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The Combinatorial Model of Pitch Contour

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Much previous work on the perception of pitch contour has concerned itself only with the contour relations among adjacent notes, which may lead to the assumption that relations among nonadjacent tones do not play a role in the mental representation of contour. Music theorists, on the other hand, have developed sophisticated models of contour in which relations among nonadjacent tones play an integral part. In order to test the salience of relations among nonadjacent melodic tones in the perception of melodic contour, musically trained participants were asked to rate the similarity of discrete pairs of stimulus melodies with regard to contour. The results suggest that although contour relations among adjacent tones are more significant than those among nonadjacent tones in determining judgments about contour similarity, nonadjacent contour relations do contribute to such judgments.

MANY music theorists find it convenient to conceive of pieces or passages of music as sets of points in a multidimensional metric space, the dimensions of which include (but are not limited to) time, pitch, amplitude, spatial placement, and various dimensions of timbre.[1] A similar conceit underlies our music-notation system, in which points (noteheads) are given meaning roughly by their location relative to the two orthogonal axes of pitch and time. So construed, music as notated in pitch-time space can be viewed as a two-dimensional projection of a more complex, higher-dimensional structure. Such a projection constitutes an abstraction that admits of an infinite number of (re-)realizations in higher-dimensional musical space.

It is useful to distinguish between two kinds of abstraction in connection with the multidimensional picture of music. The first kind of abstraction,

1. Morris (1987) gives a thorough treatment of the spatial conception of music. Particularly interesting are his views on the interaction of linear, cyclic, ordered but nonmetric, and partially ordered dimensions in higher-order spaces.

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just characterized as a kind of projection, involves the simple deletion of one or more dimensions. The second kind of abstraction, which is less destructive, involves the removal of metric information from a dimension, while maintaining order relations. For example, the abstraction from tunes to pitch patterns (defined respectively as "pitches in measured time" and "pitches in unmeasured time") involves stripping away information about the durations and metrical relations among the pitches of the tune, but preserves the temporal *order* of those pitches.

This second kind of abstraction is central to the notion of contour.[2] When we speak of the pitch contour of a melody or pitch pattern, we are concerned only with whether one note is higher or lower than another, and not how much higher or lower it is. Information about the size of intervals is discarded, while information about the direction of intervals is preserved. This leaves us with three *contour relations*—referred to in the sequel as *up, down,* and *no-change.*

Most empirical studies of contour have focused on the contour relations among adjacent notes of pitch patterns. Drawing on recent music-theoretical research, this study assesses the perceptual significance of the contour relations among nonadjacent notes as well as adjacent notes; this approach to representing contours is known as the combinatorial model of contour (Polansky & Bassein, 1992).

Perception of Pitch Contour

Contour information is thought to be a factor in the long-term memory of melodies. Contour has been shown to be as important as chroma (pitch class) and tone height (pitch) in the recall of familiar tunes. Idson and Massaro (1978) showed that when familiar melodies were altered by shifting their tones to different octaves while preserving chroma, listeners were best able to identify them when the contour of the altered version was the same as that of the original; recognition of melodies so altered, in fact, was almost as good as recognition of the original melodies. Massaro, Kallman, and Kelly (1980) achieved similar results for novel melodies taught to participants during a 2-day training phase conducted before the recognition task. Chroma must be preserved along with contour in such tasks, however, as Moore and Rosen (1979) discovered when participants failed to recognize familiar tunes transformed by uniform expansions and contrac-

2. While the term *contour* is often used in a more general way to refer to durational, registral, or timbral structures, it will be used in the more restrictive sense of "pitch contour" throughout this article. For more on the general sense, see Marvin (1989, 1995) and Hermann (1994).

tions of the logarithmic relationship between the frequencies of melodic tones (see also Dowling, 1978).

When it comes to short-term melodic memory, it seems that contour plays a more significant role, whereas chroma recedes in importance. When asked to compare unfamiliar tunes with either transposed versions of the tunes or same-contour lures, participants are unlikely to be able to distinguish targets from lures, leading to the conclusion that listeners rely on a contour strategy of short-term recall in recognition tasks (Dowling & Fujitani, 1971). Several factors mitigate this basic principle, however. Transpositions of tonal melodies are more likely to be confused with same-contour lures than are transpositions of atonal melodies (Dowling, 1978). Musically trained listeners are better at discriminating transpositions from atonal same-contour lures than are musically untrained listeners (Dowling, 1978). The amount of time between stimulus and recall has been shown to be of significance in determining whether or not listeners will use contour information in recall (Dowling, 1982, 1991; Dowling & Bartlett, 1981; Dowling, Kwak, & Andrews, 1995): only with short unfilled time-spans will they do so, and when the time is extended and filled, listeners tend to rely on scale-step or interval representations of the stimuli. In a study of infants, Trehub, Bulle, and Thorpe (1984) found that participants cannot discriminate between exact transpositions of six-note melodies and same-contour lures, provided that the melodies and lures fall within the range of approximately an octave; octave-scrambled lures were detected. Specific features of contour also affect recognition ability: Dyson and Watkins (1984) asked participants to notice changes in melodies and untransposed targets and lures. These participants proved most likely to recognize changes that affected peaks of contour (*up* followed by *down*), and to a lesser degree, contour troughs (*down* followed by *up*). Dyson and Watkins concluded that large-scale contour relations are more useful than local contour features for the recognition of transposed melodies, and that local features are more useful for the recognition of untransposed melodies.

Musically trained listeners are able to isolate the contour information in a pitch pattern when specifically asked to do so. Dowling (1986) found that trained listeners performed significantly better than untrained listeners in the recall and discrimination of contours. In several studies by Edworthy (1982, 1985), musically trained participants were required to notice when transpositions of novel pitch patterns contained errors in contour. It was found that participants fared better at this task with shorter melodies (5 notes) then with longer ones (15 notes); performance deteriorated with increasing pitch-pattern length in a study testing seven lengths. (As the length of pitch patterns increased, participants were better able to discriminate pitch errors than contour errors.)

The Role of Note Adjacency in Models of Contour

With few exceptions, empirical studies specifically directed at the perception of contour tend to focus only on the contour relations among adjacent notes. The problem with treating contour as the set of contour relations among successive adjacent notes of a melody is that such a model—henceforth a *note-to-note model*—does not preserve information about larger-scale contour relations, which may be just as significant in determining cognitive representations of melodic shape as note-to-note relations. Figure 1 displays a note-to-note contour contained in Edworthy (1985, Figure 2). The melody Edworthy gives as an instantiation of that contour (her Figure 1), is shown in Figure 2a. This melody begins and ends on C_4, first moving above that note and then approaching it from below. But the contour in Figure 1 can also be realized as a melody with a decided upward trend (Figure 2b) and one with a decided downward trend (Figure 2c). Under a model that takes into account contour relations among nonadjacent tones, the three melodies of Figure 2 might be said to have contours that are similar, but not necessarily identical.

The question of whether the concept of contour applies to nonadjacent as well as adjacent tones has a history in the literature of music scholarship. Early ethnomusicological studies (Adams, 1976; Kolinski, 1965; Seeger, 1960) focused on contour relations involving nonadjacent tones that are structurally important by virtue of being beginnings or endings, high or low notes, or emphasized in some other musical dimension, ignoring contour relations among nonstructural tones. On the other hand, one of the foundational articles of the music-theoretical literature dealt extensively with a note-to-note model of contour (Friedmann, 1985), ignoring contour relations among nonadjacent tones, regardless of structural importance. But recent theoretical work has concerned itself with models of contour that include both note-to-note and larger-scale features (Marvin & Laprade, 1987; Morris, 1987, 1993; Polansky & Bassein, 1992; Quinn, 1997).

The authors of the studies just cited all use what Polansky and Bassein (1992) call the *combinatorial* model of contour. In the combinatorial model,

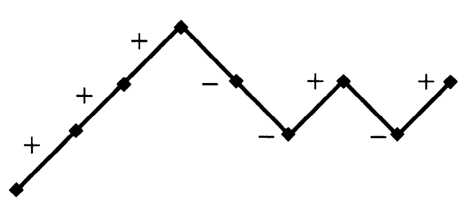


Fig. 1. A note-to-note contour (Edworthy, 1985, Fig. 2).

Fig. 2. Three melodic realizations of the contour in Figure 1: (a) a melody that ends where it begins (Edworthy, 1985, Fig. 1), (b) another realization, this time with an overall ascending trend, (c) a realization with an overall descending trend.

each note of a pitch pattern is considered in terms of its contour relationship to each of the other notes in the pitch pattern. The combinatorial contour of a pattern of n pitches can be represented as an $n \times n$ matrix. Each row and each column in the matrix corresponds to a note in the pitch pattern. The entry at cell ij in the matrix C indicates the contour relation that obtains from note i to note j as follows:[3]

$$C_{ij} = \begin{cases} 1 \text{ if } j \text{ is higher than } i \\ 0 \text{ otherwise.} \end{cases} \quad (1)$$

(Note that the entries along the main diagonal of a combinatorial contour matrix will always be zero, because every note is trivially the same as itself with respect to pitch.)

Figure 3 shows how each of the melodies in Figure 2 would be represented in the combinatorial model. The main diagonal in each matrix is set in bold type. Note that the general shape of each pitch pattern is reflected in the distribution of ones with respect to the main diagonal; in the characteristic matrix of the ascending melody (Figures 2b and 3b), the ones are above the main diagonal, and in that of the descending melody (Figures 2c and 3c), they are below it. For Edworthy's original melody, which is more or less balanced around C_4, the characteristic matrix has its ones distributed fairly evenly on either side of the main diagonal.

We know from both research and from musical intuition that if two melodies have the same note-to-note contour, it is possible to assert a rela-

3. This characterization of the combinatorial model of contour consolidates the tripartite structure of contour relations by taking *up* as the sole primitive contour relation and making a binary distinction between ascent (*up*) and nonascent (the other contour relations, *no-change* and *down*). The choice of *up* as the primitive is purely, and the model could be equally well constructed by using 1 to represent descent and 0 to represent nondescent. The implicit perceptual claim of the combinatorial model is that contour relations among nonadjacent melodic tones are salient, and not that *up* is the perceptually or cognitively privileged contour relation. A rationale for the particular characterization of the combinatorial model used here may be found in Quinn (1997).

a.

$$\begin{bmatrix} \mathbf{0} & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & \mathbf{0} & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & \mathbf{0} & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & \mathbf{0} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \mathbf{0} & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & \mathbf{0} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & \mathbf{0} & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & \mathbf{0} \end{bmatrix}$$

b.

$$\begin{bmatrix} \mathbf{0} & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & \mathbf{0} & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & \mathbf{0} & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & \mathbf{0} & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & \mathbf{0} & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & \mathbf{0} & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \mathbf{0} & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \end{bmatrix}$$

c.

$$\begin{bmatrix} \mathbf{0} & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & \mathbf{0} & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \mathbf{0} & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \mathbf{0} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \mathbf{0} & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & \mathbf{0} & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & \mathbf{0} & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & \mathbf{0} & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & \mathbf{0} \end{bmatrix}$$

Fig. 3. Combinatorial contour matrices corresponding to the three melodies in Figure 2.

tion of similarity between them: in an imaginary piece that uses the melody in Figure 2a as a main motive, one might imagine using the other two melodies in Figure 2 to change key and register while maintaining some kind of motivic coherence. At the same time, the differences between the three melodies are clear enough to be recognizable as differences of contour. The extent to which such differences override the equivalence asserted by the note-to-note model has yet to be studied empirically.

Similarity of Contours: Theoretical Models

Marvin and Laprade (1987) and Polansky (1987, 1996) independently developed a procedure for measuring the degree to which two combinatorial contours of the same length are structurally similar. The similarity measure, referred to here as C$^+$SIM, is essentially a measure of the proportion of entries that are the same in both matrices, excluding the trivial correspondences of the zeroes along the main diagonals.[4] The similarity measure takes values between zero (in the case where the matrices have nothing in common but the main diagonal) and one (in the case where the matrices are identical). Increasing values denote increasing similarity. The maximum value, 1, denotes equivalence of combinatorial contour; note-to-note contour equivalence is a necessary condition for combinatorial contour equivalence, but not a sufficient condition.

The CSIM similarity index of the contour matrices in Figures 3b and 3c can be calculated by counting the number of entries in each matrix that are common to both (which is 29; see Figure 4) and dividing that by the total number of entries in each matrix that are off the main diagonal (which is 72 in this case, and generally equal to $n^2 - n$ for n-note contours). The result is approximately 0.40—quite a low value, considering that the underlying melodies are said to have the same contour under the note-to-note model. In principle, two melodies or pitch patterns of n notes with identical note-to-note contours can have a C$^+$SIM index as low as

$$\frac{2(n-1)}{n^2 - n} = \frac{2}{n} \qquad (2)$$

in the case where the two pitch patterns differ in all contour relations except for those among adjacent notes.

Table 1 summarizes the C$^+$SIM contour similarity measurement for all three of the melodies in Figure 2. Note that according to these results, melody (a) is more similar to both melodies (b) and (c) than melodies (b)

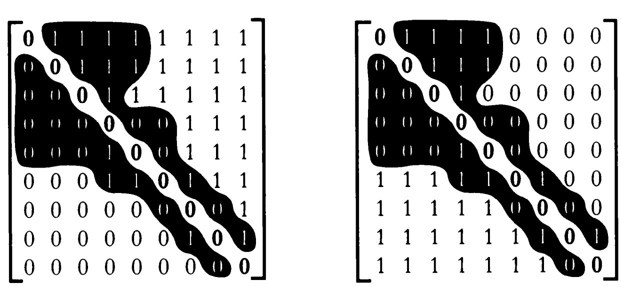


Fig. 4. Calculating the C$^+$SIM similarity index for the melodies in Figures 2b and 2c: 29 of the 72 off-diagonal entries of each matrix (40%) are common to both, a low value considering that the underlying melodies have the same note-to-note contour.

4. C$^+$SIM (Quinn, 1997) is essentially the same as the CSIM measure (Marvin & Laprade, 1987) and the OCD metric (Polansky, 1996), adapted to the characterization of the combinatorial contour model presented here.

TABLE 1
C^{+}SIM Contour Similarity Index for Pairs of Melodies in Figure 2

	Melody	
	a	*b*
b	0.60	...
c	0.81	0.40

and (c) are to each other. This is attributable to the fact that melody (a) is balanced over the long term: its moves up and down tend to cancel each other out and it ends where it began. Melody (b), on the other hand, makes larger moves when it goes up then when it goes down, and it ends on its highest note; melody (c) makes larger moves when it goes down than when it goes up, and it ends much lower than when it began. This demonstrates that the combinatorial contour model is sensitive to interval size as well as interval direction, but only interval size relative to the other intervals within a pitch pattern.

Polansky (1996) suggests that similarity measurements based on the combinatorial contour matrix might also involve weighting various portions of the matrix to model different situations. He offers two kinds of weighting schemes. The first type involves weighting the diagonals of the matrix according to how far they are from the main diagonal; this has the effect of treating note-to-note contour relations differently from other contour relations, and in general, treats contour relations differently according to their *degree of adjacency*—how many notes intervene between the two notes involved in the relation. Such a weighting scheme, he suggests, might model the intuition that note-to-note contour relations (those with minimal degree of adjacency) are more perceptually salient. The second type of weighting treats contour relations according to where in the pitch pattern the first of the notes involved falls; that is, according to how far from the upper-left corner of the matrix the entry is located. He suggests that this kind of weighting might help to model the intuition that the beginning of a melody is more important to contour perception than is the end.

Experiment

Musically trained listeners, as has been stated above, are able to compare the contours of pitch patterns when specifically asked to do so. It is therefore hypothesized that if the combinatorial model is more perceptu-

EQUIVALENCE TYPE			SIMILARITY INTERVAL					
NOTE-TO-NOTE	COMBINATORIAL		[0.5,0.6)	[0.6,0.7)	[0.7,0.8)	[0.8,0.9)	[0.9,1.0)	[1.0,1.0]
		TRIALS	**10**	**10**	**10**	**10**	**10**	**10**
no	no	**25**	1a(5)	1b(5)	1c(5)	1d(5)	1e(5)	
yes	no	**25**	2a(5)	2b(5)	2c(5)	2d(5)	2e(5)	
yes	yes	**10**						3f(10)
			CONDITION LABEL (NO. OF TRIALS)					

Fig. 5. Experimental design.

ally relevant to such a task than the note-to-note model, then such listeners will be more likely to judge a pair of melodies as similar in contour if they are identical in both the note-to-note model and the combinatorial model than if they are identical in the note-to-note model alone. It is further hypothesized that listeners' rating of the contour similarity of pairs of pitch patterns will be correlated to the C⁺SIM contour similarity index for those pairs.

METHOD

Participants

Thirty-four undergraduates (18 males and 16 females chosen at random) enrolled in first-year theory classes at the University of Rochester's Eastman School of Music participated in the study and received course credit for their participation. Nine of the participants self-reported having absolute pitch (AP); these reports were not confirmed empirically. Participants had a mean age of 18.1 (SD = 0.61) years and had studied music formally for a mean of 10.0 (SD = 3.10) years.

Design

Eleven groups of stimuli, with properties indicated in Figure 5, were tested. Each stimulus condition is labeled with a number indicating the equivalence condition (1 for no equivalence, 2 for note-to-note equivalence only, 3 for combinatorial equivalence) and a letter indicating the level of combinatorial contour similarity as measured by C⁺SIM (with letters *a–f* indicating increasing similarity). A complete factorial design (3 equivalence types × 6 similarity levels) was not possible because of the impossibility of conditions like 1*f* (no equivalence, C⁺SIM = 1.00) and 3*d* (combinatorial equivalence, C⁺SIM at least 0.80 but less than 0.90). The present design, however, allows the data to be subjected to one-way analyses of variance for both equivalence type and similarity level. Moreover, it ensures the independence of note-to-note equivalence and combinatorial similarity levels for the purpose of evaluating the relationship between a priori models of contour similarity and participants' similarity ratings.

Stimuli

Stimuli were pairs of seven-note diatonic melodies spanning less than an octave. Pitch patterns were generated by the following procedure, illustrated in Figure 6:

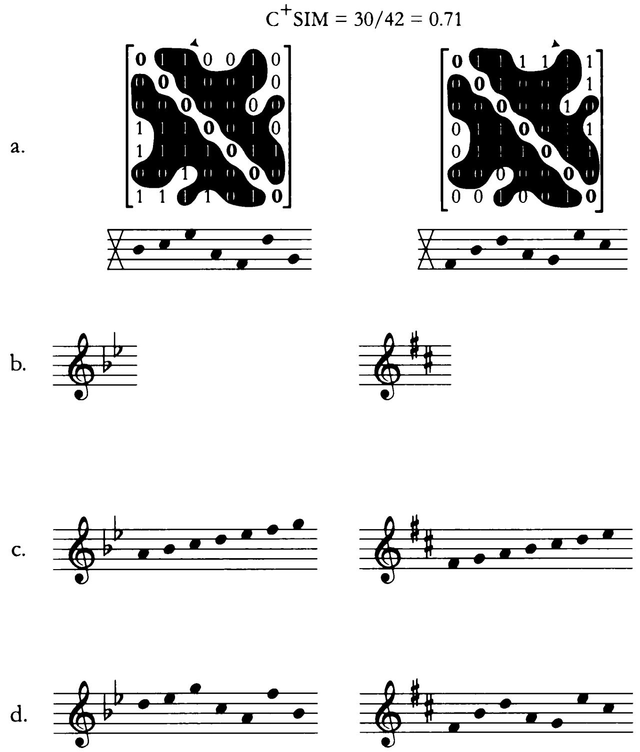


Fig. 6. Procedure for generating the stimuli used in this experiment: (a) construct a pair of combinatorial contour matrices in the appropriate equivalence and similarity relationship (this example is from condition 2*c*, so the two contours have the same note-to-note contour and a C⁺SIM index higher than 0.70 but less than 0.80), (b) select a random diatonic collection for each contour, (c) select a random diatonic note in the C_4–B_4 octave, together with the six higher notes, (d) order those seven notes to instantiate the contour specified in step (a).

1. Pairs of combinatorial contour matrices were randomly generated by a computer until a pair was found whose CSIM similarity fell in the desired range and which met the requisite equivalence condition.
2. For each stimulus in each pair, one of the 12 possible diatonic collections of pitch classes was selected at random.
3. For each stimulus in each pair, a random note from the collection of pitches C_4 to B_4 and falling in the chosen diatonic collection was chosen to be the lowest note in the pitch pattern.
4. For the other notes in each pitch pattern, the six immediately higher notes in the chosen diatonic collection were used. Given such a gamut of seven pitches, there is only one way to order them such that their contour matches the chosen contour under the combinatorial model.

The second and third steps of this procedure were intended to efface any possible effects of tonal structure on participants' similarity judgments by randomizing key distance (Step 2) and modal similarity (Step 3) within each pair of pitch patterns. Sample pairs of pitch patterns from each of the 11 conditions are listed in Figures 7–9.

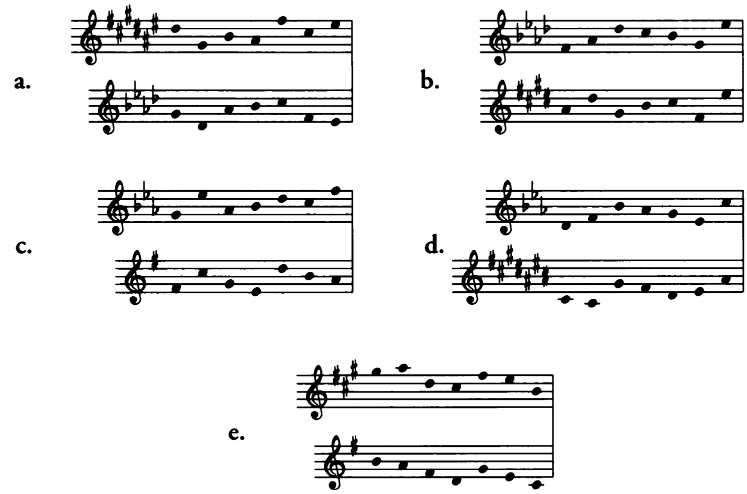


Fig. 7. Sample stimulus pairs from conditions 1*a*–1*e* (not equivalent note-to-note, not equivalent combinatorially). (a) condition 1*a*, C⁺SIM = 0.57, (b) condition 1*b*, C⁺SIM = 0.62, (c) condition 1*c*, C⁺SIM = 0.71, (d) condition 1*d*, C⁺SIM = 0.86, (e) condition 1*e*, C⁺SIM = 0.90.

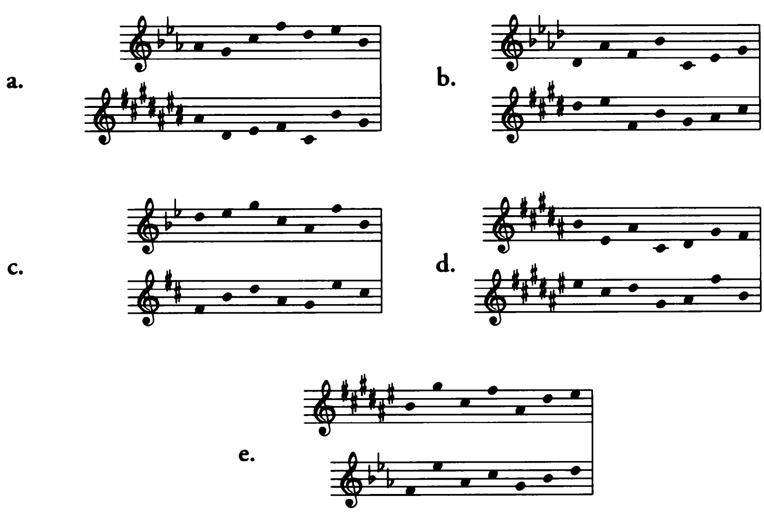


Fig. 8. Sample stimulus pairs from conditions 2*a*–2*e* (equivalent note-to-note, but not equivalent combinatorially). (a) condition 2*a*, C⁺SIM = 0.52, (b) condition 2*b*, C⁺SIM = 0.62, (c) condition 2*c*, C⁺SIM = 0.71, (d) condition 2*d*, C⁺SIM = 0.86, (e) condition 2*e*, C⁺SIM = 0.90.

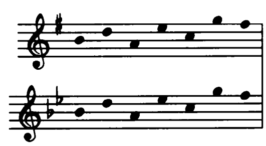


Fig. 9. Sample stimulus pair from condition 3*f* (equivalent note-to-note and combinatorially).

Apparatus

Stimuli were generated in the MIDI Studio of the Eastman Computer Music Center, using the "Stereo Grand" piano sample on a Kurzweil K2000 sampler controlled via MIDI by a Power Macintosh computer running Finale software. Samples were played at a constant MIDI velocity, amplified through a Mackie MCH-80 mixer and a TAC 860 mixing console, processed with a Lexicon PCM-70 digital sound processor, and recorded on high-quality analog audio cassette tape. Pitch patterns progressed at a tempo of 150 notes/minute, with a 2.92-s delay separating the two pitch patterns of each pair. Pairs of pitch patterns were separated by 8.24 s, and each trial was announced on the tape approximately 6 s after the previous trial had ended. Participants listened to the stimuli via loudspeakers on state-of-the-art playback equipment in Eastman classrooms at a comfortable volume. All participants heard the same random order of stimuli.

Procedure

Participants were told that their ability to judge similarity of "melodic shape" was being tested. They were played a pair of four-note pitch patterns similar to those of condition 3*e* (combinatorially equivalent) and told "These melodies have the same shape," and a pair of four-note pitch patterns similar to those of condition 1*a* (equivalent under neither the note-to-note model nor the combinatorial model, with a CSIM similarity rating of 0.50) and told "These melodies have dissimilar shape." In the interest of comprehensibility, the instructions avoided the use of the words "pitch pattern" and "contour" in favor of "melody" and "shape," respectively. Participants then undertook three practice trials and were asked if they had questions about the task (none did).

Participants were instructed to "rate the similarity of each pair of melodies purely on the basis of their shape, ignoring all other features of the melodies." Sixty stimulus pairs were presented in a single random order to all participants. Halfway through the experiment (after 30 trials), participants were given a 5-min rest, during which they were instructed to stay in their seats and remain silent. During the rest period, they were played a recording of Ella Fitzgerald singing "Lover" from Volume 2 of *The Rodgers and Hart Songbook* (Verve 821 579-2) in order to provide aural distraction and to forestall conversation. The remaining 30 trials followed immediately.

Data Collection

Participants' similarity ratings were collected on a paper instrument with 60 answer blanks arranged in two columns of 30. Each answer blank consisted of a stimulus number on the left, followed by the letters *A, B, C, D, E,* and *F,* equally spaced. At the head of each column, the legend "Least similar shape" appeared directly over the column of *A*s, and the legend "Most similar shape" appeared directly over the column of *F*s. Letters were used instead of numbers in order to steer participants away from using counting strategies. A scale with an even number of steps was used in order to avoid central-value effects.

At the top of the paper instrument, space was provided for participants to specify their age, sex, number of years of musical training, primary instrument, and self-reported AP ability (yes or no). Following the experiment, all data were entered into a computer by hand.

RESULTS

Because participants with AP (n = 9) were observed using AP-specific strategies (including performance of the pitch patterns on imaginary keyboards and notation of the pitches on the response form), a two-way repeated-measures analysis of variance (ANOVA; stimulus × AP), with participants treated as within-factor for both stimulus and AP, was performed on individual similarity ratings. That analysis revealed an effect of stimulus, $F(59, 1979) = 20.07$, $p < .0001$, but no effect of AP, $F(1, 1979) = 1.60$, $p = .21$. Therefore, subsequent analyses were performed within all subjects.

A one-way unbalanced ANOVA over the three equivalence conditions showed an effect of equivalence type, $F(2,57) = 44.80$, $p < .0001$. A second one-way ANOVA over the six similarity conditions showed an effect also of similarity level as measured by CSIM, $F(5,54) = 16.86$, $p < .0001$. Means for these two ANOVAs are graphed in Figures 10a and 10b, respectively. Studentized Newman-Keuls tests of the significance of differences among means at $\alpha = .05$ confirmed the differences among all three equivalence conditions, but showed that not all differences among the adjacent similarity levels were significant (see Table 2).

The predictive power of C⁺SIM with respect to participants' similarity ratings was tested by taking the correlation coefficient between C⁺SIM values and mean participant similarity ratings for each stimulus. The result, $r = 0.78$, $F(1,58) = 37.76$, $p < .0001$, suggests that C⁺SIM predicts only 61% of the variance in mean participant similarity ratings. This result, together with the significant effect of equivalence type, suggests that a combination of these two factors might produce a better predictive model. A hierarchical cluster analysis (arithmetic-mean linkage, pair-group method) was performed on the participants' mean ratings for each stimulus pair, using the absolute difference between mean ratings as the distance measure. The top levels of the partition structure are shown in Figure 11 along with a summary of the content of the clusters by stimulus group. A clear hierarchy emerges, in which note-to-note contour relations take precedence over the

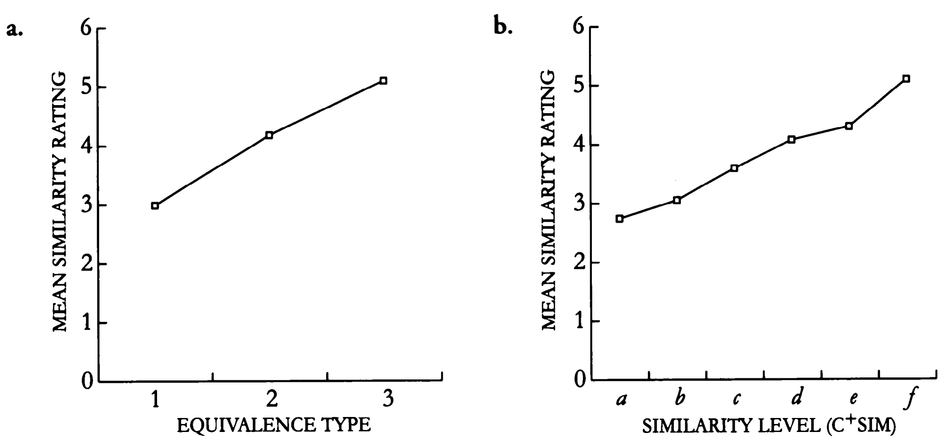


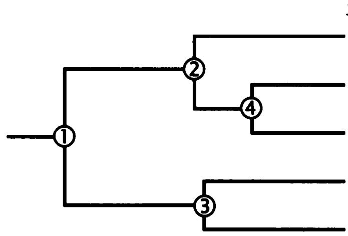
Fig. 10. Mean participant ratings for (a) the three equivalence conditions, (b) the six C⁺SIM similarity levels.

TABLE 2
Significant Differences Among Mean Participant Similarity Ratings for Each C⁺SIM Similarity Level (Studentized Newman-Keuls Test, $\alpha = 0.05$)

	Similarity Level					
	a [0.5,0.6)	*b* [0.6,0.7)	*c* [0.7,0.8)	*d* [0.8,0.9)	*e* [0.9,1.0)	*f* [1.0,1.0]
a		*	*	*	*	
b		*	*	*	*	
c	*	*		*	*	
d	*	*			*	
e	*	*	*			*
f	*	*	*	*	*	

degree of combinatorial similarity as measured by C⁺SIM. This suggests that a weighting scheme similar to the one proposed by Polansky (1996) in connection with degrees of adjacency may be operative.

Figure 12 shows a possible connection between degree of adjacency and the distances among participants' mean similarity ratings. Each graph in Figure 12 corresponds to a branch in the clustering tree and compares the two clusters that are produced at that branch with the supercluster that produced them. In these graphs, a_1 corresponds to the mean proportion of contour relations among adjacent notes that are invariant between the two members of each stimulus pair in a cluster; that is, the proportion of identical entries among those that are one cell away from the main diagonal in the combinatorial contour matrix. Similarly, a_2 corresponds to the mean proportion of contour relations among next-to-adjacent notes that are invariant (those that are two cells away from the main diagonal), a_3 to the mean proportion of invariant contour relations among notes that are separated by two intervening notes, and so forth.



CLUSTER	1a	1b	1c	1d	1e	2a	2b	2c	2d	2e	3f	TOTALS
	CONTENTS OF CLUSTER BY STIMULUS CONDITION											
I										3	8	11
II					1		1	1	5	2	2	12
III			2	2	2	2	2	4				14
IV		1	1	2	2	2	2					10
V	5	4	2	1		1						13

Fig. 11. Results of a hierarchical cluster analysis (average linkage, pair-group method) of the mean participant rating for each stimulus.

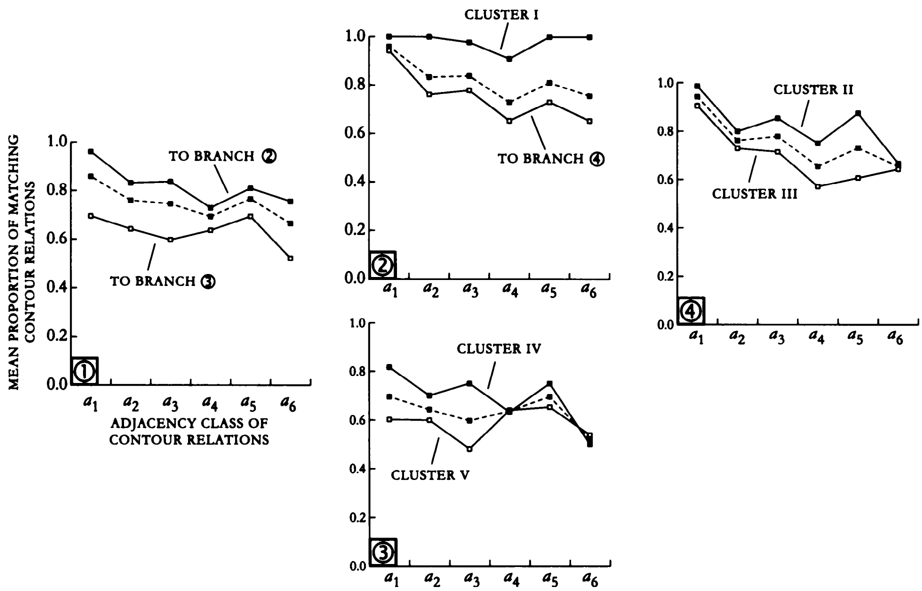


Fig. 12. Classification of stimuli at the branching points of the tree from Figure 11, analyzed in terms of contour similarity as broken down by degree of adjacency.

These graphs suggest that contour relations with higher degrees of adjacency (those closest to the main diagonal of the combinatorial matrix) have their primary influence at a higher hierarchical level, and that contour relations with higher degrees of adjacency (those further from the main diagonal) have their primary influence at lower hierarchical levels. At Branch 1, stimuli are sorted by whether or not their note-to-note contours are identical or nearly identical. At Branches 2 and 3, they are sorted by the a_2 and a_3 relations, and at Branch 4, the contour relations with lower degrees of adjacency—a_3, a_4, and a_5 come into play.

This interpretation is supported by a multiple regression analysis of participants' mean ratings for each stimulus pair, with the variables a_1, a_2, ..., a_6 taken as predictor variables. The results of that analysis are shown in Table 3, with coefficients of those variables for C⁺SIM given for comparison. Overall, the regression model—which amounts to a weighted version of C⁺SIM—performs markedly better than unweighted C⁺SIM, $r = 0.91$, $F(6,53) = 44.50$, $p < .0001$. According to the regression model, note-to-note contour relations (a_1) play a far greater role in participants' similarity ratings than other relations. Surprisingly, the regression model suggests that a_3 relations contribute more to participants' judgments than a_2 relations, even though the reverse is true in the C⁺SIM model. This regression model, which corresponds conceptually to Polansky's adjacency weighting scheme,

TABLE 3
Multiple Regression Analysis (Ordinary Least-Squares Method) of Mean Participant Similarity Ratings, Predicted by Proportion of Identical Contour Relations Within Each Adjacency Level

Variable	Coefficient C+SIM[a]	Coefficient Ratings	Std. Error	t
Constant	0.00	−1.10	0.31	−3.51**
a_1	0.29	3.67	0.33	11.16***
a_2	0.24	0.83	0.29	2.81*
a_3	0.19	0.96	0.28	3.47**
a_4	0.14	0.23	0.22	1.07
a_5	0.09	0.17	0.19	0.89
a_6	0.05	0.16	0.17	0.97

[a]For comparison.
$^*p < .01$. $^{**}p < .001$. $^{***}p < .0001$.

performed better than another regression model based on Polansky's distance-from-beginning weighting scheme, $r = 0.82$, $F(6,53) = 17.72$, $p < .0001$.

Discussion

The results of this experiment suggest that the perception of melodic contour is slightly more complicated than previous research has revealed. The established view, that contour relations among adjacent notes play a role in judgments of melodic similarity, is confirmed by these results. The data from this experiment, however, suggest that there is also a hitherto untested factor in the perception of contour: the contour relations among nonadjacent notes.

The foregoing experiment was designed to test a priori the predictions of the C+SIM contour similarity measure. Post hoc analyses, however, suggested that C+SIM itself may not tell the whole story, and that a contour relation's position within a combinatorial contour matrix may also be a factor in determining its contribution to aural judgments of similarity, especially with regard to degrees of adjacency. A neural network trained with data from this experiment, furthermore, suggested that there may be further effects resulting from (a) whether pairs of melodies have similar contours near beginnings and endings, and (b) participants' inferral of metrical structure on pitch patterns, with concomitant emphasis on metrically significant contour relations (Quinn & Mavromatis, 1997). It would be worthwhile to conduct future experiments along these lines, with stimulus sets that control more carefully for the independence of individual locations in the combinatorial contour matrix.

Polansky (1996) has also developed some theoretical models for measuring contour similarity among pitch patterns of different lengths, which is made possible by the combinatorial model. The success of the combinatorial model at predicting participants' responses in this experiment suggests that research on different-length pitch patterns might be fruitful as well. Furthermore, the more general notion of contour mentioned in the introduction to this article admits of combinatorial treatment and merits empirical study.

It is important to note that the relevance of these results to real-music settings is highly questionable. The stimuli for this experiment were carefully designed to provide an environment that previous studies have shown to be favorable for attention to contour. Music-theoretical treatments of contour are usually focused on the analysis of nontonal music, but nondiatonic pitch patterns have been shown to invite intervallic representations rather than contour-based representations. Furthermore, previous studies suggest that the presence of distracting material may also cause listeners to use non–contour-based representational strategies. Further study on the role of combinatorial contour in melodic memory is clearly warranted, as is study of the interaction between contour and tonal or rhythmic features of pitch patterns and melodies.[5]

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