantitative theory of contour structure would prove an invaluable tool, aiding in music-theoretic analyses and in determining how listeners perceive, organize, respond to, and remember musical passages. For example, one significant consequence of such a theory would be its potential use in determining similarity relations between musical passages. Such an innovation would have important implications for music-theoretic and psychological investigations of musical structure, providing predictions for theoretical structural similarity as well as psychological judgments of perceptual similarity.

Although numerous psychologists and music theorists have evinced an interest in contour, only a few formal descriptions of contour structure have been proposed. One approach to studying contour has been to categorize melodies according to feature information (Adams, 1976; Kolinski, 1965; Seeger, 1960; Polansky & Bassein, 1992). For example, Adams (1976) describes a "melodic contour typology" in which contours are defined by a set of boundary properties (the initial, final, highest, and lowest pitches within the contour), with three possible relations existing between boundary pitches (greater than, equal to, and less than). Combinations of these boundaries and relations are then used to identify primary contour features such as overall melodic slope, and secondary contour features such as repetitions of the highest or lowest pitch (see Adams, 1976). Although such systems provide a thorough typological description of a contour, they fall short as models of contour because they ultimately result in a simple list of melodic features. Whereas such a list may help in characterizing groups of melodies (e.g., how many songs within a corpus contain feature X), it is of limited utility in judging contour relatedness.

In a similar vein, Morris (1993) describes a model of contour relations in which a given contour is transformed through the reiterative application of a reducing algorithm into its fundamental or prime form. This algorithm repeatedly deletes notes from the contour, ultimately focusing in on the initial, final, maximum, and minimum points of the contour. According to Morris, these primes "play a role analogous to that of the Schenkerian background" (p. 218) and thus function as the underlying contour of the phrase in question. Similarity relations between prime forms of different contours can then be determined and used to highlight structural equivalence relations between different contours. Although this approach moves beyond the more generic taxonomic category schemes of other approaches (e.g., Adams, 1976; Kolinski, 1965; Seeger, 1960), its notion of contour similarity is restricted in that it ultimately looks only for contour equivalence, with different contours designated as being from either the same or different contour class. Unfortunately, this scheme does not contain any explicit or implicit means for quantifying varying degrees of similarity, an intuitively important psychological aspect of contour. Moreover, because of its reductive nature, this algorithm sacrifices information at the musical surface in delineating the underlying form of the contour at its highest (or deepest) hierarchical level. It is unknown whether equivalence on such an abstract basis factors into listeners' on-line processing of musical passages. Accordingly, this approach may have limited utility in defining perceived similarity relations of melodic contours.

A final set of theories have defined more explicit, continuous measures of similarity among melodic contours (Friedmann, 1985, 1987; Marvin & Laprade, 1987). These models have proposed a set of procedures for quantifying the contour of short melodic passages, with specific application to 20th century music. Friedmann (1985, 1987) suggests two such analytic tools: the contour adjacency series (CAS) and contour class (CC). The CAS codes the relative pattern of directional changes (e.g., ascending or descending), although it ignores the (actual or relative) distance between adjacent notes of a melody, and results in a sequence of +'s and –'s representing the pattern of rises and falls within the contour. This series is then succinctly described in a two-element contour adjacency series vector (CASV) that summarizes the total number of ascending and descending intervals in a given contour. The top half of Figure 1 displays the CAS and CASV for two six-note contours analyzed by Friedmann (1985),[1] taken from Schoenberg's Fantasy for Violin and Piano, op. 47, measures 1 and 2, and the Trio section of the Minuet from the Suite, op. 25, measures 1 and 2.

Friedmann's (1985) second analytic tool, the CC, provides a more complete description of contour, describing the relative pitch relations between all adjacent and nonadjacent elements. In the CC, the lowest pitch is coded as 0, the highest pitch as $n - 1$, with n equal to the number of unique pitches in the contour. The contour class notations for the melodic fragments of Figure 1 are also shown.

The individual pitch relations within the CC define a series of contour intervals (CIs) that describe the relative pitch intervals between adjacent and nonadjacent notes within the CC. For example, the CI for the adjacent interval $1 \rightarrow 2$ of the first melody in Figure 1 is +1, the CI for the next adjacent interval $3 \rightarrow 5$ is +2, and the CI for the nonadjacent interval $4 \rightarrow 0$ is –4. The entire set of CIs for a given contour produces the contour interval array (CIA), which notes the frequency of each CI, with positive (ascending) and negative (descending) intervals separated by a slash. Similar to the CAS, the CIA can be characterized by a pair of two-element vectors, the CCVI and the CCVII. The CCVI summarizes the ascending versus descending character of a contour and is produced by multiplying

1. For all theoretical explications, it will be assumed that comparisons are being made between contours of equivalent lengths. Although comparisons of unequal contour lengths are possible with these tools, such comparisons require generalizations that will not be discussed here.

Contour Adjacency Series (*CAS*) :
< +, +, +, -, - > < +, -, +, +, - >

Contour Adjacency Series Vector (*CASV*) :
< 3, 2 > < 3, 2 >

Contour Class (*CC*):
< 1, 2, 3, 5, 4, 0 > < 1, 4, 2, 3, 5, 0 >

Contour Intervals (*CI*s) :

Positive					*Negative*					*Positive*					*Negative*				
1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1-2	1-3	1-4	1-5		1-0	2-0	3-0	4-0	5-0	1-2	1-3	1-4	1-5		1-0	2-0	3-0	4-0	5-0
2-3	2-4	2-5			5-4					2-3	3-5	2-5			4-3	4-2			
3-4	3-5									4-5									
3	3	2	1	0	2	1	1	1	1	3	2	2	1	0	2	2	1	1	1

Contour Interval Array (*CIA*) :
<3, 3, 2, 1, 0/2, 1, 1, 1, 1> <3, 2, 2, 1, 0/2, 2, 1, 1, 1>

Contour Class Vectors:
CCVI < 19, 16 > *CCVI* < 17, 18 >
CCVII < 9, 6 > *CCVII* < 8, 7 >

Similarity Measures:
CASV Difference = 0
CCVI Difference = 2
CCVII Difference = 1

Fig. 1. The CAS, CC, CI, CIA, and CCV, as well as the CASV, CCVI, and CCVII difference measures proposed by Friedmann (1985) for two sample contours.

the frequency of each CI by the size of the CI and then adding together all ascending and descending intervals. The CCVII provides a more general assessment of the contour, taking into account frequency and direction of CIs irrespective of size; this measure is produced by adding the frequencies of all ascending and descending intervals. The CASV, the CCVI, and CCVII all assess contour similarity by creating a difference score between corresponding digits of the CASV, CCVI, or CCVII; calculation of these values is also shown in Figure 1. Finally, these equivalence relations are to be calculated with both contours in their original (prime) form, as well as when one contour is in prime form and the other contour has been transformed via inversion, retrograde, or retrograde-inversion operations.

Marvin and Laprade (1987) describe an alternative approach to contour analysis. Using Morris's (1987) "contour space" as their starting point, these authors propose a contour-segment (CSEG) representation that orders the elements of a contour from lowest to highest (e.g., 0 to $n - 1$), with n again equal to the number of distinct pitches within the contour. Subsets of the CSEG are possible (CSUBSEGs), with these subsets consisting of any combination of contiguous and noncontiguous pitches. Figure 2 shows the two contours of Figure 1 (here labeled CSEGs), along with three sample four-element CSUBSEGs. It should be emphasized that although this figure presents four-element CSUBSEGs,[2] subsets can be of any length, ranging from 2 to $n - 1$. If necessary, the CSUBSEG is translated to consist of integers from 0 to $n - 1$, with this translation equivalent to the initial CSUBSEG representation.

With this CSEG representation, one can generate a comparison matrix (COM-matrix), which is a two-dimensional array displaying the results of pitch comparisons between all elements in the contour. The results of the comparisons are listed as + (second note higher in pitch than the first), 0 (second note equal to the first), and – (second note less than the first). Figure 2 also displays the COM-matrices for the two contours.

So far, the relation between Friedmann's (1985) and Marvin and Laprade's (1987) theories is fairly transparent. Marvin and Laprade's CSEG representation is equivalent to Friedmann's CC, and the COM-matrix can easily be used to generate the CAS, CASV, and CCVII. The CAS appears immediately to the right of the center diagonal of the COM-matrix, and the CCVII can be calculated by totaling the +'s and –'s of the upper-half of the COM-matrix. The COM-matrix also gives rise to a unique measure of similarity, called the contour similarity function (CSIM). The CSIM is calculated by counting the correspondences (for either the upper or lower half matrix) of the positions of the +'s and –'s between two COM-matrices, with this number divided by the total number of positions. As with Friedmann (1985), CSIM values can be calculated between contours in prime form and between one prime contour and one transformed (inversion, retrograde, and retrograde-inversion) contour. The CSIM value for the two sample contours is also shown in Figure 2.

Marvin and Laprade (1987) also suggest a contour similarity measure called the contour mutually embedding function (CMEMB), which counts the number of CSUBSEGs that are mutually embedded in two contours, and divides this overlap by the total number of CSUBSEGs. Figure 3 presents the calculation of the CMEMB for the sample contours, showing all four-element CSUBSEGs for these contours, in 0 to $n - 1$ notation when necessary. The total for each CSUBSEG pattern is then determined, and the number of CSUBSEGs shared by both contours is divided by the total number of CSUBSEGs. The CMEMB can be calculated for CSUBSEGs vary-

2. In total there exist 15 four-element contiguous and noncontiguous subsets of a six-element set. The formula for calculating the total number of subsets of a given length (m) in a larger set (n) is: $n! / (m! * (n-m)!)$ (Marvin & Laprade, 1987; Rahn, 1980).

Contour Segments (*CSEGs*):

< 1, 2, 3, 5, 4, 0 >   < 1, 4, 2, 3, 5, 0 >

CSUBSEGs of Length 4:

< 1, 2, 3, 5 > = < 0, 1, 2, 3 >   < 1, 4, 2, 3 > = < 0, 3, 1, 2 >
< 1, 2, 3, 4 > = < 0, 1, 2, 3 >   < 1, 4, 2, 5 > = < 0, 2, 1 ,3 >
< 3, 5, 4, 0 > = < 1, 3, 2, 0 >   < 2, 3, 5, 0 > = < 1, 2, 3, 0 >

Comparison Matrix (*COM-Matrix*):

	1	2	3	5	4	0
1	0	+	+	+	+	-
2	-	0	+	+	+	-
3	-	-	0	+	+	-
5	-	-	-	0	-	-
4	-	-	-	+	0	-
0	+	+	+	+	+	0

	1	4	2	3	5	0
1	0	+	+	+	+	-
4	-	0	-	-	+	-
2	-	+	0	+	+	-
3	-	+	-	0	+	-
5	-	-	-	-	0	-
0	+	+	+	+	+	0

Similarity Measure:
Contour Similarity Function (*CSIM*): 12 / 15 = 0.80

Fig. 2. The CSEG, three sample CSUBSEGs of length 4, the COM-matrix, and the CSIM measure, proposed by Marvin and Laprade (1987) for two sample contours.

ing in length from 2 to $n - 1$, and for one contour in prime form and a second contour in prime, retrograde, inversion, or retrograde-inversion form.

Both Friedmann (1985) and Marvin and Laprade (1987) assume these measures define equivalence relations, such that contours with comparable structural descriptions are psychologically associated. For example, Friedmann (1985) justifies the need for contour descriptions of 20th century music not because of any paucity of theories describing pitch and segclass relations (Forte, 1973; Rahn, 1980), but because contour is more readily perceived by the majority of listeners than pitch class information, and thus is more likely to characterize the listener's experience.

Although rigorous and systematic, this focus on the interval content or contour subset information neglects a crucial aspect of melodic contour—namely, the global shape of the contour. Although global contour shape can be discerned from these representations (imagine the CC or CSEG as line drawings), neither model adequately characterizes this information. One aspect of global shape that may be important is the degree of oscillation (e.g., up and down movement) in the contour. For example, the sample contours of Figures 1–3 are distinguishable in that the second contour seems

Contour Segments (*CSEGs*):

< 1, 2, 3, 5, 4, 0 >   < 1, 4, 2, 3, 5, 0 >

***CSUBSEGs* of length 4:**

< 1, 2, 3, 5 > = < 0, 1, 2, 3 >	< 1, 4, 2, 3 > = < 0, 3, 1, 2 >
< 1, 2, 3, 4 > = < 0, 1, 2, 3 >	< 1, 4, 2, 5 > = < 0, 2, 1 ,3 >
< 1, 2, 3, 0 > = < 1, 2, 3, 0 >	< 1, 4, 2, 0 > = < 1, 3, 2, 0 >
. . . .	. . . .
. . . .	. . . .
. . . .	. . . .
< 3, 5, 4, 0 > = < 1, 3, 2, 0 >	< 2, 3, 5, 0 > = < 1, 2, 3, 0 >

Pattern	Total	Pattern	Total
< 0, 1, 2, 3 >	2	< 0, 1, 2, 3 >	1
< 0, 1, 3, 2 >	3	< 0, 2, 1, 3 >	2
< 1, 2, 3, 0 >	7	< 0, 3, 1 ,2 >	1
< 1, 3, 2, 0 >	3	< 1, 2, 3, 0 >	5
		< 1, 3, 2, 0 >	2
		< 2, 0, 1, 3 >	1
		< 2, 1, 3, 0 >	1
		< 3, 1, 2, 0 >	2

Overlapping Patterns:	$CSEG_1$	$CSEG_2$
< 0, 1, 2, 3 >	2	1
< 1, 2, 3, 0 >	7	5
< 1, 3, 2, 0 >	3	2

Similarity Measure:
Contour Mutual Embedding (*CMEMB*): 20 / 30 = 0.67

Fig. 3. The CMEMB, proposed by Marvin and Laprade (1987), for two sample contours.

to contain more oscillation than the first. One method of quantifying the degree of oscillation is to simply count the number of reversals in direction in this contour; in this case, the first contour has one reversal (ascend → descend) whereas the second contour contains three reversals (ascend → descend → ascend → descend). An additional measure is based on the distance in pitch (semitone) space encompassed by these reversals.[3] For the first sample contour, the ascending motion encompasses 25 semitones ($B\flat_3$ → B_5), whereas the descending motion covers 28 semitones (B_5 → G_3). In comparison, the ascending and descending motions of the second contour cover 13, 10, 11, and 15 semitones.

Numerous possible quantifications can be derived by using this information; two such measures are the mean pitch interval size and the summed pitch interval size for all intervals in the contour, with these values charac-

3. It would also be possible to count intervals in contour space, using the same contour coding procedure as that of Friedmann and Marvin and Laprade. In fact, these two methods give highly comparable results.

terizing oscillation somewhat differently. Because mean pitch interval information is normalized by the number of contour reversals, it treats each ascending and descending motion within the contour equally; thus, mean pitch interval is related to individual interval size within the contour. In contrast, because summed pitch interval information aggregates across all intervals, it provides a global measure of pitch divergence within the contour. For both interval measures (as well as for the reversals), similarity is calculated using difference scores for these values.

The distinction between the two pitch interval measures can be appreciated by considering the mean and summed interval information for the two sample contours. The first sample contour has a mean pitch interval value of 26.5 semitones, whereas the second contour has a value of 12.5 semitones. In contrast, the first sample contour has a summed interval value of 53 semitones, whereas the second contour has a value of 49 semitones. Thus, the summed pitch interval measure suggests a greater similarity between the contours than does the mean pitch interval measure.

An alternative characterization of the global shape of a contour involves looking for the presence of repeated or cyclical patterns. For example, the contours of Figures 1–3 are distinguishable in terms of the number of repeated patterns in each. Along these lines, the first contour is characterized by a single repetition of an ascending and descending motion, whereas the second contour contains two cycles of up-down motions. Again, intuitively it seems that this difference could be important in one's perception of these contours, as well as being related to one's sense of the similarity between the contours.

One typical procedure for quantifying cyclical information involves the application of Fourier analysis techniques. Described simply, Fourier analysis converts a signal from the temporal domain into the frequency domain, providing a mathematical decomposition of the signal into a set of harmonically related sine waves. Each of these sine waves is characterized by an amplitude (strength) and phase (timing relation) value, with the relative amplitudes and phases of the sine wave components providing a quantitative measure of the different cyclical patterns within the signal. Considering all these frequency components, Fourier analysis provides a general description of the shape of the contour, taking into account both slow moving, low-frequency movement such as general trend, as well as any high frequency, point-to-point fluctuation in the contour.

Figure 4 displays the results of Fourier analyzing the sample contours of Figures 1–3, listing the amplitude and phase spectra for cyclical components of one, two, and three repetitions per pattern. These spectra support the qualitative descriptions just provided. Based on its amplitude spectrum, the first contour is characterized strongly by a single repetition per cycle (Har. $1/R_m$), with weaker components for two and three repetitions per cycle. In

Contours:

1 2 3 5 4 0   1 4 2 3 5 0

Fourier Analysis Results:

	A_m	B_m	R_m	Φ_m
Mean	2.50	0.00	2.50	0.00
Har. 1	1.80	-0.14	1.09	0.13
Har. 2	0.25	0.43	0.50	-1.05
Har. 3	-0.17	0.00	0.17	0.00

	A_m	B_m	R_m	Φ_m
Mean	2.50	0.00	2.50	0.00
Har. 1	0.58	-0.14	0.60	0.24
Har. 2	-0.25	1.01	1.04	1.33
Har. 3	-0.17	0.00	0.17	0.00

Similarity Measures:

***Correlation Measure*:**

Amplitude: r(contour$_1$, contour$_2$) = 0.352
Phase: r(contour$_1$, contour$_2$) = -0.962

***Difference Score Measure*:**

Amplitude: 0.343
Phase: 0.830

Fig. 4. The results of Fourier analysis of the two sample contours. Shown are the real (A_m), imaginary (B_m), amplitude (R_m), and phase (Φ_m) components produced by the Fourier analysis and the correlations between amplitude and phase spectra.

contrast, the second contour consists of a strong component of two cycles per repetition (Har. 2/R_m), with weaker components at one and three cycles.

Fourier analysis has a number advantages for contour analysis. One strength is that it provides an obvious measure of similarity—contours with comparable cyclical structure are perceived as related by listeners. The degree of association between contours can be assessed in any number of ways. One procedure involves correlating amplitude and phase spectra. A correlation coefficient is attractive in that it compares only relative patterns of ups and downs, collapsing across absolute differences in the spectra, and has associated tables of statistical significance. It is possible, however, that the magnitude of differences in the spectra are meaningful. To capture this aspect, one can calculate an absolute difference score between corresponding components of the spectra, with contour similarity based on the amount of difference between individual frequency components, or on an average difference calculated across all harmonics. Regardless of the associative measure used, the implication is that the degree of association between contours will be related to the perception of contour similarity.

A second advantage is that the output of a Fourier analysis is largely invariant in the face of different transformations of the contour. For example, Fourier analysis is essentially scale independent, such that a contour consisting of large interval leaps will produce comparable phase and amplitude spectra to a similar contour made up of small steps. In the same vein, the low-frequency components of the output of a Fourier analysis will be relatively invariant in the face of melodic ornamentation, such as grace notes, passing tones, and neighbor tones; higher frequency components will, however, vary somewhat. In both of these cases, the coding of the input representation becomes important. For scale independence, different codings produce outputs that can vary from highly similar to identical. As for melodic ornamentation, the degree of similarity between outputs will vary depending on whether or not the input representation contains rhythmic information, although both rhythmic and nonrhythmic inputs should produce highly related outputs; further consideration of rhythm in contour analysis is taken up in the general discussion. Irrespective of these final issues, it seems clear that Fourier analysis of contour is a potentially powerful technique.

Applying Fourier procedures to the analysis of melodic contours is not without some analytic pitfalls, however. One serious concern is that Fourier analysis requires a variety of assumptions, some of which are violated in this application. For example, one important assumption is that the series being analyzed via Fourier techniques is an extended sequence that represents the sampling of an infinitely periodic signal; in contrast, melodic contours are short and discrete. This concern has both theoretical and practical implications. Theoretically, the concern is that because the series to be analyzed does not meet this criterion, the results of the analysis, in terms of its ability to forecast future cyclical patterns, is suspect. Practically, the concern is that with a short, discrete series, a Fourier analysis will be disproportionately influenced by information at the beginning and ending of the sequence, with such "edge effects" distorting the Fourier spectra, also resulting in decreased predictive power.

In defense of the theoretical viability of this application, it should be remembered that the goal here is not the typical predictive forecasting commonly associated with time-series analyses (the family of analytic procedures to which Fourier analysis belongs). In contrast, Fourier analysis is being used strictly as a convenient tool to quantify the presence of repetitive patterns in a melody. Fundamentally, Fourier analysis is simply a mathematical decomposition procedure that is applicable to any numerical series. Although care must be taken in interpreting the output of this procedure, there is no reason why this technique cannot be used to provide a description of any numerical series, including a melodic contour.

As for the practical considerations, one procedure used to control edge effects involves mathematically transforming the series by using windowing techniques (e.g., Hamming or Kaiser windows). Such windows reduce edge effects by weighting the beginning and ending of a sequence less than the middle of the sequence. Unfortunately, given the length of the series tested in this work, such procedures actually alter the shape of the contours themselves; thus, similarity measures based on such altered contours are of questionable utility. As such, it is ultimately difficult to control edge effects, meaning that the results of a Fourier analysis of contour may be too distorted to characterize the melody adequately. As indirect support for the viability of this approach, Fourier analysis has proven effective in analyzing short, discrete series of tonal and rhythmic information (Chiappe & Schmuckler, 1997; Cuddy & Badertscher, 1987; Cuddy & Thompson, 1992; Krumhansl, 1990; Krumhansl & Schmuckler, 1986; Palmer & Krumhansl, 1990; Schmuckler, 1990, 1997). It is an open question, though, whether Fourier analysis procedures will also be applicable to melodic contours.

In summary, a number of procedures for quantifying contour and predicting contour similarity have been developed. Two of these approaches, those of Friedmann (1985) and Marvin and Laprade (1987), are related in that they grow out of the same music-theoretic tradition, adopting similar assumptions. For example, these theories are concerned with what Polansky and Bassein (1992) call the "combinatorial contour," which consists of the interval relations between both contiguous and noncontiguous contour elements, with all such information important for determining similarity relations. Additionally, both approaches accept the idea that transformations of a melody, such as retrograde, inversion, and retrograde-inversion, not only have psychological reality but can also underlie perceived contour associations. Thus, despite differences in these theories (see Friedmann, 1987, for a cogent comparison of these approaches), they share many characteristics. Two different approaches, involving Fourier analysis and the degree of oscillation in a contour, have also been developed. These ideas represent a more dramatic departure from the tradition of Friedmann (1985) and Marvin and Laprade (1987) in that they are concerned with "linear contour" (Polansky & Bassein, 1992), focusing on an analysis of global shape.

The goal of these studies was to test the ability of these models to predict perceived contour similarity. Toward this end, all of these models quantified individual contours and predicted similarity relations between pairs of contours. These similarity measures were then compared with a listener-generated derived measure of perceived contour similarity. The decision to use a derived measure of similarity, as opposed to gathering direct similarity ratings of pairs of melodies, was in large part pragmatic. Pilot work suggested that listeners had great difficulty providing direct similarity ratings for pairs of melodies (using the stimulus melodies of Experiment 1, described later), with listeners frequently reporting that they had forgotten the first melody by the end of the second melody. In keeping with these reports, there was little intrasubject or intersubject reliability for contour similarity ratings. Thus, an alternative procedure for generating similarity data was used, involving gathering contour ratings of individual melodies, and then intercorrelating aggregate ratings to produce a derived similarity matrix. This approach is a widely accepted alternative to a direct similarity rating procedure (Kruskal & Wish, 1978; Wish & Carroll, 1974), having been used successfully to generate proximities for factor analysis and multidimensional scaling applications (Banks & Gregg, 1965; Guttman, 1966; Weisberg & Rusk, 1970).

These experiments also tested the generality of these models by examining a range of melodic contours. Experiment 1 examined a set of 20th century, nontonal pieces. Whereas both the Fourier analysis and oscillation measures are neutral in terms of the style of music to which they can be applied, the theories of Friedmann (1985) and Marvin and Laprade (1987) were developed specifically for the analysis of 20th century music; thus, these stimuli represent the most appropriate test for these models. Experiment 2 provided a subsequent test of these models by examining simple tonal melodic patterns. Such a test is critical in that successful prediction of perceived similarity across the divergent stimulus sets of the two experiments establishes the general applicability of these models to the analysis of melodic contour per se, as opposed to a more limited application to a specific musical corpus.

Experiment 1: Similarity of 20th-Century Tone Rows

METHODS

Subjects

Sixteen students (mean age, 19.6 years), who either volunteered their services or were students in an introductory psychology course at the University of Toronto at Scarborough participated in this study, receiving either extra course credit or $7 for participating. All listeners were musically trained, with a mean of 7.4 years of formal training, a mean of 3.0 hr per week engaged in music making, and a mean of 18.2 hr per week spent listening to music. All listeners reported normal hearing, and none indicated that they were familiar with the passages of music played during the experiment.

Experimental Apparatus and Stimuli

Stimuli were generated with a Yamaha TX816 synthesizer, controlled by an IBM-compatible 286-MHz computer, connected with a Roland MPU-401 MIDI controller. The timbre used by the synthesizer was harmonically complex, approximating the sound of a piano (see Schmuckler, 1989). All tones were input into a Mackie 1202 mixer, and amplified and presented using a BOSS MA-12 micro-monitor, at a comfortable listening level.

The stimuli for this experiment consisted of 12-note melodies, based on the prime row form of twenty 20th-century 12-tone pieces (these rows are shown in Figure 5). Each trial consisted of a presentation of one contour, with the duration of each note equal to 400 ms. On each trial, the lowest note of the contour was set to a random pitch between $F\#_3$ and F_4, with the remaining notes of the contour similarly transposed. Listeners heard four repetitions (blocks) of each contour, with contours presented in a different random order for each listener.

Procedure

Listeners were told they were participating in an experiment on contour perception. They were informed that on each trial they would hear a 12-note contour and that they should rate the complexity of this contour, using a 9-point scale, with 1 indicating not very complex and 9 indicating very complex. Listeners typed their responses on the computer keyboard, and as soon as their response was entered, the computer began the next trial. Listeners were free to take breaks between the blocks of trials. Subsequent to the final block of trials, listeners completed a musical background questionnaire and were debriefed as to the purpose of the experiment. The entire experiment lasted approximately 30–45 min.

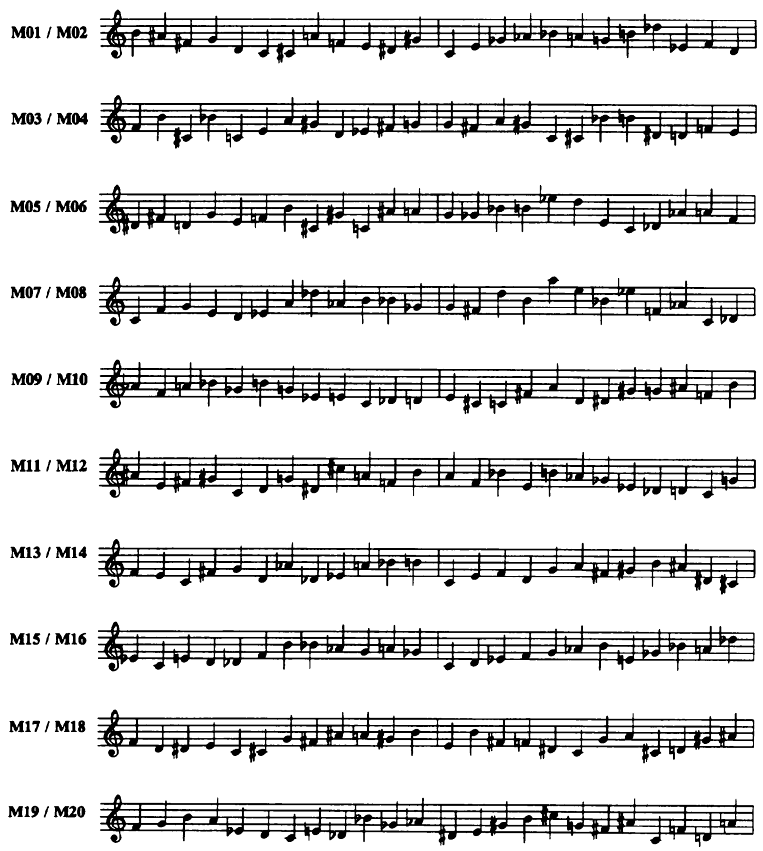

Fig. 5. The 20 stimulus contours used in Experiment 1.

RESULTS

The first step in the analysis involved quantifying contour similarity on the basis of the various models. All of these models produce multiple measures of similarity. Friedmann (1985) provides differences in the CASV, the CCVI, and the CCVII; because they are difference scores, these values represent dissimilarity, with small numbers reflecting similarity and large numbers dissimilarity. Marvin and Laprade (1987) measure similarity via CSIM and CMEMB values. For both of these theories, measures are calculated between two contours in prime form, as well as between one contour in prime form and the second contour in retrograde, inversion, or retrograde-inversion form. Thus, contour similarity can be based on similarity between any of these forms, or the maximum similarity value across these forms; in fact, Marvin and Laprade (1987, pp. 237, 245) assume that contour similarity is a function of this "maximum" value. Fourier analysis also produces multiple similarity measures, including correlations of the amplitude or phase spectra for pairs of contours, as well as difference scores between the harmonic components for the amplitude and phase spectra. Finally, contour oscillation also produces multiple similarity values, involving difference scores based on the number of contour reversals, the mean pitch interval, and the summed pitch interval. Again, because these are differences they produce dissimilarity values, and hence should be negatively related to perceived similarity. Table 1 summarizes these different mea-

TABLE 1
Summary of Contour Similarity Predictors

Predictor		Contour Form			
Friedmann					
CASV	Prime	Retrograde	Inversion	Retrograde-Inversion	Maximum
CCVI	Prime	Retrograde	Inversion	Retrograde-Inversion	Maximum
CCVII	Prime	Retrograde	Inversion	Retrograde-Inversion	Maximum
Marvin and Laprade					
CSIM	Prime	Retrograde	Inversion	Retrograde-Inversion	Maximum
CMEMB	Prime	Retrograde	Inversion	Retrograde-Inversion	Maximum
Fourier Analysis					
Amplitude		Correlation	Difference Score		
Phase		Correlation	Difference Score		
Oscillation					
Reversals					
Average Interval Size					
Summed Interval Size					

Note—CASV = Contour Adjacency Series Vector, CCVI and CCVII = Contour Class Vectors, CSIM = Contour Similarity Function, CMEMB = Contour Mutually Embedding Function.

M01:	11	10	6	7	2	0	1	9	5	4	3	8
M12:	9	5	10	4	11	8	6	3	1	2	0	7
M16:	0	1	2	4	6	7	10	3	5	9	8	11

Friedmann:

Diff. Score:	*CASV*			*CCVI*			*CCVII*		
1st Contour	M01	M01	M12	M01	M01	M12	M01	M01	M12
2nd Contour	M12	M16	M16	M12	M16	M16	M12	M16	M16
Prime	0	5	5	33	165	198	6	32	38
Retrograde	3	2	2	131	67	34	24	14	8
Inversion	3	2	2	131	67	34	24	14	8
Retro-Inver	0	5	5	33	165	198	6	32	38
Maximum	3	5	5	131	165	198	24	32	38

Marvin & Laprade:

Contour	*CSIM* 2nd Contour Form					*CMEMB* 2nd Contour Form				
1st / 2nd	Prime	Retro	Inver	R-Inv	Max	Prime	Retro	Inver	R-Inv	Max
M01 / M12	0.52	0.48	0.34	0.55	0.55	0.35	0.27	0.22	0.42	0.42
M01 / M16	0.24	0.76	0.58	0.42	0.76	0.20	0.40	0.41	0.18	0.41
M12 / M16	0.42	0.58	0.70	0.30	0.70	0.11	0.53	0.44	0.12	0.53

Fourier Analysis:

	M01		M12		M16	
	R_m	Φ_m	R_m	Φ_m	R_m	Φ_m
Har. 1	1.567	0.027	1.751	-1.434	1.261	-0.953
Har. 2	1.341	-1.155	0.939	0.568	1.530	-1.434
Har. 3	1.067	0.896	0.425	-0.197	0.755	-0.111
Har. 4	0.382	-1.237	0.520	-1.328	0.520	1.328
Har. 5	0.270	0.155	1.156	1.489	1.064	-0.292
Har. 6	0.833	-0.000	0.667	0.000	0.333	-0.000

	Correlation			Average Difference Score		
	$r_{(m01,m12)}$	$r_{(m01,m16)}$	$r_{(m12,m16)}$	$r_{(m01,m12)}$	$r_{(m01,m16)}$	$r_{(m12,m16)}$
Amplitude	0.437	0.530	0.639	0.403	0.373	0.306
Phase	0.174	-.0122	-0.349	0.950	0.880	1.168

Oscillation Measures:

	Raw Value			Difference Score		
	m01	m12	m16	m01, m16	m01, m16	m12, m16
Reversals	5	7	4	2	1	3
Mean PI	5.5	5.25	5.8	0.25	0.30	0.55
Summed PI	33	42	29	9	4	13

Fig. 6. The various theoretical similarity measures defined by Friedmann (1985), Marvin and Laprade (1987), the Fourier analysis approach, and the oscillation model, as applied to three stimulus contours (M01, M12, M16) from Experiment 1.

sures.[4] Figure 6 shows the similarity measures produced after applying these models to three of the stimulus contours of Figure 5. The end result of these applications was a series of half-matrices indicating the similarity (or dissimilarity) between all melodic contours.

4. The CMEMB values were actually calculated as the total percent overlap, aggregating across CSUBSEGs of length 2 to 11. It is also, however, possible to calculate this value as an average percent overlap for CSUBSEGs of length 2 to 11 individually. In fact, all analyses for the CMEMB model were calculated in both ways and provided virtually identical patterns. Accordingly, only the results for the total percent overlap are presented. For CASV, CCVI, and CCVII models, these values represent the average absolute difference score between corresponding (e.g., positive and negative) digits in the vectors.

The next step involved producing the perceived similarity matrix. First, contour ratings were analyzed in a two-way analysis of variance (ANOVA), with the within-subject variables of *contour* (Contour 1, Contour 2, ... Contour 20) and *repetition* (Block 1, Block 2, Block 3, Block 4). This analysis revealed main effects of contour, $F(19,285) = 2.18$, $MSE = 4.64$, $p < .005$, suggesting that complexity ratings differed across the contours, and repetition, $F(3,45) = 4.61$, $MSE = 6.00$, $p < .01$, with ratings for Block 1 lower than ratings for Blocks 2–4. There was no interaction between the two variables, $F(57,855) = 1.03$, $MSE = 2.95$, n.s. Contour ratings were then averaged across repetition for each listener and used to create contour vectors by aggregating the ratings for each contour across listeners. These 16-element contour vectors were then intercorrelated, producing a half-matrix of correlations representing contour similarity (Kruskal & Wish, 1978; Wish & Carroll, 1974).

Finally, regression techniques fit the theoretical models to contour similarity; Table 2 displays the results of these analyses. For the music-theoretic models, two measures predicted similarity judgments—the maximum value of the CCVI, $r(188) = .182$, $p < .05$, and the maximum value of the CCVII, $r(188) = .179$, $p < .05$. Although significant, these findings must be viewed skeptically; because these measures index dissimilarity, they should have correlated negatively with contour similarity. Both global measures fared

TABLE 2
Summary of Correlations for Experiment 1

	Contour Form				
Predictor	**Prime**	**Retrograde**	**Inversion**	**Retrograde-Inversion**	**Maximum**
Friedmann					
CASV	.024	–.011	–.011	.024	–.018
CCVI	.036	.124	.124	.036	.182*
CCVII	.014	.115	.115	.014	.179*
Marvin and Laprade					
CSIM	–.033	–.001	.033	.001	.042
CMEMB	.078	–.082	–.019	.003	.046
Fourier Analysis	Correlation	Difference Score			
Amplitude	.324**	–.238**			
Phase	.026	–.053			
Oscillation					
Reversals		–.251**			
Average Interval Size		–.084			
Summed Interval Size		–.454**			

Note—CASV = Contour Adjacency Series Vector, CCVI and CCVII = Contour Class Vectors, CSIM = Contour Similarity Function, CMEMB = Contour Mutually Embedding Function.
* $p < .05$. ** $p < .01$.

better. For the Fourier analysis, amplitude spectra similarity predicted similarity judgments for both correlation, $r(188) = .324$, $p < .001$ and difference score measures, $r(188) = -.238$, $p < .001$. Similarly, the number of contour reversals predicted similarity judgments, $r(188) = -.244$, $p < .001$, as did the summed interval size measure, $r(188) = -.451$, $p < .001$.

Given that multiple variables correlated with similarity judgments, a final analysis looked at the interrelation of these variables in predicting contour similarity. Toward this end, a multiple regression analysis predicted derived similarity measures from predictors based on the number of reversals, the summed interval size, and amplitude spectra. For this last variable, the correlation measure of similarity was used, given that it had produced the strongest correlation with the derived similarity judgments previously. Of the three predictors, summed interval size correlated significantly with amplitude spectra similarity, $r(188) = -.326$, $p < .001$ and with contour reversals, $r(188) = .382$, $p < .001$; amplitude spectra and reversal measures were unrelated, $r(188) = -.110$. Together, these three factors significantly predicted contour similarity ratings, $R(186) = .495$, $p < .0001$. Despite the significant intercorrelations between these factors, both amplitude spectra and summed interval size contributed significantly to the fit, with betas of .199 and –.352, *p*s < .005, respectively. In contrast, reversals did not add significantly to the regression equation, beta = –.088.

DISCUSSION

The primary finding of this study was that perceived contour similarity was predictable from similarity measures based on the presence of cyclical information, as adjudged by amplitude spectra similarity, and by the degree of oscillation, as indexed by the summed size of the pitch intervals outlined in contour changes. In contrast, neither Friedmann's (1985) nor Marvin and Laprade's (1987) model significantly predicted perceived similarity, suggesting that these models do not necessarily characterize this psychological aspect of contour.

Fourier analysis was not uniformly powerful in its predictive value, however. Phase information, in contrast to amplitude information, did not correlate with derived similarity. Whereas it is possible that phase information is simply unrelated to contour similarity, it is also possible that the complexity of these stimuli did not provide a clear sense of the phase relations of the cyclical components. If true, then similarity of simpler cyclical patterns with more distinct phase relations might show an effect of phase; Experiment 2 tested this hypothesis.

For the oscillation measure, the best predictor was the summed interval size variable; although reversals in direction also correlated with similarity judgments, this variable did not contribute in the multiple regression model. As discussed earlier, summed interval size represents a more global contour measure than does mean interval size. Accordingly, this result, combined with that of the amplitude spectra, suggests that listeners are sensitive to aspects of the overall shape of the contour and not to specific intervals within the contour.

Although this experiment was successful in predicting contour similarity, it does contain some limitations. First, these models have only been applied to a particular corpus of music (20th century nontonal melodies). Although these stimuli were chosen to provide the most appropriate context for testing the music-theoretic models, this choice nevertheless raises concerns as to the generality of these findings. Second, despite the fact that the multiple regression model demonstrated reliable predictive power, the impact of any single model was at best modest, although the large number of comparisons (a 20 x 20 half-matrix) undoubtedly plays a role here. Both concerns can be addressed by replicating these results with a different stimulus set than that used in Experiment 1. A successful application of these models to different melodies, using an independent sample of listeners, provides strong evidence in support of these approaches to the quantification of contour similarity.

Experiment 2: Similarity of Simple Melodic Patterns

Experiment 2 provided an opportunity for replicating Experiment 1, predicting similarity relations among simple tonal melodies. Use of such contours extends the generality of all of these models and provides another chance for the models of Friedmann (1985) and Marvin and Laprade (1987) to predict contour similarity. Moreover, if the phase information of the melodies of Experiment 1 was indistinct because of the general complexity of these melodies, then using simpler contours containing more distinct phase relations might now uncover a relation between phase spectra information and perceived contour similarity.

METHODS

Subjects

Sixteen undergraduate students (mean age, 20.9 years) participated in this experiment, receiving either course credit in introductory psychology or $7 for participating. All listeners were musically trained, with a mean of 6.7 years of formal instruction, a mean of 3.7 hr per week currently involved in music-making, and a mean of 13.2 hr per week listening to music, and reported normal hearing.

Experimental Apparatus, Stimuli, and Procedure

Stimuli were generated and presented to listeners using the same equipment as in Experiment 1. These stimuli, shown in Figure 7, consisted of 20 tonal melodies designed to con-

Fig. 7. The 20 stimulus contours used in Experiment 2.

tain cyclical information and simple phase relations. Listeners heard four randomly ordered blocks of 20 experimental trials, with the characteristics of the individual tones (note duration and transposition) comparable to Experiment 1. Instructions and procedures for this study were the same as in Experiment 1.

RESULTS

Analyses proceeded along the same lines as in Experiment 1. The theoretical models of Friedmann (1985), Marvin and Laprade (1987), the Fourier analysis approach, and the oscillation approach, were applied to the contours of Figure 7. These procedures produced a set of half-matrices, representing similarity (or dissimilarity) between all pairs of contours.

Contour ratings were examined in a two-way ANOVA, with the variables of *contour* (Contour 1, Contour 2, ... Contour 20), and *repetition* (Block 1, ... Block 4). This analysis revealed a main effect of contour, $F(19,285) = 38.84$, $MSE = 3.54$, $p < .001$, indicating that the ratings varied as a function of the contour, but no effect for repetition, $F(3,45) = 0.45$, $MSE = 5.61$, n.s. The interaction between the variables was significant, $F(57,855) = 1.63$, $MSE = 1.94$, $p < .005$. Inspection of this interaction revealed that, although the ratings for the contours varied across repetitions, they remained globally consistent, with, for example, highly rated contours receiving relatively high ratings across all four blocks. Accordingly, ratings were averaged across repetitions for subsequent analyses.

Individual contour ratings generated contour similarity ratings by intercorrelating contour vectors, consisting of each listener's average rating of each contour. This similarity measure was then predicted by the theoretical similarity measures already described; Table 3 displays the results of these comparisons. In this study, the maximum value of Friedmann's CCVI predicted similarity judgments, $r(188) = .170$, $p < .05$; unfortunately, because this measure reflects dissimilarity, this relation should have been positive rather than negative. For Marvin and Laprade's model, the maximum value for both CSIM and CMEMB measures predicted contour similarity, with $rs(188) = .227$ and $.326$, $ps < .01$, respectively, as did the similarity value for the inversion form of the CMEMB model, $r(188) = .209$, $p < .01$. For the Fourier analysis model, both correlation and difference scores measures for the amplitude spectra again predicted perceived similarity ratings, $r(188) = .220$, $p < .01$, and $r(188) = -.397$, $p < .001$, respectively. In addi-

TABLE 3
Summary of Correlations for Experiment 2

	Contour Form				
Predictor	**Prime**	**Retrograde**	**Inversion**	**Retrograde-Inversion**	**Maximum**
Friedmann					
CASV	.074	−.012	−.012	.074	.089
CCVI	.014	−.040	−.040	.014	.104
CCVII	.053	−.013	−.013	.053	.170*
Marvin and Laprade					
CSIM	−.115	−.063	.136	−.050	.277**
CMEMB	.000	.120	.209**	.016	.326**
Fourier Analysis		Correlation	Difference Score		
Amplitude		.220**	−.392**		
Phase		.300**	−.382**		
Oscillation					
Reversals		−.108			
Average Interval Size		−.081			
Summed Interval Size		−.536**			

Note—CASV = Contour Adjacency Series Vector, CCVI and CCVII = Contour Class Vectors, CSIM = Contour Similarity Function, CMEMB = Contour Mutually Embedding Function.
* $p < .05$. ** $p < .01$.

tion, both correlation and difference score measures from the phase spectra predicted perceived similarity, $r(188) = .300$ and $-.302$, $ps < .001$. For the oscillation measures, in contrast to Experiment 1, contour reversals failed to predict similarity judgments, $r(188) = -.108$, although the summed pitch interval measure once again significantly predicted similarity, $r(188) = -.536$, $p < .001$.

Because multiple models significantly predicted the derived similarity ratings, multiple regression analyses were once again used to assess the interrelations among the models themselves and to see how the variables combined in predicting perceived similarity. Initially, this analysis included all variables that (interpretably) predicted contour similarity, along with the contour reversal variable. This final variable was included on the basis of its role in the previous experiment. For the CSIM and CMEMB measures, the maximum values were used, and for the amplitude and phase spectra variables, the difference score measures were used, given that these values were more predictive of contour similarity, based on the simple correlations. Table 4 gives the intercorrelation matrix between these predictors as well as the results of the multiple regression. Overall, these measures tended to be related, a finding that is not surprising given that these variables generally predicted similarity judgments. Of more interest, however, is the result of the multiple regression analysis, in which these six

TABLE 4

Interfactor Correlation Matrix, Averaging Across Prime, Retrograde, Inversion, Retrograde-Inversion, and Maximum Values, and the Results of the Multiple Regressions Predicting Perceived Similarity from the Various Models

	CSIM	CMEMB	Reversals	Summed PI	Amplitude
CMEMB	.857**				
Reversals	–.461**	–.399**			
Summed PI	–.191*	–.306**	.076		
Amplitude	–.477**	–.455**	.375**	.404**	
Phase	–.671**	–.642**	.351**	.266**	.412**

Multiple correlation	.604**	.602**	.601**
		Beta	
CSIM	–.026	–.046	—
CMEMB	.030	.030	—
Reversals	.061	—	—
Summed PI	–.414**	–.420**	–.426**
Amplitude	–.153*	–.139[a]	–.132[a]
Phase	–.228**	–.224**	–.214**

Note—CMEMB = Contour Mutually Embedding Function, CSIM = Contour Similarity Function, PI = pitch interval.

[a] $p < .057$. * $p < .05$. ** = $p < .01$.

variables significantly predicted contour similarity judgments, $R(183) = .604$, $p < .0001$. Of these six variables, three contributed significantly: amplitude spectra similarity, phase spectra similarity, and summed pitch interval similarity (see Table 4). Two subsidiary analyses were performed. The first predicted similarity judgments from all variables except contour reversals, whereas the second predicted similarity judgments from only amplitude spectra, phase spectra, and summed pitch interval factors. Both of these analyses produced comparable results, with $R(184) = .602$ and $R(186) = .601$, $ps < .001$, respectively.

DISCUSSION

Replicating Experiment 1, listeners' perceived contour similarity was again predicted by measures indexing the global shape of the melody. The first measure was the summed distance (in semitones) covered by the various ascending and descending patterns within the contour. The second measure involved the strength of the cyclical patterns within these contours; this information was indexed by the amplitude spectra of these melodies. Finally, a third measure of contour involved the phase relations between the cyclical components of these contours. This finding suggests that phase information can play a role in contour similarity with stimuli in which such information is clear and distinct.

Another new finding in this study was that the maximum value for Marvin and Laprade's (1987) CSIM and CMEMB models reliably correlated with listeners' perceived similarity, although the results of the multiple regression analyses do raise some concerns about these results. At face value, however, the fact that the maximum (and in one case inversion) model provided this fit does imply that listeners can perceive the inherent relations between contour transformations such as prime and inversion/retrograde, a finding that has been only weakly supported in previous work (e.g., Dowling, 1971, 1972; Dowling & Fujitani, 1971; Krumhansl, Sandell, & Sargeant, 1987). From a psychological stance, the most compelling support for CSIM or CMEMB measures would involve significant fits between modeled and perceived similarity for both contours in prime (heard) form. Thus, combined with the implications of the multiple regression analyses, the psychological status of the CSIM and CMEMB constructs remains unclear; such issues could be addressed in future work.

General Discussion

Taken together, these studies provide some insight into how to characterize, both structurally and psychologically, melodic contour. In these studies different models of contour were quantitatively developed, and the abilities of these approaches to predict a derived measure of perceived contour similarity were compared. These models met with varied success, with one approach never predicting contour similarity, two models consistently predicting contour similarity, and one sometimes related to similarity.

Before discussing these models in detail, some methodological considerations should be explored. Methodologically, the most obvious concern with these studies involves the choice of using a derived measure of perceived similarity, as opposed to having listeners directly rate contour similarity. As mentioned earlier, the decision to use this paradigm was pragmatic, based on the findings of pilot work; this approach was justified and supported, however, by the literature on multidimensional scaling that suggests that derived similarity data (such as gathered here) produces scaling metrics comparable to more direct similarity measures. Nevertheless, whether or not the derived similarity judgments truly reflect perceived contour similarity per se remains an issue.

It should be remembered, though, that any concerns regarding this similarity metric are applicable only to listeners' judgments and not to the models' predictions of similarity. All of the models were developed with the explicit purpose of directly measuring contour similarity; as such, the only issue regarding these models is whether or not the measures do, in fact, capture such similarity. Accordingly, a significant relation between listeners' judgments and the model's similarity assessments has the two-pronged effect of demonstrating the model's abilities to capture contour similarity and validating the appropriateness of the derived measure of perceived similarity.[5] Admittedly, in situations in which a model fails to predict listeners' judgments, it is unclear whether the failure is due to an inadequacy in the model or a problem in the perceived similarity judgment; however, the fact that at least one model (and in some cases more than one) did successfully predict perceived similarity does shift the locus of the problem onto the predictive power of the remaining, unsuccessful models. Nevertheless, given these concerns, it would be reassuring if future work, using both direct (e.g., explicit comparisons of two contours) and indirect (e.g., derived similarity measures, memory confusion matrices) were to replicate these results.

A second methodological consideration is that the indirect measure used in this study involved a rating of contour complexity, a psychologically complex component of a melody or a musical passage that may or may not capture the essence of contour, and one that has a rich history in aesthetics in its own right (e.g., Konečni, 1982). The response to this issue is much

5. It is possible that a significant relation could occur because both the model and the derived similarity data are each related to a third parameter and not to an aspect of melodic contour per se. Unfortunately, without any theory, or at least intuition, of what this parameter is, it is difficult to address this issue, although it does seem somewhat fortuitous (and admittedly unlikely) that both model and perceptual judgments would inadvertently measure an unforeseen, and unknown variable.

along the lines just presented; contour similarity, as assessed by complexity judgments, was predictable from explicit models of this similarity. This result suggests that at the least, an important component of melodic contour per se can be captured by the psychological dimension of complexity, with this dimension playing a significant role in perceived similarity judgments. As indirect support for the importance of complexity as a fundamental aspect of contour, Morris (1993) gives a central role to the dimension of complexity in his algorithm for contour reductions, with the number of reiterations required of the algorithm to produce the contour's prime form (the contour's "depth") an explicit measure of the contour's complexity (see Marvin, 1995, for a discussion). Thus, there appears to be a strong relation between a contour's complexity and its underlying nature, although the two are not the same.

Turning now to the findings regarding the specific tests of these models, the first question that could be raised involves why there was such variation in the predictive power of these models. In many ways, all of these models are analytically elegant, identifying structural similarities between widely diverse melodic contours. One key aspect of the models, however, is the unit of analysis employed. For Friedmann's (1985) theory, similarity results from the overlap of two-note interval information, with similar contours containing comparable numbers of ascending and descending intervals of varying sizes. Marvin and Laprade (1987) assess contour similarity for units varying in size (at least for the CMEMB model) from two-note intervals up to contour subsets of almost the entire length. Moreover, and relatedly, both of these measures focus on combinatorial contour, including in their similarity metrics information concerning both contiguous and noncontiguous intervals. In contrast, both the Fourier analysis and oscillation approaches focus on the linear contour, assessing the global shape of the contour, either in terms of the repeating patterns, or the amount of pitch deviation. Either of these variables—a focus on linear as opposed to combinatorial contour, or an analysis of global as opposed to local contour structure—could underlie the observed differences between the models.

Unfortunately, it is not possible to distinguish fully between these possibilities with the current data; such distinctions ultimately await further work. In considering this question, though, it should be noted that virtually all of the examples and analyses used by both Friedmann (1985) and Marvin and Laprade (1987) involve short contours of no more than about six notes. Longer contours, which contain much more constituent interval information, might be ultimately more difficult to retain, making the only information available to listeners global aspects such as shape, trend, and a general sense of pitch deviation. In contrast, shorter contours will contain less interval information overall, potentially rendering such information more accessible to listeners. Moreover, because Experiment 2 used simplistic tonal patterns, these melodies might have contained a more varied set of intervals than the melodies used in Experiment 1, with some intervals relatively infrequent (e.g., the tritone) and other intervals much more common (e.g., the major second); such interval variation is common in tonal sequences (Brown, 1988; Brown & Butler, 1981; Browne, 1981; Butler, 1989). Together, these distinctions implicate the importance of interval content in contour perception, although this is by no means conclusive.

One topic conspicuously absent from this paper has been any serious consideration of the role of rhythm in the perception of melodic contour. In the experiments themselves, rhythm was consciously rendered impotent by presenting the stimuli in an equitemporal fashion; this lack of rhythmic variation makes it unlikely that rhythm significantly influenced contour similarity. Rhythm is obviously a crucial component of a melody, however, and as such ultimately needs to be addressed in any model of contour perception. In considering rhythm, one issue involves whether or not any of these models can capture rhythmic variation, thereby enabling its inclusion in contour analysis. For the music-theoretic approaches, because the various similarity metrics operate on an input representation consisting only of ordered pitch information, duration and rhythmic information are lost. In fact, this inability to address rhythm has led Marvin (1991) to propose an explicit model of rhythm contour perception. This model is again developed for the analysis of 20th century music and proceeds along analogous lines as the models of pitch contour described in Marvin and Laprade (1987), using many of the same analytic tools (e.g., COM-matrix similarity).

As for the oscillation model, there is similarly no obvious way to incorporate note duration or rhythmic information into these analyses; hence, these measures are also blind to rhythm. In contrast, because Fourier analysis is unconstrained in the coding of its input, it can analyze the rhythmic information of a contour along with its pitch information, provided that the rhythm can be encoded into the input representation. One way of incorporating rhythm would be to provide a distinct value for every sounded beat or subbeat of the melody, taking the shortest duration as the unit of analysis. For example, the first sample contour of Figures 1–4, which was coded as 1 2 3 5 4 0, could be represented rhythmically with the series 1 1 1 1 1 2 3 5 4 4 0 0 0 0 0 0, with the first tone containing 5 sixteenth notes, the second through fourth tones 1 sixteenth note each, and so on. Such an input essentially weights pitch information by its rhythm and provides a means for incorporating this parameter into an analysis of pitch contour.

This discussion of rhythm raises a basic issue regarding the relation between pitch and temporal information in perceived contour. The idea that, given an appropriate input representation, Fourier analysis can incorporate rhythm into its contour description assumes that the pitch and temporal information of a melody are, on some level, fundamentally integrated;

such an assumption arises because, in the world of Fourier transform, periodicity and rhythm are essentially inseparable. This idea that the impact of rhythm on the perception of pitch contour might be captured by analyzing a rhythmically weighted pitch representation fits well with a psychological characterization of pitch and temporal information as fundamentally interdependent and interactive (e.g., Boltz, 1989, 1993; Boltz & Jones, 1986; Deutsch, 1980; Jones, 1993; Jones & Boltz, 1989; Jones, Boltz, & Kidd, 1982).

An alternative psychological description of the relation between pitch and temporal information has been to view these two parameters as independent (e.g., Monahan & Carterette, 1985; Palmer & Krumhansl, 1987a, 1987b; Thompson & Sinclair, 1993). With regard to the current discussion, this suggests that another viable method of integrating temporal and/or rhythmic information into contour descriptions is by explicitly analyzing a contour's rhythm and using this rhythmic analysis as an independent factor in the quantification and prediction of contour similarity. This approach is inherent in the music-theoretic analysis of rhythm by Marvin (1991), described earlier; in fact, Marvin (1995) generalizes the idea of contour analysis to a number of diverse musical dimensions, including pitch, rhythm, loudness, timbre, and so on. Along these lines, interesting questions involve looking for points of congruence, or similar contour structures, for different musical segments within the same dimension (e.g., similar pitch contours in different sections of a piece or across pieces), or for different dimensions within the same musical segment (e.g., similar pitch and loudness contours in the same musical phrase). Psychological research has only begun to explore contour formation across varying auditory dimensions such as pitch, loudness, and duration (see Schmuckler & Gilden, 1993); accordingly, the impact on contour perception of congruity versus incongruity of contour information is not well understood. Clearly, though, this is an intriguing avenue for future work, both in its own right and as it relates to musical contour similarity.

The preceding discussion of rhythm, and how it might be integrated into a model of contour perception, underscores the general finding that contour similarity was a joint function of multiple, independent variables (amplitude spectra and pitch deviation similarity, and sometimes phase spectra information). Two very general issues arise here: First, what other variables might be important in predicting perceived contour similarity, and second, will these same variables always be predictive of perceived contour similarity?

In considering other variables, the impact of rhythm, either characterized within a pitch contour representation or as a separate parameter, has already been much discussed. A different set of variables that might be important involves internalized representations of musical information. One obvious such candidate is tonal hierarchy similarity (see Krumhansl, 1990, for a description of tonal hierarchies), or the degree to which two contours invoke similar percepts of tonality. Although not formally presented in this article, a series of analyses examined the impact of tonality on contour similarity[6] and failed to uncover any significant association between tonal similarity and derived contour similarity. It should be remembered, though, that these experiments were designed to minimize the impact of tonality by transposing melodies to randomly chosen keys on every presentation, not to mention that the contours of Experiment 1 were assumed, by definition, to be nontonal. As such, the role of tonality in contour similarity is an open question.

Along with tonal hierarchy information, metrical hierarchy information (see Palmer & Krumhansl, 1990, for a description of metrical hierarchies) might play in role in contour similarity, with two contours that instantiate similar metrical hierarchies heard as similar. Previous work (Schmuckler, 1990), for example, has shown that metrical hierarchy information can be used to characterize performances of complex melodic and combined melodic-harmonic musical passages. Given the nature of the current stimuli, the possibility of metrical hierarchy similarity is a moot point in the present studies; thus, as with tonality, the impact of this variable remains to be tested.

The finding that contour similarity is predictable from multiple factors demonstrates that music can be simultaneously characterized via multiple psychological and/or music-theoretic descriptions, as opposed to a single analytic description. In this regard, Fourier analysis, and to a lesser extent the oscillation model, provides an alternative to the more typical descriptions of musical structure involving hierarchical melodic (e.g., Deutsch & Feroe, 1981; Jones, 1981; Jones, Maser, & Kidd, 1978; Narmour, 1990, 1992; Schenker, 1979), tonal-harmonic (e.g., Krumhansl, 1979, 1990; Lerdahl & Jackendoff, 1983; Schenker, 1954), or rhythmic content (e.g., Essens, 1986; Essens & Povel, 1985; Jones, 1976; Lerdahl & Jackendoff, 1983; Palmer & Krumhansl, 1990; Povel, 1981, 1984). In contrast, Fourier analysis of contours is more in keeping with fractal analyses of auditory (e.g., Schmuckler & Gilden, 1993; Voss & Clarke, 1978) and visual (e.g., Cutting & Garvin, 1987; Gilden, Schmuckler, & Clayton, 1993; Gilden, Thornton, & Mallon, 1995; Knill, Field, & Kersten, 1990) stimuli. Such analyses have provided an alternative, and often complementary, description of the information contained in auditory and visual sources.

6. For the atonal contours of Experiment 1, the 12 tones were weighted using a procedure similar to that described by Krumhansl et al. (1987), and the tonality of these contours and those of Experiment 2 were quantified by using Krumhansl and Schmuckler's (1986) key-finding algorithm (see Krumhansl, 1990). Tonal similarity was assessed by then comparing the output of the key-finding algorithm for all contours.

The second general issue involves whether or not the same variables will be predictive of contour similarity across a range of stimuli and psychological tasks. Although in many ways this issue simply awaits future research, the results of the impact of phase information do demonstrate that the variables underlying contour similarity can vary with the nature of the stimuli. As an aside, it was interesting that amplitude information consistently predicted similarity ratings in that this result diverges from research on the identification of visual scenes (e.g., Banks & Ginsberg, 1985; Kleiner, 1987; Kleiner & Banks, 1987) in which phase information is preeminent. This finding does, however, coincide with work on the perception of fractal contours (e.g. Gilden et al., 1993, 1995; Schmuckler & Gilden, 1993) that has demonstrated that amplitude spectra information is critical in identification and discrimination. This issue aside, these results suggest that Fourier analysis and oscillation measures, along with any other indices, may vary in predicting contour similarity.

In sum, this paper is just a first step in developing a model of contour description and perception, and suggests a number of possible directions for future work. The ultimate goal of such explorations is to provide as comprehensive and as global a theory of musical contour as possible, and hopefully, a theory of the perception of melodies more generally. Such theories will aid not only in the analysis of musical organization and structure, but will also provide insight into the fundamental psychological processes involved in the perception and cognition of complex auditory and musical information.[7]

References

Adams, C. R. (1976). Melodic contour typology. *Ethnomusicology*, *20,* 179–215.

Banks, M. S., & Ginsburg, A. P. (1985). Early visual preferences: A review and new theoretical treatment. In H. W. Reese (Ed.), *Advances in child development and behavior* (pp. 207–246). New York: Academic Press.

Banks, A. S., & Gregg, P. M. (1965). Grouping political systems: Q-factor analysis of a cross-polity survey. *American Behavioral Scientist*, *9,* 3–6.

Bartlett, J. C., & Dowling, W. J. (1980). Recognition of transposed melodies: A key-distance effect in developmental perspective. *Journal of Experimental Psychology: Human Perception and Performance*, *6,* 501–515.

Boltz, M. (1989). Rhythm and "good endings": Effects of temporal structure on tonality judgments. *Perception & Psychophysics*, *46,* 9–17.

Boltz, M. (1993). The generation of temporal and melodic expectancies during musical listening. *Perception & Psychophysics*, *53,* 585–600.

Boltz, M., & Jones, M. R. (1986). Does rule recursion make melodies easier to reproduce? If not, what does? *Cognitive Psychology*, *18,* 389–431.

7. This research was supported by a grant from the Natural Sciences and Engineering Research Council of Canada to the author. Portions of this work were presented at the 35th meetings of the Psychonomic Society, 1994, St. Louis, MO.

Brown, H. (1988). The interplay of set content and temporal context in a functional theory of tonality perception. *Music Perception, 5,* 219–249.

Brown, H., & Butler, D. (1981). Diatonic trichords as minimal tonal cue-cells. *In Theory Only, 5,* 37–55.

Browne, R. (1981). Tonal implications of the diatonic set. *In Theory Only, 5,* 3–21.

Butler, D. (1989). Describing the perception of tonality in music: A critique of the tonal hierarchy theory and a proposal for a theory of intervallic rivalry. *Music Perception, 6,* 219–241.

Chiappe, P., & Schmuckler, M. A. (1997). Phrasing influences the recognition of melodies. *Psychonomic Bulletin and Review, 4,* 254–259.

Croonen, W. L. M. (1994). Effects of length, tonal structure, and contour in the recognition of tone series. *Perception & Psychophysics, 55,* 623–632.

Croonen, W. L. M. (1995). Two ways of defining tonal strength and implications for recognition of tone series. *Music Perception, 13,* 109–119.

Croonen, W. L. M., & Kop, P. F. M. (1989). Tonality, tonal scheme and contour in delayed recognition of tone sequences. *Music Perception, 7,* 49-68.

Cuddy, L. L., & Badertscher, B. (1987). Recovery of the tonal hierarchy: Some comparisons across age and levels of musical experience. *Perception & Psychophysics, 41,* 609–620.

Cuddy, L. L., & Thompson, W. F. (1992). Asymmetry of perceived key movement in chorale sequences: Converging evidence from a probe-tone analysis. *Psychological Research, 54,* 51–59.

Cutting, J. E., & Garvin, J. J. (1987). Fractal curves and complexity. *Perception & Psychophysics, 42,* 365–370.

Deutsch, D. (1969). Music recognition. *Psychological Review, 76,* 300–307.

Deutsch, D. (1972). Octave generalization and tune recognition. *Perception & Psychophysics, 11,* 411–412.

Deutsch, D. (1980). The processing of structured and unstructured tonal sequences. *Perception & Psychophysics, 28,* 381–389.

Deutsch, D., & Feroe, J. (1981). The internal representation of pitch sequences in tonal music. *Psychological Review, 88,* 503–522.

DeWitt, L. A., & Crowder, R. G. (1986). Recognition of novel melodies after brief delays. *Music Perception, 3,* 259–274.

Dowling, W. J. (1971). Recognition of inversions of melodies and melodic contours. *Perception & Psychophysics, 9,* 348–349.

Dowling, W. J. (1972). Recognition of melodic transformations: Inversion, retrograde, and retrograde inversion. *Perception & Psychophysics, 12,* 417–421.

Dowling, W. J. (1978). Scale and contour: Two components of a theory of memory for melodies. *Psychological Review, 85,* 341–354.

Dowling, W. J. (1982). Melodic information processing and its development. In D. Deutsch (Ed.), *The psychology of music* (pp. 413–429). New York: Academic Press.

Dowling, W. J. (1984). Musical experience and tonal scales in the recognition of octave-scrambled melodies. *Psychomusicology, 4,* 13–32.

Dowling, W. J. (1991). Tonal strength and melody recognition after long and short delays. *Perception & Psychophysics, 50,* 305–313.

Dowling, W. J., & Bartlett, J. C. (1981). The importance of interval information in long-term memory for melodies. *Psychomusicology, 1,* 30-49.

Dowling, W. J., & Fujitani, D. S. (1971). Contour, interval and pitch recognition in memory for melodies. *Journal of the Acoustical Society of America, 49,* 524–531.

Dowling, W. J., & Harwood, D. (1986). *Music cognition.* Orlando, FL: Academic Press.

Dowling, W. J., & Hollombe, A. W. (1977). The perception of melodies distorted by splitting into octaves: Effects of increasing proximity and melodic contour. *Perception & Psychophysics, 21,* 60–64.

Essens, P. J. (1986). Hierarchical organization of temporal patterns. *Perception & Psychophysics, 40,* 69–73.

Essens, P. J., & Povel, D. J. (1985). Metrical and nonmetrical representations of temporal patterns. *Perception & Psychophysics, 37,* 1–17.

Forte, A. (1973). *The structure of atonal music.* New Haven: Yale University Press.

Friedmann, M. L. (1985). A methodology for the discussion of contour: Its application to Schoenberg's music. *Journal of Music Theory, 29,* 223–248.

Friedmann, M. L. (1987). My contour, their contour. *Journal of Music Theory, 31,* 268–274.

Gilden, D. L., Schmuckler, M. A., & Clayton, K. (1993). The perception of natural contour. *Psychological Review, 100,* 460–478.

Gilden, D. L., Thornton, D., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science, 267,* 1837–1839.

Guttman, L. (1966). Order analysis of correlation matrices. In R. B. Cattell (Ed.), *Handbook of multivariate experimental psychology* (pp. 438–458). Chicago: Rand McNally.

Idson, W. L., & Massaro, D. W. (1978). A bidimensional model of pitch in the recognition of melodies. *Perception & Psychophysics, 24,* 551–565.

Jones, M. R. (1976). Time, our lost dimension: Toward a new theory of perception, attention, and memory. *Psychological Review, 83,* 323–345.

Jones, M. R. (1981). A tutorial on some issues and methods in serial pattern research. *Perception & Psychophysics, 30,* 492–504.

Jones, M. R. (1993). Dynamics of musical patterns: How do melody and rhythm fit together. In T. J. Tighe & W. J. Dowling (Eds.), *Psychology and music: The understanding of melody and rhythm* (pp. 67–92). Hillsdale, NJ: Lawrence Erlbaum Associates.

Jones, M. R., & Boltz, M. (1989). Dynamic attending and responses to time. *Psychological Review, 96,* 459–491.

Jones, M. R., Boltz, M., & Kidd, G. (1982). Controlled attending as a function of melodic and temporal context. *Perception & Psychophysics, 32,* 211–218.

Jones, M. R., Maser, D. J., & Kidd, G. (1978). Rate and structure in memory for auditory patterns. *Memory & Cognition, 6,* 246–258.

Kleiner, K. A. (1987). Amplitude and phase spectra as indices of infants' pattern preferences. *Infant Behavior and Development, 10,* 45–55.

Kleiner, K. A., & Banks, M. S. (1987). Stimulus energy does not account for 2-month-olds' face preferences. *Journal of Experimental Psychology: Human Perception and Performance, 13,* 594–600.

Knill, D. C., Field, D., & Kersten, D. (1990). Human discrimination of fractal images. *Journal of the Optical Society of America, 7,* 1113–1123.

Kolinski, M. (1965). The structure of melodic movement: A new method of analysis (revised version). *Studies in Ethnomusicology, 2,* 96–120.

Konečni, V. J. (1982). Social interaction and musical preference. In D. Deutsch (Ed.), *The psychology of music* (pp. 497–516). New York: Academic Press.

Krumhansl, C. L. (1979). The psychological representation of musical pitch in a tonal context. *Cognitive Psychology, 11,* 346–374.

Krumhansl, C. L. (1990). *Cognitive foundation of musical pitch.* London: Oxford University Press.

Krumhansl, C. L., Sandell, G. J., & Sargeant, D. C. (1987). The perception of tone hierarchies and mirror forms in twelve-tone serial music. *Music Perception, 5,* 31–77.

Krumhansl, C. L., & Schmuckler, M. A. (1986). Key-finding in music: An algorithm based on pattern matching to tonal hierarchies. Paper presented at the 19th annual Mathematical Psychology meeting, Cambridge, MA.

Kruskal, J. B., & Wish, M. (1978). *Multidimensional scaling.* Beverly Hills, CA: Sage Publications.

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

Marvin, E. W. (1991). The perception of rhythm in non-tonal music: Rhythmic contours in the music of Edgard Varèse. *Music Theory Spectrum, 13,* 61–78.

Marvin, E. W. (1995). A generalization of contour theory to diverse musical spaces: Analytic applications to the music of Dallapiccola and Stockhausen. In E. W. Marvin & R. Hermann (Eds.), *Concert music, rock and jazz since 1945: Essays and analytic studies* (pp. 135–171). Rochester, NY: University of Rochester Press.

Marvin, E. W., & Laprade, P. A. (1987). Relating musical contours: Extensions of a theory for contour. *Journal of Music Theory, 31,* 225–267.

Massaro, D. W., Kallman, H. J., & Kelly, J. L. (1980). The role of tone height, melodic contour, and tone chroma in melody recognition. *Journal of Experimental Psychology: Human Perception and Performance, 6,* 77–90.

Monahan, C. B., & Carterette, E. C. (1985). Pitch and duration as determinants of musical space. *Music Perception, 3,* 1–32.

Morris, R. (1987). *Composition with pitch classes: A theory of compositional design.* New Haven, CT: Yale University Press.

Morris, R. D. (1993). New directions in the theory and analysis of musical contour. *Music Theory Spectrum, 15,* 205–228.

Narmour, E. (1990). *The analysis and cognition of basic melodic structures.* Chicago, IL: University of Chicago Press.

Narmour, E. (1992). *The analysis and cognition of melodic complexity.* Chicago, IL: University of Chicago Press.

Palmer, C., & Krumhansl, C. L. (1987a). Independent temporal and pitch structures in determination of musical phrases. *Journal of Experimental Psychology: Human Perception and Performance, 13,* 116–126.

Palmer, C., & Krumhansl, C. L. (1987b). Pitch and temporal contributions to musical phrases: Effects of harmony, performance timing, and familiarity. *Perception & Psychophysics, 51,* 505–518.

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

Polansky, L., & Bassein, R. (1992). Possible and impossible melody: Some formal aspects of contour. *Journal of Music Theory, 36,* 259–284.

Povel, D. J. (1981). Internal representation of simple temporal patterns. *Journal of Experimental Psychology: Human Perception and Performance, 7,* 3–18.

Povel, D. J. (1984). A theoretical framework for rhythm perception. *Psychological Research, 45,* 315–337.

Rahn, J. (1980). *Basic atonal theory.* New York: Longman.

Schenker, H. (1954). *Harmony* (E. M. Borgese, Trans.). Chicago, IL: The University of Chicago Press.

Schenker, H. (1979). *Free composition* (E. Oster, Trans.). New York, NY: Longman Inc.

Schoenberg, A. (1967). *Fundamentals of musical composition.* London: Faber and Faber Ltd.

Schmuckler, M. A. (1989). Expectation in music: Investigation of melodic and harmonic processes. *Music Perception, 7,* 109–150.

Schmuckler, M. A. (1990). The performance of global expectations. *Psychomusicology, 9,* 122–147.

Schmuckler, M. A. (1997). Expectancy effects in memory for melodies. *Canadian Journal of Experimental Psychology, 51,* 292–305.

Schmuckler, M. A., & Gilden, D. L. (1993). Auditory perception of fractal contours. *Journal of Experimental Psychology: Human Perception and Performance, 19,* 641–660.

Seeger, C. (1960). On the moods of a music-logic. *Journal of the American Musicological Society, 13,* 224–261.

Thompson, W. F., & Sinclair, D. (1993). Pitch pattern, durational pattern, and timbre: A study of the perceptual integration of auditory qualities. *Psychomusicology, 12,* 3–21.

Toch, E. (1948). *The shaping of musical forces.* New York: Dover Publications. (Reprinted 1977)

Voss, R. F., & Clarke, J. (1978). 1/f noise in music: Music from 1/f noise. *Journal of the Acoustical Society of America, 63,* 256–263.

Weisberg, H. F., & Rusk, J. G. (1970). Dimensions of candidate evaluation. *American Political Science Review*, *64*, 1167–1185.
Wish, M., & Carroll., J. D. (1974). Applications of individual differences scaling to studies of human perception and judgment. In E. C. Carterette & M. P. Friedman (Eds.), *Handbook of Perception* (Vol. 2, pp. 449–491). New York: Academic Press.