Feature description and corpus-based musicology: Tools for modelling music cognition

Daniel Müllensiefen, David Lewis, Geraint Wiggins (Goldsmiths College, University of London)

Overview

1. The M^4S project (*Modeling Music Memory and the Perception of Melodic Similarity*)
2. The methods:
   - Feature description: Melodic Contour, Melodic Accents
   - Corpus-based musicology
3. The data base
4. Current tasks: Lead-sheet computation and segmentation
5. Perspectives of corpus-based musicology

The M^{4}S project: Goals

Main goal: Address questions about music memory

- What can ordinary people remember from a tune heard just once?
- Explain typical memory errors for melodies
- Determine cognitively relevant features of melodies

The M^4S project: Steps

- Automatically analyse and annotate large pop song collection
- Define computable features of pop music (inspired by analytical approaches, e.g. Tagg, Moore, Everett)
- Test features for cognitive validity in psychological experiments
- Describe statistical distributions of features in pop song collection
- Model (implicit) human memory for pop music melodies

The methods: Feature description

- Feature: Characteristic property of (musical) object that is used for cognitive discrimination and processing
- Distinction: a) Static features, b) sequential features (n-grams)
- Levels of feature computation: Individual event (note, chord), phrase, section, piece
- Feature construction:

1. Literature research (music psychology and analysis) => Approaches
2. Operationalisation of approaches => Algorithms
3. Behavioural experiment using ‘real’ music => Data
4. Data modelling using algorithms => Feature

The methods: Feature description

Static features relevant for melody processing:

- Melody contour (Frieler et al., in press; current)
- Segmentation (Müllensiefen et al., 2007)
- Rhythm classification
- Self-similarity / fractal dimensionality / complexity (current)

Sequential features:

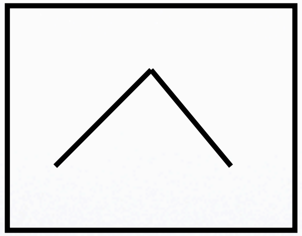
- Harmonic content (Rhodes et al., 2007)
- Accent structure (Pfleiderer et al., submitted)
- Expectedness / Entropy / Information content (Pearce & Wiggins, 2006)

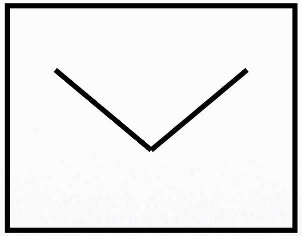
The methods: Feature description: Melody contour

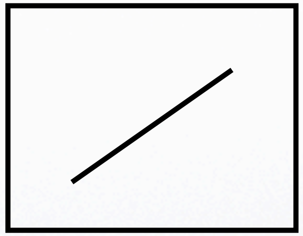
- Feature properties: Early and accurate representation in melody perception and memory (Dowling & Fujitani, 1971; Edworthy, 1985; Cutietta & Booth, 1996 …)
- Goal: Classify melodic phrase into prototypical class according to pitch contour
- Contour definitions: Dowling (1978), Steinbeck (1982), Huron (1996), Eerola & Bregman (2007), (Frieler, Müllensiefen & Riedemann, in press)
- Examples: Huron's contour classes, Polynomial contour fit

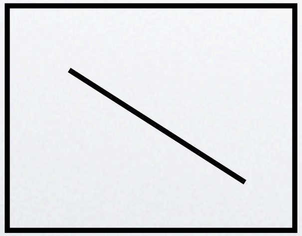
The methods: Feature description: Melody contour

Huron's contour classes (1996): Define contour according to relative position of beginning, mean and end pitch => 9 classes, reduced to 6

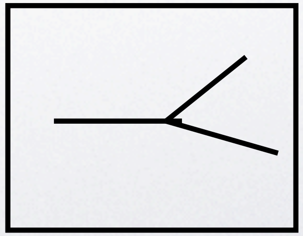

Convex


Concave


Ascending


Descending


Horizontal


Other

The methods: Feature description: Melody contour

Polynomial contour fit (Frieler, Müllensiefen, & Riedemann, in press):

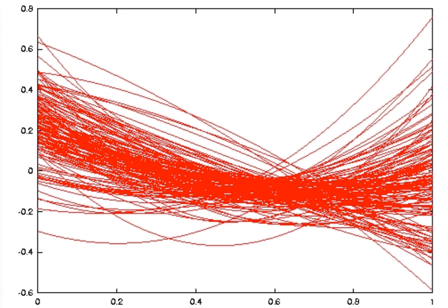
1. Fit polynomial curve of fixed order to pitch-onset sequence

$$f(x) = a + bx + cx^2 + \ldots + mx^n$$

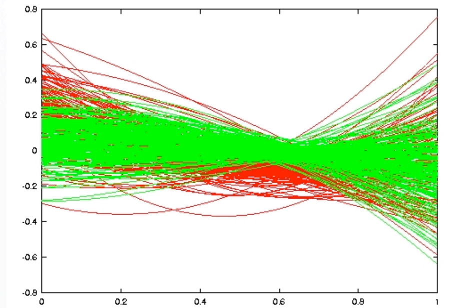
2. Take vector of parameter values as representations of contour
3. Use unsupervised (EM-clustering) clustering to find 'organisational' contour clusters in sample of songs

The methods: Feature description: Melody contour

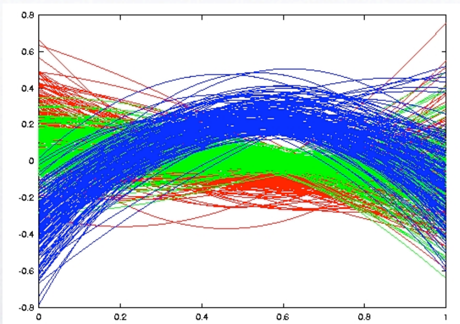
Polynomial contour fit:



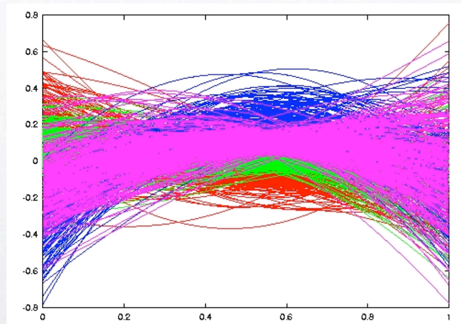
Cluster 1 (concave)



Cluster 1, 2 (descending)



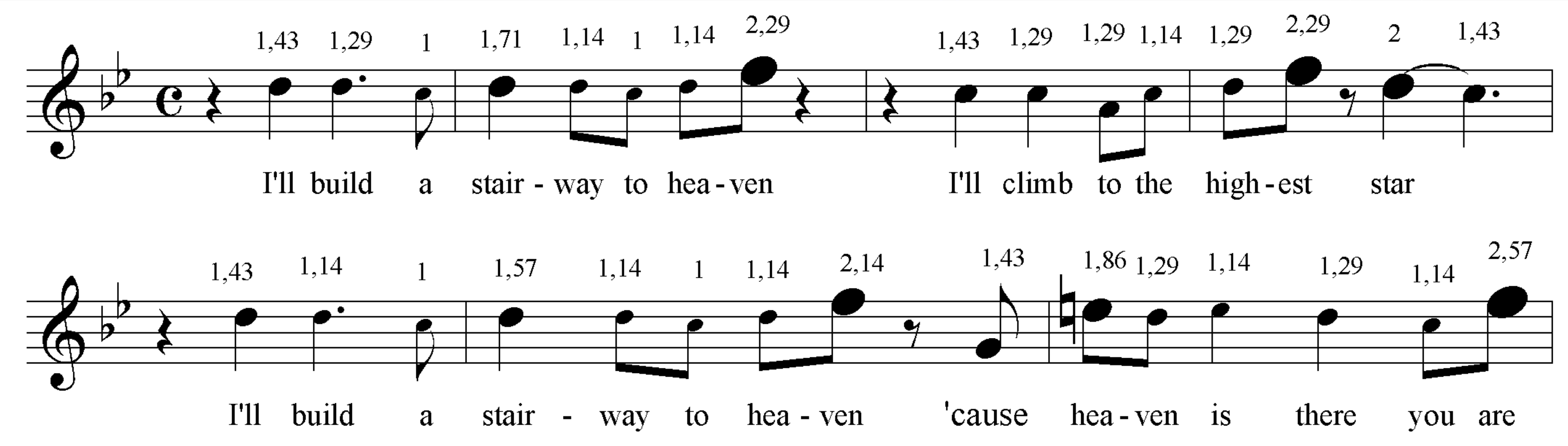
Cluster 1, 2, 3 (convex)



Cluster 1, 2, 3 , 4 (ascending)

The methods: Feature description: Melodic accents

- Rule based accent computation (Pfleiderer, Müllensiefen & Frieler, submitted)
- Goal: Determine accent strength of each melody note or binary accent attribute



The methods: Feature description: Melodic accents

Approach: Operationalisation of of accent rules (e.g. Thomassen, 1982; Boltz, 1999)

=> 40 rules from 6 different categories

RULE NAME	Description
	Pitch Interval
JUMPAFT[3,4,5]	Accent on note after a jump of at least 3, 4 or 5 semitones
JUMPBEF[3,4,5]	Accent on note before a jump of at least 3, 4 or 5 semitones
JUMPBEA[3,4,5]	Accent on notes before and after a jump of 3, 4 or 5 semitones
JUMPLOC	Accent on second note of an interval that is at least two semitones larger than its successor and predecessor interval
	Pitch Contour
PEXTREM	Accent on note where predecessor and successor notes are both lower or higher
PEXTRST	Same as PEXTREM but filtering for change notes in the definition of Steinbeck
PEXTRMF	Same as PEXTREM but filtering for change notes in the definition of Müllensiefen & Frieler
PEXTRSTA	Accent on note following note accented by PEXTRST
THOM	Accent weight according to Thomassen's algorithm (1982), which is based on the even possible pitch direction patterns that can be formed by 2-interval chains (3- note patterns)
THOMTHR	Dichotomous version of thom. All values <0.5 are assigned the value 0, all other values are set to 1.
	Interonset Interval
LONGPR	Accent on note starting an IOI longer than predecessor IOI
LONG2PR	Accent on note starting an IOI at least 2x as long as predecessor IOI
LONGMOD	Accent on note starting an IOI longer than mode of IOIs in melody
LONG2MOD	Accent on note starting an IOI at least 2x as long as the mode of IOIs in melody
SHORTPR	Accent on note starting an IOI shorter than predecessor IOI

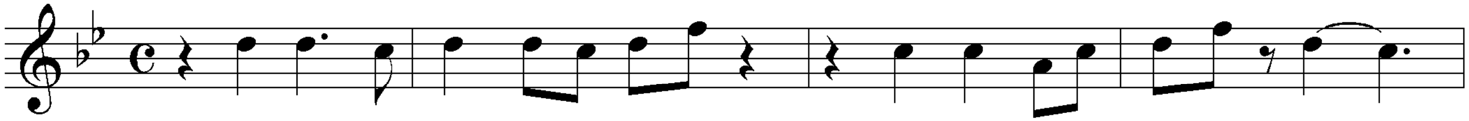
The methods: Feature description: Melodic accents

Algorithmic accent rules (cont'd):

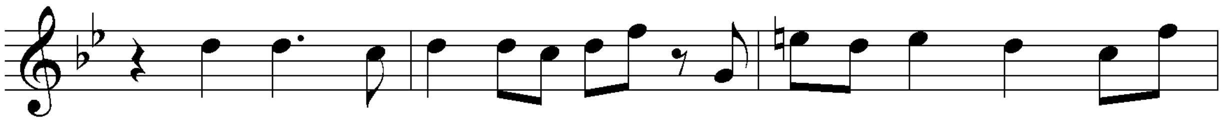
RULE NAME	Description
	Position in Phrase
PHRASEBEG	Accent on phrase beginning
PHRASEND	Accent on phrase end
SHORTPHR	Accent on second note of melody phrase consisting of only two notes
	Meter / Syncopation
BEAT1	Accent on beat 1 of a bar
BEAT13	Accent on beat 1 and 3 of a bar
BEAT1234	Accent on all beats of a bar
SYNK1	Accent on note with onset not on any beat of a bar and with IOI extending over the next beat
SYNK2	Accent on note with onset less than a crotchet before beats 1 or 3 of a bar and with IOI extending over next beat 1 or 3
SYNC1234	Accent on a note not on any beat of a bar and with IOI extending over the next beat position
SYNCHALF	Accent on a note with an onset on beat 2 or 4 of a bar and an IOI extending over next beat position 3 or 1
SYNC0	Accent on a note with an onset on the first subdivision level of the beat level (quaver or quaver triplet) with IOI longer than the time span of the subdivision.
SYNC8S	Accent on a note with an onset on a second subdivision level of the beat level (semiquaver or semiquaver sextuplet) with an IOI longer than the time span of the subdivision .
SYNC16S	Accent on a note with an onset on a third subdivision level of the beat level with inter-onset interval longer than the IOI of the subdivision .
	Harmony
HARMONY	Accent on note that is part of the accompanying harmony
DISSBEAT	Accent on note on a beat but not part of the accompanying harmony

The methods: Feature description: Melodic accents

Application of binary rules to melody:



longpr	0	1	0	1	0	0	0	1	0	0	0	0	0	1	0	1
longmod	1	1	0	1	0	0	0	1	1	1	0	0	0	1	1	1
jumpaft3	0	0	0	0	0	0	0	1	1	0	1	1	0	1	1	0
phrasend	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
beat13	0	1	0	1	0	0	1	0	0	1	0	0	1	0	0	0
sync1234	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	1



longpr	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0
longmod	1	1	0	1	0	0	0	1	0	0	0	1	1	0	0
jumpaft3	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1
phrasend	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
beat13	0	1	0	1	0	0	1	0	0	1	0	0	1	0	0
sync1234	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1

The methods: Feature description: Melodic accents

- Modelling experimental data with different techniques: Linear regression, classification trees, logistic regression
- Differing in: Data types, variable (rule) selection, parameter estimation
- Best performing model after evaluation: Logistic regression model with parameter set z_n for monophonic melodies:

$$p_n(a=1) = \frac{1}{1+e^{-z_n}}$$

$$z_n = -7.966 + 3.907 \cdot beat13 + 3.311 \cdot sync1234 + 2.748 \cdot jumpaft4$$
$$+2.457 \cdot pextrem + 2.233 \cdot t\mathrm{hom}thr + 2.965 \cdot phrasend + 1.277 \cdot long\mathrm{mod}$$

The methods: Corpus-based musicology

General motivation:

- Observation about musical piece is only meaningful with reference to corpus of comparable pieces.
- Define relevant musical structures explicitly and unambiguously (where possible).
- Quantify musical structures in reference corpus.

The methods: Corpus-based musicology

- Idea: (Multivariate) distribution of features in music corpus is interesting and necessary frame of reference
- References: Lockwood, 1970; Steinbeck, 1982; Jürgensen & Knopke, 2004; Huron, 2006; Sadakata et al., 2006; Temperley, 2007
- Cornerstones:
  - Determine distribution of musical features in coherent corpus of musical works
  - Find statistical associations between features in corpus
  - Frequent feature combinations: Musical style prototypes or laws?
  - Infrequent feature combinations: Awkward or original cases?

The method: Corpus-based musicology

Impossible:

- Detection of subtle differences (find mass not class)
- Providing (cultural) explanations
- Detection of aesthetic connotations, meaning and interpretations

Possible:

- Detecting general mechanisms / laws / properties of music corpus
- Comparing music corpora for general properties
- Tracing individual musical patterns over pieces, styles, and time
- Comparing musical patterns with cultural data (style analysis, chart data, composer background)

The data base

The collection: 14,067 high-quality transcriptions of full pop songs from 1950s-2006

Raw data:

- Polyphonic MIDI files
- Lyrics
- Discographical database
- Chart data

The data base

Information contained: Compositional structure and arrangement (melodies, harmonies, rhythms, instrumental voices)

Information only partially contained: Timbre and performance (‘real’ sounds, expressive deviations in rhythm and pitch)

Assumption: Collection represents implicit knowledge of average listener about pop compositions

The pop music data base: Example

Lead-sheet computation

Lead-sheet: Basic representation for comparative analysis of songs

Components:

a) Identification of all song sections (incl. repetition information)
b) Harmonic progression (chord labeling)
c) Prototypical (monophonic) tune
d) Lyrics

Lead-sheet computation: Song segmentation

Goals:

- Partition song in meaningful sections,
- Establish relationships between sections
- Associate attributes for functional description

Algorithm: Combination of supervised and unsupervised classification and attribute filtering in five steps.

Lead-sheet computation: Song segmentation

Example: Labeled song sections (at #beats from the beginning) in *Englishman in New York*

Part 1	Part 2	Part 3	Part 4
Verse/Intro	Verse	Verse	Chorus
Beat: 8	40	72	104

Perspectives of corpus-based musicology

A) Compare feature distributions between different corpora, e.g. Huron's contour classes

Contour type	**Essen folk songs** (%, n=36,075)	**M^{4}S pop songs** (%, n=442,107)
Concave	9.7	11.2
Convex	38.6	23.4
Ascending	19.4	22.4
Descending	28.8	15.9
Horizontal	.5	6.2
Other	3.1	21.1

Perspectives of corpus-based musicology

B) Describe generic properties / patterns e.g.: Most frequent harmonic patterns

- 52% of all chord sequences used in database are combinations of **I IV** and **V** chords
- Very frequent turnaround sequence (see Moore, 2006; Kramarz, 2007: **I vi IV V**) in 5% of sequences, and in 16% of all 14000 songs
- Most frequent after **I IV V** combinations are alternations between **I** and **vi** and **I** and **ii** (each 3.5% of chord sequences)
- Specific sequences are much less frequent …

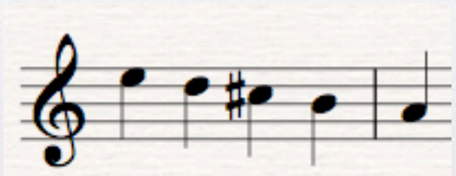
Perspectives of corpus-based musicology

B) Describe generic properties / patterns , e.g.: Most frequent melodic patterns

- Most frequent melodic phrases, pitch intervals only:
- Note repetitions (#1)

- Combinations of note repetitions and seconds (#5)

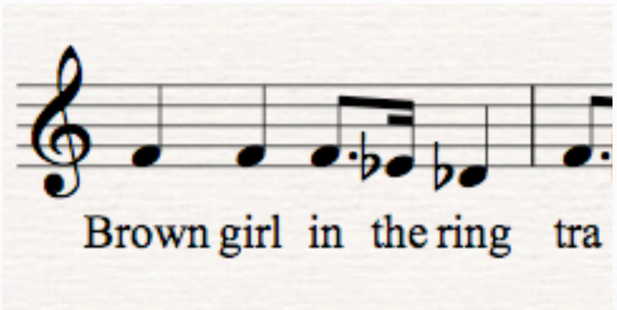
- Descending major scale: first pattern with range >maj3 (#35)



Perspectives of corpus-based musicology

C) Find particular patterns (motifs/riffs) through music history e.g.:

- Melodic patterns, e.g. opening phrase of *Brown girl in the ring*:



- Represented as tuples of intervals and duratio ratios: (0,1) (0,.75) (-2,.3) (-2,4) (+4,.75)
- => Occurs in 26 different songs in database, e.g. Rick Astley: *Together forever*; The Beatles: *Maxwell's silver hammer*; Bon Jovi: *In these arms*
- => Any relations to Jamaican children's rhyme or Boney M. song?

Perspectives of corpus-based musicology

C) Find particular patterns through music history e.g.: Harmonic patterns, e.g. opening chord sequence from *Yesterday*: **I vii III vi IV**

- only in 14 songs, e.g. Make me smile (Chicago), Sara (Jefferson Starship), Yesterday (Wet Wet Wet)
- only in one song by The Beatles
- relatively common in jazz standards

- Similarly: Find rhythmical patterns, e.g. the Bo Diddley riff:
- || **1**+2**+**3+**4**+ | 1+**2**+**3**+4+ :||

Perspectives of corpus-based musicology

<u>Potential of approach:</u>

- Give quantified structural descriptions of music corpora, styles and identify style prototypes
- Write history of composition in corpus, e.g. pop music, through re-use of feature patterns and pattern associations (co-occurences)
- Model listeners' implicit knowledge and expectations concerning music from specific corpus
- Detect structurally interesting instances / pieces in corpus for further analysis
- Correlate cultural phenomena with multi-featured descriptions of music structure (e.g. Mannheim style, Tin Pan Alley, 'Hit Song Science', etc.)

Next steps

1. Use more sophisticated algorithms for

    the generation of descriptive features, i.e. melody contours, melodic accents, rhythm patterns, melodic expectation, harmonic content, segmentation

and for

    the establishment of similarity relations between musical entities, e.g. melodic, harmonic, and rhythmic similarity (Müllensiefen and Frieler, 2004, 2006, 2007)

2. Test cognitive validity of algorithmic features
3. Address more interesting questions from a music analytic perspective
4. Model human music memory behaviour

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