Detecting Changes in Musical Texture

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Atte Tenkanen, University of Turku, Finland
Fernando Gualda, Queen's University of Belfast, UK
Aims

• To detect articulative boundaries in a composition by taking the changes in several musical features into account.
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• To offer an extension to a music analytical method called *Comparison Set Analysis* (CSA) (Huovinen & Tenkanen 2007).
Comparison Set Analysis

• Main parts of the *comparison set analysis*:

  1) overlapping segmentation, 2) comparison function, 3) comparison set and 4) result graph.
Comparison Set Analysis

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• CSA is a method with which, for example, formal articulations of a composition can be perceived.

• Feature extraction: In CSA musical units like pitch classes (derived from pitches) in a composition are segmented into overlapping sets of the same cardinality.

• These segments are then compared with a selected comparison set, constructed from similar units.
Comparison Set Analysis

• The comparison set embodies a chosen musical property whose **prevalence** is evaluated through a composition.
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• The results can be presented in different types of graphs, for example, trend curves which represent changes in harmonic features or mean points for classification of musical pieces.
Comparison Set Analysis

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• For example, in the case of pitch-class set segmentation, we associate the most proximate pitch-class set of the chosen cardinality to each note in the score.
Comparison Set Analysis

![Flowchart Diagram]

1. Score
2. Event list
3. Segmentation
4. Classification of segments
5. Frequency analysis
6. Comparison set
7. Calculation with similarity function
8. Graphs etc.
Example graphs

- Proportions of the ’Mystic chord’ (SC 6-34A) segments in some of Scriabin’s piano pieces.
  (Tenkanen, MCM2007)
Example graphs

• An example of CSA. Olli Linjama, *Improvisation nr. 756* (2004):
Boundary detection

- There is no connection between the mechanical overlapping segmentation and the real 'musical' segmentation.

- We can, however, use CSA to detect boundaries in musical texture.
Boundary detection

- In the present study we utilize several musical features.
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• two consecutive time windows of equal size are moved over the musical piece:
Boundary detection

Sibelius, Symphony Nr. 5, 3\textsuperscript{rd} movement. Bars 102-112.
Boundary detection

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• All the distance values are normalized to zero mean and unit variance for each feature separately.
Boundary detection

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\[ U(x, c_i) = \frac{\sum_{k=1}^{K} U(x_k, c_i) \cdot d(x, x_k)^{-2/(m-1)}}{\sum_{k=1}^{K} d(x, x_k)^{-2/(m-1)}} \]
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• The classifier frees an analyst from defining the exact attributes for the group of comparison sets.

• It's only one way to define the comparison set based on highly different features.
## Vector types, relation functions and segmentation cardinalities

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<td>REL</td>
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<td>same segmentation</td>
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<td>melodic transition vectors</td>
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- Melodic transition vectors are generated from each instrumental part by markov chains.
About Circle-Of-Fifths -relation

- Sample application: Short term 'modulations' based on COF. Note example C.P.E. Bach, Die Neue Litaney.
Analysis: Sibelius 5\textsuperscript{th} Sym. 3 mov.

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- Eleven randomly selected vectors (?) were used as the opposite class members (class 0) in the fuzzy k-nn classifier (where k=5 and the fuzzifier m=2).
- The texture-change curve was created by calculating the bar based means of all the training epochs (n=100).
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- Unlike the other features, the rhythm set approach did not show any significant correlation ($p>>0.05$) with the texture classifier curve.
- We are also studying our intuition, because the texture chance places were chosen by hand.
Future plans

• Go on developing the multidimensional CSA.
• Iterative use of CSA.
• Stand alone application for music analysis.
• Could be used in MIR if audio data is first converted into MIDI or other symbolic form.
References


Thank you!