### Introduction to Audio Content Analysis

Module 9.7: Music Structure Detection

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introduction overview

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#### corresponding textbook section

#### Section 9.7

#### lecture content

- structure in music
- self similarity and self distance matrices
- structure detection approaches

### learning objectives

- summarize basic difficulties in ground truth annotations of musical structure
- explain and interpret self similarity and self distance matrices
- summarize three domains for approaching music structure detection



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## music structure introduction

- music is inherently formal/organized/structural
- various hierarchical structural levels
  - groups of notes build rhythmic/melodic/harmonic patterns
  - measures group multiple events
  - phrases group several measures
  - sections contain several phrases
  - several sections can comprise piece/movement
  - ...
- grouping of musical elements/patterns is influenced by
  - 1 contrasts & novelty
    - rhythmic, harmonic, melodic patterns
  - 2 similarity and repetitions
    - rhythmic, harmonic, melodic patterns
  - 3 homogeneity within a section
    - ▶ instrumentation, tempo, harmony

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### objective

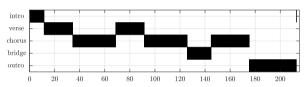
- reveal structural properties and relationships
- generate a list of parts and repetitions

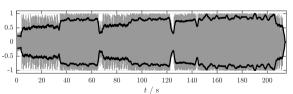
#### typical processing steps

- 1 feature extraction
- 2 Self Distance Matrix (SDM) or Self Similarity Matrix (SSM)
- 3 detect segments
  - novelty
  - homogeneity
  - repetition

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### music structure analysis features 1/2

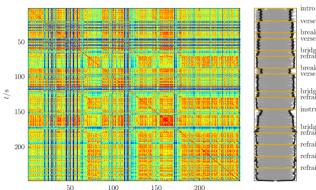
- features from all categories can have impact on structure
  - timbre
    - ▶ instrumentation, playing technique, effects, . . .
  - tonal content
    - ▶ melodic and harmonic patterns, range, ...
  - rhythm content
    - ▶ tempo, rhythmic patterns, ...
  - dynamics
    - ▶ loudness, range, . . .
- **■** feature aggregation
  - use texture window, or
  - aggregate features per beat or downbeat

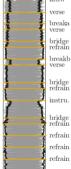
### music structure analysis self similarity matrix

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$$S(n_{\mathrm{A}}, n_{\mathrm{B}}) = \mathrm{s}(v(n_{\mathrm{A}}), v(n_{\mathrm{B}}))$$

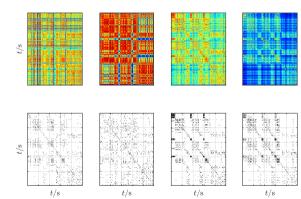






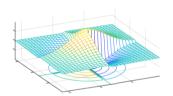
## music structure analysis feature dependency of similarity

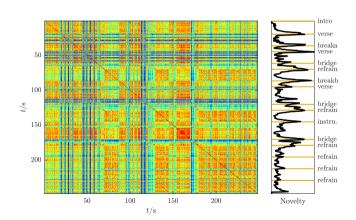
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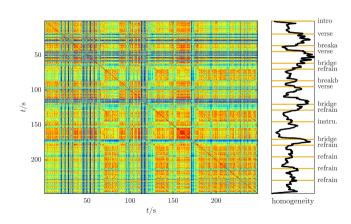
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## music structure analysis novelty analysis





### music structure analysis homogeneity analysis 1/2



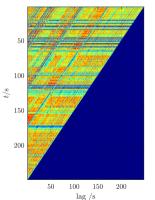
## music structure analysis homogeneity analysis 2/2

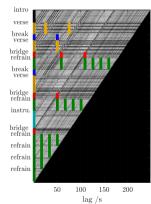
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- can also be used as post-processing step after novelty-based approach, e.g.
  - 1 describe each segment with features
  - 2 cluster and see which segments are grouped together

### music structure analysis repetition analysis 1/2

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- while in many cases it 'looks' easy, automatic extraction is error-prone
- ⇒ typical approaches for **enhancing** the distance/similarity/lag matrix
  - filtering (low pass smoothing, high pass edge detection)
  - use matrices with different time resolutions
  - image processing methods (e.g., erosion & dilation)
  - thresholding
  - "path search" through probability matrix

### music structure analysis repetition analysis 2/2

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- evaluation of structure detection challenging
  - ground truth
    - structure itself may be ambiguous
    - depending on annotator, varying hierarchical level of labels, e.g.

ann 1	intro	A				A				outro
ann 2	intro	vei	rse	cho	orus ve		rse	cho	rus	outro
ann 3	intro	$V_1$	$V_2$	$C_1$	C <sub>2</sub>	$V_1$	$V_2$	$C_1$	$C_2$	outro

- method and metric
  - boundary matching
  - frame level, e.g., pairwise match
- typical range of results
  - F = 50...70%

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### summary lecture content

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- self similarity/distance matrices
  - shows pairwise similarities/distances
  - depends on input features
- **■** structure detection
  - 1 novelty
  - 2 homogeneity
  - 3 repetitions

