Exploring and modeling melodic similarity

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Approach Müllensiefen & Frieler (2003-2005)

1. Represent monophonic melodies as sequence of tuples <pitch, onset>
2. Transform sequences into all meaningful representations:

Musical Dimension	**Transformation method**
Pitch	a) none, b) step/leap, c) Parsons Code
Rhythm	a) Categorisation of durations into 5 classes, b) 'Gaussification'
Contour	a) Interpolation of pitch values between melodic turning points, b) Fourier Transform
Implicit harmonic content	Tonality calculation (Krumhansl-Schmuckler)
Micro-motives	n-gram chains

Approach Müllensiefen & Frieler (2003-2005)

3. Apply various comparison techniques to transformed melodies:
   - Edit Distance
   - n-grams Comparisons
   - Correlation Measures
   - Difference Measures
4. Compare computed similarities to expert judgements
5. Pick best individual similarity measures (algorithmic chains) and combine them in hybrid measures

Result: The *SIMILE* toolbox

Implemented algorithmic chains (1)

VPN_MEAN	Mean of human subjects‘ ratings	FOURR	Fourier (ranks)
Qbh	Fraunhofer qbh-measure (June 2003)	FOURRST	Fourier (ranks), weighted, 0-1
RAWED	Raw pitch edit distance	FOURRW	Fourier (ranks), weighted
RAWEDW	Raw pitch edit distance weighted	FOURRWST	Fourier (ranks), weighted, 0-1
RAWPC	Raw pitch Pears. Brav. correlation	FOURRI	Fourier (ranks, intervals)
RAWPCST	Raw pitch P-B. corr, weighted, 0-1	DIFFED	Intervals (Edit distance)
RAWPCW	Raw pitch Pears. Brav. Corr. Weighted	DIFF	Intervals (Mean difference)
RAWPCWST	Raw pitch P-B. Corr. weighted, 0-1	DIFFEXP	Intervals (Mean difference, exp.)
RAWCC	Raw pitch crosscorrelation	DIFFFUZ	Intervals (fuzzy), Edit Distance
RAWCCW	Raw pitch crosscorrelation weighted	DIFFFUZC	Intervals (fuzzy contour)
CONSED	Contour (Steinbeck) edit distance		
CONSPC	Contour (Steinbeck), P-B. correlation		
CONSPCST	Contour (Steinbeck), P-B. corr., 0-1		
CONSCC	Contour (Steinbeck), Crosscorrelation		
CONED	Contour, Edit distance		
CONPC	Contour, Pearson-Bravais correlation		
CONPCST	Contour, Pearson-Bravais corr., 0-1		
CONCC	Contour, Crosscorrelation		

Result: The *SIMILE* toolbox

Implemented algorithmic chains (2)

NGRSUMCO	n-grams Sum Common (intervals)	RHYTGAUS	Rhythm (gaussified onset points)
NGRUKKON	n-grams Ukkonnen (intervals)	RHYTFUZZ	Rhythm (fuzzy, Edit distance)
NGRCOORD	n-grans Coordinate Matching (intervals)	ESFMAX	Selfridge-Field (max.)
NGRSUMCR	n-grams Sum Common (interval dir.)	ESFMOD	Selfridge-Field (modus I)
NGRUKKOR	n-grams Ukkonnen (interval dir.)	ESFMODK	Selfridge-Field (modus II)
NGRCOORR	n-grams Coord. Match. (interval dir.)	ESFSIGN	Selfridge-Field (signs)
NGRSUMCF	n-grams Sum Common (fuzzy int.)	HARMCORR	Harmonic correlation (type I)
NGRUKKOF	n-grams Ukkonnen (fuzzy int.)	HARMCORK	Harmonic correlation (type II)
NGRCOORF	n-grams Count distinct (fuzzy int.)	HARMCORE	Harmonic correlation (Edit distance)
NGRSUMFR	n-grams sum common (fuzzy rhythm)	HARMCORC	Harmonic correlation (circle)
NGRUKKFR	n-grams Ukkonnen (fuzzy rhythm)	JOINT52	Accent similarity measure
NGRCOOFR	n-grams Coord. Match. (fuzzy rhythm)		

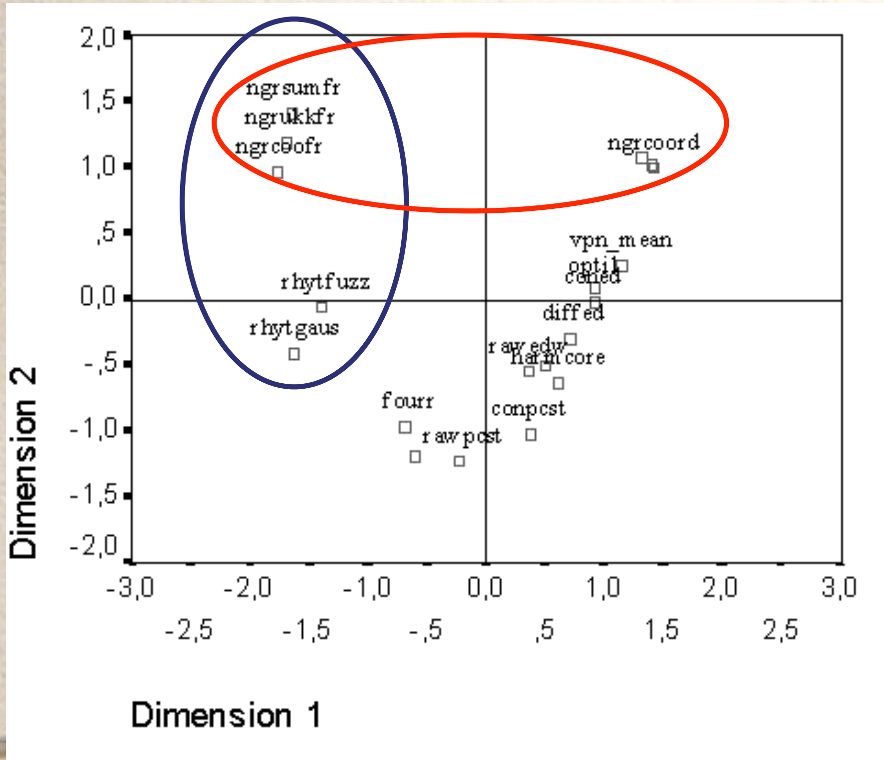
Application: Exploration of the space of similarity measures

- How similar are the implemented similarity measures?
- How do they differ?
- What do the different measures actually measure?

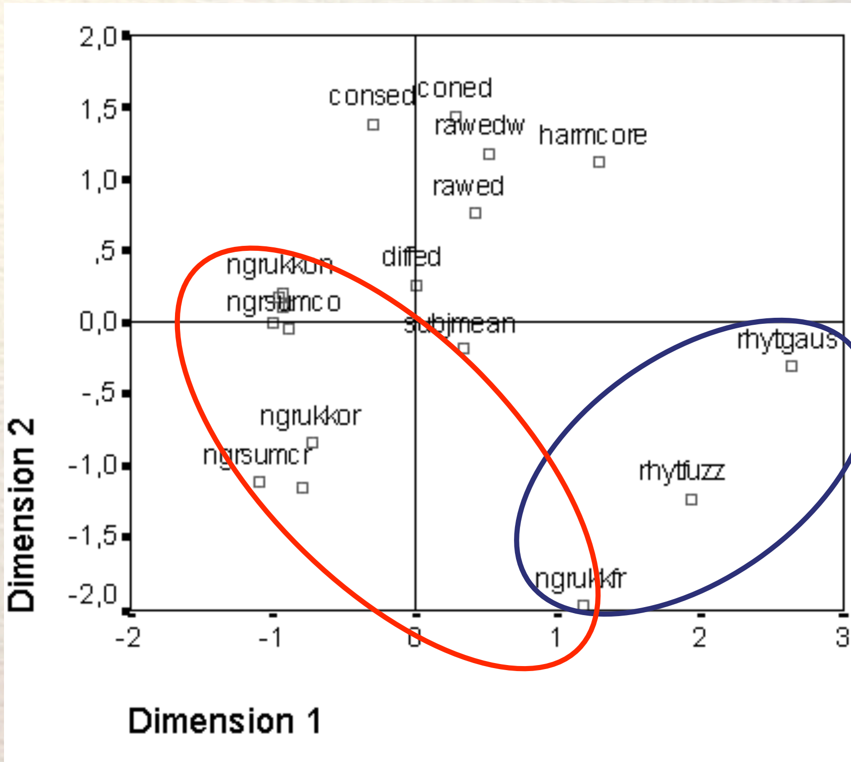
Explore the space of similarity measures with MDS:

- Select 18 “best” similarity measures + human judgements
- Calculate euclidean distances between measures over 84 (24) pairs of melodies
- Ordinal MDS, ALSCAL algorithm
- Measures of fit for 2-dimensional solution:
  - Stress: 0.085 (0.075)
  - RSQ: 0.97 (0.98)

Application: Exploration of the space of similarity measures



MDS on data from Exp.1, M&F, 2004
(84 melody pairs)



MDS on data from Exp.2, M&F, 2004
(24 melody pairs)

Result: Optimised similarity measures

1. Measure for variations of same melody:

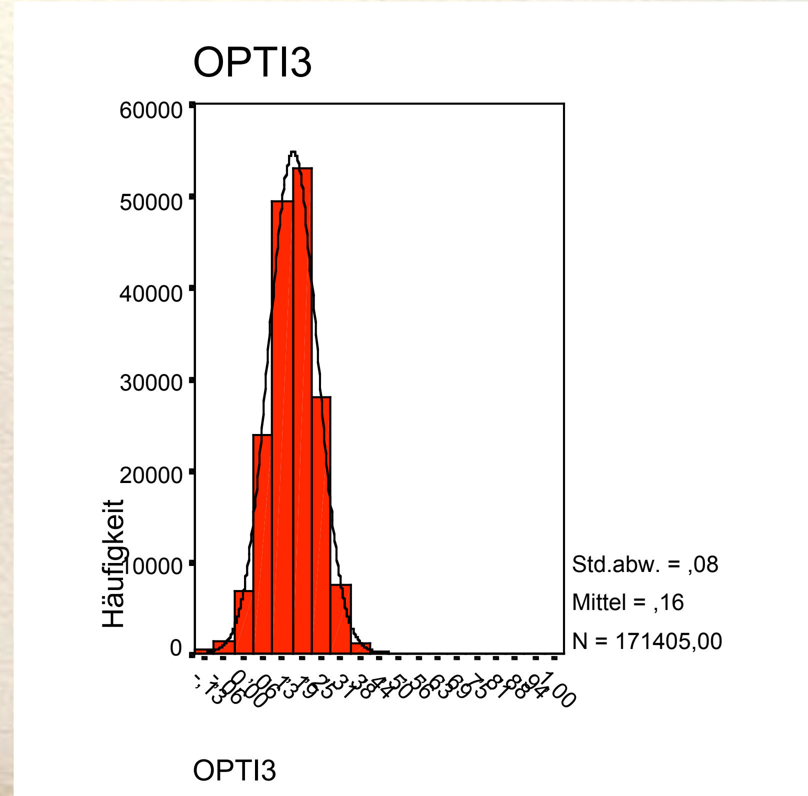
   $opti1 = 3.355 \cdot rawEdw + 2.852 \cdot nGrCoord$

2. Measure for finding similar melodies from general melody collection:

   $opti3 = 3.027 \cdot ngrUkkon + 2.502 \cdot rhythFuzz + 1.439 \cdot harmCorE$

Application: Finding similar melodies in a folk tune collection

Distribution of 171405 similarity values (*opti3* measure) between 586 folk songs from Luxembourg



Application: Finding similar melodies in a folk tune collection

Manual inspection:

1. Related melodies - High similarity?
   - 19 melodies marked as variants
   - 14 musically related
   - All with similarity (*opti3*) > 0.6
   - 8 with *opti3* > 0.8
   - Only 1 exception (*opti3* = 0.27)

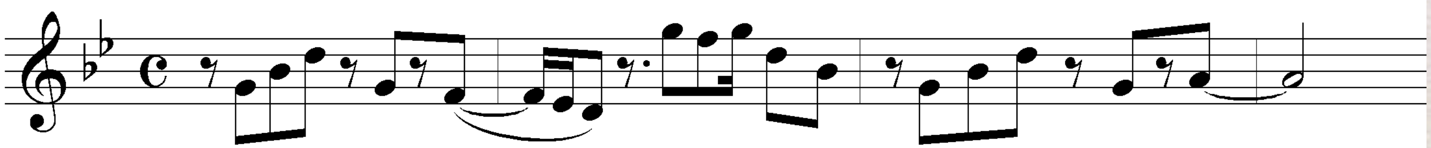
2. High similarity - Related melodies?
   - 49 melodies with *opti3* > 0.6
   - 37 duplicates (nearly same melody and title)
   - 10 ‘parodies’ (nearly same melody, different title and lyrics?)
   - 2 recitatives (note repetitions)

New Perspectives: High level transformations

Idea: Compare higher level structures in two melodies

Example: Melodic accent profiles

1. Apply Gestalt-like rules to melody
2. Find best combination of rules
3. Calculate accent weight for each note from rule combination
4. Compare sequences of accent values



longpr	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	1
longmod	0	0	1	1	1	0	1	0	0	0	0	1	0	0	1	1	1
jumpaft3	0	1	1	1	0	0	0	1	0	0	1	1	1	1	1	1	0
phrasend	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
beat13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
synk2	0	0	1	0	1	0	0	1	0	0	0	0	0	0	1	0	1

New Perspectives: High level transformations

Sum accents: 1011422011410114220014

Sum accents: 10113120013121013121013013

Similarity Value
(e.g. Edit Distance with cost function)

New Perspectives: High level transformations

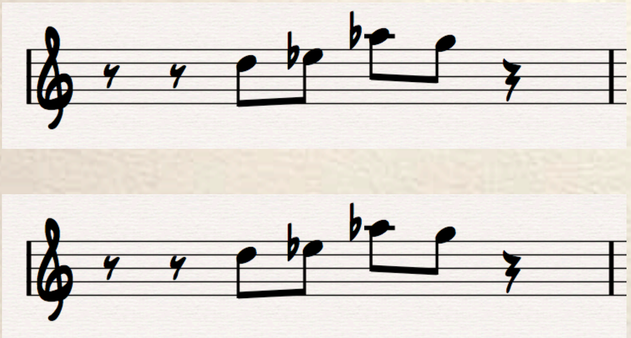
Other high level transformations:

- Implication-Realization rules (Narmour, 1990)
- Melodic driving structures (Rauhe, 1978)
- Structural formulas (Meyer, 1956; Schmuckler, 1990)
- Phrase-based features (Entropy, classified contour etc.)

New Perspectives: Modeling melodic knowledge

Idea: Take frequency of melodic feature / formula into account when comparing melodies for feature

Example: TF-IDF measure for n-grams



More decisive, if present in two melodies

Less decisive, if present in two melodies

New Perspectives: Modeling melodic knowledge

Generalisation:

- Weight every melody feature or sequence of transformation values by its prevalence in music corpus
- Compute similarity by matching weighted features in two melodies
- Observe distribution of features and melodic / harmonic formulas in 14,000 MIDI files (vaguely) representative of pop music history

⇒ Project *Modeling Music Memory and the Perception of Melodic Similarity* (2006-2009) at Goldsmiths College

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