Detecting Changes in Musical Texture

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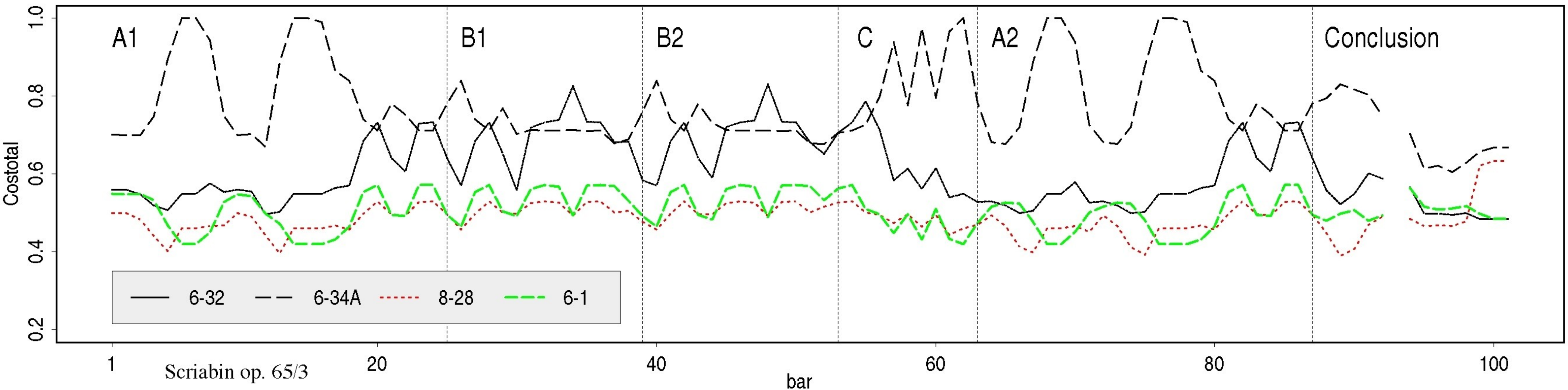
Atte Tenkanen, University of Turku, Finland
Fernando Gualda, Queen's University of Belfast, UK



Scriabin op. 65/3

Aims

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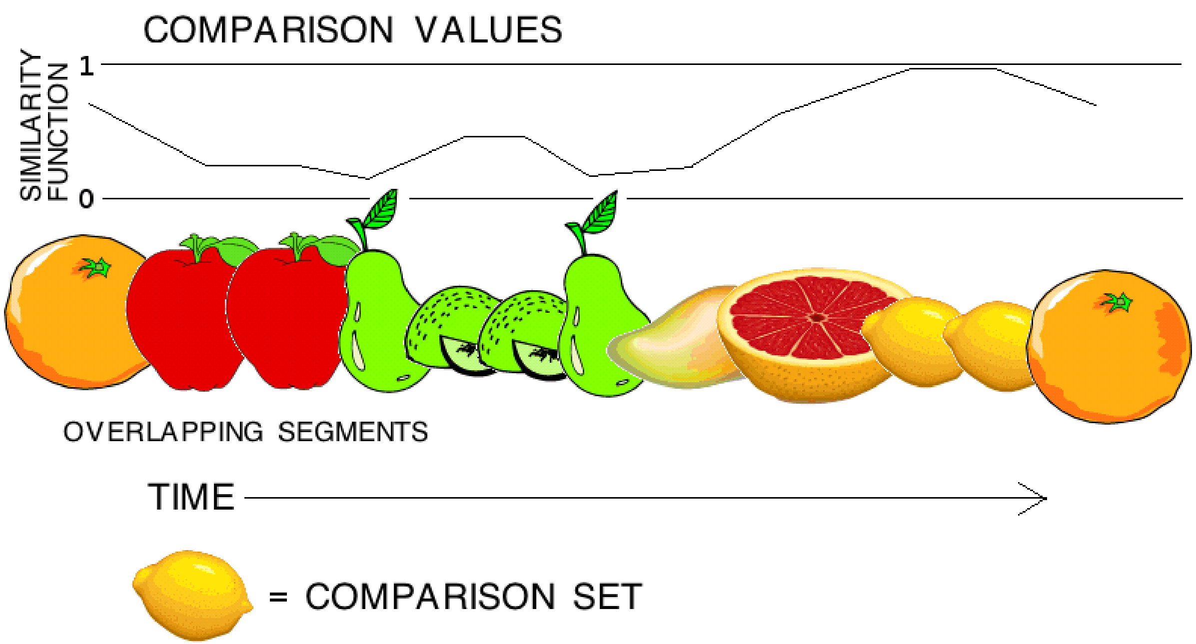
- To offer an extension to a music analytical method called *Comparison Set Analysis* (CSA) (Huovinen & Tenkanen 2007).

Comparison Set Analysis

- Main parts of the *comparison set analysis:*

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



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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

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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.

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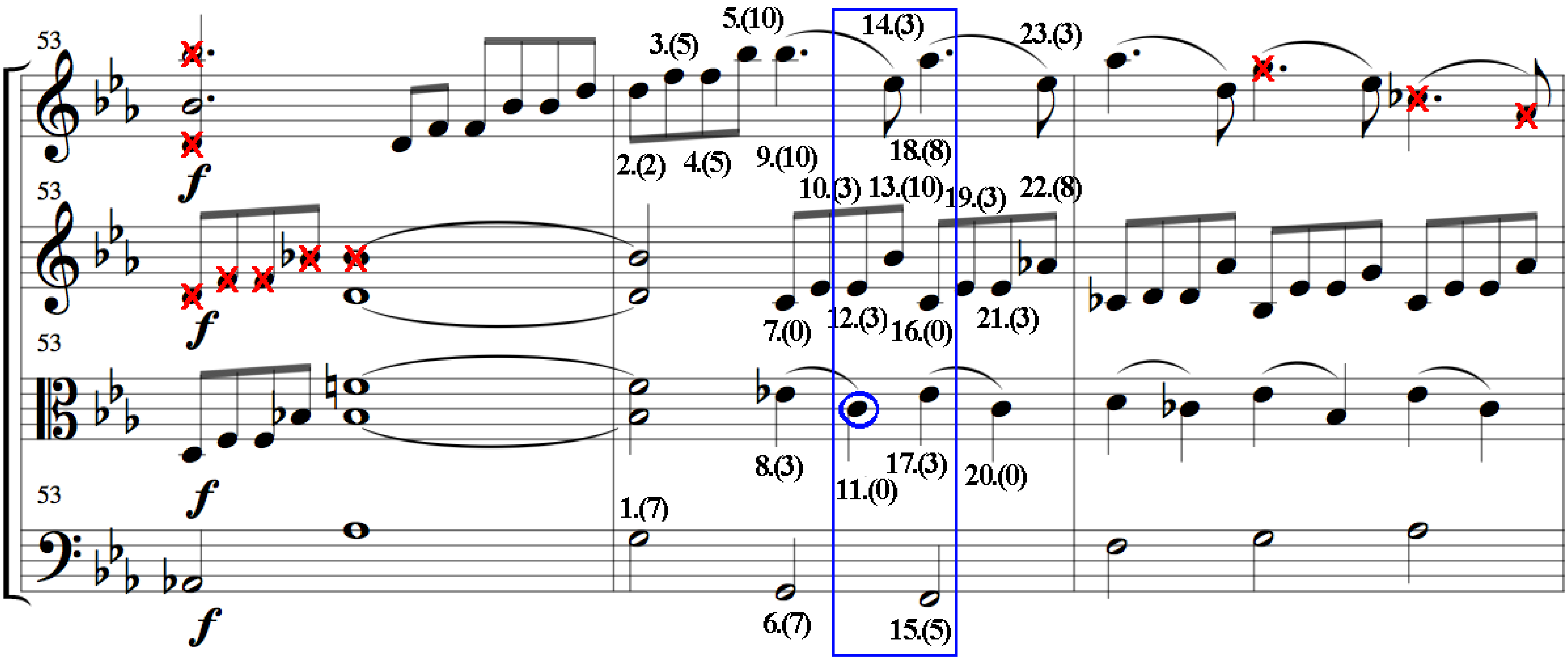
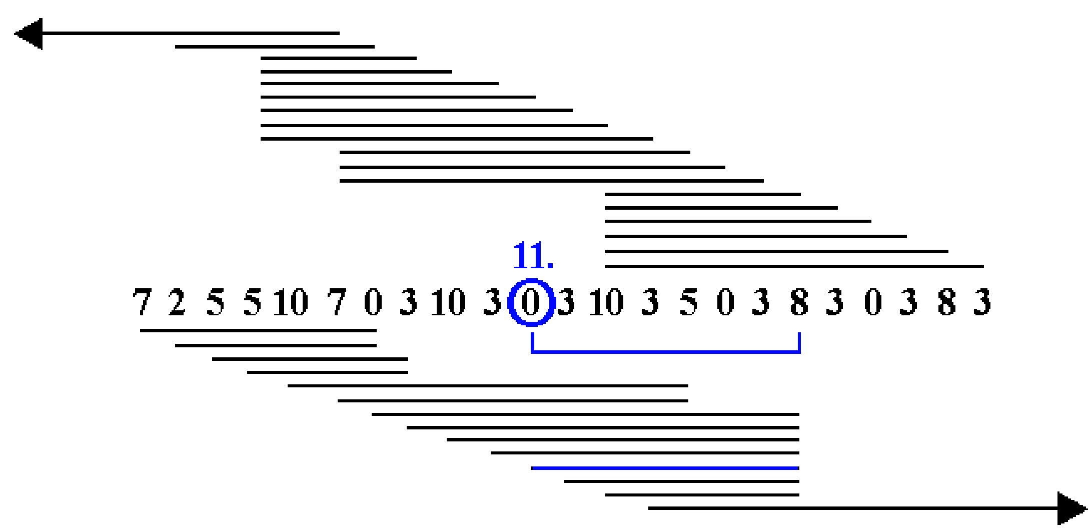
- For example, in the case of *pitch-class set segmentation*, we associate the most proximate pitch-class set of the *chosen cardinality* to each note in the score.

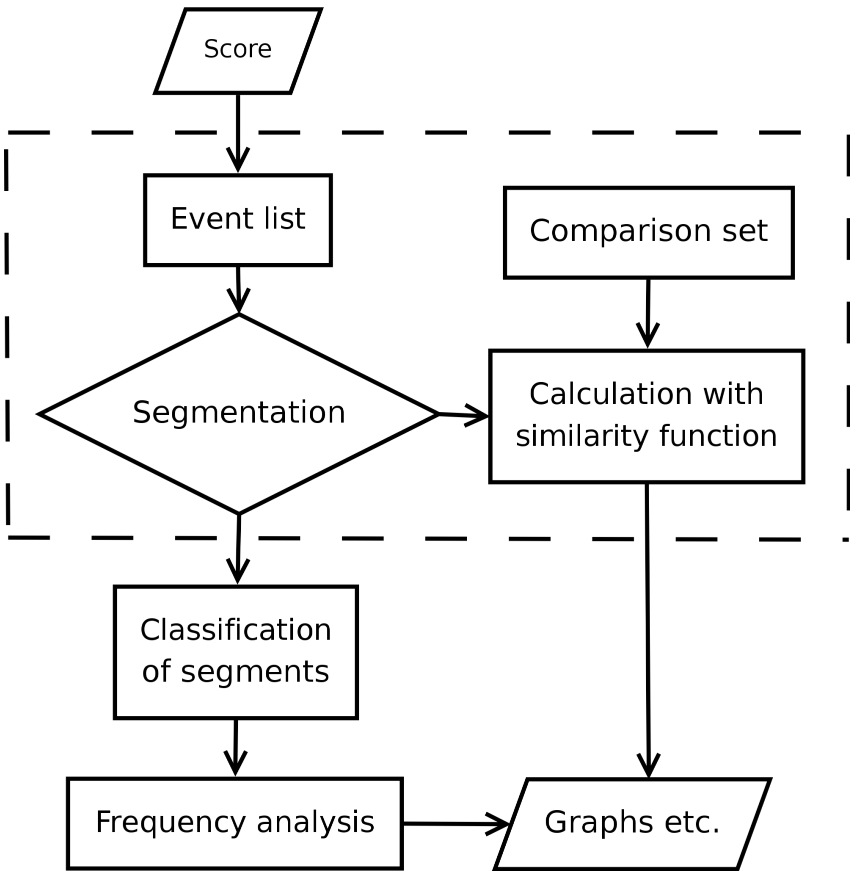


	Bar	Tick	Dur	Pc	Pitch	SegWth	SC	pc1	pc2	pc3	pc4	pc5
1011	54	325632	2048	7	55	2048	130	0	2	5	7	10
1012	54	325632	512	2	74	2048	130	0	2	5	7	10
1013	54	326144	512	5	77	1536	130	0	3	5	7	10
1014	54	326656	512	5	77	1024	130	0	3	5	7	10
1015	54	327168	512	10	82	1024	130	0	3	5	7	10
1016	54	327680	2048	7	43	1024	130	0	3	5	7	10
1017	54	327680	512	0	60	1024	130	0	3	5	7	10
1018	54	327680	1024	3	63	1024	130	0	3	5	7	10
1019	54	327680	1536	10	82	1024	130	0	3	5	7	10
1020	54	328192	512	3	63	1536	130	0	3	5	7	10
1021	54	328704	1024	0	60	1024	130	0	3	5	8	10
1022	54	328704	512	3	63	1024	130	0	3	5	8	10
1023	54	329216	512	10	70	512	130	0	3	5	8	10
1024	54	329216	512	3	75	512	130	0	3	5	8	10
1025	54	329728	2048	5	41	512	130	0	3	5	8	10
1026	54	329728	512	0	60	512	130	0	3	5	8	10
1027	54	329728	1024	3	63	512	130	0	3	5	8	10
1028	54	329728	1536	8	80	512	130	0	3	5	8	10
1029	54	330240	512	3	63	1024	130	0	3	5	8	10
1030	54	330752	1024	0	60	1024	126	0	3	5	8	11
1031	54	330752	512	3	63	1024	126	0	3	5	8	11
1032	54	331264	512	8	68	512	124	2	3	5	8	11
1033	54	331264	512	3	75	512	124	2	3	5	8	11

Imbricated pentachords



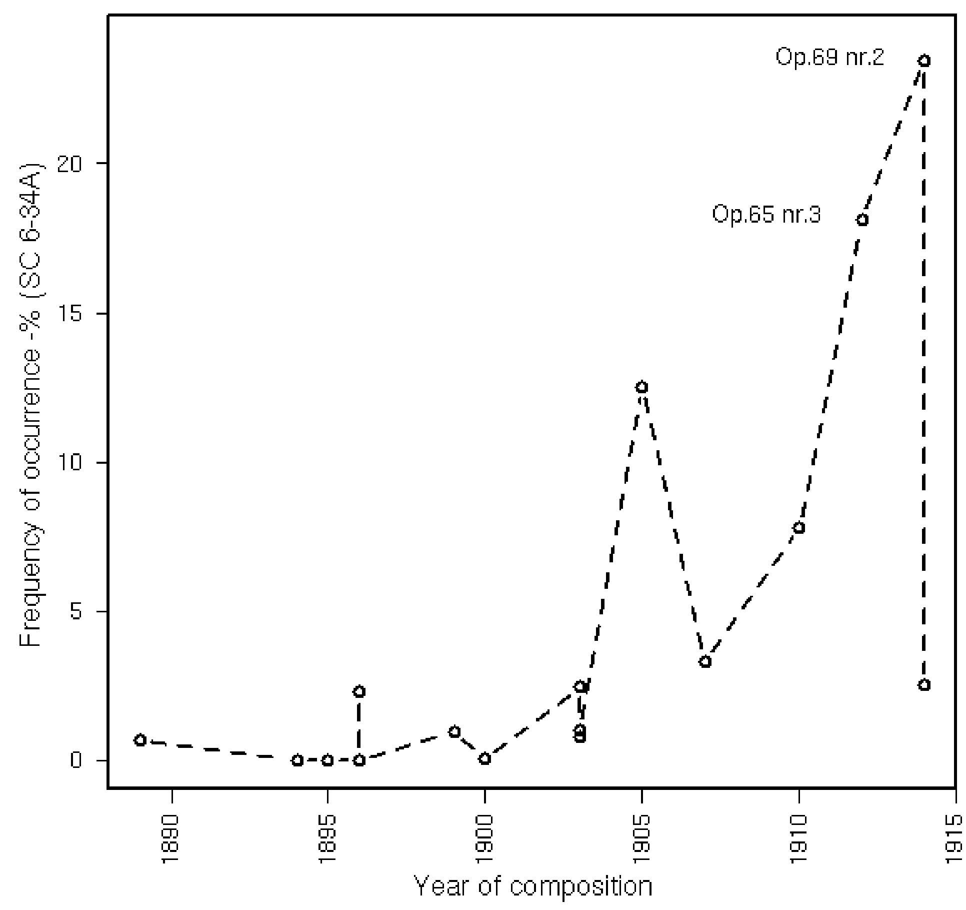
Comparison Set Analysis



Example graphs

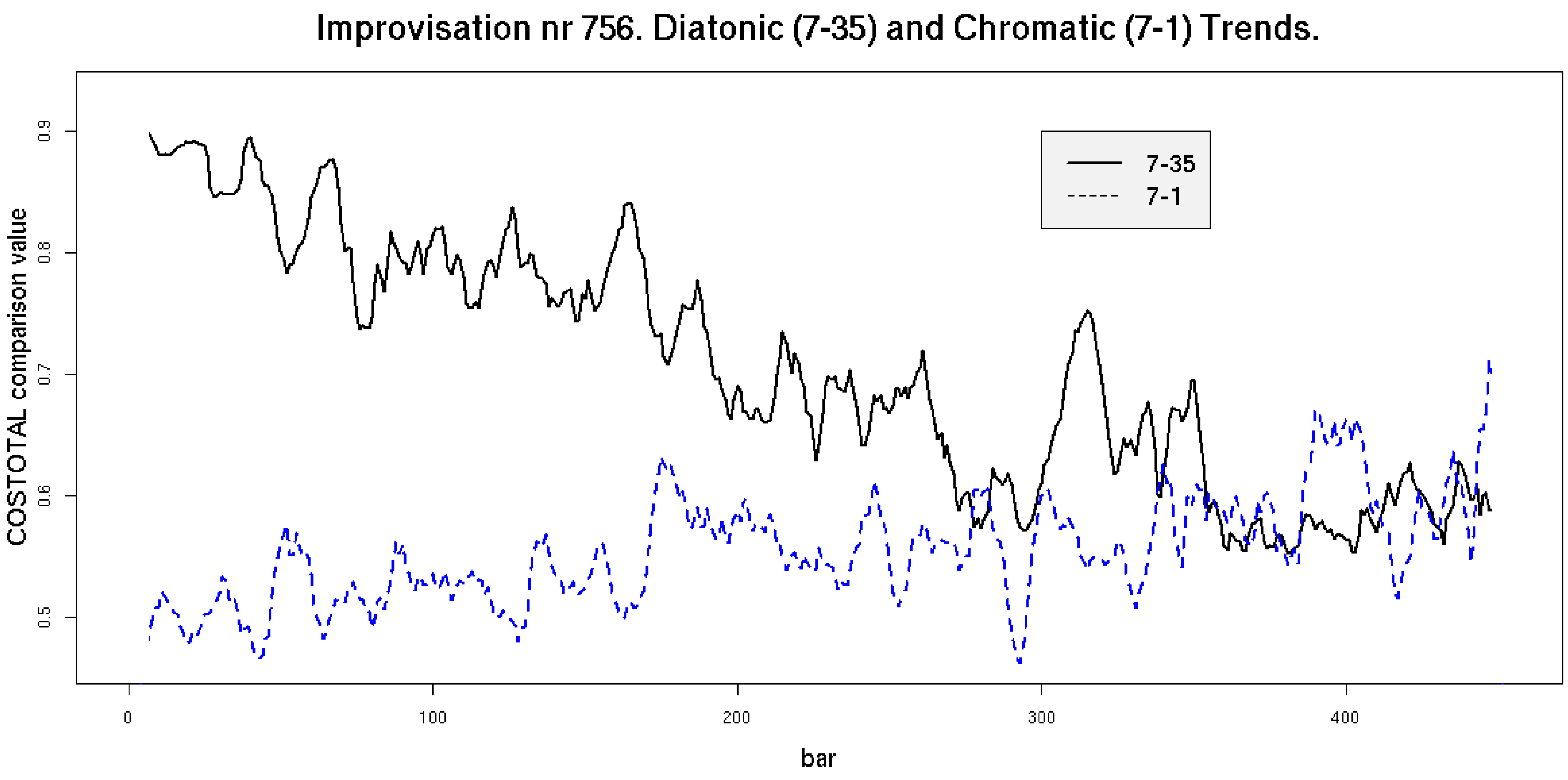
- Proportions of the ’Mystic chord’ (SC 6-34A) segments in some of Scriabin’s piano pieces.

  (Tenkanen, MCM2007)



Example graphs

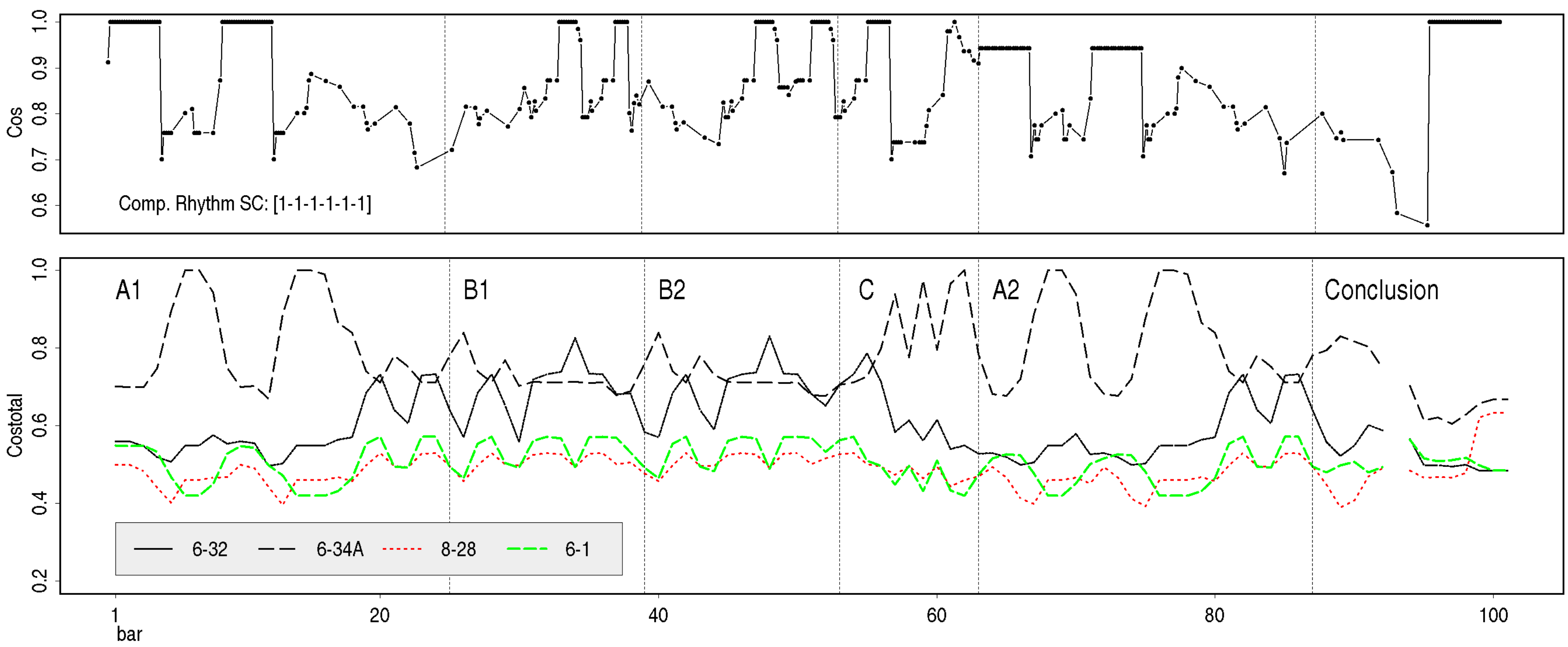
- An example of CSA. Olli Linjama, *Improvisation nr. 756* (2004):



Play

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.



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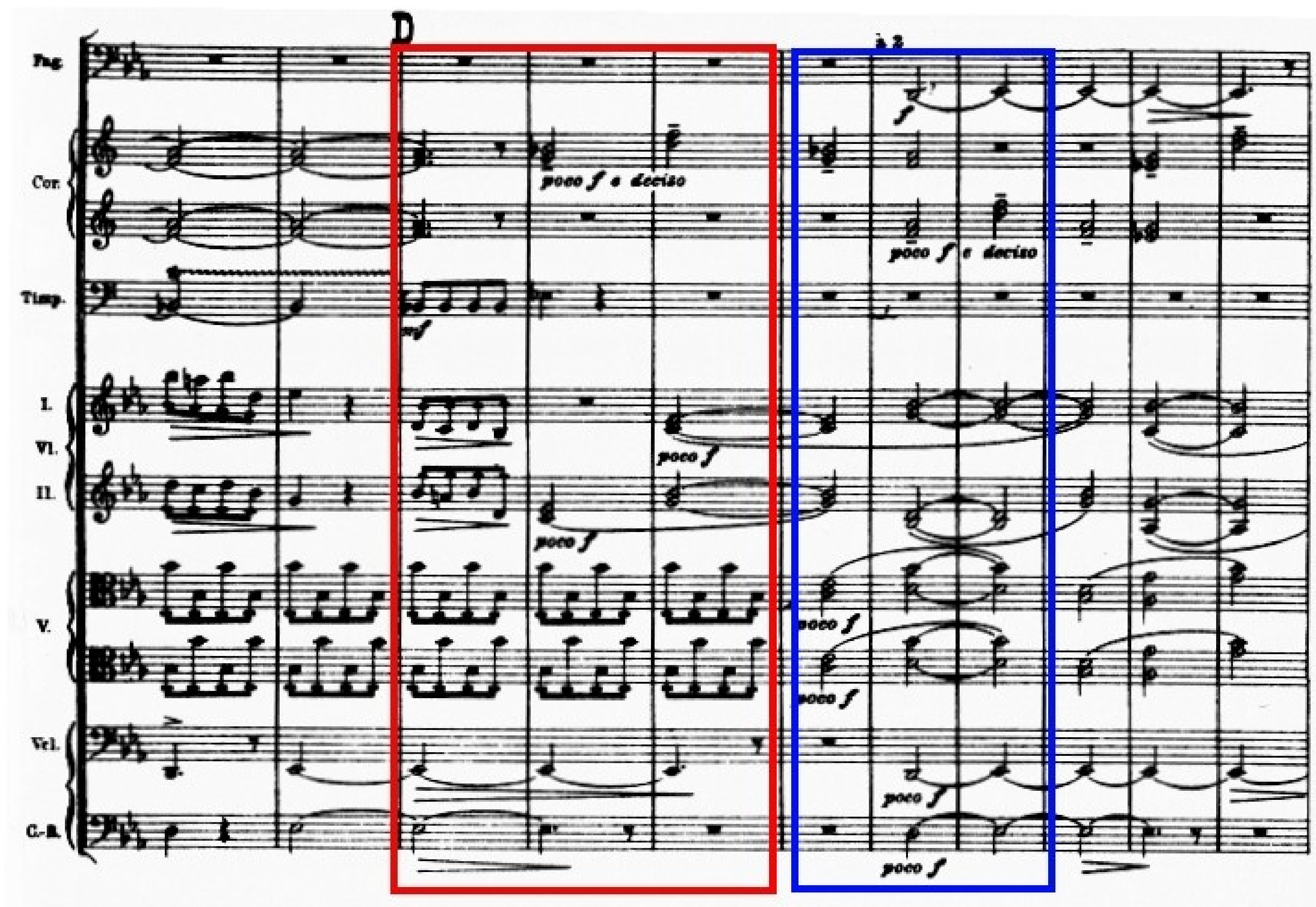
- an analyst chooses by hand some notes which are associated with the interesting musical characters, here, **changes in musical texture**. For that purpose...
- two consecutive time windows of equal size are moved over the musical piece:

Boundary detection



Sibelius, Symphony Nr. 5, 3rd movement. Bars 102-112.

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

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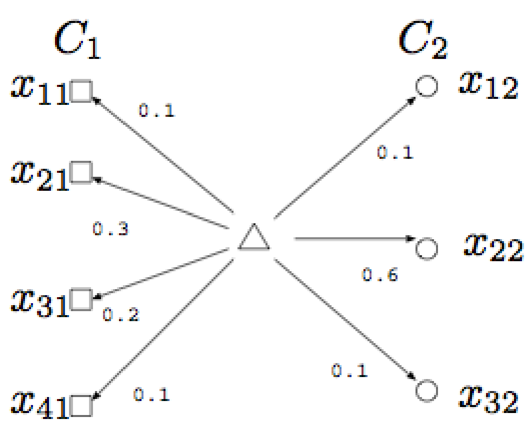
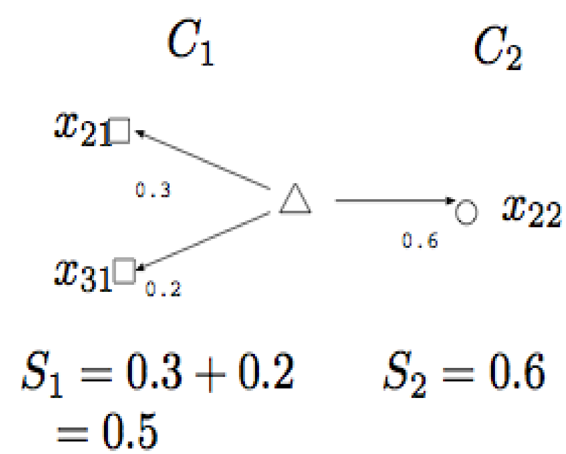
$$U(x, c_i) = \frac{\sum_{k=1}^{K} U(x_k, c_i) * d(x, x_k)^{-2/(m-1)}}{\sum_{k=1}^{K} d(x, x_k)^{-2/(m-1)}}$$





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- It's only one way to define the comparison set based on highly different features.

Vector types, relation functions and segmentation cardinalities

Feature vectors	Cardinality	Distance/Similarity Relation measure
set-classes	4	REL
pitch-class sets	same segmentation	cofrel
rhythm sets	4	cosine distance
melodic transition vectors	4	euclidean dist. between transition probability matrices
note duration distributions	-	euclidean dist. between normalized distributions
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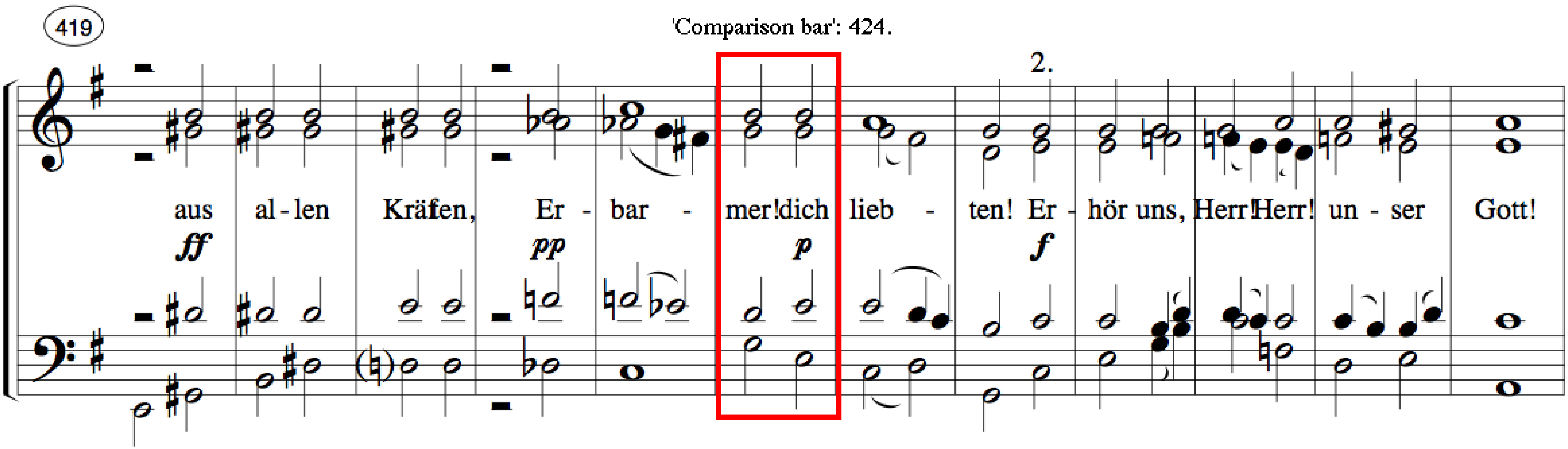
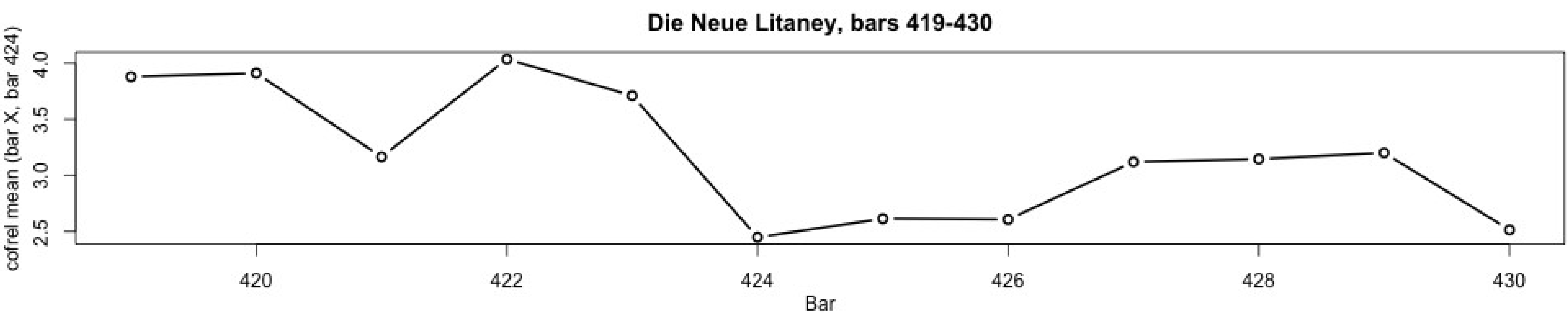
- Overlapping rhythm sets are constructed from the proportions between unique consecutive note onsets.
- Melodic transition vectors are generated from each instrumental part by markov chains.

About Circle-Of-Fifths -relation

- Sample application: Short term 'modulations' based on COF. Note example C.P.E. Bach, *Die Neue Litaney*.





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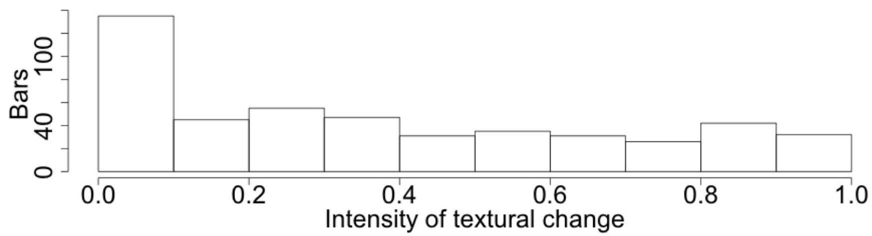
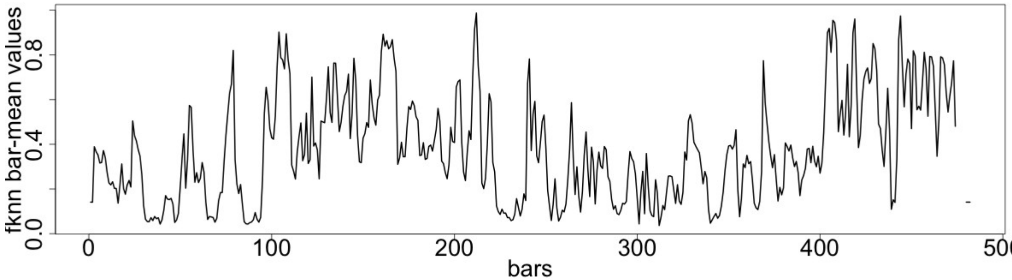
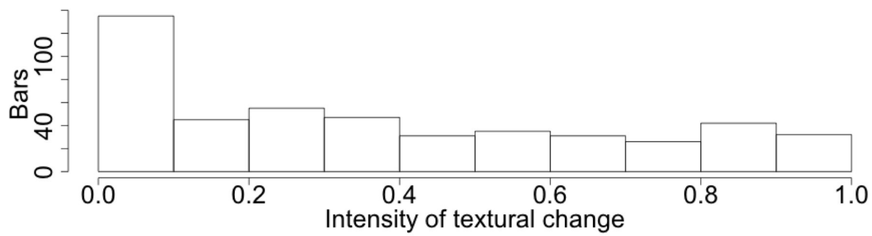
- Eleven randomly selected vectors (?) were used as the opposite class members (class 0) in the fuzzy k-nn classifier (where k=5 and the fuzzifier m=2).
- The texture-change curve was created by calculating the bar based means of all the training epochs (n=100).

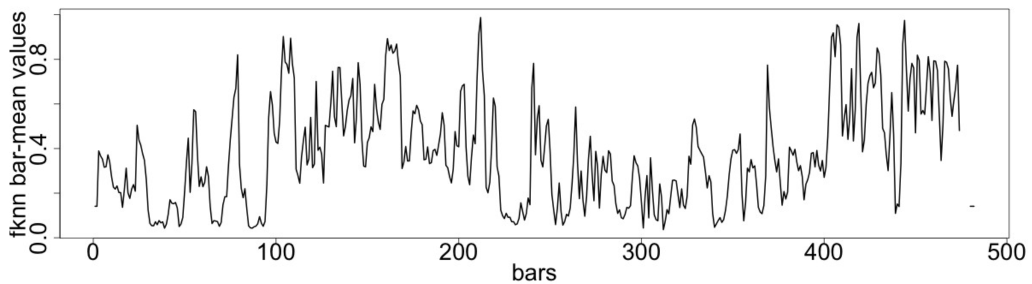
Results


Bars
0
40
100
0.0
0.2
0.4
0.6
0.8
1.0
Intensity of textural change


fknn bar-mean values
0.0
0.4
0.8
0
100
200
300
400
500
bars

Results





- The texture is nearly constant for about 140 bars.

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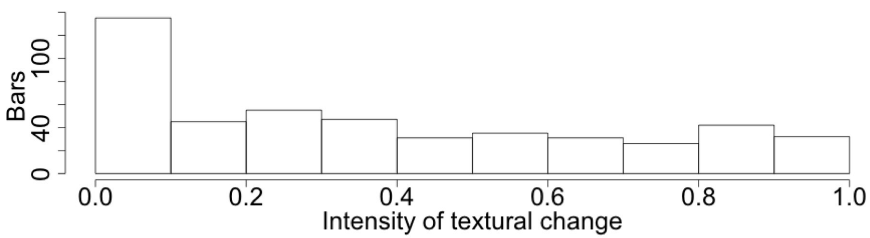

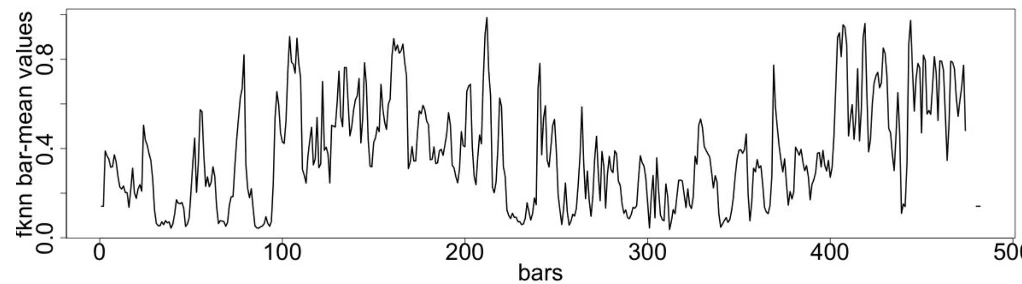

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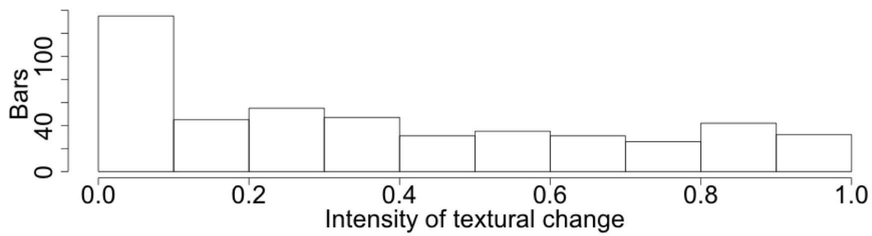

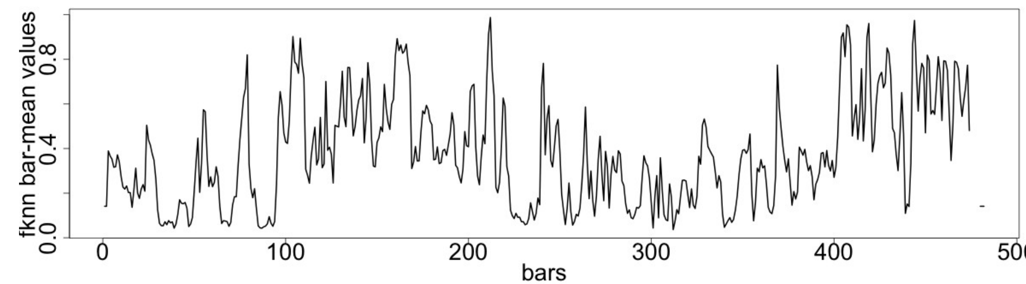

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- Unlike the other features, the rhythm set approach did not show any significant correlation (p>>0.05) with the texture classifier curve.
- We are also studying our intuition, because the texture chance places were chosen by hand.

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

- Huovinen Erkki and Atte Tenkanen. 2007. Bird’s Eye Views of the Musical Surface - Methods for Systematic Pitch-Class Set Analysis. *Music Analysis* 26(1-2): 159-214.
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- Lewin, David. 1980. A Response to a Response: On Pcset Relatedness. *Perspectives of New Music* 18(2): 498-502.

Thank you!