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Automatic Audio Segmentation: Segment Boundary and Structure Detection in Popular Music

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Abstract, Kurzfassung

Abstract

Automatic Audio Segmentation aims at extracting information on a song's structure, i.e., segment boundaries, musical form and semantic labels like *verse, chorus, bridge* etc. This information can be used to create representative song excerpts or summaries, to facilitate browsing in large music collections or to improve results of subsequent music processing applications like, e.g., *query by humming*.

This thesis features algorithms that extract both segment boundaries and recurrent structures of everyday pop songs. Numerous experiments are carried out to improve performance. For evaluation a large corpus is used that comprises various musical genres. The evaluation process itself is discussed in detail and a reasonable and versatile evaluation system is presented and documented at length to promote a common basis that makes future results more comparable.

Kurzfassung

Automatische Segmentierung von Musikstücken zielt darauf ab, Informationen über die Struktur eines Musikstücks maschinell zu extrahieren. Diese Informationen umfassen die Zeitpunkte von Segmentgrenzen, den allgemeinen musikalischen Aufbau eines Liedes und semantisch sinnvolle Bezeichnungen (*Strophe, Refrain, Bridge*, u.a.) für viele oder alle Segmente. Mithilfe dieser Daten können repräsentative Hörbeispiele aus Liedern generiert werden um die Navigation in großen Musikkollektionen zu erleichtern. Weiters können dadurch Ergebnisse von nachgeschalteten Anwendungen wie z.B. *Query-by-humming* verbessert werden.

Die vorliegende Masterarbeit präsentiert Verfahren, die einerseits die Segmentgrenzen bestimmen und andererseits die Liedstruktur schematisch abbilden. Zahlreiche Experimente zur Performanzverbesserung und deren Auswirkung auf die Resultate werden beschrieben. Zur Evaluierung der Ergebnisse wird ein großer Korpus verwendet, der verschiedenartige Musikgenres umfasst. Der Evaluierungsprozess selbst wird ausführlich beschrieben. Dies soll die Etablierung eines einheitlichen Prozesses fördern, um zukünftige Ergebnisse besser miteinander vergleichen zu können.

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Chapter 1

Intro

In the last years there has been a significant change in how music is distributed to, organized by and listened to by individuals. With the advent of large amounts of electronic storage capacity at a cheap rate, the internet and MPEG Layer 3 as a de-facto standard for transparent music compression, *Music Information Retrieval (MIR)* as a new research field has emerged.

As in related *Information Retrieval* research fields MIR aims at providing computational models, techniques and algorithms that can handle digital audio streams (e.g., mp3 files) in an "intelligent" way. Audio files may have textual meta-information attached to it like song title, artist, album title, genre and year of release. Mostly, however, MIR techniques do not rely on these but instead use the audio signal directly which is of course always available.

This thesis' topic, *Automatic Audio Segmentation* (AAS), is a subfield that aims at extracting information on the musical structure of songs in terms of segment boundaries, recurrent form (e.g., `ABCBDBA`, where each distinct letter stands for one segment type) and appropriate segment labels like intro, verse, chorus, refrain, bridge, etc.

The document is organized as follows. The remainder of this chapter discusses applications of AAS, informs about related literature as well as about audio segmentation in musicology literature and last but not least gives a list of my contributions.

Chapter 2 presents the evaluation system. It includes considerations about how evaluation should deal with ambiguity, details about the corpus used and how the performance measures are computed.

Chapters 3 and 4 comprise the algorithms, experiments and results for segment boundary and structure detection, respectively.

Finally, Chapter 5 presents results of a five-fold cross validation and of an independent test set. A few case studies of automatically extracted segmentations are discussed, the major aspects of the thesis are concluded and a number of directions for future work are mentioned.

The appendix contains additional resources like an overview of software used for this thesis and a detailed description of the corpus used.

Groundtruth segmentations, HTML reports, source code and demonstration songs where information about segment boundaries and types is included in the audio stream can be accessed through the thesis' webpage[1].

1.1 Applications

Automatically extracted structural information about songs can be useful in various ways.

Browsing of digital music collections Many online music or CD stores allow you to listen to a short excerpt of each audio piece that is available. It seems reasonable to select this excerpt according to the musical structure in such a way that it starts at a segment boundary and is somehow "representative" for the whole song. Facing the enormous amount of music available nowadays, this cannot be done manually. Of course, there will hardly ever be an ideal excerpt but musical structure extraction can help to provide a better-than-random song extract. This field of application is often referred to as audio thumbnailing, chorus detection or music summarization.

Music file seeking New features for audio playback devices are possible, such as skipping individual song segments or exclusively listening to segments of the same type to have a direct comparison between them, e.g., for practicing purposes.

Reduction of computational effort MIR algorithms more and more move from research institutes' computers where they are developed to portable electronic devices where they are used. Since mobile phones (so far) have significantly less computational power than an average home computer it is desirable to make the algorithms computationally less expensive. One possibility is to restrict expensive processing steps to one chorus section as it is probably a good representation of the entire song. Maybe results are even superior as the

[1] `http://www.ifs.tuwien.ac.at/mir/audiosegmentation/`

algorithms are not 'distracted' by irrelevant parts of the song. (Irrelevant to the application at hand, that is, not to the human listener.)

Basis for subsequent MIR tasks There are also other advantages if only one chorus section has to be considered instead of the whole song: less storage capacity is required for music databases, the accuracy of query-by-humming systems could be higher because most of the time the user will hum part of the chorus as this typically is the most catchiest and rememberable part of the song. In addition the musical form itself could explicitly be modeled as a song's feature, leading to more accurate song similarity estimations.

Finally, structural information could generally help on tasks like music transcription and alignment, or lyrics identification and extraction.

1.2 Related work

What research has been undertaken in this field so far?

Ong [Ong05] provides a comprehensive overview describing different approaches at length. I recommend that paper as an introductory text. Here, I shall only give a short summary of methods used. The main part of this section deals with details I have compiled from my references in a summarizing, comparative and tabular way I find handy. This can be useful to you if, e.g., you are about to employ chromagram features in your work and you are interested in comparing your results with already published ones where the same type of features have been used.

Although I cite quite a number of articles, PhD theses and technical reports as literature related to Automatic Audio Segmentation, the final outcome or purpose is not the same. Some concentrate on finding repeated patterns (so they do not care about sections that occur only once), some try to attach semantically meaningful labels to the sections found (whereas others concentrate on finding correct boundaries).

All those procedures start with a feature extraction step where the audio stream is split into a number of snippets ("frames") from which feature vectors are calculated. These are taken as a representation of the respective audio snippet. The subsequent steps, however, depend on the procedure and on the goals that are to be reached.

1.2.1 Tasks and goals

Possible tasks are:

Segmentation Finds begin and end time points of segments, i.e., the segment boundaries.

Structure / musical form detection Assigns generic identifiers like `A`, `B` or `C` to each segment. Segments of same type and/or function get the same identifiers. Thus, the musical form of a song can be written as a string like `ABCBDBA`.

Audio summary extraction Often referred to as *Audio Thumbnailing*, the output of this task is an excerpt that should contain all segment types once. In this sense, the excerpt summarizes the whole song.

Key phrase / chorus detection Finds the most significant part of the song which is basically the chorus section.

Semantic label assignment Assigns semantically meaningful labels like *verse*, *chorus*, *bridge*, *intro*, etc., to each segment.

Vocal / instrumental section detection The information whether a segment contains voice or not helps with semantic label assignment.

It is not possible to give a fixed order in which these tasks are performed. For example, algorithms which produce an audio summary do not necessarily compute segment boundaries or the musical form. Table 1.1 gives an overview about which subtasks are dealt with in which paper. For convenience, this thesis is referred to as [Pei07] in this and subsequent tables.

1.2.2 Features

Quite a number of different feature sets are used throughout related literature. Many of them are well-known in the MIR community and I shall not repeat their definitions here.

Many authors do not rely on the ubiquitous *Mel-Frequency Cepstrum Coefficients* (MFCCs) when tackling the specific task of audio segmentation because they are known to rather describe timbre content and hence the feature set values of one chorus featuring distorted guitar play and of another one lacking guitar sound would differ quite a lot. So a range of feature sets is proposed that should capture the melody, or harmony, of a song.

Table 1.1 gives a survey of various feature sets used. For their mathematical definitions and to learn how to compute them please refer to the respective publication.

Constant Q transform (CQT) [LWZ04, ANS+05] can be used to directly map pitch height to western twelve semitone scale if appropriate values for minimal frequency f_0 (e.g., 130.8 Hz as the pitch of note C3) and the number of semitones per octave b are chosen. Most papers set $b = 12$ whereas other ones extract 36 values per octave. The size of the feature vector is the product of b and the number of octaves.

Chromagram, also called *Pitch Class Profile* (PCP) [BW01, Got03], is essentially a generalization of the twelve bin CQT feature set. All pitch values are collapsed into a feature vector of size twelve, corresponding to twelve semitones, disregarding the octave of a note.

Octave Scale Cepstral Coefficients (OSCCs) and *Log-Frequency Cepstral Coefficients* (LFCCs) [MXKS04, Mad06] are similar to MFCCs. Instead of calculating cepstral coefficients from Mel scaled filter bank, the frequency band is divided into eight subbands (OSCC) or a logarithmic filter bank is applied (LFCC) before the coefficients are extracted.

Discrete Cepstrum [AS01] is a method to estimate the spectral envelope of a signal. It uses discrete points on the frequency/amplitude plane. These points originate from spectral peaks.

The *"Dynamic Features"* proposed in [PBR02] basically comprise those STFT coefficients of a Mel filter bank filtered audio signal that maximize Mutual Information, "represent[ing] the variation of the signal energy in different frequency bands."

Rhythm Patterns (RP) [RPM02], also called Fluctuation Patterns, and *Statistical Spectrum Descriptors* (SSD) [LR05] both represent fluctuations on critical bands (a part of RP comprise "rhythm" in a narrow sense). The first feature set uses a matrix representation whereas the latter one is a more compact "summary", employing statistical moments.

1.2.3 Techniques

The methods and mathematical models used in Automatic Audio Segmentation are widely-used in MIR, pattern recognition and image processing.

Self-Similarity Analysis Foote [Foo00] was the first to use a two-dimensional self-similarity matrix (autocorrelation matrix) where a song's frames are matched against themselves

Feature sets	**[ANS+05]**	**[AS01]**	**[BW01]**	**[BW05]**	**[CS06]**	**[Cha05]**	**[CF03, FC03]**	**[Foo00]**	**[Got03]**	**[LSC06]**	**[LC00]**	**[LWZ04]**	**[MXKS04, Mad06]**	**[Ong05]**	**[PK06]**	**[PBR02]**	**[Pei07]**	**[RCAS06]**
MFCC	✓	✓									✓		✓	✓	✓		✓	
CQT	✓									✓		✓			✓		✓	✓
Chromagram			✓	✓	✓	✓			✓				✓					
Other		✓[a]			✓[b]			✓[c]					✓[d]			✓[e]	✓[c, f]	
Subtasks																		
Segmentation	✓	✓				✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓
Recurrent structure, musical form	✓	✓			✓[g]	✓	✓			✓		✓[g]	✓		✓[g]	✓	✓	✓
Audio summary				✓		✓	✓					✓				✓		
Key phrase / chorus detection			✓						✓		✓							
Semantic labels												✓	✓					
Vocal / instrumental section detection												✓	✓					

Table 1.1: Overview of feature sets used and subtasks of individual papers.

[a] Linear prediction of spectral envelope; Discrete Cepstrum
[b] Log-Frequency Cepstral Coefficients
[c] Spectrogram
[d] Octave Scale Cepstral Coefficients
[e] "dynamic features"
[f] Rhythm Patterns, Statistical Spectrum Descriptors
[g] concentrate on repeated segments, parts of songs may be left unexplained

(Figure 3.2 top). One characteristic trait are the longer and shorter diagonal lines parallel to the main diagonal ranging from white to different shades of gray. These indicate segments of a song that are repeated at different positions, i.e., with a time lag. This inspired a restructured matrix called time-lag matrix [BW01], where these lines become horizontal, for an easier extraction of repeated segments.

Some researchers [Ong05, LWZ04] apply the basic morphological operations *dilation* and *erosion* to the matrix to improve extraction results. (If a combination of these operations are applied to the matrix the lines mentioned above become more distinct.)

Dynamic time warping (DTW) Given the self similarity matrix Chai [Cha05] uses DTW to find both segment transitions and segment repetitions. DTW computes a cost matrix from where the optimal alignment of two sequences can be derived. It is assumed that the alignment cost of a pair of similar song sections is significantly lower than average cost values.

Singular Value Decomposition (SVD) SVD is employed by some researchers [FC03, CF03] to factor a segment-indexed similarity matrix (the frame-indexed counterpart would be computationally intractable) in order to form groups of similar segments.

Hidden Markov Models (HMM) An HMM is a Markov model whose states cannot be directly observed but must be estimated by the output produced. This approach has been employed quite a few times in [ANS+05, ASRC06, AS01, LC00, Mad06, RCAS06, LSC06, LS06]. Feature vectors are parametrized using Gaussian Mixture Models (GMM). These parameters are used as the HMM's output values.

First, both the transition probability matrix and the emission probability matrix are estimated using the Baum-Welch algorithm. Second, the most likely state sequence is Viterbi decoded. Then, there are two ways to continue. Some authors use the HMM states directly as segment types, often resulting in a very fragmented song structure that has to be smoothed out afterwards. Another possibility is to use a sliding window to create short-term HMM state histograms that, in turn, are clustered using a standard clustering technique to derive the final segment type assignment. The latter approach is explained in detail in [RCAS06].

1.2.4 Corpora

One of the chronologically first tasks I performed was a detailed survey on annotated music corpora used so far for AAS. To my surprise there is no common corpus that has been used to evaluate the different approaches. Also, in previous Music Information Retrieval Evaluation eXchange (MIREX) benchmark contests, AAS was not considered as an evaluation task. Rather, institutes and research centers investigating audio segmentation have their own corpus, sometimes a subset of databases like RWC [GHNO02] or MUSIC [Hei03]. The annotations have apparently not been shared among fellow researchers outside the own institute.

Besides, the evaluation methods are not consistent. Some authors compare the mere number of segments found and segments annotated, whereas others use an elaborate roll-up procedure to take a hierarchical structure of repeated patterns into account.

Table 1.2 shows a summary of corpora and evaluation methods used.

1.2.5 Musical domain knowledge

Belonging to the general research field of *Music Information Retrieval*, the task of segmenting contemporary popular songs into their constituents like chorus, verse or bridge is quite specific. Thus, it seems advisable to take advantage of domain knowledge, i.e., musical knowledge about structure and other properties that most or all pop songs have in common. In practice such knowledge means constraints for the solution space or heuristic rules to avoid a computational intractable exhaustive search. While the use of such knowledge may narrow the range of potential songs an algorithm can successfully process, the overall improvement is probably worth it. This section summarizes domain knowledge that has been used in the literature.

After deriving a great deal of information about the song, musical form detection and semantic label assignment in [MXKS04, Mad06] finally is a matter of **strict rules** and a few **case descriptions**. The rules govern the overall song structure, the number and length of verses and choruses and the "middle eight" section. The following is an example of one case for verse/chorus detection:

> "*Case 1.* The system finds two melody-based similarity regions. In this case, the song has the structure described in item 1a [Intro, verse 1, chorus, verse 2, chorus, chorus, outro]. If the gap between verses 1 and 2 is equal and more than 24 bars,

Paper	Corpus; annotation	Evaluation	Notes
[ANS+05, LSC06, LS06, RCAS06]	14 songs; start, end time and label for each segment	performance measure from image segmentation (adapted); information-theoretic measure	annotations available from web[a], tracks 17–30
[AS01]	20 songs of various genres (folk to rock, pop, blues and orchestral music); no annotation	empirically: "The better the segmentation, the more coherent the different textures sound."	
[BW01, BW05]	93 songs; annotated chorus section; genres include dance, country-western, Christian hymns)	no evaluation of segmentation	
[CS06]	7 music tracks; start times of melodic repetitions	mean query rank	
[Cha05]	21 classical piano solo pieces, 26 Beatles songs; start, end time and label for each segment	roll-up procedure, edit distance	list of songs in [Cha05, Appendix A]
[CF03]	seven songs; number of verses and choruses	number of verses and choruses	list of songs in [CF03, Table 1]
[Got03]	100 songs from music database RWC [GHNO02]; start and end times of choruses	length of chorus sections	
[LC00]	50 Beatles songs	user tests (ten subjects)	
[LWZ04]	100 songs; annotated: repetitions, music structure	edit distance	
[MXKS04, Mad06]	50 songs; vocal/instrumental boundaries, chord transitions, key, song structure	number and length of segments	with the help of commercial music sheets; example annotation: [Mad06, Figure 7]
[Ong05]	54 Beatles songs; start, end time and label for each segment	intersection of boundaries, allowing 3 s deviation	annotation according to website[b]
[PK06]	50 songs (subset of MUSIC [Hei03] and RWC databases [GHNO02], Beatles songs); start, end time and label for each segment	adapted roll-up procedure [Cha05]	songs listed on web[c]
[Pei07]	94+15 songs (subset of [PK06]'s and [LS07]'s corpus, a few additional songs); start, end time and label for each segment, 2-level-hierarchy, alternative labels	weighted, normalized edit distance, independent evaluation of boundaries and form	see Section 2.1 for a description of my corpus and Tables A.2 and A.3 for a list of songs

Table 1.2: Overview of corpora and evaluation methods used in the literature. Songs referred to as "Beatles songs" of different papers need not be the same.

[a] `http://www.elec.qmul.ac.uk/digitalmusic/downloads/index.html#segment`
[b] `http://www.icce.rug.nl/~soundscapes/DATABASES/AWP/awp-beatles_projects.shtml`
[c] `http://www.cs.tut.fi/sgn/arg/paulus/structure/dataset.html`

> both the verse and chorus are 16 bars long each. If the gap is less than 16 bars, both the verse and chorus are 8 bars long."

In [LSC06] the authors state that conventional pop music

> "follows an extremely simple structure, dictated by the verse-chorus form of the lyrics and very predictable phrase-lengths, so that segments are a simple multiple of a basic eight-bar phrase."

Hence, a function z is presented that models the deviations of the detected segment boundaries from the nearest **fixed phrase-length position**. z is minimized over appropriate values and the detected boundaries are adapted. As you will see in Section 3.2 I also employed this idea, however, without success.

Whereas most researchers use common distance functions like Euclidean or cosine distance for their similarity matrices, Lu *et al*. propose a novel one, coined **Structure-based distance** [LWZ04]. It is based on the observation that difference vectors (that is, the differences $\mathbf{v}_d = \mathbf{v}_i - \mathbf{v}_j$ between two feature vectors) exhibit different structure properties depending on whether the note or the timbre varies. Difference vectors between the same notes but with different timbres have peaks that are spaced with some regular interval corresponding to semitones. The authors report a performance improvement over using common distance measures. The statistical significance, however, has not been tested.

Besides, the authors use a simple rule to assign the labels *intro, interlude/bridge* and *outro/coda* to instrumental sections, depending on their relative positions in the song.

Paulus *et al*. come up with an interesting assumption about segment types [PK06]. It is assumed that the durations of two segments of the same type lies within the duration ratio $r = [\frac{5}{6}, \frac{6}{5}]$. Also the converse is supposed to hold: segment pairs of duration ratio within r are of the same type. Although this frequently is indeed the case it is not difficult to present a counterexample: *Portishead: Wandering Star* contains both verse and chorus sections of a duration of approximately 24 s whereas the instrumental sections at [01:48, 02:24], [03:24, 03:36], [03:36, 04:25] and [04:25, 04:48] are of different length.

In some pop songs one of the **chorus segments** (mostly at the end of the song) is **transposed** a number of semitones upwards to increase tension and make the song more interesting[2]. This

[2]There is a (slightly ironic) website devoted to this phenomenon: `http://www.gearchange.org/index.asp`

causes problems as extracted features may not be similar to those of original repetitions. Goto explicitly takes care of this stylistic element by defining twelve kinds of extended similarities that correspond to the twelve possible semitone transpositions [Got03].

In the same paper Goto also formulates three **assumptions about song structure**, dealing with the length of the chorus section (limiting from 7.7 to 40 s), its relative position and its internal structure (tends to have two half-length repeated sub-sections). Results were best when all three assumptions were enabled.

Abdallah *et al*. introduce an explicit **segment duration** prior function to overcome the problem of very short and fragmented segments [ASRC06]. The prior function rises steeply from 5 s to a peak at 20 s, from where it starts to go down gradually to reach a value of half the peak value at 60 s. Thus, segments with a length of 0 to approximately 10 seconds are unlikely; 20 s is the duration with the highest probability.

1.3 Musical segmentation

Segmenting pieces of music into sections is ambiguous. People with little musical background will come to different results than professional musicians (provided that they are willing to engage in such an activity at all); people on the same level of 'musical proficiency' are likely to dispute each other's suggestion.

This is supported by both experiments with my groundtruth annotations and musicology literature.

1.3.1 Ambiguity

To assess the ambiguity of segmentations I compared groundtruth annotations from different subjects against each other.

The corpus data I received from other researchers contained three duplicate songs, i.e., I received three songs each having two groundtruth annotations done by two subjects. In addition, I annotated a few songs myself when taking over the annotations (see Section 2.1 on page 18 for details). This was the case when I could not agree with the received annotations at all.

Figure 1.1 shows five songs each with two "groundtruth" segmentations. The annotations have been done by two different subjects. You can clearly see that the two segmentations of the same song differ from each other in terms of segment boundaries and/or musical form.

1.3.2 Musicology

The question of musical structure analysis is also dealt with in the musicology literature. This section gives a brief overview of some approaches (following [Mid90]).

Information theory was applied for analyzing the surface structure of music [Mid90]:

> "This, in a sense, however, simply rewrites older assumptions about pattern, expectation, and the relationship of unity to variety, in terms of allegedly quantifiable probabilities; style is defined in terms of measurable 'information', product of the relative proportions of 'originality' and 'redundancy'."

This approach is heavily criticized because of its oversimplification of musical parameters and its disregard of both the listening act and the participant input. Besides, it regards repetition as negative because it has no information value; an attitude that certainly does not coincide with the "real world".

Then, methods and terms from *Structural linguistics* were adopted and applied to musical analysis. For example, it is argued that motives (in music) correspond to morphemes (in linguistics), called *musemes*, and that notes correspond to phonemes.

Another example is Steedman's approach [Ste84] which is a quite formal one. He employs generative grammar that recursively generates all recognizably well-formed transformations in a certain kind of jazz music. This naturally produces a hierarchical segmentation. Of course, this method can only be applied to music that somehow 'follows' the rules of the grammar.

Paradigmatic analysis

As to Ruwet [Ruw87], *repetition* and varied repetition, *transformation*, are the central characteristics of musical syntax. His analytical method, named **paradigmatic analysis** by others, defines

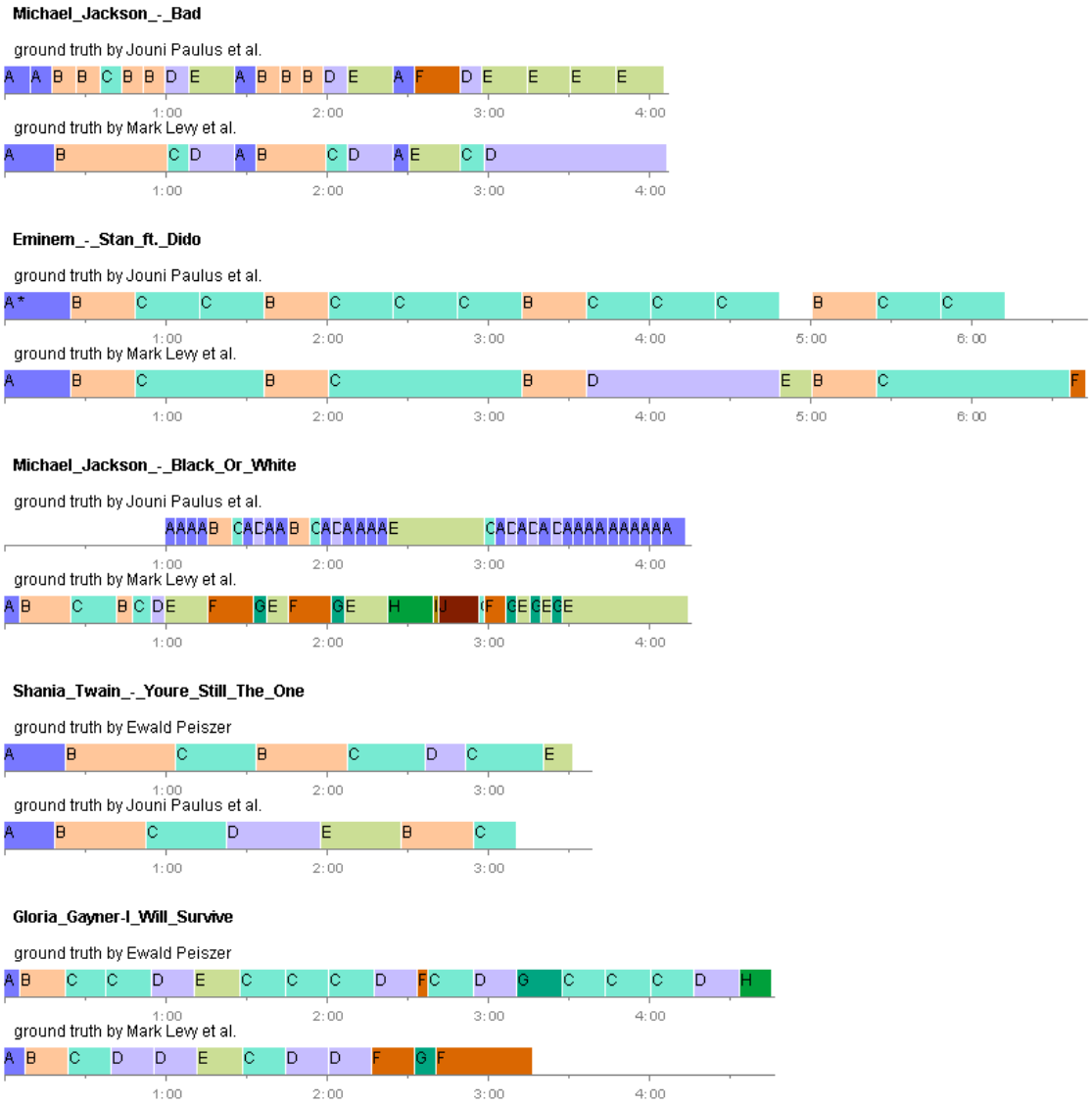


Figure 1.1: Groundtruth ambiguity: Five songs each with two "groundtruth" segmentations that have been annotated by different subjects. Each segment is represented by a colored box, segments of same type (within one panel) have the same color and letter. The colors and letters themselves do not convey any meaning, i.e., C could be a chorus, verse or outro, etc. White lines between boxes correspond to segment boundaries. Some parts of the song have been left unannotated by the respective authors.
Note, e.g., the large boundary deviations in the *Shania Twain* song and the quite different structure annotation of *Michael Jackson: Black or White*.

> "anything repeated (straight or varied) (...) as an unit, and this is true on all levels, from sections through phrases, presumably down as far as individual sounds. This means that in principal he can segment a piece without reference to its meaning, purely on the basis of the internal grammar of its expression plane. There are some problems, however. (...) What is the criteria for a judgment that two entities are sufficiently similar to be considered equivalent?"

In a nutshell, an analyst using Ruwet's method works iteratively: he breaks the song down to its constituent units of each structural level. Units of one level have roughly the same length. [Mid90, Examples 6.3–6.5] show the result of this method applied to George Gershwin's song 'A Foggy Day'.

While this method sounds quite concrete many questions remain open.

> "Are these the minimal units in the tune? And are they phonemic or morphemic?"

Or in other words: which level is the last level? Which level's units are the shortest that still convey some sort of meaning?

According to Middleton, Ruwet's method cannot answer these questions. He also shows that there are different criteria that can be applied to break up segments into smaller pieces. It is also not clearly defined how different one segment must be to another in order not to be regarded as a transformation but rather as a *contrast* to the other segment.

Schenker analysis

Middleton also discusses the application of **Schenker analysis** (which actually comes from classical music) to pop music. Generally, this method concentrates on tonality, cadences and harmonic structure and neglects 'motivic' structure and rhythm. See [Mid90, Example 6.10] for a Schenker analyzed 'A Foggy Day': The basic V-I cadence and the centrality of the tonic triad notes are revealed. Critics argue, however, that the Schenkerian principles are (too) axiomatic, according to them all valid music styles are seen essentially the same: "Thus, Schenkerian 'tonalism' could not be satisfactorily applied to much Afro-American and rock music, in which pentatonic and modal structures are important, and where harmonic structure (...) plays a comparatively small role."

Relevance for this thesis

When reading musicology literature I realized, not very surprisingly, that I lack music knowledge to really use the information and knowledge presented there. On the other hand I learned that comprehensive music knowledge would not necessarily simplify my work: I would not be better in judging whether one segmentation is superior to the other, whether two segments can be regarded as identical, as transformation of each other or contrasting to each other. Just as one might expect, even (or especially?) among experts these questions cannot be answered unambiguously. (One symptom of this is the fact that Middleton poses more questions in this book than he answers.)

For this thesis, I regard Ruwet's method as the most relevant. I think, intuitively I had some idea of his propositions in the back of the head when I prepared the ground truth for my corpus. Also, this method is not as strict regarding tonality and cadences as other ones. This is just the way my algorithm works because of the limited possibility to extract correct notes, chords and thus cadences from multi-instrumental audio files.

Paradigmatic analysis, however, can also be of direct use: One can assure that the ground truth annotations of a corpus are as homogeneous as possible if Ruwet's method is applied to each song using the same criteria and then the same level of segmentation is chosen for all songs.

1.4 Contributions

The contributions of this thesis can be summarized as follow:

Evaluation system I invested a significant amount of time in careful considerations about "good" evaluation in this case, the design and implementation of an easy-to-use evaluation program that produces both appealing and informative HTML reports. I defined a novel XML based file format for groundtruth files that is more expressive than other formats. (Chapter 2)

Large corpus The corpus on which this work is based contains 94 songs of various genres. Final evaluation runs are conducted on a 109 song corpus which is the largest corpus used so far in this research field. (Sections 2.1 and A.3)

Boundary detection I used the classic similarity matrix / novelty score approach [Foo00]. In addition, I carried out quite a few experiments to improve performance (various feature sets and parameter settings, boundary removing heuristic, boundary shifting post-processing [LSC06], Harmonic Change Detection Function HCDF [HSG06]). (Chapter 3)

Structure detection I focused on the complete annotation of all parts of the songs both with sequential-unaware approaches and an approach that takes temporal information into account. I employed cluster validity indices to find the correct number of segment types for each song. (Chapter 4)

Statistical significance All evaluation results are statistically well grounded by calculating and publishing confidence intervals from which statistical (in)significance can be derived.

1.5 Conventions

In pseudo code notation algorithms I use the following non-standard symbols.

$\cdot$ string concatenation

$\bigcirc$ empty string

$hash\{key\}$ hash array access

$string \backslash c$ removes all occurrences of character c from $string$

$\star$ special label with the meaning "not annotated"

Statistical significance Statements about statistical significance refer to confidence intervals calculated for each algorithm run. If the intervals of two runs do **not** overlap the difference of the mean values is said to be a statistically significant. I use Student's T distribution and a significance level of $\alpha = 0.05$.

1.6 Summary

This chapter introduced the reader to Automatic Audio Segmentation (AAS). I explained some prospective fields of application for this task, e.g., how AAS can facilitate the browsing in large digital music collections.

Next, I gave an overview of related work. I introduced various tasks and goals that are subsumed as AAS (boundary detection, structure detection, audio thumbnailing, semantic label assignment, etc.) I briefly explained mathematical models used (e.g., self-similarity analysis and Hidden Markov Models). Then, corpora and feature sets employed have been clearly arranged in tabular form. I pointed out that there is no common corpus so far. One section summarized different pieces of musical domain knowledge that are employed either explicitly or implicitly by authors of related literature.

The subsequent section dealt with musical segmentation as a task that generally leads to ambiguous results. I presented examples of "ground truth" annotations that differed to a certain degree. The chapter is topped off with a survey on how segmentation is perceived and discussed in musicology literature. I pointed out why Ruwet's method is the most relevant for my thesis.

Finally, I gave an overview of my contributions in this thesis.

Chapter 2

Evaluation setup

In my opinion evaluation of output of algorithms is, at least in the research phase, as important as the algorithm itself. If the evaluation procedure does not produce useful and applicable performance numbers any effort to optimize an algorithm becomes futile. In fact you would not know whether algorithm A performs better than algorithm B.

Thus, I decided to devote a significant part of my work to my evaluation system.

From my experience with similar work I know it is very handy if there is a simple-to-use procedure that automatically produces both optical appealing and informative reports. This makes it possible to have rapid feedback loops in a phase where you adjust the large number of degrees of freedoms, i.e., algorithm parameters, to get an optimal result.

This chapter describes the corpus I used, defines performance measures, introduces a new XML format for groundtruth files and explains the evalution algorithm in detail.

2.1 Groundtruth

To be able to compare results of various research studies the algorithms should run on the same corpus. Therefore I tried to collect as much annotation data as possible that has already been used in prior studies. I asked the authors of [Mad06, LWZ04, Cha05, Ong05, PK06] whether they would share their annotations. Finally I could base my work upon data used in [PK06] (50 songs, "Paulus/Klapuri corpus") and in [LS07][1] (60 songs, "qmul[2] corpus"), respectively.

[1] `http://www.elec.qmul.ac.uk/digitalmusic/downloads/index.html#segment`

[2] The annotators of this corpus are from the Centre for Digital Music, *Q*ueen *M*ary, *U*niversity of *L*ondon

A subset of the latter corpus has been used in [RCAS06, CS06, LSC06, AS01, ANS+05], too ("qmul14 corpus").

As the corpora overlap and because I could not obtain all songs my corpus which I used for my experiments finally contained 94 distinct songs. This is a multiple of some researchers' corpora and one of the largest used so far in this field. At the end I enlarged the corpus by fifteen additional songs which eventually led to the largest corpus against which an AAS algorithm has ever been evaluated. I included the corpus information ("this song belongs to which corpora?") in the groundtruth files to get also corpus-specific performance measures.

See Section A.3 for the complete list of songs I used.

2.1.1 Adaption

When I received other researcher's annotation data I had to decide if I use it 'as is' or if I adapt it.

As a matter of fact the results are less comparable if you change something at the test set used for evaluation. On the other hand the expressiveness of performance measure numbers is limited if the underlying ground truth annotations are inconsistent due to the fact that they come from several different sources.

Because of this and the fact that I introduced a novel XML audio segmentation format that is more expressive and flexible and can be used by other researchers in future studies and evaluations I decided to look through the data and carefully make some changes if necessary.

Essentially, the adaptions I made fell into two main groups:

- I introduced hierarchical segmentation and alternative labels where appropriate.
- Adjustments of start and end times of segments that are probably due to different offsets when encoding the audio file from CD, i.e., when all boundaries seemed to be shifted by a fixed offset. (I had to collect the audio files by myself because of copyright issues.)
- There were a number of songs where parts have been left unannotated.

2.1.2 Quality of audio signal

Like in other Information Retrieval tasks the quality of the output (classifications, algorithms) highly depends on the quality of the input, i.e., training data and test data. Of course, this is not clearly visible at first sight. Even if only a small and inaccurate data set was being used, the evaluation procedure would still yield perfect looking performance measure numbers with quite a few decimal places. One could be tempted to use and publish them without have a proper look at what is behind these numbers.

Thus, I took some consideration on the input data at the beginning of my work.

Lossy compression

By far the most widely used audio file format nowadays is MPEG-1 Audio Layer 3, commonly referred to as mp3. While the compressed audio should not sound different from the original one (if an appropriate bitrate is used), it certainly changes the spectrogram and extracted audio features to some degree. I wondered whether the results would be distorted when using mp3 files as input.

I did some experiments with two versions of the same song: one version was extracted from CD as uncompressed wav file, while the other one was encoded to mp3 at the rather low bitrate of 128 kbit/s. The experiments showed that, e.g., the novelty score plot was almost congruent. Thus, I decided not to exclude mp3 files as input data, especially because typically my mp3 files have a bitrate of at least 192 or even 320 kbit/s.

Sample frequency

I decided to downsample audio files to mono, 22,050 Hz as this is a good trade-off between input data quality and reduction in computation time. Ad-hoc experiments with 44,100 Hz audio files showed almost no change of results.

2.2 Performance measures

2.2.1 Level 1 - Boundaries

Evaluating segment boundaries is straight forward. Following the approach used, e.g., in [Cha05] I calculate precision P, recall R and F-measure F. Let the sets $\mathcal{B}_{algo}$ and $\mathcal{B}_{gt}$ denote begin and end times of automatic generated segments and ground truth segments respectively, then P, R and F are calculated as follows:

$$P = \frac{\mathcal{B}_{algo} \cap \mathcal{B}_{gt}}{\mathcal{B}_{algo}} \tag{2.1}$$

$$R = \frac{\mathcal{B}_{algo} \cap \mathcal{B}_{gt}}{\mathcal{B}_{gt}} \tag{2.2}$$

$$F = \frac{2RP}{R+P} \tag{2.3}$$

A parameter w determines how far two boundaries can be apart but still count as one boundary. A typical value is 3 s, i.e., all boundaries within the range of three seconds before to three seconds after a boundary b are seen as identical to b. Figure 2.1 shows the effect of w: solid black boundaries in the upper panel count as hits, dotted red ones as misses.

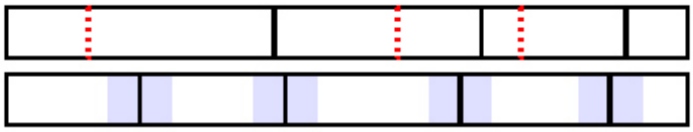


Figure 2.1: Boundary evaluation; top: detected boundaries, bottom: true boundaries (from: [Cha05, Figure 3-6], adapted)

Alternative measure Some papers [ASRC06, ANS+05, LSC06, RCAS06] use another performance measure. In order to compare my results with theirs I also compute P_{abd}, R_{abd} and F_{abd}. P_{abd} and R_{abd} correspond to [ASRC06]'s $1-f$ and $1-m$, respectively, and are calculated as follows [ASRC06]:

> "Considering the measurement M [computed segmentation] as a sequence of segments S_M^i, and the ground truth G likewise as segments S_G^j, we compute a directional Hamming distance d_{GM} by finding for each S_M^i the segment S_G^j with the maximum overlap, and then summing the difference,
>
> $$d_{GM} = \sum_{S_M^i} \sum_{S_G^k \neq S_G^j} |S_M^i \cap S_G^k|$$
>
> where $|\cdot|$ denotes the duration of a segment."

Then,

$$P_{abd} = 1 - d_{MG}/dur \tag{2.4}$$

$$R_{abd} = 1 - d_{GM}/dur \tag{2.5}$$

$$F_{abd} = \frac{2R_{abd}P_{abd}}{R_{abd} + P_{abd}} \tag{2.6}$$

where dur is the duration of the song.

The main advantage of the alternative measures is that they somehow reflect *how much* the two segmentations differ from each other: If a boundary b from computed segmentation is apart more than w from the corresponding one in the ground truth b_0, it does not count for P or R, regardless of how far they are apart (since $b \notin \mathcal{B}_{algo} \cap \mathcal{B}_{gt}$). In contrast, P_{abd} and R_{abd} will rise depending on the distance between b and b_0 since these measures are not based on the boundaries directly but rather on (overlapping) segments between them.

If applied to the same machine segmentations, I saw that mean F_{abd} is generally about 0.1 higher than mean F. In my opinion this is due to the "binaryness" of P and R as explained in the previous paragraph (either a boundary belongs to the intersection $\mathcal{B}_{algo} \cap \mathcal{B}_{gt}$ or not). Distances between "corresponding" boundaries from $\mathcal{B}_{algo}$ and $\mathcal{B}_{gt}$ are frequently a bit larger than w, leading to quite bad P and R.

2.2.2 Level 2 - Structure

Following Chai's notion I use the *formal distance* metric f which basically is the *edit distance* ed between strings representing the two structures, independent of the actual naming of the distinct

segments as long as segments with the same label get the same character. That is,

$$f(\texttt{ABABCCCABB}, \texttt{ABCBBBBACC}) = 3 \tag{2.7}$$

because

$$ed(\texttt{ABABCCCABB}, \texttt{A}\boxed{\texttt{CBCCCC}}\boxed{\texttt{A}}\boxed{\texttt{BB}}) = 3 \tag{2.8}$$

(in the second argument `B` and `C` have been swapped). To relate f to the song duration dur_s I use the formal distance ratio

$$r_f = 1 - f/dur_s \tag{2.9}$$

Details about the string representation are discussed in Section 2.3.2.

Alternative measures Another interesting performance measure can be computed following an information-theoretic approach. In [ANS+05, ASRC06] "conditional entropies" and "mutual information" are calculated, treating the joint distribution of label sequences as a probability distribution. Mutual information I (in bits) measures the amount of information contained in both the computed and the groundtruth segmentation. The conditional entropies $H(algo|gt)$ and $H(gt|algo)$ gives an impression about the amount of "spurious" information in computed segmentation and about how much of the groundtruth information is missing there, respectively. I is optimal and maximal if each segment type in the groundtruth segmentation is mapped to one and only one segment type in the computed segmentation. If so, both $H(algo|gt)$ and $H(gt|algo)$ are zero.

In my opinion this measure has one clear flaw. I increases monotonically with the number of k-means clusters k. Even if the extracted structure has obviously too many (spurious) segment types, and formal distance ratio already declines, I still ascends further. This behavior is distinctly visible in Figure 4.2.

The performance numbers for level 2 using the proposed method are independent of the boundary accuracy. This gives us the possibility to judge structure extraction performance independently from segment boundary performance.

2.3 Evaluation system

Figure 2.2 depicts the architecture of my evaluation system. It uses XML, XSD, XSLT and Perl to produce an HTML file from both automatic generated and hand made song segmentations. The system is OS independent, I used it both on *Windows (XP)* and *Linux (Debian Sarge)*.

The following subsections describe each part in some detail.

2.3.1 Audio segmentation file format

I introduced a new file format describing audio segmentations. Both ground truth annotations and automatically generated ones are encoded in this format. I decided to use *Extensible Markup Language (XML)* to model the information because it is a well established standard that is expressive enough for this application and still human readable. The file format is called **SegmXML** which is also the name of the files' root node.

Listing 2.1 shows an excerpt of an example XML file (the complete file can be seen in Listing A.1).

Listing 2.1: Britney_Spears_-_Hit_Me_Baby_One_More_Time.xml (excerpt) – segmentation XML file for *Hit Me Baby One More Time* by Britney Spears

```
<?xml version="1.0" encoding="UTF-8"?>
<SegmXML version="1.0">
  <metadata>
    <song canonicalname="Britney_Spears_-_Hit_Me_Baby_One_More_Time">
      <title>Hit Me Baby One More Time</title>
      <artist>Britney Spears</artist>
      <album year="">Hit Me Baby One More Time</album>
      <musicbrainz_trackID/>
      <duration duration_sec="212">03:32</duration>
    <genre>Rock/Pop/Dance</genre></song>
    <annotation source="ground truth">
      <done_by note="primary author(s)">Mark Levy/Geoffroy Peeters/Katy Noland</
           done_by>
      <done_by timestamp="2007-02-24" note="adapted by">Ewald Peiszer</done_by>
    </annotation>
  </metadata>
  <segmentation>
    <segment label="intro" start="00:00:000" end="00:11:572" start_sec="0.0000000"
          end_sec="11.5729710"/>
```

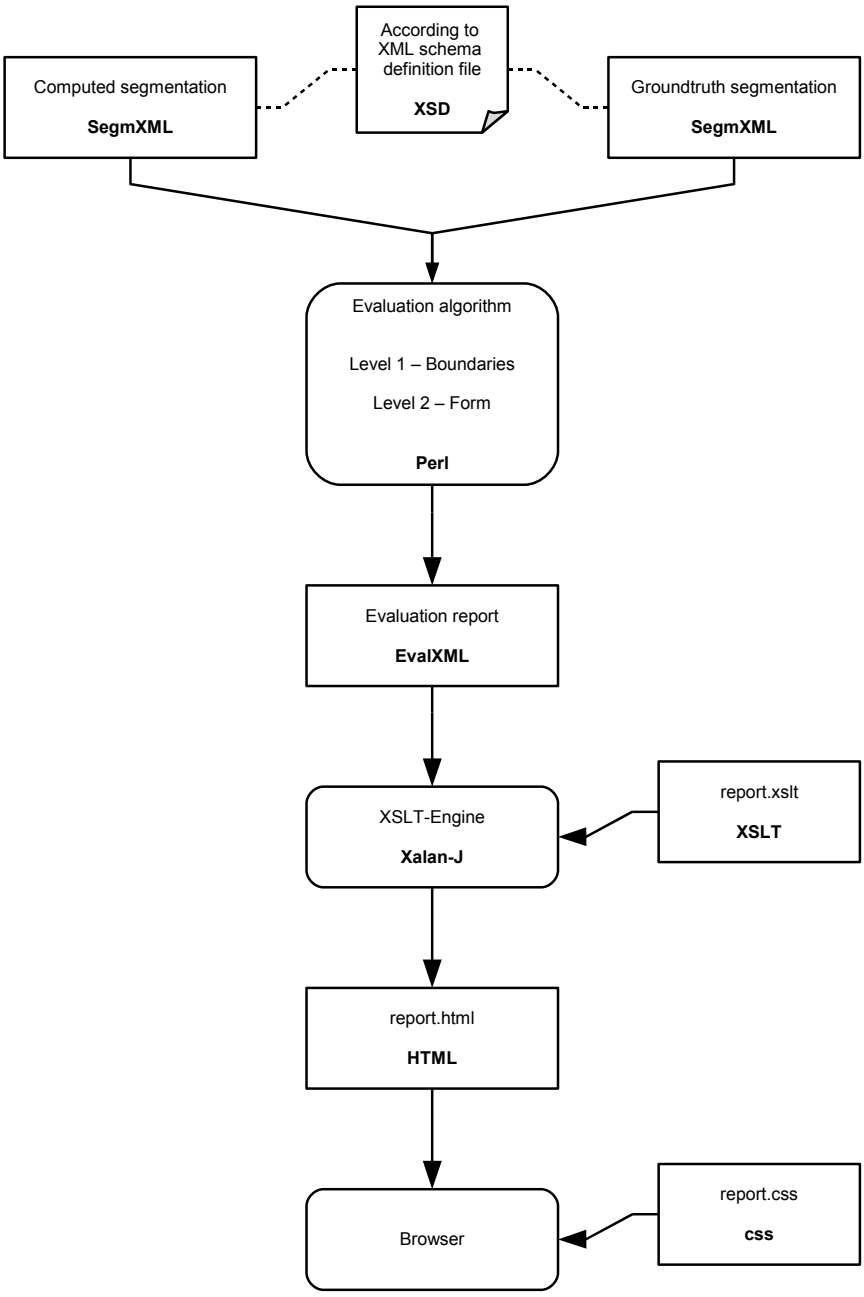


Figure 2.2: Overview of the evaluation system

```
18    <segment label="verse" start="00:11:572" end="00:21:903" start_sec="11.5729710
          " end_sec="21.9032200"/>
19    <segment label="verse" start="00:21:903" end="00:32:222" start_sec="21.9032200
          " end_sec="32.2224040"/>
20    <segment label="trans_show_me" start="00:32:222" end="00:42:549" start_sec="
          32.2224040" end_sec="42.5493880"/>
21    <segment label="chorus" start="00:42:549" end="01:03:240" start_sec="
          42.5493880" end_sec="63.2403630">
22      <segment label="part1" start="00:42:549" end="00:52:894" start_sec="
            42.5493880" end_sec="52.8948750"/>
23      <segment label="part2" start="00:52:894" end="01:03:240" start_sec="
            52.8948750" end_sec="63.2403630"/>
24    </segment>
```

Each file has two main parts: `<metadata>` and `<segmentation>`.

`<metadata>`

Ground truth files contain metadata about the respective song, e.g., title, artist, duration and *MusicBrainz TrackID*[3] and about the subject(s) who did the manual annotation. Computed segmentation files on the other hand contain information about the algorithm used and its parameters. The metadata is used to find corresponding annotation files (with the help of the mandatory attribute `/SegmXML/metadata/song/@canonicalname`) and it is displayed in the HTML report.

The song and annotation metadata is especially useful if ground truth files are shared within the scientific community. With the help of the *MusicBrainz TrackID* it is possible to link a ground truth file to exactly one song (this is, e.g., useful if one song appeared on different releases).

`<segmentation>`

Each `<segment>` node represents one annotated song segment. The nodes are in chronological order and must not overlap.

Note that some attributes of a `<segment>` node are redundant: `start_sec` and `end_sec` are defined to contain the same times as `start` and `end`, respectively, in a different notation. Although redundancy should generally be avoided, I decided to include the two notations because one is easier readable by persons while the other one is better suited for programs. Experience showed that the files are processed not only by my algorithms but also read and edited by myself from time to time.

[3] See `http://musicbrainz.org/doc/TrackID`

A `<segment>` node can contain the two additional optional attributes `instrumental` and `fade` where further information about this segment can be annotated. In this thesis I do not make use of these attributes. The main label of a segment is defined by its attribute `label`; for each alternative label a subnode `alt_label` is inserted. A `<segment>` node can contain `<segment>` subnodes only if it is a child node of `<segmentation>`, i.e., subsubnodes are disallowed in order not to make the annotation and adaption process too complicated.

There are several positions where `<remark>` nodes can be inserted. These can contain informational text that is rendered into the HTML report. As an example, remarks for segments are inserted as tooltips.

To make it easy for research colleagues who may want to use this file format as well, I created a corresponding *XML schema definition file* that contains the schema in a formal notation, c.f. Listing A.2.

Flexibility

It is hardly possible to decide upon *the one and only correct* song segmentation (see Section 1.3). This means that even if two subjects segment the same song, quite a different structure could emerge. As a matter of fact this was true for the songs that are contained in both the *Paulus/Klapuri corpus* [PK06] and the *Queen Mary corpus* [RCAS06, CS06, LSC06, AS01, ANS+05].

From this perspective I decided to add flexibility to my file format. This includes

hierarchical segments Following considerations from Section 1.3, a segment can be divided into subsegments. Figure 2.3 shows two song segmentations, one where only the supersegments are visible, the other where the subsegments are visible.

alternative labels Each segment has 1 to k labels. So, e.g., one segment can be seen as a *chorus* or as a chorus variant *chorusB*.

These flexibilities are used by ground truth files only. Segmentation algorithms always output only one hierarchical level and do not use alternative labels.

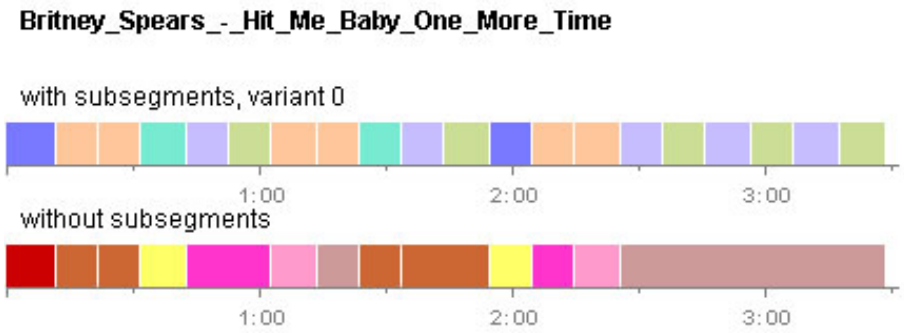


Figure 2.3: Two levels of segmentation: one with subsegments (top), the other one without (bottom). Both variants are included in one ground truth file. Segments of same color correspond to same segment label.

2.3.2 Evaluation procedure

The procedure itself is implemented in *Perl*. Because of the above mentioned flexibility of the **SegmXML** file format one ground truth file actually contains several *ground truth variants*.

The evaluation procedure is executed for each pair of computed segmentation and ground truth variant that can be extracted from the corresponding ground truth file. It consists of two stages or *levels*. The performance numbers are output into one XML file, including mean values and confidence intervals, as well as remarks, debug output and warnings if appropriate.

Semantics

Basically, I consider the segmentation with and without subsegments. Moreover, the alternative labels have impact. I do not, however, consider all permutations of them. For example, if there are segments that have two labels (i.e., one alternative label), either all main labels or all alternative labels are used, but they are not mixed. As a motivation for this behavior consider the following case.

Several segments of a song can be regarded as `chorus` segments. On the other hand some choruses are modulated in such a way that it can be argued to label them differently (e.g., `chorusB`). Now we would like to consider both annotation possibilities as valid, but we do not want to

mix them: Either all chorus-like segments are labeled `chorus` *or* the original ones are labeled `chorus` and all modulated ones are labeled `chorusB`.

As an example, the following ground truth variants can be extracted from XML Listing A.1. Segment labels that differ between variants are emphasized.

Algorithm 1 shows the algorithm in pseudo code.

```
ground truth variant 'with subsegments, variant 0'.
intro - verse - verse - trans_show_me - part1 - part2 - verse - verse -
trans_show_me - part1 - part2 - intro - verse - verse - part1 - part2 -
part1 - part2 - part1 - part2

ground truth variant 'with subsegments, variant 1'.
intro - verse - verse - trans_show_me - part1 - part2 - verse - verse -
trans_show_me - part1 - part2 - intro - verse2 - verse2 - part1 - part2 -
part1 - part2 - part1 - part2

ground truth variant 'only main segments, variant 0'.
intro - verse - verse - trans_show_me - chorus - verse - verse -
trans_show_me - chorus - intro - verse - verse - chorus

ground truth variant 'only main segments, variant 1'.
intro - verse - verse - trans_show_me - chorus - verse - verse -
trans_show_me - chorus - intro - verse2 - verse2 - chorus2
```

The performance of each pair of computed and ground truth segmentation file is the maximum of all performance numbers of the extracted ground truth variants, i.e., always the best matching variant is chosen.

Addressing hierarchy

The discussion on hierarchical song segmentation variants suggests to build an evaluation procedure that yields high performance numbers for two segmentations that are on different hierarchical levels. Chai was the first to take this into account and proposed a roll-up process followed by a drill-down process [Cha05]. Later, Paulus proposed a similar approach in [PK06].

Algorithm 1 getSegmentationVariants

Parameters: $\mathcal{S}$ // set of segments having up to k labels

1: $level_{max} \leftarrow \max |\mathcal{S}_i\{labels\}| \qquad \forall i \in (0 \dots |\mathcal{S}|)$
2: **for** $j \leftarrow 0$ to $level_{max}$ **do**
3: $maxVariants_j \leftarrow \max$ getNumberOfLabelVariants($\mathcal{S}_i$, j)
4: **end for**
5: $variants \leftarrow \sum maxVariants_j$
6: **for** $v \leftarrow 0$ to $variants$ **do**
7: **for** $i \leftarrow 0$ to $|\mathcal{S}|$ **do**
8: $segmentationvariants_v^i \leftarrow \mathcal{S}_i$
9: **if** $|\mathcal{S}_i\{labels\}| = level_{max}$ **then**
10: $segmentationvariants_v^i\{label\} \leftarrow \mathcal{S}_i\{labels\}_{\min v, level_{max}}$
11: **else**
12: $segmentationvariants_v^i\{label\} \leftarrow \mathcal{S}_i\{labels\}_{v \mod |\mathcal{S}|}$
13: **end if**
14: **end for**
15: **end for**
16: **return** $segmentationvariants$

Algorithm 2 getNumberOfLabelVariants

Parameters: $segment$, $level$

1: **if** $level = 0 \ \vee \ |segment\{labels\}| = 1 \ \vee \ |segment\{labels\}| > level$ **then**
2: **return** 1
3: **else**
4: **return** $|segment\{labels\}|$
5: **end if**

Although these methods are an advance over not considering hierarchical levels at all, in my opinion there are some problems and pitfalls.

1. If the computed and/or the ground truth segmentation are changed by the evaluation process there is the danger that *knowledge* is added to it that is neither part of the algorithmic output nor of the manually annotated ground truth. This would mean that the data has been falsified and that as a matter of fact the evaluation output would no longer be appropriate. Have a look at figure 2.4: the evaluation method in [PK06] would judge the two segmentations as being equal. This might be true but on the other hand the difference between the two panels might also be due to incorrect computed boundaries. So it could be unwise to regard this situation as a match.
2. Another problem is that such a method could roll up all segments to one segment covering the whole song. This would lead to trivial matches with all other possible segmentations. Thus, it is necessary to incorporate some kind of roll-up limit which is an additional parameter that controls performance output.

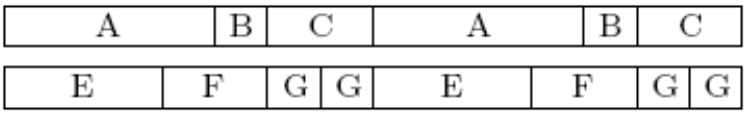


Figure 2.4: An example of differing segmentations: they could be equivalent (i.e., both correct) but one of them could also be incorrect. (from: [PK06, Figure 7])

In this thesis I determined to take another approach. I do not try to change the hierarchical level of a segmentation. I rather use the flexibility of my segmentation file format. Basically it boils down to the fact that each ground truth file can contain two levels of segmentation by using super- and subsegments. If a computed structure annotation still evaluates bad against all derived ground truth variations then I simply assume the annotation to be inappropriate which means that the algorithm and/or its parameters need be adapted.

Of course, this assumption will only be correct if the ground truth annotations are homogeneous, i.e., on the same hierarchical levels, otherwise part of the computed annotations will always be considered wrong no matter how the algorithm is tuned. When I transformed ground truth files into my file format I tried to ensure that this condition is met as well as possible.

String representation

The string representation that is used to calculate formal distance ratio r_f is based on an adapted *subpart segmentation*, originally proposed in [PK06, chapter 3.3]. The difference is that I do not assign new labels to subparts but retain the original ones. Figure 2.5 illustrates the process. r_f is weighted according to the duration of the underlying subparts.

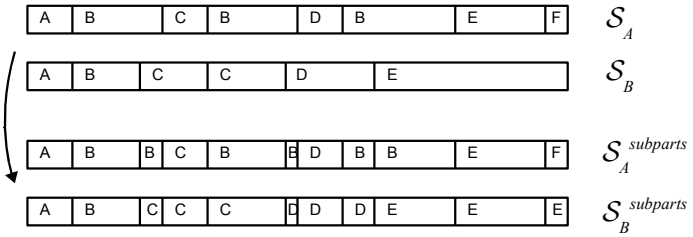


Figure 2.5: Creating subparts structure: The upper two panels represent the original groundtruth and computed segmentation, respectively. Both have their own timeline, i.e., set of boundaries. In the lower two panels each segmentation has taken over the boundaries from the other segmentation: both panels have now a common timeline. The purpose is that eventually both string representations are of equal length.

As mentioned in Section 2.2.2 r_f is invariant against the actual characters that represent the segments, as long as segments of the same type get the same character. To achieve this, I consider all possible mappings of each distinct character to another. According to these mappings the letters are swapped and edit distance is calculated. Eventually, r_f is set to the lowest edit distance.

Due to the loop through all these permutations the time complexity of this algorithm is $O(c^n)$ with n denoting the number of distinct labels of a song after the removal of *perfect matches* (Figure 2.6). Exponential time complexity is bad, however, it is feasible for this application because the values of n are limited: n's highest value in ground truth files is 10, n is often decreased by removing perfect matches (see Algorithm 6). Moreover, it is possible to set an upper limit for the numbers of allowed permutations. On the other hand, this loop seems necessary because the canonical representation is not always the best choice to calculate the distance, see the example at Equations (2.7) and (2.8) on page 23.

Algorithm 3 shows the evaluation procedure level 2 in pseudo code that is executed for each ground truth variant, algorithms 4, 5 and 6 are sub procedures used by it. Consult subsection 1.5

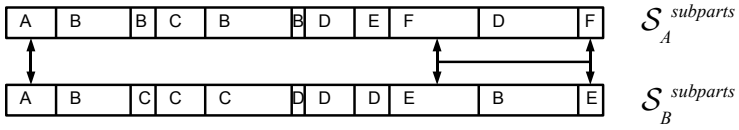


Figure 2.6: Illustration of perfect matches that are removed to reduce computation time. In this example A to A and F to E are perfect matches. These characters would be removed from strings representing the segmentations. This decreases the number of possible permutations.

for a list of notational conventions.

Output

The evaluation procedure's output is an XML file called **EvalXML**. I did not write a corresponding schema definition file as the contents of this XML file can change on short notice. Basically this file contains performance numbers, metadata about songs and the algorithm, remarks and warnings. Overall mean as well as means for each genre are calculated from the individual performance numbers.

This file is transformed into an HTML file using an XSLT file that describes how this transformation is to be done. I use `Xalan-J` as XSLT engine.

Figures 2.7 to 2.9 depict parts of an HTML report rendered by *Mozilla Firefox*.

Each report consists of five sections:

The "Summary" shows mean values of all performance measures over all songs. The background color of the first box is determined by F-measure of mean P and mean R, in the second box the formal distance ratio r_f is used to derive the appropriate color.

All parameter values used in the segmentation algorithm or the evaluation procedure are listed in two tables in "Parameters and information". In addition, brief descriptions of the performance numbers and many useful debug output lines can be found there.

In the section "Summaries by genre / corpus" one can learn how the songs of each genre or corpus performed. The contents of each box corresponds to the "Summary" box on top of the report.

Algorithm 3 Evaluation level 2

Parameters: $\mathcal{S}_A$, $\mathcal{S}_B$ // each segment has only one label

1: **for each** $X \in \{A, B\}$ **do**
2: $\quad \mathcal{T}_X \leftarrow \bigcup \mathcal{S}_X\{starttime\}$
3: $\quad \mathcal{T}_X \leftarrow \mathcal{T}_X \cup \bigcup \mathcal{S}_X\{endtime\}$
4: **end for**
5: $\mathcal{T}_{common} \leftarrow \mathcal{T}_A \cup \mathcal{T}_B$ // common timeline
6: **for each** $X \in \{A, B\}$ **do**
7: $\quad \mathcal{S}_X^{subparts} \leftarrow \text{getSubparts}(\mathcal{S}_X, \mathcal{T}_{common})$
8: $\quad representation_X^{canonical} \leftarrow \text{getCanonicalRepresentation}(\mathcal{S}_X^{subparts})$
9: **end for** // $representation$ variables are of type string
10: $(representation_A, representation_B) =$ $\text{removePerfectMatches}(representation_A^{canonical}, representation_B^{canonical})$
11: **for each** $X \in \{A, B\}$ **do** // Both $representation$ strings are of equal length by now
12: $\quad \mathcal{C}_X \leftarrow \text{getCharactersAsSet}(representation_X)$ // Returns the characters of the string as a set, removing all duplicate characters
13: **end for**
14: **if** $|\mathcal{C}_A| > |\mathcal{C}_B|$ **then** // Always permute largest set of characters
15: $\quad \mathcal{C}_{toPermutate} \leftarrow \mathcal{C}_A$
16: $\quad representation_{source} \leftarrow representation_A$
17: $\quad representation_{dest} \leftarrow representation_B$
18: **else**
19: $\quad \mathcal{C}_{toPermutate} \leftarrow \mathcal{C}_B$
20: $\quad representation_{source} \leftarrow representation_B$
21: $\quad representation_{dest} \leftarrow representation_A$
22: **end if**
23: **for each** $\mathcal{C}_{perm} \in perms(\mathcal{C}_{toPermutate})$ **do** // Iterate trough all permutations
24: $\quad mapping \leftarrow \emptyset$
25: $\quad$ **for** $i \leftarrow 0$ to $|\mathcal{C}_{perm}|$ **do**
26: $\quad\quad mapping \leftarrow mapping \cup \{\mathcal{C}_{perm}^i \mapsto \text{chr}(\text{ord}(\texttt{A})+i)\}$
27: $\quad$ **end for**
28: $\quad representation_{mapped} \leftarrow \bigcirc$
29: $\quad$ **for each** $character \in representation_{source}$ **do**
30: $\quad\quad representation_{mapped} \leftarrow representation_{mapped} \cdot mapping\{character\}$
31: $\quad$ **end for**
32: $\quad d \leftarrow ed(representation_{mapped}, representation_{dest})$
33: $\quad$ **if** $d < d_{best}$ **then**
34: $\quad\quad d_{best} \leftarrow d$
35: $\quad$ **end if**
36: **end for**
37: **return** d_{best}

Algorithm 4 getSubparts

Creates segmentation with subparts according to the common timeline. Figure 2.5 illustrates the process.

Parameters: $\mathcal{S}$, $\mathcal{B}$ // segmentation, set of boundaries
Ensure: $\mathcal{S}\{start\} \cup \mathcal{S}\{end\} \in \mathcal{B}$

for $i \leftarrow 0$ to $|\mathcal{B}| - 1$ **do**
  $bound_{this} \leftarrow \mathcal{B}$
  $bound_{next} \leftarrow \mathcal{B}_{i+1}$
  if $\exists\ S \in \mathcal{S}$ such that $bound_{this}$ within $S \wedge bound_{next}$ within S **then**
    $\mathcal{S}_{subparts} \leftarrow \mathcal{S}_{subparts} \cup$ new segment{start $\leftarrow bound_{this}$,
      end $\leftarrow bound_{next}$,
      label $\leftarrow segment\{label\}$ }
  else
    $\mathcal{S}_{subparts} \leftarrow \mathcal{S}_{subparts} \cup$ new segment{start $\leftarrow bound_{this}$,
      end $\leftarrow bound_{next}$,
      label $\leftarrow \star$ } // special label with the meaning "not annotated"
  end if
end for
return $\mathcal{S}_{subparts}$

Algorithm 5 getCanonicalRepresentation

Creates string where each character corresponds to one segment. Segments with the same label get the same characters.

Parameters: $\mathcal{S}$

$index_{ord} \leftarrow \text{ord}(\texttt{A})$
$\mathcal{M} \leftarrow \emptyset$ // mappings from label strings to characters
$representation \leftarrow \bigcirc$
for each $S \in \mathcal{S}$ **do**
  if $\exists\ M \in \mathcal{M}$ such that $\{S\{label\} \mapsto c\}$ **then**
    $representation \leftarrow representation\ \cdot c$
  else
    $\mathcal{M} \leftarrow \mathcal{M} \cup \{S\{label\} \mapsto \text{chr}(index_{ord})\}$
    $representation \leftarrow representation \cdot \text{chr}(index_{ord})$
    $index_{ord} \leftarrow index_{ord} + 1$
  end if
end for
return $representation$

Algorithm 6 removePerfectMatches

Removes characters where each segment with the same label of $representation_A$ corresponds to segments that all have the same labels in $representation_B$ and vice versa. See Figure 2.6 for an illustration.

Parameters: $representation_A, representation_B$

1: $counter \leftarrow 0$
2: **repeat**
3: $char \leftarrow \text{getCorrespondingChar}(representation_A, representation_B, representation_A[counter])$
4: **if** $char \neq \bigcirc$ **then**
5: $char' \leftarrow \text{getCorrespondingChar}(representation_B, representation_A, char)$
6: **if** $char' \neq \bigcirc$ **then**
7: $representation_A \leftarrow representation_A \backslash char'$
8: $representation_B \leftarrow representation_B \backslash char$
9: $counter \leftarrow -1$
10: **end if**
11: **end if**
12: $counter \leftarrow counter + 1$
13: **until** $counter > |representation_A|$ // Note that $|representation_A| = |representation_B|$
14: **return** $representation_A, representation_B$

Notes:

line 3 getCorrespondingChar(A, B, c) looks for the characters in B at the positions where c occurs in A. If only one distinct character is found, this one is returned. Otherwise the function returns $\bigcirc$.

Evaluation report: 2007-06-12_12_48_55---beats---fftn16384---mfccs40log---eucl---C96

Timestamp: Tue Jun 12 20:04:43 2007

Summary
Parameters and information
Summaries by genre / corpus
Individual songs
About this document

Summary (93 songs)

(jump to top of page)

Boundaries	P = **0.55 +-0.038** , R = **0.77 +-0.037** , F * = **0.64** , F (mean) = **0.62 +-0.031** Pabd = **0.67 +-0.024** , Rabd = **0.86 +-0.017** , Fabd * = **0.75**
Form (structure)	formal distance = **66.16**, ratio = **0.707 +-0.025** H(algo|gt) = **0.655 +-0.064** , H(gt|algo) = **0.618 +-0.078** , I = **1.355 +-0.063** , I-ratio = **0.680 +-0.028**

** F-measure of mean P and mean R values*

Parameters and information

(jump to top of page)

About algorithm

beats	**extrapolated from last beat to end**
fft size, window size (specified)	**16384**
num_ceps_coeffs	**40, including first coeff**
features	**mfccs, log scaled**
distance function @ SM	**euclidean**
kernel	**C96**
filter	**moving average**
filter n	**8**
cluster features	**means over segment´s variables**
Cluster method	**k-means**
Mode	**means**
number of clusters	**5**
filter	***shifted (1/2*filter_n)-1 to the left***
boundaries:	***excluded, if amplitude sum is lower than threshold***

About evaluation

P, R, F	**Ratios of bounds found both in computed segmentation and groundtruth segmentation divided by bounds in computed segmentation (or groundtruth segmentation resp.). F is harmonic mean of P and R.**
P_abd, R_abd, F_abd	**Ratios of maximum overlaps of corresponding segments divided by song length. See Abdallah2006 for details. F_abd is harmonic mean of P_abd and R_abd.**
formal distance	**Weighted edit distance between string representations of segmentations, minimum over all possible permutations.**
formal distance ratio	**1 - formal distance / song duration**
H(algo|gt)	**information-theoretic measures proposed in Abdallah2006. H(algo|gt)... amount of "spurios" information in computed segmentation, (lower=better)**

Figure 2.7: Head of an HTML report, rendered by Mozilla Firefox browser

Summaries by genre / corpus

(jump to top of page)

Pop (25 songs)

Boundaries	P = **0.64 +-0.092** , R = **0.74 +-0.085** , F = **0.65 +-0.074** P_{abd} = **0.7 +-0.055** , R_{abd} = **0.83 +-0.043** , F_{abd} = **0.76**
Form (structure)	formal distance = **70.84**, ratio = **0.71 +-0.06** H(algo|gt) = **0.51 +-0.13** , H(gt|algo) = **0.75 +-0.16** , I = **1.41 +-0.16** , I-ratio = **0.69 +-0.06**

Folk (3 songs)

Boundaries	P = **0.38 +-0.396** , R = **0.8 +-0.299** , F = **0.51 +-0.439** P_{abd} = **0.57 +-0.114** , R_{abd} = **0.92 +-0.165** , F_{abd} = **0.7**
Form (structure)	formal distance = **81.30**, ratio = **0.61 +-0.26** H(algo|gt) = **1.07 +-1.25** , H(gt|algo) = **0.48 +-0.94** , I = **1.10 +-1.00** , I-ratio = **0.58 +-0.36**

Dance (5 songs)

Boundaries	P = **0.6 +-0.3** , R = **0.79 +-0.277** , F = **0.67 +-0.277** P_{abd} = **0.71 +-0.166** , R_{abd} = **0.85 +-0.114** , F_{abd} = **0.77**
Form (structure)	formal distance = **58.43**, ratio = **0.72 +-0.08** H(algo|gt) = **0.52 +-0.34** , H(gt|algo) = **0.76 +-0.34** , I = **1.40 +-0.42** , I-ratio = **0.68 +-0.14**

qmul14 (14 songs)

Boundaries	P = **0.69 +-0.094** , R = **0.73 +-0.13** , F = **0.67 +-0.073** P_{abd} = **0.77 +-0.052** , R_{abd} = **0.8 +-0.089** , F_{abd} = **0.79**
Form (structure)	formal distance = **77.17**, ratio = **0.70 +-0.07** H(algo|gt) = **0.55 +-0.13** , H(gt|algo) = **0.70 +-0.28** , I = **1.32 +-0.16** , I-ratio = **0.68 +-0.08**

Rock (31 songs)

Boundaries	P = **0.6 +-0.071** , R = **0.74 +-0.066** , F = **0.64 +-0.056** P_{abd} = **0.7 +-0.043** , R_{abd} = **0.84 +-0.04** , F_{abd} = **0.77**
Form (structure)	formal distance = **77.72**, ratio = **0.71 +-0.05** H(algo|gt) = **0.59 +-0.11** , H(gt|algo) = **0.72 +-0.16** , I = **1.36 +-0.12** , I-ratio = **0.68 +-0.05**

MUSIC (33 songs)

Boundaries	P = **0.57 +-0.071** , R = **0.76 +-0.062** , F = **0.62 +-0.052** P_{abd} = **0.64 +-0.044** , R_{abd} = **0.86 +-0.025** , F_{abd} = **0.73**
Form (structure)	formal distance = **76.52**, ratio = **0.72 +-0.05** H(algo|gt) = **0.59 +-0.11** , H(gt|algo) = **0.67 +-0.14** , I = **1.40 +-0.11** , I-ratio = **0.69 +-0.05**

Paulus_beatles (6 songs)

Boundaries	P = **0.6 +-0.131** , R = **0.72 +-0.251** , F = **0.64 +-0.164** P_{abd} = **0.69 +-0.101** , R_{abd} = **0.83 +-0.078** , F_{abd} = **0.75**

Figure 2.8: Part of genre / corpus summary, rendered by Mozilla Firefox browser

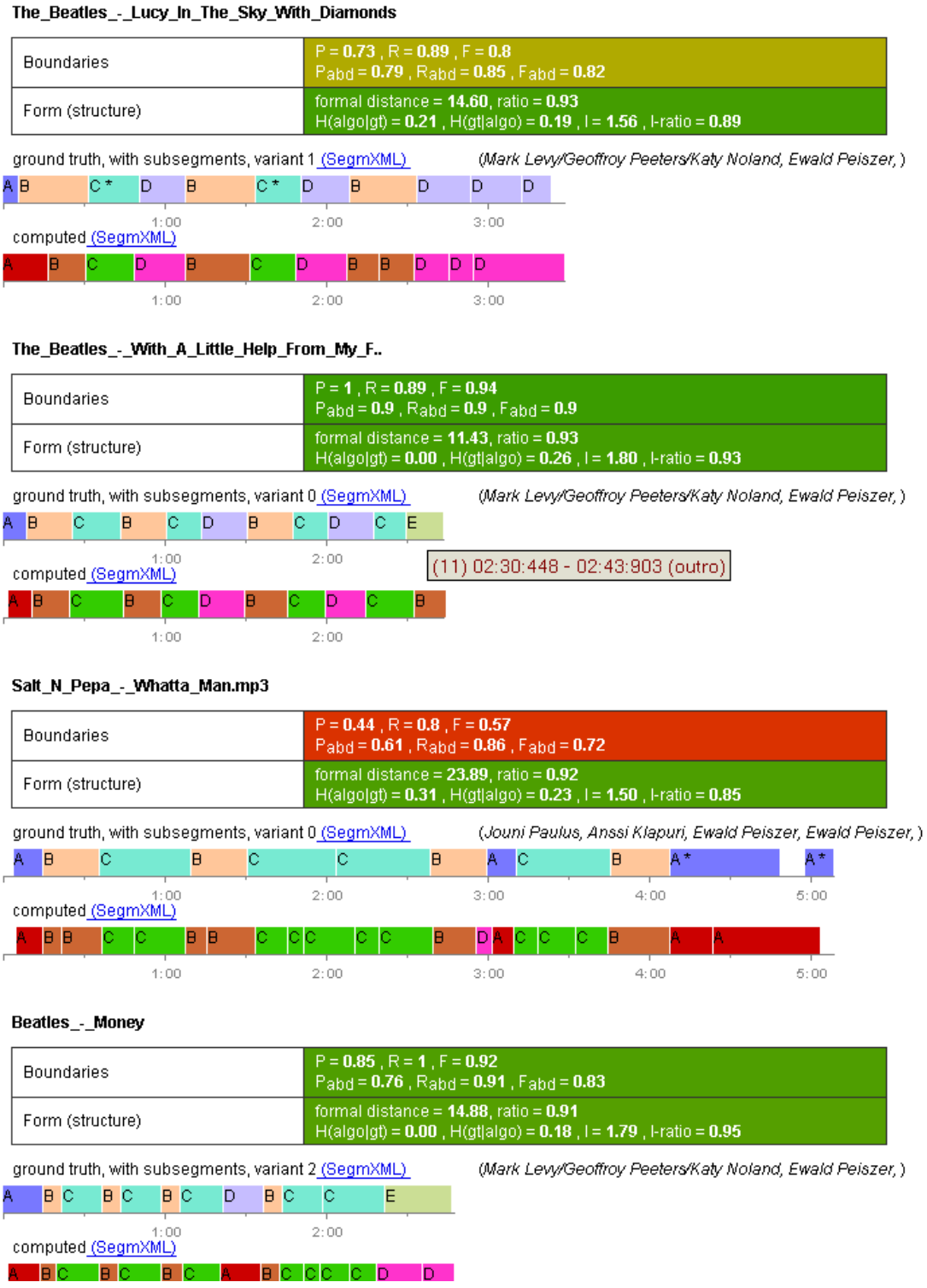


Figure 2.9: Part of body of an HTML report, rendered by Mozilla Firefox browser

The largest part of the report gives you information about each individual song: performance numbers, debug output, information about the groundtruth file and last but not least a graphical representation of both the groundtruth annotation and the computed segmentation. Segments with the same label have the same color, each segment has a tooltip with information about start and end time, label and an optional comment which is indicated by an asterisk. Hyperlinks make the underlying SegmXML files directly accessible.

The footer of the report contains general information about the document.

The colors of the boxes range from red (if the respective performance number is lower than 0.6) over yellow (if around 0.75) to green (if greater than 0.9).

2.4 Ambiguity revisited

As already stated in Section 1.3.1, it can happen that two annotators produce different segmentations for the same songs. In Figure 1.1 we saw five examples of that situation.

On the other hand, it must be noted that not all segmentations differ that much. This leads to the conclusion that some songs have a more ambiguous structure than others. One idea would be to determine an upper limit for the performance measures for each song individually and scale results according to this limit. This limit could be the mean of performance numbers that result if various manual segmentations are evaluated against each other. Let F^{gt} and r_f^{gt} denote these limits for boundary evaluation and musical form evaluation, respectively.

Example (*Michael Jackson: Black or White*) r_f^{gt} values if evaluating Paulus corpus groundtruth and Queen Mary corpus groundtruth against my official (flexible, two-level) annotation are 0.84 and 0.68, the mean is 0.76. This can be considered to be the upper limit for this song: r_f of computed structure against groundtruth need not be any higher. One result of a computed annotation for this song is $r_f = 0.66$. If you scale it according to the upper groundtruth limit the resulting $r_f^{0.76} = 0.868$.

I do not have different groundtruth segmentations for the majority of the songs, and the number of different annotations available for the rest is not large enough to derive well-grounded F^{gt} and r_f^{gt} values. Thus, I decided not to scale evaluation numbers.

2.5 Additional coding

Throughout my thesis I implemented additional conversion routines whose relationships are depicted in Figure 2.10. All routines are platform independent.

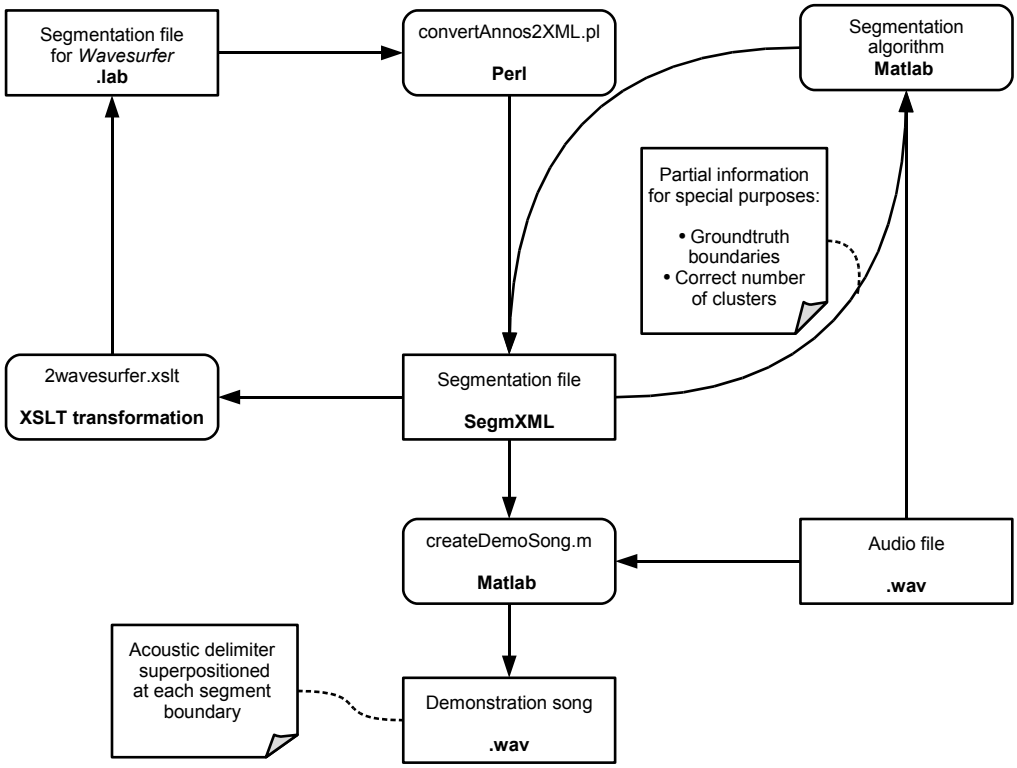


Figure 2.10: Data flow diagram of core algorithm and additional conversion routines

I used the application *Wavesurfer* (see Table A.1) for the annotation task. Thus, I wrote routines for bidirectional conversion of segmentation data. Wavesurfer files are converted into SegmXML format by a Perl script. This script can read ID3 tags of an appropriate mp3 file to get information about artist, title, genre and song duration which can be stored in the XML file. For the reverse conversion an XSLT file was the most simple solution. This file contains rules that govern how the XML data has to be rearranged to produce a valid *.lab* file.

For an easy and impressive audible demonstration of computed segmentations I implemented a Matlab script that produces audio files where a short acoustic delimiter is superpositioned at each

segment boundary. This delimiter also indicates the segment type of the respective subsequent segment (“one”, “two”, “three”, etc.).

2.6 Summary

This chapter discussed how evaluation has been carried out in this thesis.

First, I described the groundtruth corpus which is one of the largest used so far in this research field. Together with the additional “test set” songs it is indeed the largest one.

Since annotation file formats used so far seemed too strict to me for the purpose at hand I introduced a novel file format based on XML (*SegmXML*) that can contain two hierarchical levels of segmentation as well as alternative labels for each segment. Besides, song metadata can be stored to ease the retrieval of specific song recordings (e.g., with the help of *MusicBrainz TrackID*). I explained how this flexible annotation format is used by the evaluation algorithm.

Performance measures for both algorithm tasks have been defined. For the first phase, boundary detection, these are precision P, recall R and F-measure F, as well as alternative measures P_{abd}, R_{abd} and F_{abd} which express similar concepts but have different properties. The second phase, structure extraction, makes use of formal distance ratio r_f and the alternative information-theoretic measure “mutual information” I. Especially the measure for the second phase has been motivated thoroughly as musical form evaluation is quite sophisticated and not as straight forward as one might think in the beginning (see the discussion on hierarchical segmentations in Section 2.2.2).

I included the most important sub functions of the evaluation algorithm in pseudo code notation and explained all relevant parts of the evaluation reports that are generated by the system.

One section presented an idea how the inherent segmentation ambiguity can be used explicitely to get more accurate evaluation numbers. As noted, this would require a number of groundtruth annotations for each song and is thus not feasible for this thesis.

The chapter ended with a brief overview of additional coding that has been carried out, e.g., to convert annotation data from one file format to another or to produce audio files for acoustic demonstration.

Chapter 3

Boundary detection

This chapter explains phase 1 of my algorithm. This phase tries to detect the segment boundaries (also called transitions) of a song, i.e., the time points where segments begin and end. The output of this phase is used as the input for the next phase, structure detection.

When designing the algorithm I especially took care of the following properties:

Robustness Since my corpus consists of songs covering a broad range of genres it is desirable that the output is satisfactory for all or most of the songs, not just for one narrowly defined genre.

Recall It is commonly known that the two evaluation measures *precision* and *recall* as defined in Section 2.2.1 are inversely proportional to each other. That is, at a certain limit, if you change parameters of your algorithm in such a way that precision rises, recall on the other hand will decline. Usually one tries to find a trade-off where recall is about the same value as precision (resulting in the maximal F-measure).

In my situation, however, it is desirable that phase 1 finds as many of the real transitions as possible, because inappropriate transitions can be cut out later; on the other hand, a transition not detected at this early stage cannot be included in the final output.

It is not part of this thesis to implement a ready-to-deploy industrial strength algorithm, hence I did not concentrate on the efficiency of my implementation. The commercial math program *Matlab* allows for rapid and easy prototyping, that is why I chose this system as an implementation basis. See Table A.1 for more information on this and other software I used during working on this thesis.

The rest of this chapter describes the algorithm, various experiments I carried out to improve performance, and final evaluation results, also compared to results from related literature. In the end, remarkable points are discussed.

3.1 Algorithm

I chose a frequently used approach [Foo00, FC03, Ong05] that uses local information change through time as the basis.

First, the 22,050 Hz audio stream is split into variable sized, non overlapping frames. The frames are beat-synchronized. To extract the beat onsets of the songs, I used Simon Dixon's freely available beat tracker *BeatRoot*[1] [Dix01]. I regard segment boundaries as a subset of beat onsets since a new verse or chorus will not start between two beats. The durations typically range from 400 to 550 ms. As the individual beat intervals change a bit, I do not use fixed size frames. Sometimes the beat tracker does not detect all beat onsets of the entire song (especially those in a soft fade-out section near the end of a song are frequently missed). In this case I extrapolated the missing onsets using the song's mean beat duration.

From each of the frames a feature vector $\mathbf{v}$ is extracted. I tried various types of features: simple spectrogram, a timbre-related feature set (Mel Frequency Cepstrum Coefficients, [RJ93]), two rhythm-based feature set (Rhythm Patterns, [RPM02], Statistical Spectrum Descriptors [LR05]) and harmony related features (Constant Q Transform, [BP92]). Especially the latter ones have been frequently used in related literature (see Table 1.1).

The self-similarity matrix $\mathbf{S}$ between these feature vectors is calculated, using a distance function $d_{\mathbf{S}}$:

$$\mathbf{S}(i,j) = d_{\mathbf{S}}(\mathbf{v}_i, \mathbf{v}_j) \quad i,j = 1,\ldots,n \tag{3.1}$$

Novelty score N is derived as follows

$$N(i) = \sum_{m=-k_{\mathbf{C}}/2}^{k_{\mathbf{C}}/2} \sum_{n=-k_{\mathbf{C}}/2}^{k_{\mathbf{C}}/2} \mathbf{C}_k(m,n)\mathbf{S}(i+m, i+n) \tag{3.2}$$

[1] The beats have been extracted from 44,100 Hz audio files since the program works much better on these than on the 22,050 Hz files.

where $\mathbf{C}_k$ denotes a Gaussian tapered checkerboard kernel of size $k_{\mathbf{C}}$, radially symmetric and centered on $0, 0$ (Figure 3.1). $\mathbf{S}$ is zero padded.

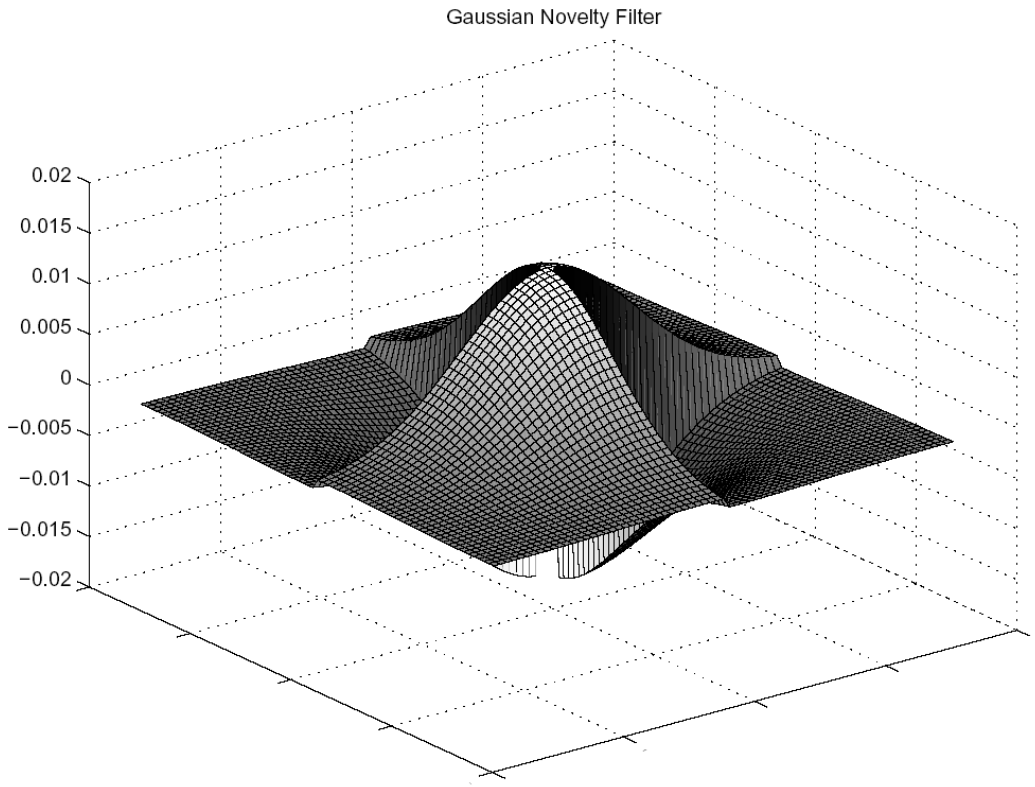


Figure 3.1: Gaussian kernel of size $k_{\mathbf{C}} = 80$. (from: [FC03])

Since N appears to be quite jagged I applied a low-pass filter H to get a smoother novelty score H_N, this reduces the number of local maxima. I used a moving average filter with a sliding window size of n_H. This type of filter is optimal for this task: noise reduction while retaining a sharp step response [Smi97, Chapter 15].

$$H_N(i) = 1/n_H \sum_{j=-n_H/2}^{n_H/2} N(i+j) \tag{3.3}$$

Empirically, I found out that if there is a local maximum during a period of low amplitude it should not be considered as a segment boundary. Thus, I introduced an amplitude threshold

T_{ampl}: maxima in a region with an amplitude $a < T_{ampl}$ will not be regarded as segment boundaries. This step removes approximately one to four boundaries mainly from the beginning and end of a song (fade-in and fade-out).

Finally, I set up an interval restriction that prevents two boundaries that are closer than a threshold T_{close} (in this case the maximum with the higher H_N value is chosen). For $T_{close} = 6$ seconds about only 60 to 80 per cent of the original boundaries remain.

The process described produces a set of possible segment boundaries $\mathcal{B}_1$.

Figures 3.2 to 3.4 illustrate this process for three songs with varying output quality.

3.2 Experiments

The algorithm description indicates that there are many parameters or *degrees of freedom* that have to be adjusted: choice of feature set, feature set related parameters, $d_{\mathbf{S}}$, $k_{\mathbf{C}}$, type and parameters of H, etc.

These parameters span a high dimensional solution space, the exhaustive search for the best parameter settings seems intractable to me. Therefore I systematically investigated this space by two methods. In the first place I acted at my own discretion, using comments from the literature, common music knowledge and machine learning experience as basis to set parameters to values that might lead to good results. For example, since two choruses are more likely to share the same melody than the same instruments, the use of CQT features seemed advisable.

Secondly I fixed all parameters but one and let the mutable variable loop through an appropriate value range to see whether the results would change significantly.

From all feature sets I used MFCC features provided the best results. This is surprising since CQT features (when using appropriate values for f_0, f_{max} and $bins$) would model the properties of musical signals more specifically than the widely used MFCCs that actually come from speech processing: Bartsch *et al*. report better results with 'harmony aware' features than with MFCC [BW05]. Aucouturier *et al*., however, report MFCC to be superior if 8–10 coefficients are taken [AS01]. I found that ten coefficients are too little, even results with 30 coefficients are (insignificantly) inferior to those with 40 (c.f. Figure 3.7).

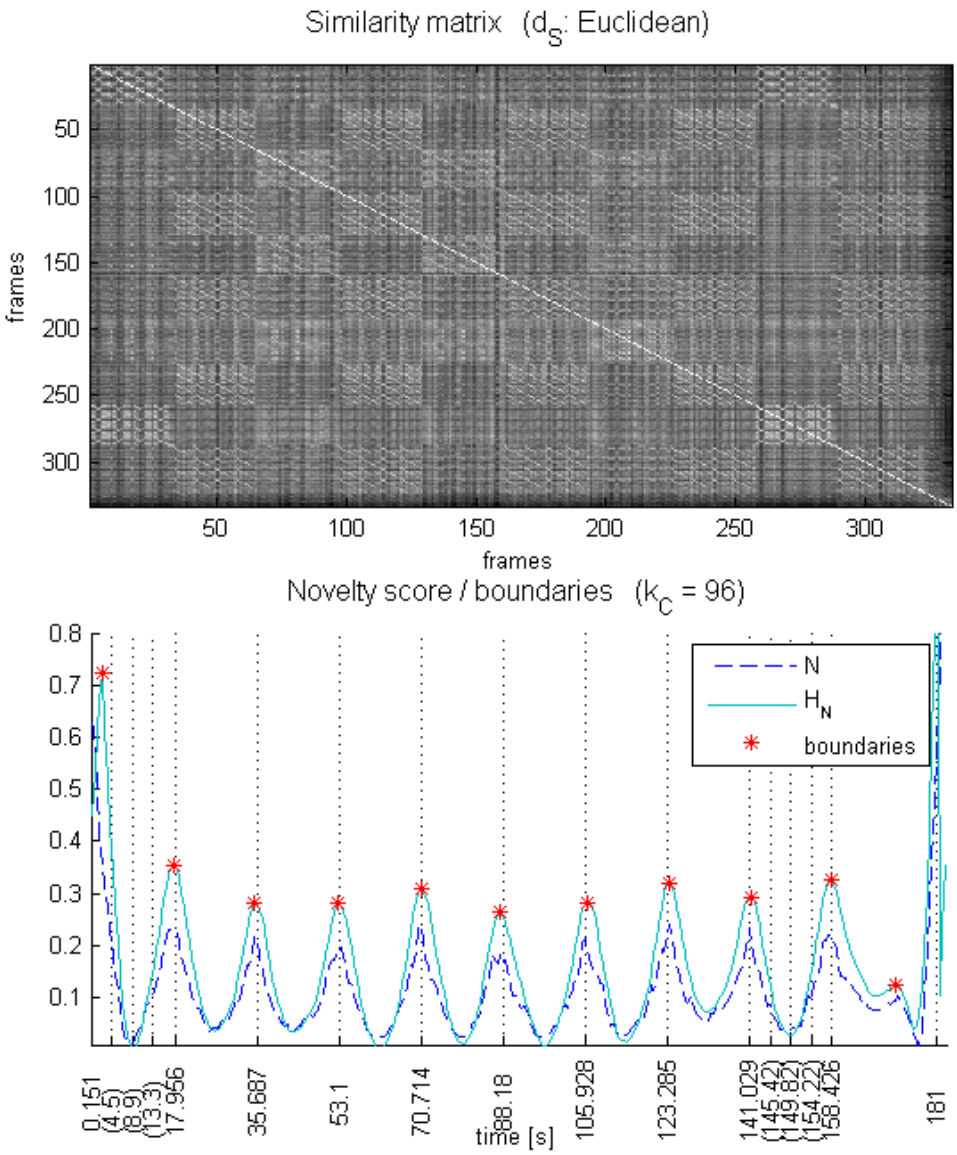


Figure 3.2: Boundary detection in *KC and the Sunshine Band: That's the Way I Like It*. Vertical dotted lines indicate groundtruth boundaries, subsegment boundaries are in parentheses. These are also clearly visible in the similarity matrix. Result for this computation is $P = R = F = 1$ for $w = 3$.

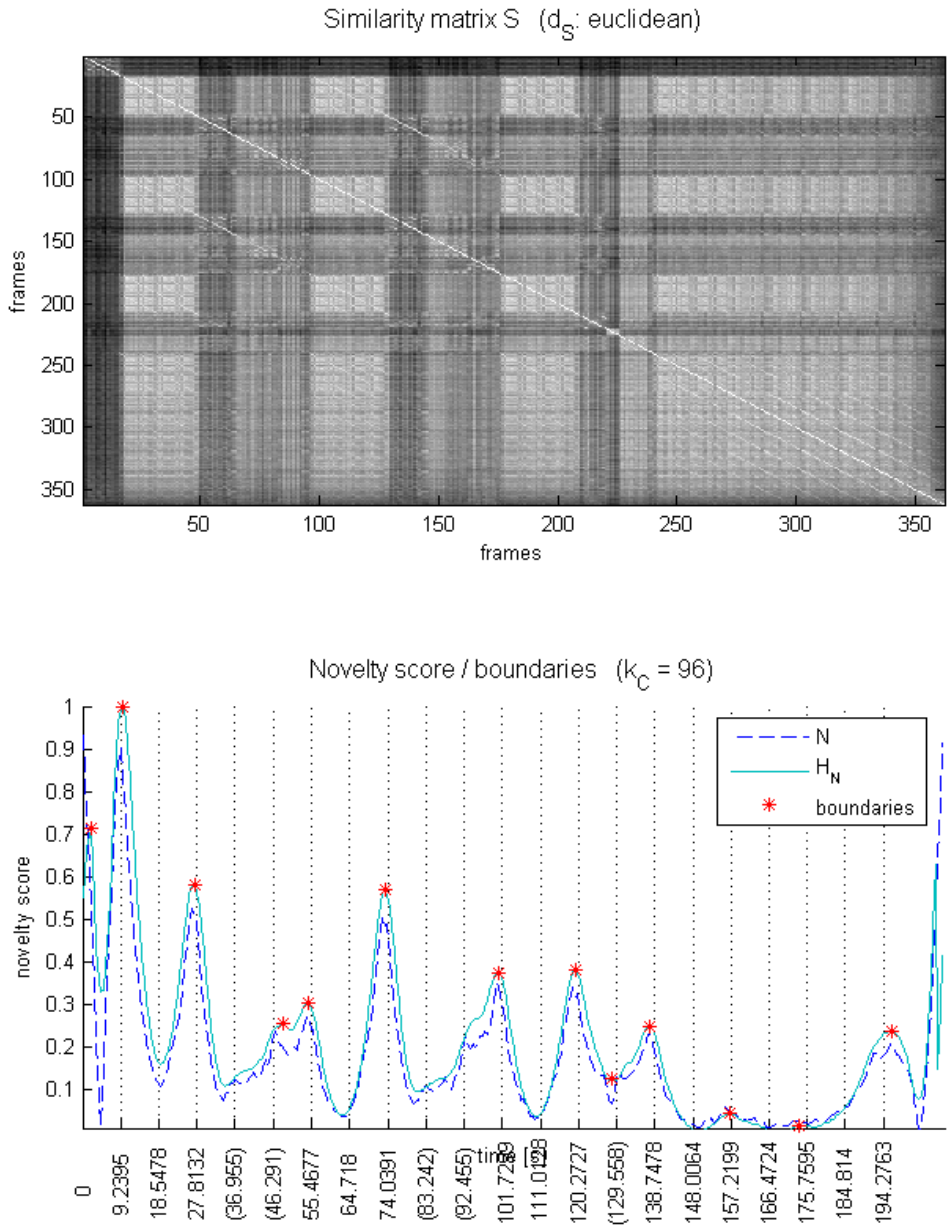


Figure 3.3: Boundary detection in *Chumbawamba: Thubthumping*. Vertical dotted lines indicate ground-truth boundaries, subsegment boundaries are in parentheses. Not all boundaries have been detected. There are no false positives, though. Result for this computation is $P = 1$, $R = 0.5$, $F = 0.67$ for $w = 3$.

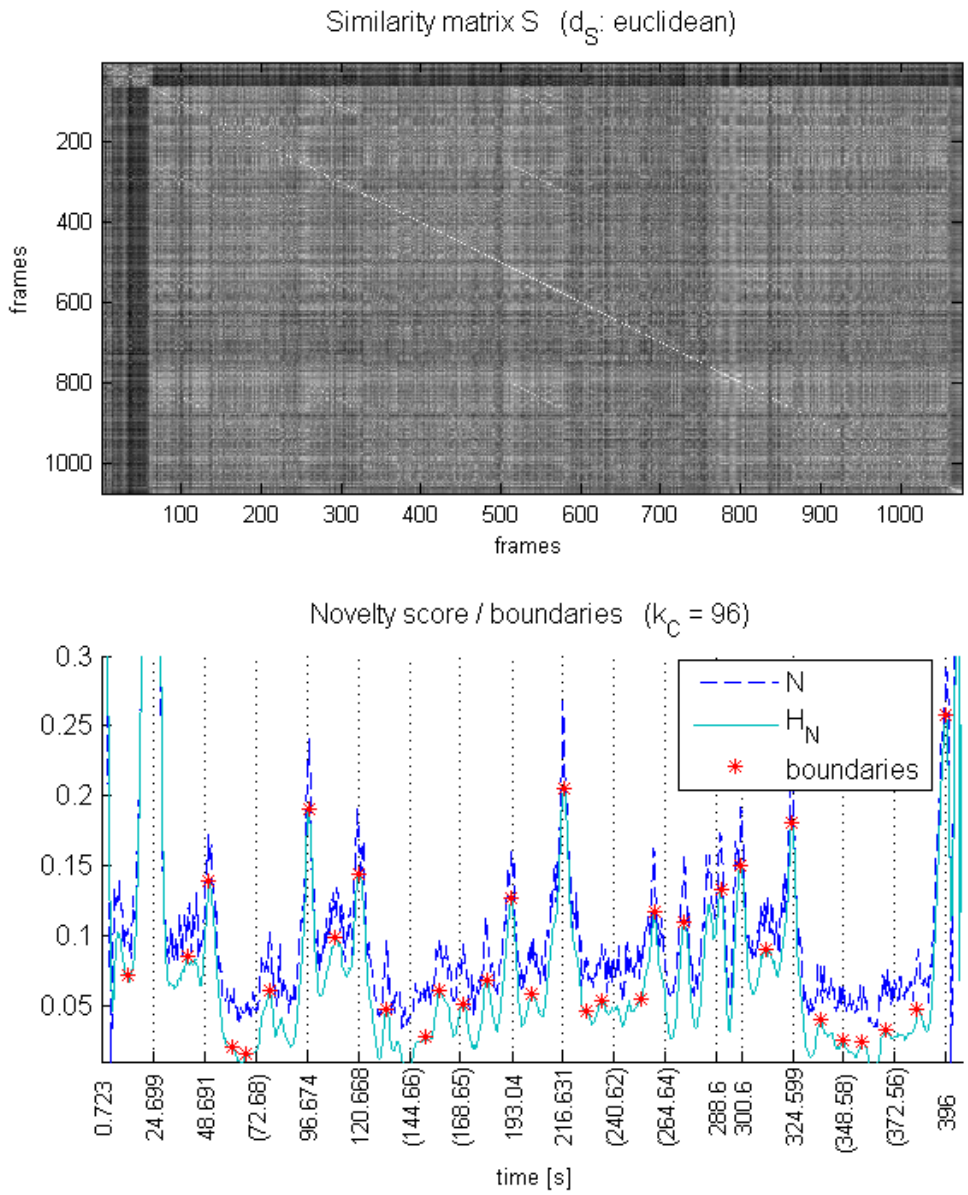


Figure 3.4: Boundary detection in *Eminem: Stan*. Vertical dotted lines indicate groundtruth boundaries, subsegment boundaries are in parentheses. Y axis is cropped to interval $[0, 0.3]$. H_N exhibits many peaks that do not correspond to true boundaries. Each detected bound, however, is correct. Result for this computation is $P = 0.27$, $R = 1$, $F = 0.42$ for $w = 3$.

Parameter set	Parameter changed	Results
MFCC40	$d_{\mathbf{S}}$: Euclidean	$P = 0.55 \pm 0.038$, $R = 0.78 \pm 0.035$, $F = 0.65$
MFCC40	$d_{\mathbf{S}}$: cosine	$P = 0.55 \pm 0.039$, $R = 0.76 \pm 0.038$, $F = 0.64$
CQT1	$n_H = 8$	$P = 0.45 \pm 0.04$, $R = 0.77 \pm 0.037$, $F = 0.56$
CQT1	$n_H = 12$	$P = 0.46 \pm 0.043$, $R = 0.7 \pm 0.04$, $F = 0.56$
CQT1	$n_H = 16$	$P = 0.52 \pm 0.044$, $R = 0.64 \pm 0.042$, $F = 0.58$
CQT1	$n_H = 18$	$P = 0.52 \pm 0.043$, $R = 0.62 \pm 0.041$, $F = 0.57$
MFCC40	$k_{\mathbf{C}} = 48$, $n_H = 4$	$P = 0.49 \pm 0.035$, $R = 0.77 \pm 0.03$, $F = 0.6$
MFCC40	$k_{\mathbf{C}} = 96$, $n_H = 8$	$P = 0.55 \pm 0.038$, $R = 0.78 \pm 0.035$, $F = 0.65$
MFCC40	$k_{\mathbf{C}} = 128$, $n_H = 8$	$P = 0.59 \pm 0.039$, $R = 0.72 \pm 0.039$, $F = 0.65$
MFCC40	$k_{\mathbf{C}} = 128$, $n_H = 14$	$P = 0.62 \pm 0.038$, $R = 0.67 \pm 0.041$, $F = 0.65$
MFCC40	boundary removing heuristic ($T_1 = 10$, $\beta = \lvert\mathcal{B}_1\rvert/4$)	$P = 0.57 \pm 0.038$, $R = 0.75 \pm 0.038$, $F = 0.65$
MFCC40	[LSC06] post processing	$P = 0.55 \pm 0.038$, $R = 0.78 \pm 0.037$, $F = 0.64$

Table 3.1: Evaluation results of selected experimental algorithm runs. The numbers indicate that there is no statistically significant difference between the individual results of each experiment. See Table 3.2 for an explanation of the parameter sets.

Selected evaluation results of the experiments described in this section are summarized in Table 3.1.

I tried to **merge**, i.e., concatenate, two feature sets, these combined feature sets did not show any improvement regardless of their internal weighting.

Later, I also tested the use of fixed sized frames for feature extraction, hop size still being variable, though, according to beat onset information. Again, there was no significant difference between the results.

As **distance function** $d_{\mathbf{S}}$ I employed both cosine distance and Euclidean distance. No significant difference could be seen (Table 3.1, first row).

I tried two types of **low-pass filters**, using various values for their parameters. Although the performance of many songs varied the mean segmentation quality was neither better nor worse. (For experiment results using moving average filter with different values for sliding window size see Table 3.1, second row.)

I did algorithm runs using different **kernel sizes**. Again, there was no difference in the mean

performance. Finally, I decided to take $k_{\mathbf{C}} = 96$ beats which corresponds to approx. 38 seconds, depending on the beat length of course. Figure 3.5 and the third row of Table 3.1 show the effect of various kernel sizes.

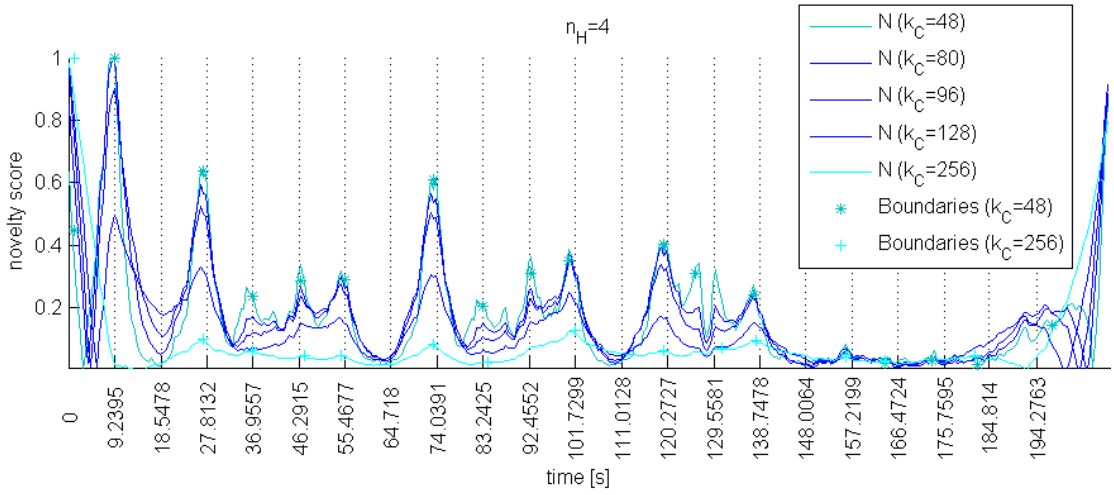


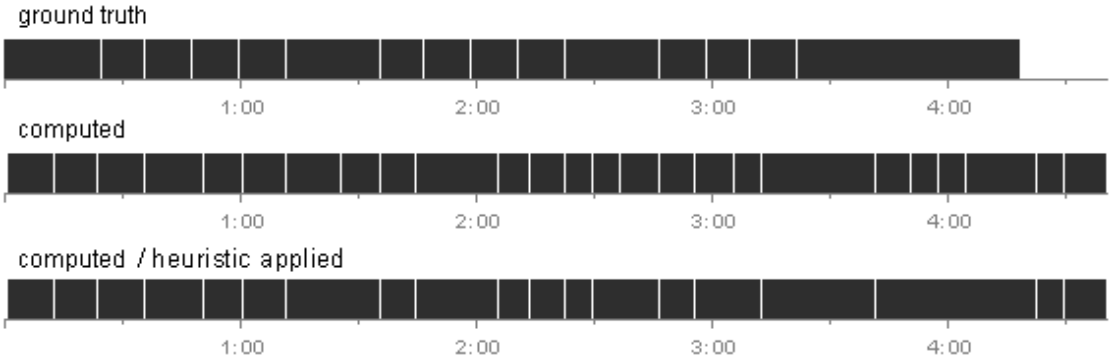
Figure 3.5: Novelty scores and resulting boundaries of *Chumbawamba: Thubthumping* when using different kernel sizes. Although the latter kernel is more than five times larger than the first one there are not that many more segment boundaries as one might expect because many peaks are very close to each other and hence are not regarded as boundaries. $k_{\mathbf{C}} = 48$: $P = 0.93$, $R = 0.7$, $F = 0.8$; $k_{\mathbf{C}} = 256$: $P = 1$, $R = 0.65$, $F = 0.79$.

I employed **Principal Component Analysis** (PCA) to reduce the size of the feature vectors for the subsequent calculation steps. Most of the time, however, this step neither reduced the overall runtime very much nor improved the results.

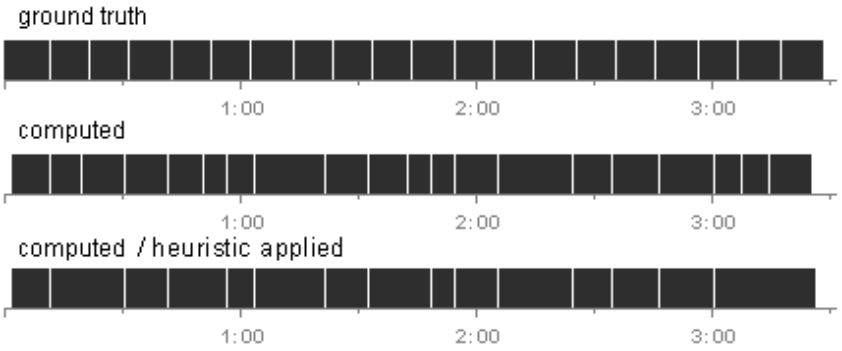
I tried a **boundary removing heuristic** to improve performance of the worst songs: From some songs (for instance *Eminem: Stan*, see Figure 3.4) too many peaks of H_N are interpreted as boundaries. I computed the bounds per minute ratio $r_{bm} = |\mathcal{B}_1|/dur$, dur being the song's duration in minutes, and compared it with a threshold T_1 (e.g., $T_1 = 10$). If $r_{bm} > T_1$ then β boundaries with the lowest corresponding H_N values are removed (e.g., $\beta = |\mathcal{B}_1|/4$). This heuristic worked well for the Eminem song (F rose by 0.13), the overall results were not better, though (Table 3.1, fourth row). In my opinion there are two reasons for that.

First, there are also songs which natively *have* a high r_{bm} in their groundtruth annotation. These songs' performance declines. Second, sometimes it is indeed the case that segments begin or

end at positions where H_N is low. So this heuristic would remove correct boundaries, resulting in an even lower precision value. See Figure 3.6 for two example songs.



(a) Segmentations of *The Roots: You Got Me*. Ground truth (top); computed (middle), $F = 0.61$; computed with heuristic applied (bottom), $F = 0.73$.



(b) Segmentations of *Britney Spears: Hit Me Baby One More Time*. Ground truth (top); computed (middle), $F = 0.80$; computed with heuristic applied (bottom), $F = 0.67$.

Figure 3.6: Effect of boundary removing heuristic ($T_1 = 10$, $\beta = |\mathcal{B}_1|/4$) applied to two songs. White vertical lines within dark gray panels indicate segment boundaries.
Figure (a) shows a song where applying the heuristic improved F. Figure (b), on the contrary, shows an example of a song where the F-measure has declined. Checking the novelty score, I saw that it was indeed the case that H_N had rather low values at some positions where correct boundaries are located.

Another attempt to cope with low precision can be called **two-iterations-approach**. Since songs like the above mentioned *Eminem: Stan* produce way too many computed boundaries one should regard them only as boundary candidates from which the final boundaries can be selected by a second **S** / N / H_N iteration. This means in fact that the "segments" from the first iteration are considered to be the "frames" for the second one: each "frame" now comprises a longer period of time. Naturally this leads to less boundaries.

Unfortunately even the outcome of Eminem's song was not better using this approach. I noticed that the similarity matrix resolution for the second pass was very low (one discreet time step was about 7 s), thus, novelty score computation could not be performed properly. Especially the low-pass filter had problems with the low time resolution.

Levy *et al*. proposed a **post-processing** method which takes musical domain knowledge into account [LSC06]. The idea is to restrict the possible locations where a segment boundary may be to downbeat locations (i.e., where a measure starts) since it is unlikely that a segment begins within a measure. The authors employed a brute-force algorithm to find a phrase-length m and an offset o such that the squared differences between detected boundaries and positions matching m and o becomes minimal. o should eventually correspond to the position of the first downbeat; m can be regarded as the length of one measure.

I tried two value ranges for m. First, I let m iterate trough values close ($\pm \frac{1}{6}$) to half of the mean segment length. Results were statistically insignificantly worse. Then I chose a value range around 4, 8 and 16 times the mean beat length. The results were almost equal to the results without this post-processing method (Table 3.1, fourth row).

One reason for this is the fact that most of the incorrectly detected boundaries are a greater period of time away from the closest groundtruth boundary than half of the measure (for a measure of eight beats this would be approximately 1.6 s, depending on the beat lengths). So the possibly largest shift correction could not turn these incorrect transitions into correct ones. It is also quite common that some computed boundaries are actually superfluous and should be deleted, not shifted, further decreasing the potential positive effect of this method in my case.

As one of the last attempts to improve results I employed a recently presented method called **Harmonic Change Detection Function** (HCDF) [HSG06]. Here, twelve bin chroma vectors are mapped into a 6 D polytop (i.e., six dimensional generalization of a polygon) based on the Harmonic Network or *Tonnetz* which is a representation of pitch relations. Using the original Matlab code written by the authors it appeared that the results were significantly worse than already obtained ones, also after some experimenting with HCDF parameters. One reason might be that HCDF is originally used for chord detection, an application that needs a higher resolution of the harmonic changes. The HCDF can probably be adapted to work for audio segmentation as well. In view of the very low performance numbers, their robustness against various HCDF parameters settings and the experience with previous unsuccessful improvement attempts I did not go any further into adapting the HCDF.

3.3 Results

Figure 3.7 depicts the results of my segment boundary detection algorithm using different parameter sets. For the specifications of these parameter sets please refer to Table 3.2.

Evaluation results depend on the allowed deviation w between computed and groundtruth boundaries. Figure 3.8 shows the effect of different values for w.

In Figure 3.9 P and P_{abd} of each song is plotted against the respective R and R_{abd} values.

Baseline As baseline results I generated four sets of segmentations. Each segmentation consists of segments of equal length $l \in \{10, 15, 20, 30\}$. The position of the first boundary was $l/2$. Following my expectations these results were pretty bad.

Comparison In Table 3.3, Figures 3.10 and 3.11 performance of my output is compared to performance measures that have been published in related literature.

Both Lu *et al*. [LWZ04] and Levy *et al*. [LSC06] include a histogram over distances of computed boundaries from the nearest groundtruth boundary. Since the precise numbers are not included I can only estimate the evaluation number *precision*.

Chai [Cha05] and Ong [Ong05] publish results in terms of *precision* and *recall*, defined in the same way as I did in Section 2.2.1.

Please note, however, that not all mentioned papers use the same corpus, thus the comparability of the numbers is limited. To overcome this limitation I included results based on qmul14 corpus that has been used in [LWZ04] and [LSC06].

If you look at *mean* P and F, disregarding the confidence interval, you can notice that qmul14 results are (much) higher (Figure 3.10, last two columns). This shows one fact very impressively: The evaluation numbers depend to a larger degree on the corpus than on the algorithm or parameters. This again emphasizes the importance of carefully selecting songs for a common corpus if an audio segmentation benchmark evaluation is going to take place. You can also see how important it is to compute and publish proper confidence intervals: the mean values alone could be misleading.

Parameters	**SPEC**	**MFCC10**	**MFCC30**	**MFCC40**
feature set	spectrogram	MFCCs, 10 / 30 / 40 coefficients, included first coefficient, log scaled		
frame size	1 beat	740ms (2^{14} points)		
hop size	1 beat			
$d_{\mathbf{S}}$	Euclidean			
$k_{\mathbf{C}}$	96			
H	Moving average with n_H sized sliding window			
n_H	8			
T_{ampl}	0.2			

Parameters	**RP**	**SSD**	**CQT1**	**CQT2**
feature set	Rhythm Patterns	Statistical Spectrum Descriptor	CQT with $f_0 = 64.4$, $bins = 12$, $f_{max} = 7902.1$	CQT with $f_0 = 64.4$, $bins = 12$, $f_{max} = 988.7$
frame size	Approx. 6 s (2^{17} points)		370 ms (8096 points)	
hop size	2 beats		1 beat	
$d_{\mathbf{S}}$	Euclidean			
$k_{\mathbf{C}}$	48	64	96	
H	Moving average with n_H sized sliding window			
n_H	4	2	8	
T_{ampl}	0.2			

Parameters	**MRG1**	**MRG2**		
feature sets, frame size, hop size	merged MFCC40 and RP; weighted 2:1	merged MFCC40 and CQT1; weighted 3:1		
$d_{\mathbf{S}}$	Euclidean			
$k_{\mathbf{C}}$	48	96		
H	Moving average with n_H sized sliding window			
n_H	4	8		
T_{ampl}	0.2			

Table 3.2: Parameter value sets that are referenced in figures

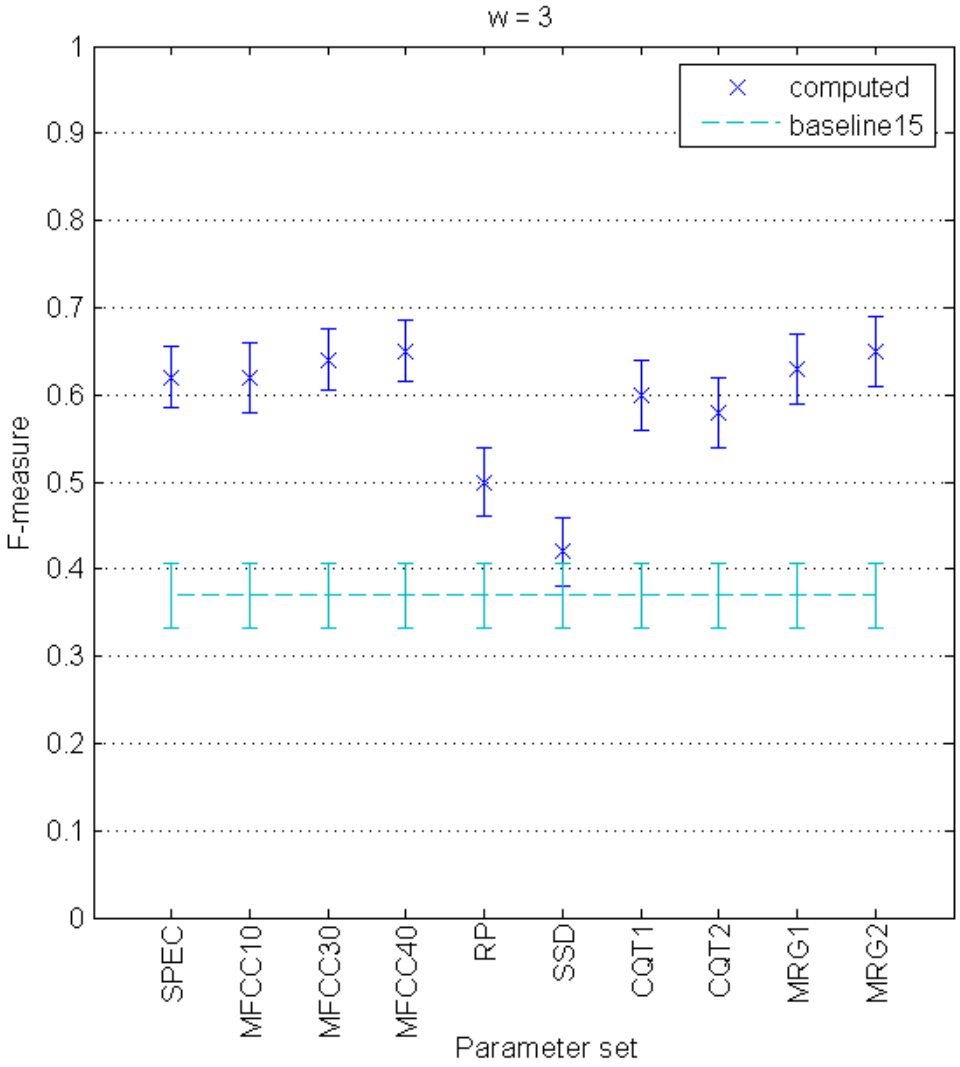


Figure 3.7: Comparisons of results when using various parameter settings. Refer to Table 3.2 for an explanation of them. The cyan dashed line indicates the baseline. All but one parameter set perform better than baseline. I was surprised, however, that quite different settings in terms of kernel length, filter size and the feature vectors in general produced that similar results.

Source	Results	Corpus	Remark / source
[LWZ04]	$P \approx 0.69$	qmul14	boundary shift histogram (Fig. 8)
[LSC06]	$P \approx 0.69$	qmul14	boundary shift histogram (Fig. 2b)
[LS06]	$R \approx 0.77$	100 pop songs	interpolated from $R = 0.82$ at $w = 4$ and $R = 0.72$ at $w = 2$
[Cha05]	$P \approx 0.71$, $R \approx 0.75$, $F \approx 0.73$	26 Beatles songs	Fig. 4-14
[Ong05]	$P = 0.71$, $R = 0.79 \hat{\pm} 0.11$, $F = 0.75$	54 Beatles songs	$\hat{\pm}$ indicates standard deviation
[Pei07]	$P = 0.56 \pm 0.037$, $R = 0.78 \pm 0.034$, $F = 0.65 \pm 0.03$	full corpus	MFCC40 parameter set
[Pei07]	$P = 0.69 \pm 0.085$, $R = 0.74 \pm 0.124$, $F = 0.68 \pm 0.069$	qmul14	
[RCAS06]	$F_{abd} = 0.78$	qmul14	
[ANS+05]	$P_{abd} \approx 0.78 \pm 0.02$, $R_{abd} \approx 0.79 \pm 0.02$, $F_{abd} \approx 0.785$	qmul14	Fig. 2 and 3; $K = 5$, 80 HMM states
[ASRC06]	$P_{abd} \approx 0.78 \pm 0.01$	qmul14	Fig. 12(b); $K = 5$, Wolff segmentation
[Pei07]	$P_{abd} = 0.67 \pm 0.023$, $R_{abd} = 0.85 \pm 0.017$, $F_{abd} = 0.75$	full corpus	MFCC40 parameter set
[Pei07]	$P_{abd} = 0.77 \pm 0.044$, $R_{abd} = 0.8 \pm 0.082$, $F_{abd} = 0.78$	qmul14	MFCC40 parameter set

Table 3.3: List of evaluation numbers from different sources. Allowed deviation $w = 3\,\mathrm{s}$, $\pm$ indicates confidence intervals. See Figures 3.10 and 3.11 for an illustration and Table 1.2 for more information about corpora. Figure numbers of last column refer to the respective publications mentioned in the first column.

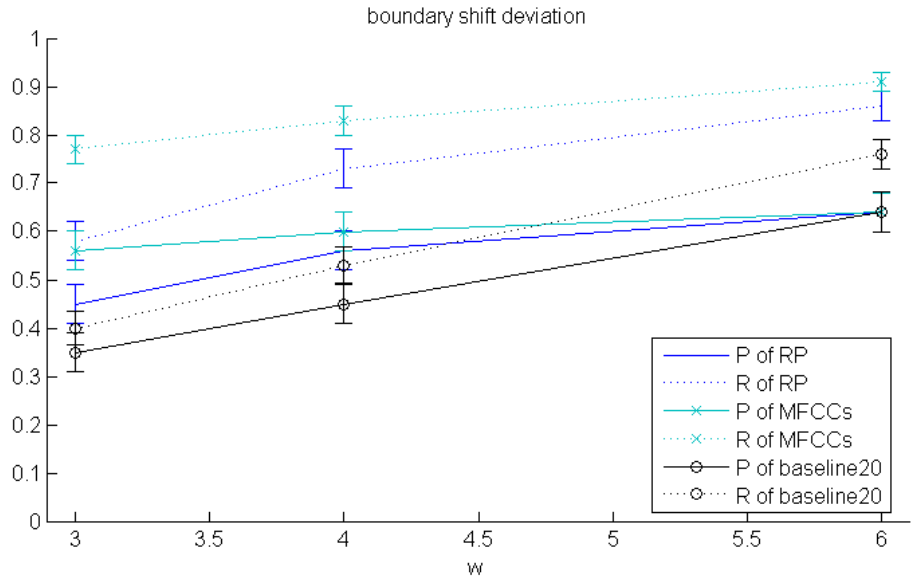


Figure 3.8: Evaluation results with different values for w, error bars indicate the confidence interval. At $w = 6$ P values are identical with baseline. At $w = 3$ precision of MFCC40 is significantly better than the baseline whereas precision of RP is not.

3.4 Discussion

I would say that automatic segment boundary extraction results are quite acceptable if you consider that

- the algorithm operates exclusively on local information, i.e., it does not take large scale data into account.
- it does not make use of domain knowledge which means that there is also no restriction about the songs that can be processed.
- the corpus contains songs of various different genres.
- the evaluation numbers have not been related to the songs' "inherent" ambiguity that can make it impossible to reach the perfect value of $F = 1$ (see Sections 1.3.1 and 2.4).

It can be noticed that computed segmentations tend to have too many boundaries which leads to a rather low precision value. Reasons for that may be:

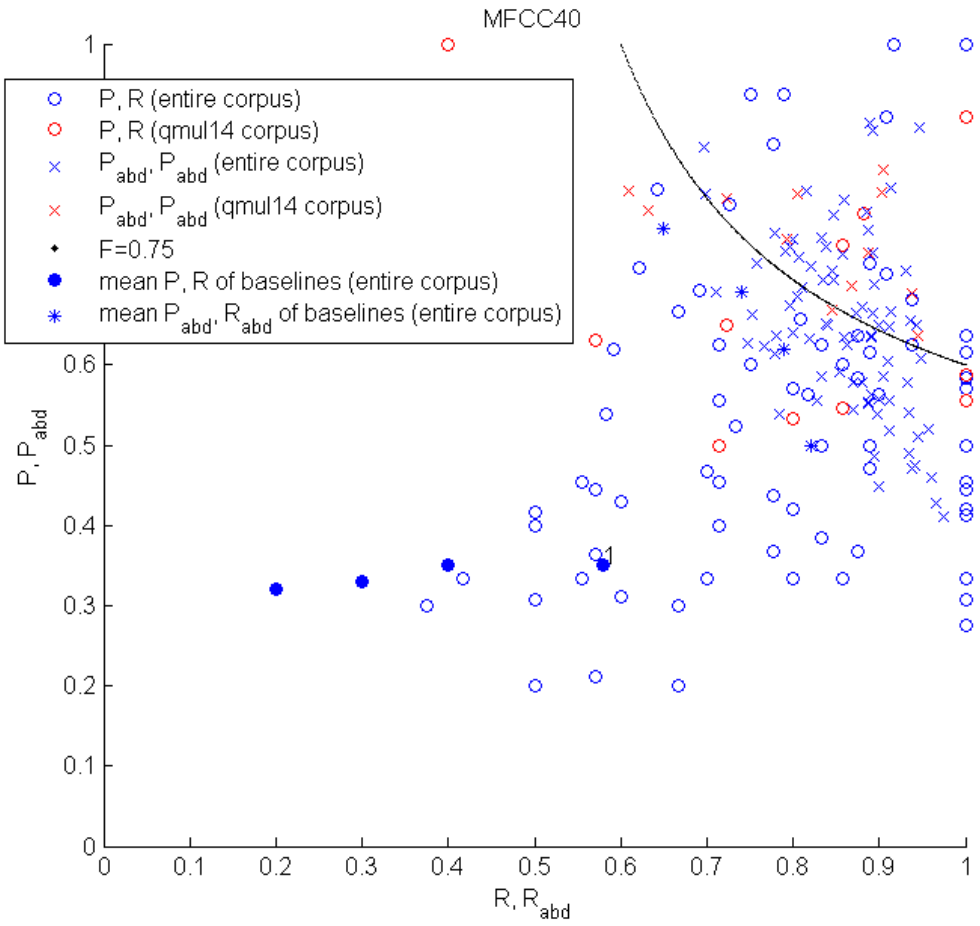


Figure 3.9: Values of P and P_{abd} plotted against values of R and R_{abd} over all songs. See Table 3.2, column *MFCC40* for parameter settings used for this pass. The black line corresponds to an F-measure of 0.75. Values of *qmul14 corpus* songs are colored red. Filled circles and asterisks mark baseline values. *1* marks baseline with $l = 10$. Allowed boundary deviation $w = 3$. The following points are observable:
• Especially circles but also x-marks agglomerate on the right side. This corresponds to the fact that the algorithm rather pays attention to recall than to precision.
• P_{abd} and R_{abd} values are generally higher than P and R of the same song. This is also reflected by the much higher baseline values of the alternative performance measure. While the highest values in the corpus are still P and R, its mean tends to be lower by roughly 0.1 as I noted empirically when looking at various evaluation reports.
• It is surprising that R values of baselines increase while precision remains equal (in contrast to P_{abd} and R_{abd} values where a clear trade-off point at approximately (0.76, 0.65) is visible). I conclude that these baseline values are very sensitive to the offset of the equally spaced boundaries, especially if the allowed deviation is as low as $w = 3\,s$.

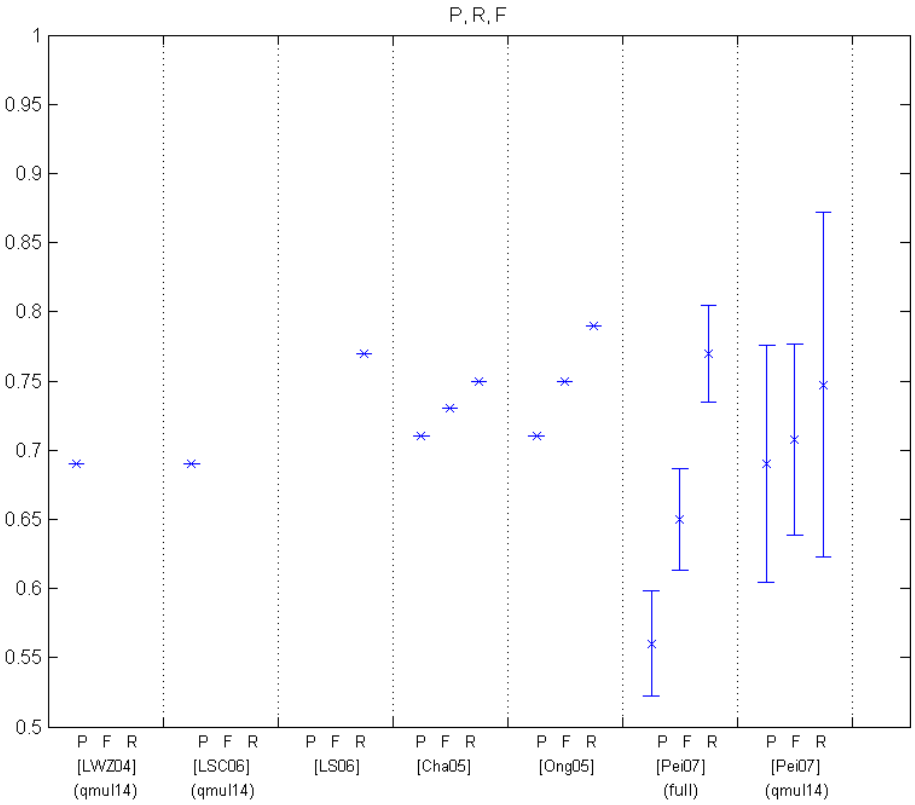


Figure 3.10: Illustration of evaluation numbers collected from various papers. Error bars indicate confidence interval (where available). Results based on qmul14 corpus are marked, all other columns cannot be compared directly since the are not based on a common corpus. Each column corresponds to one row of upper part of Table 3.3 where you can find more information. Precision of all three qmul14 results are on an equal level (see first, second and last column).

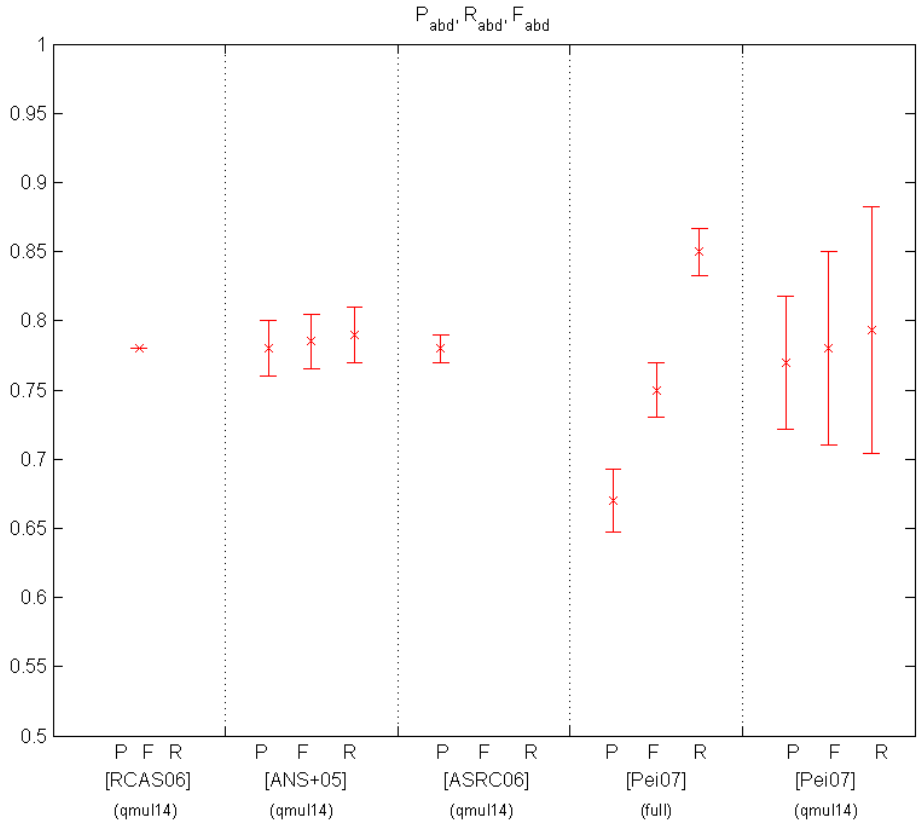


Figure 3.11: Illustration of alternative evaluation measure collected from various papers. Error bars indicate confidence interval (where available). Each column corresponds to one row of lower part of Table 3.3 where you can find more information. Corpora used are given in parentheses in the last line. Note that my qmul14 results (last column) are equal to those of other studies (first three columns).

- Frequently there is a novelty score peak at the change of instrument, e.g., in soli, leading to false positives.
- Boundaries in slow and soft songs are often shifted some time from the correct positions since the edges in the similarity matrix are not that distinct (for instance in *Sinhead O Connor: Nothing Compares To You*).
- On the other hand, non-melodic audio parts like in rap songs exhibit fast changing feature vector distances leading to a jagged Novelty Score and too many boundaries.
- Also, songs with dense, distorted guitar sound seem to perform worse than melodic ones.
- The values of N or H_N themselves cannot be used to distinguish between correct and incorrect boundaries.

In view of the fact that my improvement attempts did not produce significantly better results I got a feeling that it might not possible to further improve segmentation. A plausible reason may be that the data set contains a certain amount of noise which is due to the ambiguity of song segmentations as discussed in Sections 1.3.1 and 2.4.

I learned from the evaluation reports that it were not always the same songs which performed badly. There are, of course, songs that generally are easier to segment, e.g., *KC and the Sunshine Band: That's the Way I Like It*, but the songs on the lower end change according to the feature set used and other parameters.

To find a clue about which "type" of songs perform better with which feature set I compared the 24 worst performing songs (which is a quarter of the entire corpus) of one algorithm run with those of another. Consecutively, I built the intersection between these two sets. The idea was to find some similarity between the bad performing songs *not* contained in the intersection.

For clarification please have a look at the following example.

First I ran the algorithm using MFCC features, the second run was based on CQT features. The intersection of each run's 24 worst performing songs contained 17 songs. This means that there are seven songs for which MFCC features work better and seven other songs for which CQT features are the better choice. The songs of these two sets are, in no special order:

Set 1 (performs better with MFCC features):
The Beatles: Within You Without You, The Beatles: Being For The Benefit Of Mr. Kite, Britney Spears: Oops I Did It Again, Faith No More: Epic, The Beatles: Help, The Beatles: Sgt. Peppers Lonely Hearts Club Band, Beatles: Till There Was You

Set 2 (performs better with CQT features):
The Beatles: She's Leaving Home, Björk: It's Oh So Quiet, Simply Red: Stars, Red Hot Chili Peppers: Parallel Universe, Depeche Mode: It's no good, Artful Dodger Craig David: Rewind, A-HA: Take on me

It can be said that Set 2 is quite melodic and does not contain strong guitar sound, whereas most of the songs of Set 1 exhibit a strong rhythm and dominant guitar timbre. On the other hand there are also rather melodic songs in Set 1 (Oops I Did It Again, Till There Was You). In this light it might be the case that MFCC features are better suited for rock songs. This conclusion is, however, not evidenced by the mean performance numbers of rock genre in the respective evaluation reports: those numbers do not differ significantly.

I repeated this ad-hoc investigation a few times, however, without finding strong evidence. Thus, I suggest to do a systematically analysis on this matter in subsequent studies.

Finally, to summarize the results verbally one can state that every other computed segment boundary is correct and that three quarters of the boundaries are detected automatically without human interaction across a diverse set of songs.

3.5 Summary

This chapter dealt with the first phase of my audio segmentation algorithm, which is automatic boundary extraction. Its output is a set of time points where song segments start or end.

The approach I used is the quite traditional similarity matrix / novelty score method introduced in [Foo00]. There, differences between neighbouring feature vectors are used to detect more or less sudden changes in the song.

Then, I mentioned and explained numerous experiments I carried out to improve performance (various feature sets and parameter settings, boundary removing heuristic, boundary shifting post-processing, Harmonic Change Detection Function HCDF). Some of those attempts have been illustrated by examples, and the change in performance results of selected algorithm runs have been summarized in a table. Several times I pointed out that all these experiments did not produce statistically significant changes in the mean performance, one exception being HCDF whose results were significantly inferior. (I stated, however, that this may be because HCDF is intended for chord detection rather than for boundary detection.)

I presented final results in various figures, also comparing them to already published numbers. These latter figures (3.10 and 3.11) showed that my results of qmul14 corpus subset can be assumed to be equal to those of other authors. However, no statistically grounded statement can be made since other papers lack confidence intervals. It was clearly visible that mean performance numbers depend to a large degree on the underlying corpus. Another interesting observation was the fact that the alternative performance measures whose definitions I took over from related literature tend to be more positive than the ones I decided to use (c.f. Figure 3.9).

At the end, I could state that boundary detection results are quite acceptable if some points are taken into account (no domain knowledge used, the theoretically optimal result of $F = 1$ is probably inherently unreachable, etc.). Melodic songs which lack rap passages and prominent distorted guitar sound and which do not have a too slow rhythm perform best.

Chapter 4

Structure detection

This chapter explains phase 2 of my algorithm. This phase tries to detect the structure of the song, also referred to as musical form, i.e., a label is assigned to each segment where segments of the same type (verse, chorus, intro, etc.) get the same label. The labels themselves are single characters like `A`, `B`, `C`, etc., and thus not semantically meaningful.

4.1 Algorithm

The algorithm takes $\mathcal{B}_1$, a set of prospective segment boundaries, from phase 1 as the input. The set of prospective segments $\mathcal{S}_1$ is created by setting

$$\mathcal{S}_1 = \{S_n | S_n.start, S_n.end \in \{1, dur\} \cup \mathcal{B}_1 \wedge S_n.start < S_n.end \wedge b \notin \mathcal{B}_1 | S_n.start < b < S_n.end\} \quad (4.1)$$

where dur denotes the song duration. That is, the gaps between the time points are regarded as segments, including the first segment starting at the beginning of the song and the last segment ending at the song's end.

As stated in the previous chapter there is a possibility that $\mathcal{B}_1$ contains too many segment transitions. Therefore, boundaries between two segments whose distance is lower than a threshold T_{merge} are removed and the consecutive segments are merged.

I assume that segments of the same type are represented by similar features. Thus, I employ unsupervised clustering in four variations.

4.1.1 Clustering approaches

Means-of-frames Each segment is represented by a feature vector that contains the mean values over all frame feature vectors of the segment. This approach discards any temporal information. The resulting feature vectors are clustered using a standard k-means approach. The cluster centroids are initialized by choosing some feature vectors at random. Since the initial setting is important for k-means the clustering is repeated ten times and the solution with the lowest within-cluster sums of point-to-centroid distances is chosen. Since k-means expects the number of cluster centers k as input parameter I investigated some heuristics and cluster validity indices. See Section 4.2 for details.

Agglomerative Hierarchical Clustering The segment representation is the same as before but this time I employ a hierarchical clustering approach. With this method in each step the two most similar clusters (starting with the individual data points) are merged, eventually leading to one cluster that comprise all data points. This process is frequently visualized using a dendrogram. After some initial algorithm runs I decided to use complete linkage function, i.e., the cluster-to-cluster distance is seen as the maximum of the distances between any data points of the respective clusters. Single linkage function results were inferior to those with complete linkage.

It can, however, be problematic to just take the mean of the feature vectors over all frames of a segment. Imagine a song segment S_1 that actually somehow lies between two segment types. Looking at the mean values it is likely that the clustering process assigns one centroid exclusively to this segment. This has two disadvantages: First, the number of available clusters for the remaining segments is lower and thus maybe to little. Second, it is likely that S_1 belongs to one of the neighboring segment types and is not a type of its own. Thus, S_1 would be misclassified, resulting in a lower performance. To avoid this effect I moved on to an approach called "voting".

Voting The clustering process is employed to cluster all frame feature vectors together, again using k-means clustering. Then the segment type of each segment is assumed to be the cluster number that is assigned to most of its frames. This approach still does not take temporal information into account but it allows more freedom in terms of number of clusters k. Setting k

to a higher number than existent segment types is not much of a problem because only a few frames will be assigned to the "superfluous" clusters and these frames will be disregarded in this "first-past-the-post" voting system. K-means is repeated 100 times for each song since there are many more points to cluster with this approach.

Glancing at real-world elections I introduced the concept of "run-off polls": If the percentage of the most frequently occurring cluster number is lower than a threshold T_{runoff} then all frames "vote" again but this time only the two most frequently occurring clusters are allowed. This should avoid that some distracting frames turn the election result upside down.

Dynamic Time Warping The forth approach uses *Dynamic Time Warping* (DTW) to compute a segment-indexed similarity matrix $\mathbf{S}_{segs}$ of size (m, m). From this matrix a configuration matrix is calculated by classical multidimensional scaling (MDS), such that this matrix contains points in the m dimensional space (one point per segment) whose distances correspond to the distances in $\mathbf{S}_{segs}$.

DTW is also widely used in speech processing and recognition to allow approximate matching of two audio streams (or, in the general case, two sequences of values) $U = u_1 u_2 \dots u_m$ and $V = v_1 v_2 \dots v_n$ that may vary in terms of tempo. This can also be the case in popular music where tempo can change or where some break beats that extend a chorus section by two beats can be introduced as a stylistic element. DTW is carried out by a dynamic programming approach and produces a cost matrix $\mathbf{C}$ whose $(i, j)^{\text{th}}$ element denote the cost of aligning $u_1 u_2 \dots u_i$ with $v_1 v_2 \dots v_j$. Thus, $\mathbf{C}(m, n)$ is used to calculate the distance between a pair of segments S_i, S_j, adapting [Cha05, Eq. 4-6]:

$$\mathbf{S}_{segs}(i, j) = \frac{\mathbf{C}(m, n)}{\min\left\{\|S_i\|, \|S_j\|\right\} \cdot \sqrt{|S_i|^2 + |S_j|^2}} \tag{4.2}$$

Inspired by [PK06], the DTW distance is normalized by an additional factor. Imagine two chorus segments where one is significantly longer than the other. Their DTW distance $\mathbf{C}(m, n)$ will be quite high although their frames' feature vectors are probably similar. To avoid a high $\mathbf{S}_{segs}(\cdot, \cdot)$ value the DTW distance is divided by the length of the $\mathbf{C}$ diagonal to account for this situation.

To compute the frame-level similarity matrices I use cosine distance. Tests showed that the final clustering result is not affected by the choice of Euclidean distance at this step. Prior to MDS $\mathbf{S}_{segs}$ is log-scaled to smooth out large values.

Figure 4.1 shows similarity matrices and clustering results for the song *KC and the Sunshine Band: That's the Way I Like It* of all three approaches. It must be mentioned that this song performs well in general.

I used Dan Ellis' freely available Matlab code for DTW[1].

4.2 Experiments

Again, I list and describe ideas, experiments and adjustments carried out and note whether they had a positive or negative effect on the overall performance. In order not to depend on $\mathcal{B}_1$ I frequently did not use computed segment boundaries but rather loaded them from the groundtruth XML files to fully concentrate on musical form detection.

I tried to find the most suitable value for the above mentioned **threshold** T_{merge} by performing multiple algorithm passes using groundtruth boundaries. I increased T_{merge} step-by-step to find the value where the F-measure of boundary evaluation starts to decline. The assumption is that groundtruth boundaries are ideal and perfect boundaries that should not be removed by this heuristic. Since F started to decline at $T_{merge} = 0.18$ ($T_{merge} = 0.05 : F = 1, T_{merge} = 0.1 : F = 0.996, T_{merge} = 0.18 : F = 0.965, T_{merge} = 0.26 : F = 0.932$) I set $T_{merge} = 0.16$ for further algorithm runs.

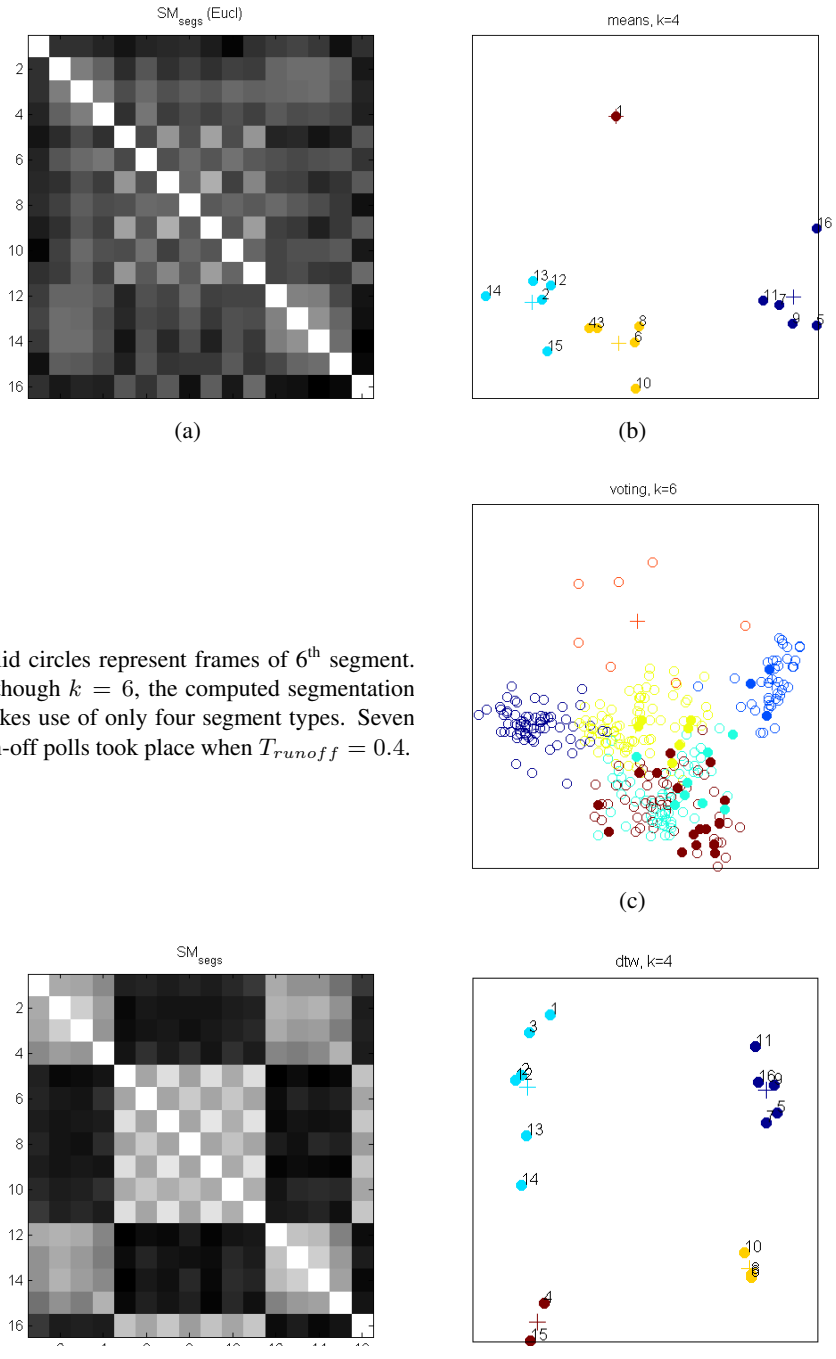
In addition to taking the mean of all frames of a segment I tried to take **mean and standard deviation** of the segments' feature vectors. Those results, however, proved to be inferior compared to taking the mean values alone.

4.2.1 Finding the correct number of clusters

Let us introduce some variables that will be referred to in this section. Let $\mathcal{L}_s$ be the set of (distinct) labels of song s, thus $|\mathcal{L}_s|$ is the number of segment types. $\mathcal{L}_s^{gt}$ and $\mathcal{L}_s^{algo}$ refer to the groundtruth and computed segmentation, respectively. Let dur_s be the duration of song s.

One open problem that remained is how to find the appropriate input parameter for k-means and hierarchical clustering, the number of cluster centroids k (as for voting approach the exact

[1] `http://www.ee.columbia.edu/~dpwe/resources/matlab/`



(a) (b)

(c)

(d) (e)

Solid circles represent frames of 6th segment. Although $k = 6$, the computed segmentation makes use of only four segment types. Seven run-off polls took place when $T_{runoff} = 0.4$.

Figure 4.1: Clustering of *KC and the Sunshine Band: That's the Way I Like It* segments using three approaches. Numbered circles indicate segments, crosses mark cluster centroids. (a), (b) show the means-of-frames approach ($r_f = 0.93$); (c) uses "voting" ($r_f = 0.86$); (d), (e) use distance measures originating from DTW ($r_f = 0.95$). Groundtruth boundaries have been used.
Difference values in (d) are clearly more distinct than in (a), both results are very good, though.

value of k is not critical). In the beginning I did several algorithm runs where I increased k consecutively, covering values from 3 to 7. Figure 4.2 shows the evolution of formal distance ratio r_f using two clustering approaches.

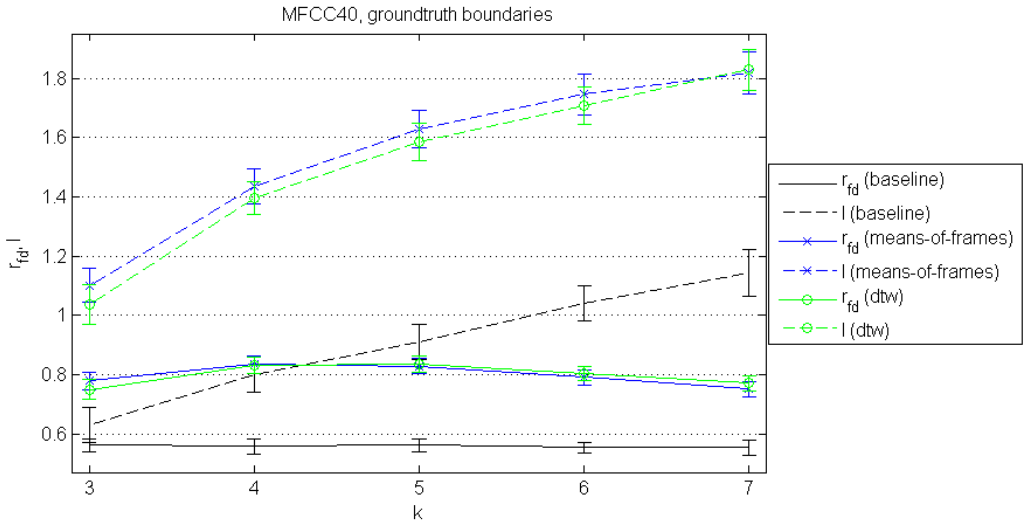
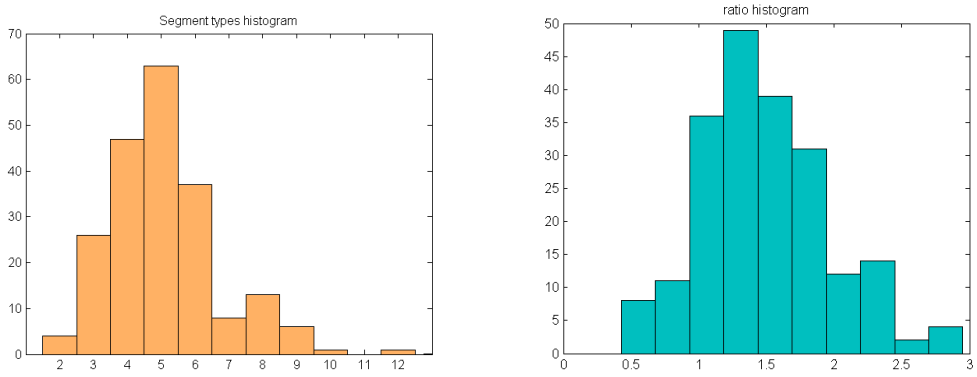


Figure 4.2: Formal distance ratio r_f and mutual information I plotted against number of clusters k from 3 to 7 using groundtruth boundaries. Baseline is included. There are four notable points to observe.
• Both clustering methods behave almost identical in terms of r_f.
• There is a slight r_f peak at $k = 4$ and $k = 5$.
• I itself rises monotonically. It can, however, be seen that the highest gain in mutual information takes place from $k = 3$ to $k = 4$.
• Computed structure performs better than the baseline in all cases.

Investigating the groundtruth annotations I learned that the median of segment types over all groundtruth variants is 5 ($\text{mean} = 5.08$, $\min = 2$, $\max = 12$, $\sigma = 1.6254$). Figure 4.3 (a) depicts the histogram.

Since five is not the best choice for all songs I employed a method to decide on k song by song using *cluster validity indices*. A cluster validity index is a numerical value that should correspond to the "quality" of a clustering result, depending, e.g., on compactness and separation. In this way the index helps to assess various clustering results to find an optimal one. Halkidi *et al.* provide a good survey on cluster validity indices [HBV01].

From the range of proposed indices I use two which are based on relative criteria, thus avoiding high computational effort that would be necessary for indices based on internal or external



(a) Histogram of $|\mathcal{L}_s^{gt}|$ over all groundtruth variants of all songs

(b) Histogram of ratio of segment types to song duration $r_1^s = |\mathcal{L}_s^{gt}|/dur_s$. Most songs have about 1.3 different types of segments per minute or, to put it in another way, each segment type comprises 46 s on average.

Figure 4.3: Histograms related to segment types

criteria because of statistical tests that would be needed.

Dunn index This index tries to identify "compact and well separated" clusters and is computed as defined by Equation 4.3. $d(c_i, c_j)$ is the distance between two clusters c_i and c_j and is originally defined as the distance of the two closest members of c_i and c_j, respectively. Since I noted that this value can be disproportionately small if one ore even both clusters have outliers I set $d(c_i, c_j)$ to be the distance of the respective cluster centroids. It can be assumed that large $dunn_k$ values correspond to clustering results where clusters centers are far apart and the clusters itself have small dispersions.

$$dunn_k = \min_{i=1,\ldots,k} \left\{ \min_{j=i+1,\ldots,k} \left(\frac{d(c_i, c_j)}{\max_{l=1,\ldots,k} \left(\max_{x,y \in c_l} d(x, y) \right)} \right) \right\} \tag{4.3}$$

Davies-Bouldin (DB) index In contrast to Dunn index the Davies-Bouldin index takes all cluster points into account by using the mean point-to-center distances. Here, we take the minimum of the index values to find the most appropriate value for k.

$$DB_k = \frac{1}{k} \sum_{i=1}^{c} \max_{j \in c, j \neq i} \left\{ \frac{\sigma_i + \sigma_j}{d(c_i, c_j)} \right\} \tag{4.4}$$

where $\sigma_i = 1/c_i \sum_{y \in c_i} d(y, \mu_i)$ is the measure of "scatterness" of a cluster i, i.e., the mean distance to the cluster center μ_i.

Hence, clustering is performed several times for each song with k iterating through a range of values, then the best value for k is chosen. The first few algorithm runs, however, showed that both indices frequently favor either very few classes ($k = 2$) or too many classes (k is about the number of segments). Thus, a limitation of the range such that $k_{min} \leq k \leq k_{max}$ was advisable, also in respect to computation time.

I decided to use the ratio of number of segment types to song duration in minutes $r_1^s = |\mathcal{L}_s^{gt}|/dur_s$ to estimate the range for k for each song. Figure 4.3 (b) shows the distribution of r_1^s over all groundtruth variants. First I chose the lower and upper quartile (1.16 and 1.79). Since the mean of the differences between $|\mathcal{L}_s^{gt}|$ and actually chosen number of segment types $|\mathcal{L}_s^{algo}|$ turned out to be as high as about 1.5 I extended the limit to the range from 15 percentile to 85 percentile r_1^s values (1 to 1.97).

Results showed very clearly that increasing k's range even decreases formal distance ratio r_f (which is bad). Therefore I tried a third run setting the range to $[4, 5]$ which provided best results, however, without statistical significance. Figure 4.4 summarizes the performance measure values obtained by various settings for k_{min} and k_{max}, compared with the result using a fixed $k = 5$.

Semi-supervised approach [LS06] states that

> "research into parallel problems in image segmentation suggests that a small amount of supervision may offer large gains in segmentation accuracy."

In this sense I set up an experimental algorithm run where the "user" is required to set k to an appropriate value for each song. In real life this situation can easily be imagined: the user wants a song segmentation and enters the number of distinct segment types he/she wants to obtain into his device. This allows him or her to request different segmentations that differ in granularity. Finally, the user can select the most appropriate suggestion for the purpose at hand.

In fact I extracted the number of distinct segment labels from each groundtruth annotation. The algorithm then loaded this value for each song and used it for clustering. I tried three variants:

1. groundtruth *without* subsegments

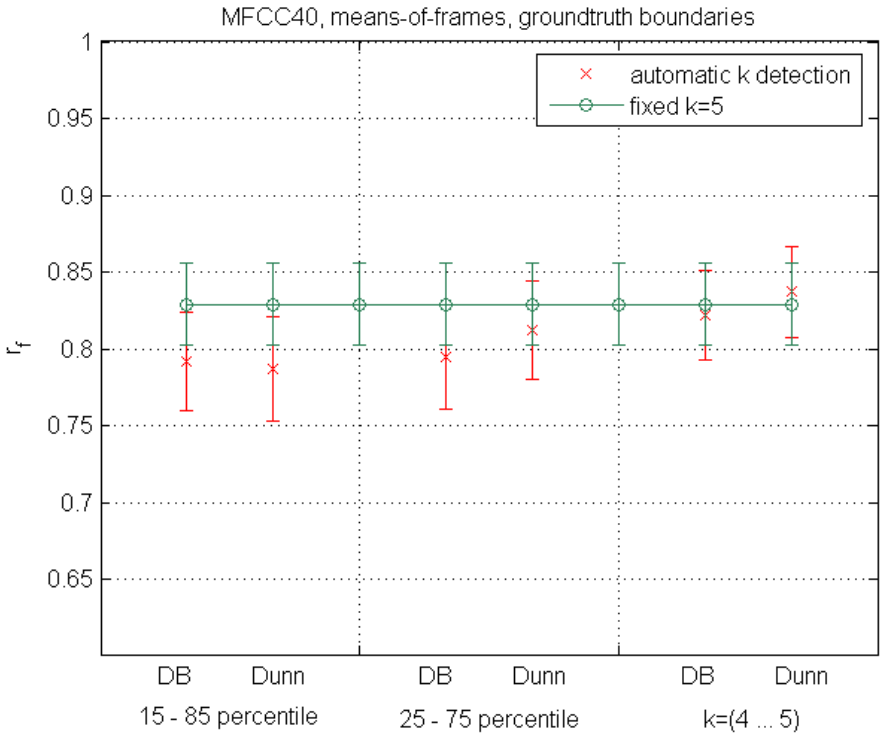


Figure 4.4: Results of choosing k according to a validity index (Davies-Bouldin, Dunn) compared to fixed k. Range for k is set according to different percentile values of r_1^s (first two columns) or to a fixed interval (third column). It can be seen that automatic selection of cluster numbers delivers (insignificantly) worse results which are better the narrower k's range is defined. (Except for Dunn index in the last column which produced an insignificantly better result.)

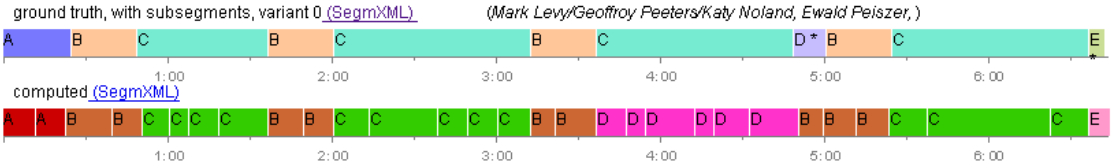


Figure 4.5: Segmentations of *Eminem: Stan*. Top panel: groundtruth, bottom panel: computed structure. Note the spurious boundaries especially between the `C` segments of the bottom panel.

2. groundtruth *with* subsegments
3. rounded mean of variants 1 and 2.

The results were similar for all three variants, being insignificantly better than results without simulated user input: $r_f = 0.717 \pm 0.028$ (variant 3) in contrast to $r_f = 0.707 \pm 0.025$ (fixed $k = 5$).

Boundary post processing Looking at some machine segmentations like the one in Figure 4.5 it seems to be a prospective idea to remove all or most of the boundaries between two segments of the same segment type.

As expected, mean precision rose quite a lot, whereas mean recall declined, so that eventually the F-measure was insignificantly higher. Here are the full details:

- All boundaries between segments of same type removed: P = 0.68 $\pm$ 0.045, R = 0.64 $\pm$ 0.045, F = 0.66
- Boundaries between segments of same type removed if the distance between the two adjacent segments is lower than the mean distance between all consecutive segments of same type: P = 0.61 $\pm$ 0.039, R = 0.72 $\pm$ 0.041, F = 0.66
- No post processing: P = 0.55 $\pm$ 0.038, R = 0.77 $\pm$ 0.037, F = 0.64

4.3 Results

Figure 4.6 informs about results of algorithm runs with various feature sets.

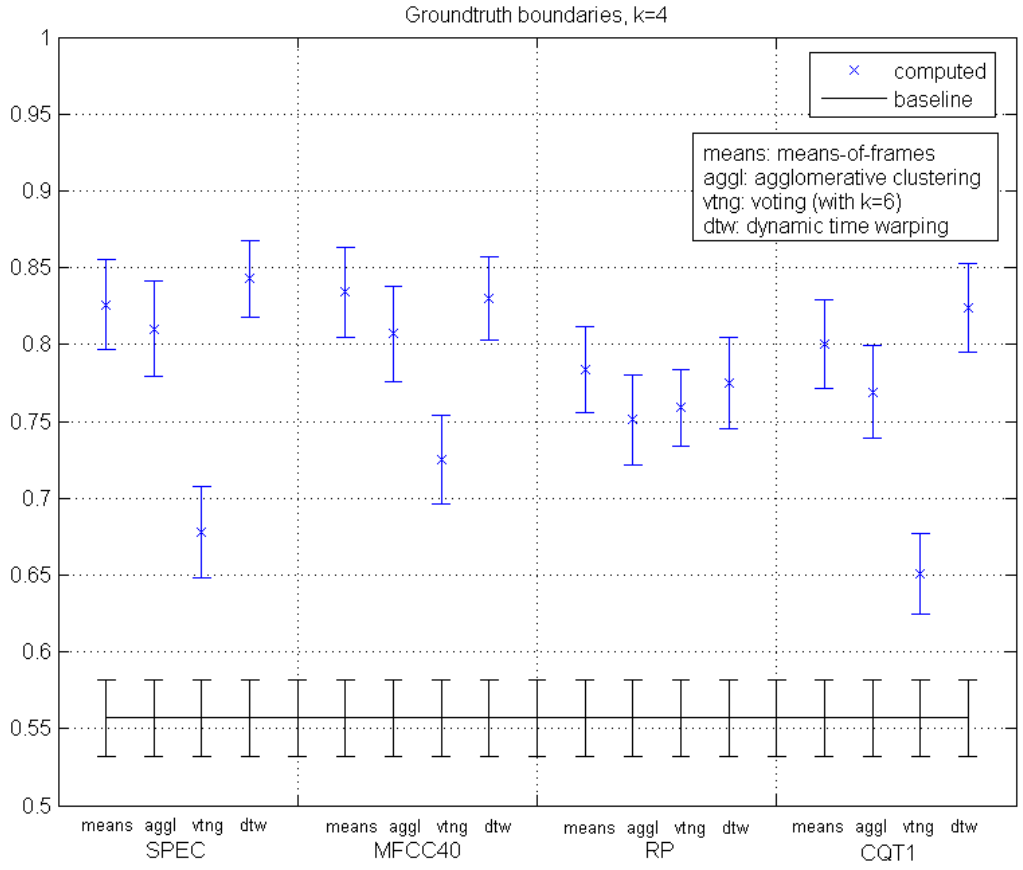


Figure 4.6: Comparison of results of structure detection when using different parameter and feature sets and different clustering methods. k was set to 4, except for voting approach where a k of 6 was used since this approach usually produces segmentations with less than k segment types. For an explanation of the parameter sets refer to Table 3.2. Note that means-of-frames, agglomerative clustering and DTW approach perform similar, voting approach is significantly worse, though (except for RP, see Section 4.4 for a discussion on this). It is quite interesting that SPEC has in fact the highest mean r_f.

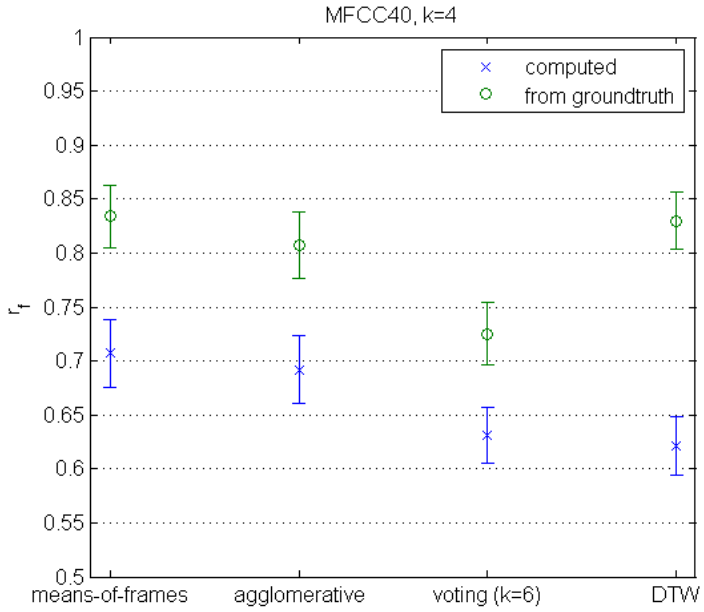


Figure 4.7: Comparison of r_f values using groundtruth boundaries and computed boundaries. The parameter set used is MFCC40, $k = 4$ except for voting where again $k = 6$. The decline of r_f is clearly visible in all four cases. The DTW result based on computed boundaries, however, is *much* lower than the respective result using groundtruth. See the following section for a dicussion about that.

As one might expect r_f is lower if automatically obtained segment boundaries are used and not the groundtruth boundaries (which can be seen as "perfect" boundaries). Figure 4.7 illustrates this decline in performance.

A histogram of the formal distance ratios if the groundtruth is not used in any way is shown as Figure 4.8.

Baseline Two types of baseline have been calculated where the first one can actually be considered as a special case of the second one. First I assigned the same label to each segment, second I selected one of k segment types at random ($k \in (2, \ldots, 6)$). For baseline calculation I used groundtruth boundary positions. Values of r_f were around 0.56 which again is pretty bad compared to the algorithmic results.

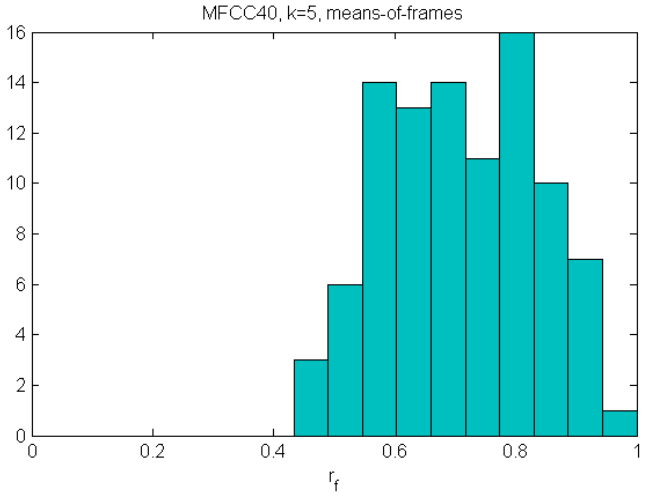


Figure 4.8: Histogram of formal distance ratios r_f. No groundtruth information has been used. Mean r_f is 0.707 ± 0.025.

Comparison Unfortunately my performance numbers cannot be compared to many already published results. The reasons are:

1. Both Chai [Cha05] and Lu *et al*. [LWZ04] publish mean edit distances in their evaluation section, they do, however, not normalize them against song duration. Clearly, if structure strings are somehow like `ABCBD` then edit distance will be lower than if a song's structure is represented by a string like `AABBBBCBBCBBCCCAAA`. Thus, I cannot use their numbers.
2. Abdallah *et al*. [ASRC06] actually uses the information-theoretic measure I implemented, unfortunately H and I values are given for only *one* song, mean performance results are not included in the article.

The only comparable figures I found are those in [ANS+05]. Table 4.1 compares them with mine. Please also note the discussion on this performance measure in Section 2.2.2.

4.4 Discussion

Although both F that measures the accuracy of computed segment boundaries and formal distance ratio r_f which indicates the performance of structure detection, are normalized in respect to song duration, these values cannot be compared directly. Still, it is characteristic that the best

k	**[ANS$^+$05]** (qmul14)	**[Pei07]** (full corpus)	**[Pei07]** (qmul14)
3	$\approx 1.09 \pm 0.05$	0.943 ± 0.059	1.05 ± 0.18
5	$\approx 1.45 \pm 0.07$	1.390 ± 0.063	1.42 ± 0.17
7	$\approx 1.71 \pm 0.09$	1.610 ± 0.070	1.76 ± 0.19

Table 4.1: Comparison of mean I values for different (fixed) k, based on automatically extracted segment boundaries. Data taken from [ANS$^+$05, Figure 4, bottom, 20 HMM states]. You can see that the qmul14 corpus results are almost identical. Full corpus results are only insignificantly lower.

mean F is lower than the best mean r_f, even if r_f is based on (imperfect) automatically extracted boundaries. This coincides with my subjective impression that computed recurrent form results are more useful and accurate than the boundaries.

Again, I was surprised that simulated user input and other experiments did not much improve results. Especially the performance of cluster validity indices was disappointing. For reasonable large range for k to choose from, these results were even inferior to those with a fixed k. From this fact we learn that none of the employed indices can be used to derive the correct number of clusters.

One of the few significant observations was the bad performance of the voting approach compared to the other three clustering methods. In order to find an explanation for this I investigated badly performing segmentations produced by this approach. Frequently, there was a very dominant segment type that covered about one half to three quarters of the entire song (c.f. Figure 4.9). Unfortunately, I could not find a legitimate reason for that. It seemed to me, however, that particularly songs that have a quite pronounced rhythm perform rather badly using voting approach. This assumption is also supported by the fact that there is no significant difference between all four clustering methods anymore if the Rhythm Pattern feature set is used.

Another remarkable point is the bad performance of the clustering approach using DTW. Although its results are comparable to those of other methods if segment boundaries are loaded from groundtruth, the performance drops if computed bounds are taken as the basis. I verified that this is the case regardless of the feature set used. Thus, it seems that DTW is very sensitive to incorrect boundaries. This makes sense since this method determines the similarity of two segments by how good they can be aligned.

Imagine that a boundary is shifted from the correct position. Then either the beginning or the end of the adjacent segment is truncated, i.e., this snippet now belongs to the neighbouring

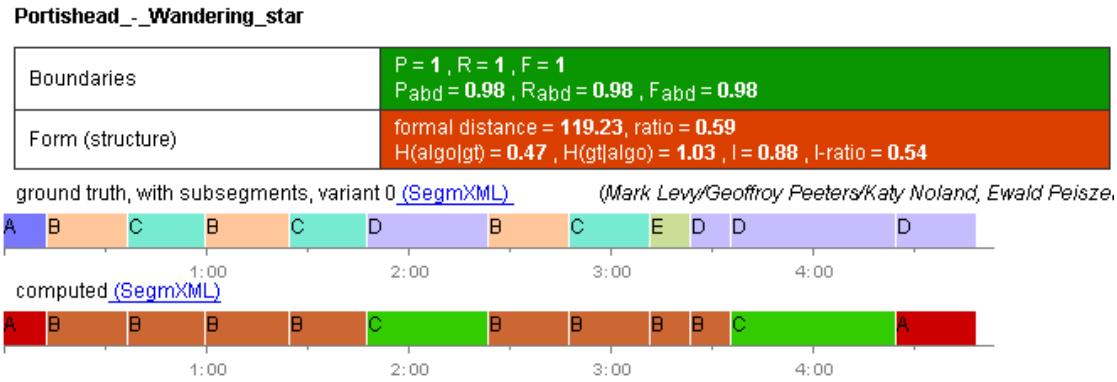


Figure 4.9: Evaluation of *Portishead: Wandering Star*. Top panel: groundtruth, bottom panel: computed segmentation. Voting approach has been used for segment clustering: note that `B` segments cover half of the song although these segments are actually of different types. Therefore formal distance ratio is quite low ($r_f = 0.59$). (Boundaries have been loaded from groundtruth.)

segment). Thus, the alignment process starts actually somewhere in the middle of a segment and will therefore not deliver a good result.

Carefully reading through a number of evaluation reports generated I frequently noted that a finer structure is extracted, especially if sections are subdivided by "incorrect" boundaries. As Goto assumed in [Got03] many chorus sections contain two subsegments. If phase 1 finds this boundary phase 2 sometimes assigns two different segment types to those segments. This decreases performance numbers but informally it is obvious that the extracted segmentations can still be useful.

4.5 Summary

The current chapter presented my work on another AAS subtask: structure detection, also referred to as musical form extraction. This phase outputs a string like `ABCBDBA` which represents the song structure. Each character stands for one segment, segments of the same type get the same character. Note that these letters do not indicate whether the respective song segment is a chorus or verse section, etc.

I employed clustering in four variants to group segments according to their similarity: k-means and hierarchical clustering with the segments being represented by one mean feature vector,

"voting" approach, and k-means with the segment similarity being computed using Dynamic Time Warping (DTW).

In the experiments section I explained how I employed cluster validity indices (Davies-Bouldin and Dunn) to find the correct number of cluster centroids, i.e., segment types, for each song. This, however, had no positive effect on the mean performance. Besides, I investigated a semi-supervised approach where this parameter is loaded from groundtruth, simulating a possible user input.

The last experiment was the removal of boundaries whose adjacent segments were of the same type. I pointed out that these experiments did produce statistically insignificantly better results only.

I provided evaluation numbers of various algorithm runs, grouped by parameter set used and clustering approach. From these figures it could be seen that most of the time (except for RP parameter set) the voting approach was inferior to other methods. Another remarkable point was that the DTW approach was very sensitive to the correctness of the segment boundaries. Unfortunately, I could compare my results with those of only one other paper. The comparison showed that my qmul14 corpus results are equal to those of the other study.

Chapter 5

Outro

In this chapter I present the results of a five-fold cross validation to measure a possible bias in my corpus. Besides, I conducted an algorithm run on a test set of fifteen additional songs that have not been used for parameter selection so far. After a few case studies I conclude the major aspects of the thesis and address possible future work. The chapter ends with a summary of the entire thesis.

5.1 Cross validation

In order to assess the bias of the data I performed a five-fold cross validation. For this example I tried to find an optimal value for parameter n_H which is the size of the sliding window for the low-pass filter employed in boundary detection. I let n_H iterate through values from 1 to 20, $n_H \in \{1, 2, 4, 6, 8, 10, 12, 16, 20\}$.

Cross validation is a technique to avoid training and validation on the very same data while still using as much of the data available as possible. In my case of a five-fold cross validation I partitioned the music files into five disjoint subsets. The union of four of these subsets ("training set") are used for finding the optimal value for n_H while the fifth one ("validation set") is used to perform evaluation. This procedure is repeated five times, each subset acting as the validation set exactly once.

Table 5.1 summarizes the results.

Quite surprisingly, the evaluation results of the validation sets are almost the same as those of the training sets. This indicates that there is not much bias in the data. The optimal value for n_H

seems to be 11 since it is the rounded mean of the five "best n_H" values and thus a "combination" of the best individual values.

Fold	Best n_H	Trainings set	Validation set
1	12	$F = 0.66, \sigma = 0.136$	$F = 0.68, \sigma = 0.183$
2	10	$F = 0.65, \sigma = 0.150$	$F = 0.68, \sigma = 0.128$
3	12	$F = 0.68, \sigma = 0.140$	$F = 0.67, \sigma = 0.146$
4	10	$F = 0.66, \sigma = 0.150$	$F = 0.60, \sigma = 0.121$
5	10	$F = 0.65, \sigma = 0.146$	$F = 0.68, \sigma = 0.128$
mean values		$F = 0.66, \sigma = 0.144$	$F = 0.662, \sigma = 0.141$

Table 5.1: Results of five-fold cross validation to find the optimal value for low-pass filter parameter n_H. σ denotes standard deviation. There is no statistically significant difference between any two F values in this table. The optimal choice for n_H would be 11 since this is the rounded mean of the five "best n_H" values.

5.2 Test with additional songs

I decided to apply one of the best performing parameter sets to a larger corpus than the one used so far. The fifteen additional songs comprise ten songs from the RWC pop collection [GHNO02] that also are part of the corpus used by Paulus *et al.* [PK06], and five songs that are personal favorites of the respective annotators[1]. See Table A.3 for a list of them. In a Machine Learning sense this set can be seen as a test set, i.e., a set whose contents have been omitted completely in the parameter selection phase. The test set should contain data that is representative for the training and validation sets. It is at least arguable whether that rule is fulfilled in this case since the "full corpus" of 94 songs does not contain RWC pop songs.

Table 5.2 gives the parameter settings used and Table 5.3 contains the results for the traditional corpus, for the set of additional songs and for the union set.

From the figures it is observable that there is no statistically significant difference between the results of the traditional corpus that has been used for parameter selection and those of the unseen test set. Thus, it can be concluded that no overfitting took place and that the algorithm in combination with these parameter values is general enough to be applied also to unseen songs.

[1] Andrei Grecu (three songs) and me (two songs)

Parameter	Value
feature set	MFCCs
MFCC coefficients	40
frame size	740ms (2^{14} points)
hop size	1 beat
$d_{\mathbf{S}}$	Euclidean
$k_{\mathbf{C}}$	96
H	Moving average with n_H sized sliding window
n_H	11
T_{ampl}	0.2
T_{merge}	0.16
clustering approach	means-of-frames
number of clusters k	5

Table 5.2: One of many equally well performing parameter value sets

Corpus	Boundary detection	structure extraction
"full" (94 songs)	$F = 0.66 \pm 0.034$	$r_f = 0.698 \pm 0.024$
"test set" (15 songs)	$F = 0.7 \pm 0.083$	$r_f = 0.668 \pm 0.088$
union (109 songs)	$F = 0.67 \pm 0.031$	$r_f = 0.694 \pm 0.024$

Table 5.3: Evaluation results of the independent test set as well as of the full corpus and the union of these two corpus sets. Note that the test set does not perform statistically significantly worse than the "full" corpus. The test set's mean F-measure is even higher than that of the traditional corpus.

5.3 Case studies: evaluation of selected songs

Feedback loop I present one example where the output was actually useful for extending and improving the groundtruth file. Of course, I continued to evaluate against the old groundtruth version in order to retain consistency with older evaluation reports.

While examining an evaluation report I saw that the analysis result of *Coolio: The Devil is Dope* contained more information than the groundtruth (also indicated by a high $H(algo|gt)$). Thus, I carefully listened to the song and checked whether the additional information was appropriate (Figure 5.1).

As indicated by the analysis result the beginning of the song actually consists of two small segments. In addition there are two more segments at the end: the first one is indeed of type `D` (but does not consist of two segments as incorrectly shown in the second row), the segment type of the last one corresponds to a previous occurring one (`B`). (Letters refer to third row in Figure 5.1.)

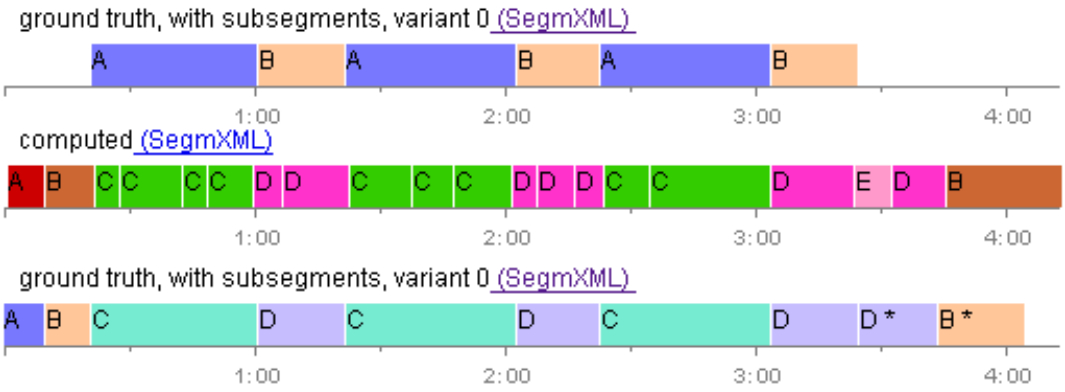


Figure 5.1: Segmentations of *Coolio: The Devil is Dope*. From top: groundtruth; extracted result; adapted groundtruth. Segments of same type have the same color and letter (per row).

More detail / finer structure A number of papers, e.g., [PK06], contain automatically extracted structures. Often they do not quite match the groundtruth but in some cases this mismatch can conclusively be explained, if, e.g., a finer structure is revealed that is not annotated in the groundtruth.

One example from my work can be seen in Figure 5.2. Both verse and chorus sections (`B` and `C` in the upper panel) consist of two smaller parts. The parts of the chorus sections do indeed differ from each other such that the assignment of two different segment labels (`C` and `A` in the lower panel) seems to be justified. In addition it can also be stated that the intro sounds much like the second part of each chorus.

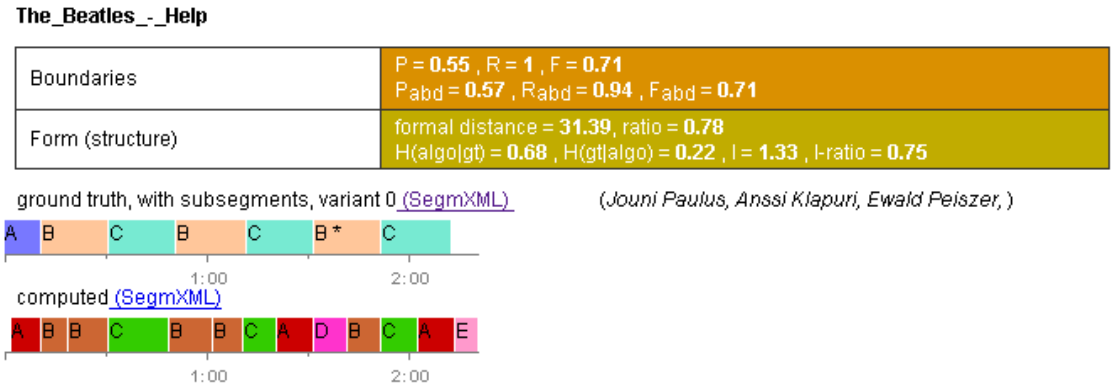


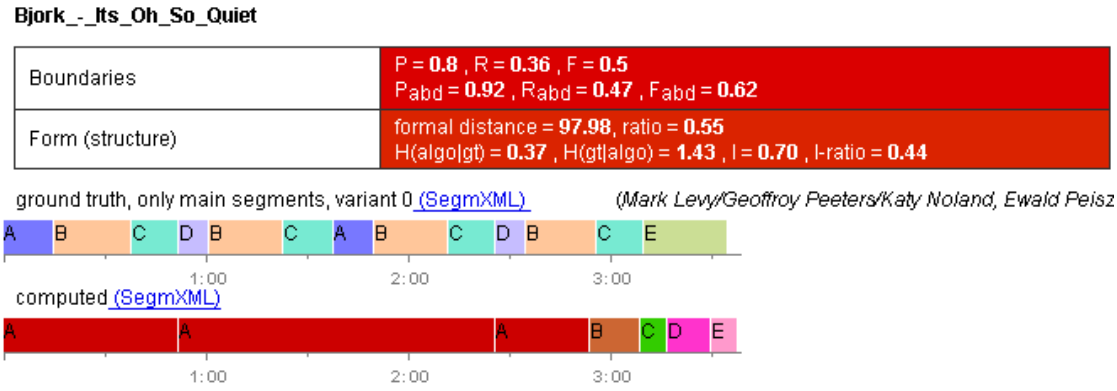
Figure 5.2: Groundtruth (top panel) and computed segmentation (bottom panel) of *Beatles: Help!*. Same color and letter within one panel correspond to same segment type.

Soft song As already mentioned slow and soft songs perform rather bad. If you have a look at the computed segmentation of Figure 5.3 you see that many boundaries are missed and hence clustering feature sets have been blurred so that the result looks degenerated.

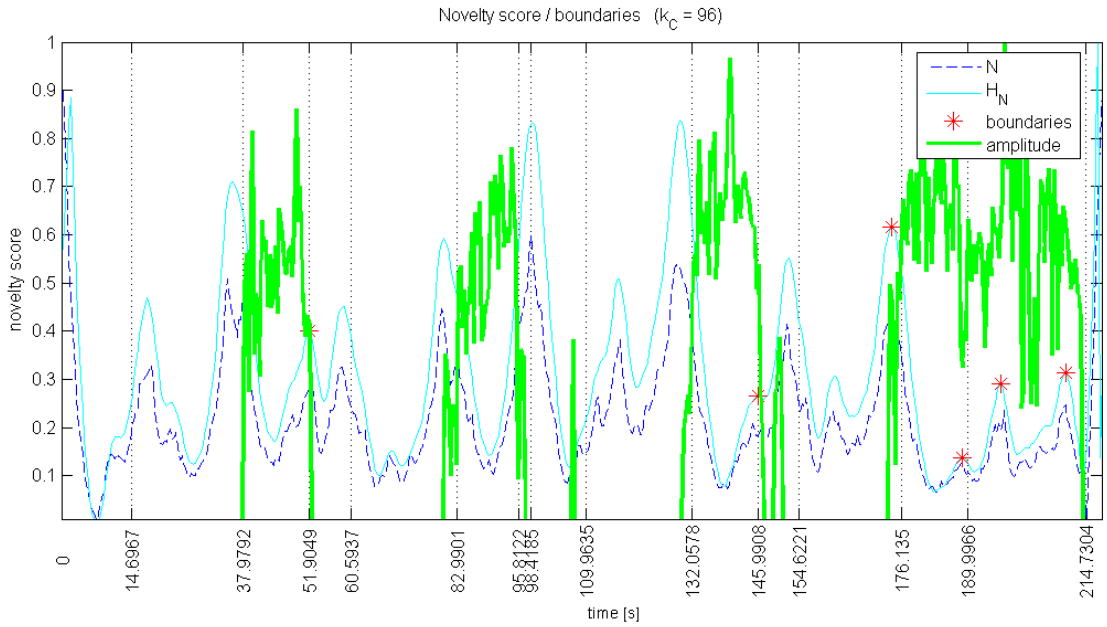
The bad boundary extraction result is due to an inappropriate value of threshold T_{ampl}. (N_H peaks in song sections with an amplitude lower than this threshold are ignored.) Changing this value globally does lead to worse mean performance, though. Thus, an adaptive threshold setting method is advisable.

5.4 Conclusions and future work

As already stated in previous chapters, automatically segmenting songs into their constituents is somehow feasible. It works well especially for songs where segment types differ in terms of spectral content or timbre.



(a) Segmentations of *Björk: It's Oh So Quiet*. Top panel: groundtruth; bottom panel: extracted result. Same color and letter within one panel correspond to same segment type. Note the low F-measure $F = 0.5$.



(b) Novelty score plot of *Björk: It's Oh So Quiet*. For illustration purposes, amplitude values (thick green line) with a sliding average lower than $T_{ampl} = 0.2$ are not visible. Note that only six boundaries remain although there are quite a few H_N peaks that would lead to correct boundaries.

Figure 5.3: Investigation of bad performance of *Björk: It's Oh So Quiet*. For this song a T_{ampl} value of 0.2 is clearly too high.

On the other hand the algorithm presented has problems with slow songs that do not have a distinct transition between their segments, as well as with not-quite-melodic audio content like rap songs.

I was surprised that the large number of experiments and heuristics I tried did not lead to a significant mean performance improvement. As already mentioned one heuristic typically improves segmentation of a subset of songs and impairs results of the rest, leading to almost the same mean performance measure. One reason could be that the groundtruth annotations I used are not consistent enough. Another possibility is that there is noise in terms of segmentation ambiguity which cannot be eliminated. This is supported by tests I carried out as described in Section 2.4.

Results of both phases, boundary detection and structure extraction, are distinctly better than the respective baselines, though.

As to musical form extraction we can conclude that a certain amount of extraction error is not due to using the incorrect number of cluster centers k for k-means. The experiment where k is provided as "minimal user input" showed that even if k is correct, evaluation results show only a modest improvement. Thus, further investigation into more reliable cluster validity indices (which aim at finding correct values for k) seems not too promising.

Again, I would like to note that it is not easy to compare the published performance numbers to results in other papers. We saw that the choice of the underlying corpus has a larger effect on the final evaluation numbers than the change of algorithm parameters and the use of heuristics.

Similarly, it is not obvious how evaluation should take place. As stated, the two performance measures F and F_{abd} produce different results, the latter normally being a bit higher. Consideration must especially be given to the ambiguity of song segmentations. I decided to model it explicitly in the groundtruth annotation data.

Finally, I give the following suggestions for further research:

Chords Chord transcription can be used to obtain the chord sequence of a song. It can be investigated whether this chord representation used as feature vectors improves results over using audio signal feature vectors directly.

Select parameter values song-by-song Since the songs that perform poorly are different for various parameter configurations it seems advisable to develop a procedure or criterion to be able to select an appropriate parameter setting from a pool for each song individually (e.g., for T_{ampl} as noted in *Björk: It's Oh So Quiet* case study in Section 5.3).

User input The potential improvement of minimal user input can further be looked into. Maybe results become even better if the system works iteratively, reacting on user input. Possibilities of simple user input include: indication of beginning and end of *one* section; rejection of individual incorrect segment boundaries; etc.

Evaluation (Consistent groundtruth) The groundtruth annotations I used are a bit ad-hoc. It is desirable to have a well-founded groundtruth, e.g., by consistently employing always the same musicology approach (Section 1.3.2) to all songs. In addition, the performance numbers could be related to the mean evaluation results among groundtruth annotations from different subjects as suggested in Section 2.4.

Simplify Facing the unsuccessful improvement attempts one could also try the other way and simplify the algorithm as much as possible to make a potential implementation in mobile devices easier.

Plugins One obvious practical task is the development of audio player plugins that make use of structure information, e.g., for XMMS, Winamp or Audacity. These plugins could offer features like skipping back and forth between segment boundaries or just visualize the structure.

Statistical evaluation At this place I like to make an appeal to fellow researches to encourage them to compute and publish not the mere mean values of performance measures but also statistical information like confidence intervals.

Flexer compiled a survey on evaluation performance figures published in ISMIR proceedings articles [Fle06]. He states that not even 4 % of articles that publish mean values also report statistical information like significance tests results or confidence intervals that would

> "allow us to express the amount of uncertainty that comes with every experiment. They also enable use to compare the outcome of experiments under different conditions."

The different conditions could be different corpora in our case. Remember Figure 3.10 on page 60 where confidence intervals clearly indicate the high variability of qmul14 corpus results. Mean values alone would be misleading.

Working together It can be fruitful for this research field to consult the musical expertise of professional musicians in an interdisciplinary manner.

5.5 Summary

In the first chapter the reader was introduced to the research field of Automatic Audio Segmentation (AAS).

As a motivation I explained some prospective fields of application for this task, e.g., how AAS can facilitate the browsing in large digital music collections. Next, I gave an overview of related work. I introduced various tasks and goals that are subsumed as AAS (boundary detection, structure detection, audio thumbnailing, semantic label assignment, etc.) I briefly explained mathematical models used (e.g., self-similarity analysis and Hidden Markov Models). Then, corpora and feature sets used in the individual papers have been compared. I pointed out that there is no common corpus so far for benchmark evaluation in this field.

At the end of the first chapter, I showed that musical segmentation is a task that generally leads to ambiguous results and summarized how segmentation is perceived and discussed in musicology literature.

In the next chapter I discussed how evaluation has been carried out in this thesis.

First, I desribed the groundtruth corpus which is one of the largest used so far in this research field. It contains 94 songs collected from two sources. The corpus contains contemporary popular songs of different genres (dance, rock, pop, rap, R&B, etc.).

A novel annotation file format based on XML (*SegmXML*) has been described. This format is flexible, i.e., it can contain two hierarchical levels of segmentation as well as alternative labels for each song segment.

Performance measures for both algorithm tasks have been defined: For the first phase, boundary detection, these are precision P, recall R and F-measure F. The second phase, structure extraction, uses formal distance ratio r_f which is based on edit distance. Besides, also alternative measures have been introduced and discussed. In subsequent chapters these have been used to compare my figures with those of other studies.

I discussed the problem of hierarchical segmentations (two annotations may actually be equivalent but on a different hierarchical level) and described how the evaluation process handles such cases. I decided to explicitely include two levels of segmentation into the groundtruth files.

The evaluation algorithm which is implemented in Perl has been defined in pseudo code notation. At the end of the evaluation process HTML reports are generated. These reports contain performance numbers (mean values over the entire corpus, mean values grouped by genre / corpus and the values of the individual songs), metadata about songs as well as algorithm and evaluation parameter settings and visual representations of each segmentation.

The subsequent two chapters dealt with the algorithm I implemented. It has a segment boundary detection phase followed by a structure extraction phase. The first phase outputs a set of time points where song segments start or end, whereas the output of the second phase is a string like `ABCBDBA` which represents the song structure. Each character stands for one segment, segments of the same type get the same character. Note that these letters do not indicate whether the respective song segment is a chorus or verse section, etc.

For the boundary detection task I used the traditional similarity matrix / novelty score method. There, the similarity between feature vectors of neighbouring song frames are used to compute a novelty score whose peaks indicate more or less sudden changes in the song.

I carried out a number of experiments to improve performance (various feature sets and parameter settings, boundary removing heuristic, boundary shifting post-processing, Harmonic Change Detection Function HCDF). I, however, had to point out that none of these experiments did improve the mean performance in a statistically significant way.

When comparing my figures to those of other studies it could be seen that they were on an equal level. From these figures we could also see that mean performance numbers depend to a large degree on the underlying corpus.

At the end, I could state that boundary detection results are quite acceptable if some points are taken into account (no domain knowledge used, the theoretically optimal result of $F = 1$ is probably inherently unreachable, etc.). Melodic songs which lack rap passages and prominent distorted guitar sound and which do not have a too slow rhythm perform better than other ones.

Turning to musical form detection, I employed clustering in four variants to group segments according to their similarity: k-means and hierarchical clustering with the segments being represented by one mean feature vector, "voting" approach, and k-means with the segment similarity being computed using Dynamic Time Warping (DTW). Evaluation of various algorithm runs showed that the "voting" and DTW approaches are inferior to the other ones if automatically extracted segment boundaries are used.

I explained how I employed cluster validity indices (Davies-Bouldin and Dunn) to find the correct number of cluster centroids, i.e., segment types, for each song. This, however, had no positive effect on the mean performance. Besides, I investigated a semi-supervised approach where this parameter is loaded from groundtruth, simulating a possible user input. The last experiment was the removal of boundaries whose adjacent segments were of the same type. I pointed out that these experiments did produce statistically insignificant better results only.

Again, I compared my evaluation results with those of another paper. The comparison showed that my qmul14 corpus results, again, are equal to the already published numbers.

In the last chapter I presented the results of a five-fold cross validation. Those numbers indicated that the training set (four fifth of the corpus) had no bias: evaluation results of both the training set and the validation set did not differ.

Also, I did one algorithm run on a test set of fifteen additional songs that have not been used for parameter selection so far. Again, the results were not significantly different and thus quite promising: It seems that no overfitting took place and the algorithm together with (at least) this parameter set is general enough to apply it to new songs.

Next, I presented two case studies where computed segmentation actually delivered more information than the respective groundtruth annotation files contained. This is a good sign for the practical application of the algorithm.

There are, however, open issues: the case study of a rather soft and slow song revealed that it is advisable for some parameters not to set them to a fixed value for all songs but to make them change adaptively. This and other suggestions for future work have been listed in the last section of this chapter.

You can find groundtruth annotations, HTML reports, segmented songs for acoustic demonstration purposes as well as Perl and Matlab source code at `http://www.ifs.tuwien.ac.at/mir/audiosegmentation/`.

Appendix A

Appendix

A.1 Software used

Name	Used for	URL
Wavesurfer	manual segmentation	http://www.speech.kth.se/wavesurfer/
Matlab 7.0.1	feature extraction, prototyping.	http://www.mathworks.com/products/matlab/
Signal Processing Toolbox	feature extraction	included in Matlab 7.0.1
Dan Ellis' DTW toolbox	similarity matrix, Dynamic Time Warping	http://www.ee.columbia.edu/~dpwe/resources/matlab/
Somtoolbox	k-means clustering, DB cluster validity index	http://www.cis.hut.fi/projects/somtoolbox/
LaTeX(Miktex)	typesetting	http://www.miktex.org/Default.aspx
TeXnicCenter	editor	http://www.toolscenter.org/
Perl	evaluation system, conversion scripts	http://www.perl.com
Xalan-J	XSLT engine	http://xml.apache.org/xalan-j/

Table A.1: Programs used for this thesis

A.2 SegmXML example file and schema definition file

Listing A.1: Britney_Spears_-_Hit_Me_Baby_One_More_Time.xml – segmentation XML file for *Hit Me Baby One More Time* by Britney Spears

```
<?xml version="1.0" encoding="UTF-8"?>
<SegmXML version="1.0">
  <metadata>
    <song canonicalname="Britney_Spears_-_Hit_Me_Baby_One_More_Time">
      <title>Hit Me Baby One More Time</title>
      <artist>Britney Spears</artist>
      <album year="">Hit Me Baby One More Time</album>
      <musicbrainz_trackID/>
      <duration duration_sec="212">03:32</duration>
    <genre>Rock/Pop/Dance</genre></song>
    <annotation source="ground truth">
      <done_by note="primary author(s)">Mark Levy/Geoffroy Peeters/Katy Noland</
          done_by>
      <done_by timestamp="2007-02-24" note="adapted by">Ewald Peiszer</done_by>
    </annotation>
  </metadata>
  <segmentation>
    <segment label="intro" start="00:00:000" end="00:11:572" start_sec="0.0000000"
        end_sec="11.5729710"/>
    <segment label="verse" start="00:11:572" end="00:21:903" start_sec="11.5729710
        " end_sec="21.9032200"/>
    <segment label="verse" start="00:21:903" end="00:32:222" start_sec="21.9032200
        " end_sec="32.2224040"/>
    <segment label="trans_show_me" start="00:32:222" end="00:42:549" start_sec="
        32.2224040" end_sec="42.5493880"/>
    <segment label="chorus" start="00:42:549" end="01:03:240" start_sec="
        42.5493880" end_sec="63.2403630">
      <segment label="part1" start="00:42:549" end="00:52:894" start_sec="
          42.5493880" end_sec="52.8948750"/>
      <segment label="part2" start="00:52:894" end="01:03:240" start_sec="
          52.8948750" end_sec="63.2403630"/>
    </segment>
    <segment label="verse" start="01:03:240" end="01:13:709" start_sec="63.2403630
        " end_sec="73.7090269"/>
    <segment label="verse" start="01:13:709" end="01:23:840" start_sec="73.7090269
        " end_sec="83.8408160"/>
    <segment label="trans_show_me" start="01:23:840" end="01:34:186" start_sec="
        83.8408160" end_sec="94.1863950"/>
    <segment label="chorus" start="01:34:186" end="01:54:824" start_sec="
        94.1863950" end_sec="114.8248530">
      <segment label="part1" start="01:34:186" end="01:44:489" start_sec="
          94.1863950" end_sec="104.4897960"/>
```

```
30      <segment label="part2" start="01:44:489" end="01:54:824" start_sec="
            104.4897960" end_sec="114.8248530"/>
31    </segment>
32    <segment label="intro" start="01:54:824" end="02:05:136" start_sec="
          114.8248530" end_sec="125.1361450"/>
33    <segment label="verse" start="02:05:136" end="02:15:239" start_sec="
          125.1361450" end_sec="135.2390183">
34      <alt_label>verse2</alt_label>
35    </segment>
36    <segment label="verse" start="02:15:239" end="02:25:801" start_sec="
          135.2390183" end_sec="145.8019950">
37      <alt_label>verse2</alt_label>
38    </segment>
39    <segment label="chorus" start="02:25:801" end="03:28:551" start_sec="
          145.8019950" end_sec="208.5515650">
40      <alt_label>chorus2</alt_label>
41      <segment label="part1" start="02:25:801" end="02:36:307" start_sec="
            145.8019950" end_sec="156.3073933"/>
42
43      <segment label="part2" start="02:36:307" end="02:46:467" start_sec="
            156.3073933" end_sec="166.4679370"/>
44      <segment label="part1" start="02:46:467" end="02:56:753" start_sec="
            166.4679370" end_sec="176.7531970"/>
45      <segment label="part2" start="02:56:753" end="03:07:189" start_sec="
            176.7531970" end_sec="187.1892060"/>
46
47      <segment label="part1" start="03:07:189" end="03:17:631" start_sec="
            187.1892060" end_sec="197.6319782"/>
48
49      <segment label="part2" start="03:17:631" end="03:28:551" start_sec="
            197.6319782" end_sec="208.5515650"/>
50    </segment>
51  </segmentation>
52 </SegmXML>
```

Listing A.2: XML Schema Definition for SegmXML files version 1.0

```
1  <?xml version="1.0"?>
2  <xs:schema xmlns="http://thesis.ewald-peiszer.com" xmlns:xs="http://www.w3.org
       /2001/XMLSchema" targetNamespace="http://thesis.ewald-peiszer.com">
3    <xs:element name="SegmXML">
4      <xs:complexType>
5        <xs:sequence>
6          <xs:element name="metadata">
7            <xs:complexType>
8              <xs:sequence>
9                <xs:element name="song">
10                 <xs:complexType>
```

```
11                  <xs:all>
12                    <xs:element name="title" type="xs:string"/>
13                    <xs:element name="artist" type="xs:string"/>
14                    <xs:element name="album">
15                      <xs:complexType>
16                        <xs:simpleContent>
17                          <xs:extension base="xs:string">
18                            <xs:attribute name="year" type="xs:positiveInteger"/>
19                          </xs:extension>
20                        </xs:simpleContent>
21                      </xs:complexType>
22                    </xs:element>
23                    <xs:element name="recordlabel" minOccurs="0" type="xs:string"/
                          >
24                    <xs:element name="genre" type="xs:string"/>
25                    <xs:element name="duration">
26                      <xs:complexType>
27                        <xs:simpleContent>
28                          <xs:extension base="time_mm_ss">
29                            <xs:attribute name="duration_sec" type="
                                   xs:positiveInteger"/>
30                          </xs:extension>
31                        </xs:simpleContent>
32                      </xs:complexType>
33                    </xs:element>
34                    <xs:element name="musicbrainz_trackID" type="xs:token"/>
35                  </xs:all>
36                  <xs:attribute name="canonicalname" type="xs:normalizedString"
                        use="required"/>
37                </xs:complexType>
38              </xs:element>
39              <xs:element name="annotation">
40                <xs:complexType>
41                  <xs:sequence>
42                    <xs:element name="done_by" maxOccurs="unbounded">
43                      <xs:complexType>
44                        <xs:simpleContent>
45                          <xs:extension base="xs:string">
46                            <xs:attribute name="timestamp" type="xs:string"/>
47                          <xs:attribute name="note" type="xs:string"/>
48                            </xs:extension>
49                          </xs:simpleContent>
50
51                        </xs:complexType>
52                    </xs:element>
53                    <xs:element name="remark" minOccurs="0" type="xs:string"/>
54                  </xs:sequence>
55                  <xs:attribute name="source" type="xs:string" use="required"/>
```

```
56                </xs:complexType>
57              </xs:element>
58            </xs:sequence>
59          </xs:complexType>
60        </xs:element>
61        <xs:element name="segmentation">
62          <xs:complexType>
63            <xs:sequence>
64              <xs:element name="segment" maxOccurs="unbounded">
65                <xs:complexType>
66                  <xs:sequence>
67                    <xs:element name="alt_label" minOccurs="0" type="xs:string"/>
68                    <xs:element name="remark" minOccurs="0" type="xs:string"/>
69                    <xs:element name="segment" minOccurs="0" maxOccurs="unbounded"
                           >
70                      <xs:complexType>
71                        <xs:attribute name="label" type="xs:string" use="required"
                               />
72                        <xs:attribute name="start" type="time_mm_ss_millis" use="
                               required"/>
73                        <xs:attribute name="end" type="time_mm_ss_millis" use="
                               required"/>
74                        <xs:attribute name="start_sec" type="xs:decimal" use="
                               required"/>
75                        <xs:attribute name="end_sec" type="xs:decimal" use="
                               required"/>
76                        <xs:attribute name="instrumental" type="xs:boolean"/>
77                        <xs:attribute name="fade" type="T_fade"/>
78                      </xs:complexType>
79                    </xs:element>
80                  </xs:sequence>
81                  <xs:attribute name="label" type="xs:string" use="required"/>
82                  <xs:attribute name="start" type="time_mm_ss_millis" use="
                         required"/>
83                  <xs:attribute name="end" type="time_mm_ss_millis" use="required"
                         />
84                  <xs:attribute name="start_sec" type="xs:decimal" use="required"/
                         >
85                  <xs:attribute name="end_sec" type="xs:decimal" use="required"/>
86                  <xs:attribute name="instrumental" type="xs:boolean"/>
87                  <xs:attribute name="fade" type="T_fade"/>
88                </xs:complexType>
89              </xs:element>
90            </xs:sequence>
91          </xs:complexType>
92        </xs:element>
93      </xs:sequence>
94      <xs:attribute name="version" type="xs:decimal" use="required"/>
```

```
95      </xs:complexType>
96    </xs:element>
97    <xs:simpleType name="time_mm_ss_millis">
98      <xs:restriction base="xs:string">
99        <xs:pattern value="[0-9]{2}:[0-9]{2}:[0-9]{3}"/>
100     </xs:restriction>
101   </xs:simpleType>
102   <xs:simpleType name="time_mm_ss">
103     <xs:restriction base="xs:string">
104       <xs:pattern value="[0-9]{2}:[0-9]{2}"/>
105     </xs:restriction>
106   </xs:simpleType>
107   <xs:simpleType name="T_fade">
108     <xs:restriction base="xs:string">
109       <xs:enumeration value="in"/>
110       <xs:enumeration value="out"/>
111     </xs:restriction>
112   </xs:simpleType>
113 </xs:schema>
```

A.3 Corpus

Table A.2 lists the 94 songs that have been used for experiments and parameter selection. The fifteen additional songs of the "test set" are given in Table A.3. For each song, the membership in other author's corpora and in music databases like RWC is stated. The corpus names are explained in Section 2.1 (page 18).

Table A.2: 94 song corpus for experiments and parameter selection

Artist	**Title**	**Belongs to ... corpus**
A-HA	Take on me	qmul, qmul14
ABBA	SOS	Paulus, MUSIC
ABBA	Waterloo	Paulus, MUSIC
Alanis Morissette	Head Over Feet	qmul, qmul14
Alanis Morissette	Thank You	qmul, qmul14
Artful Dodger feat. Craig David	Rewind	Paulus, MUSIC
Beastie Boys	Intergalactic	qmul
Beatles	All I've Got To Do	qmul

Artist	**Title**	**Belongs to ... corpus**
Beatles	All My Loving	qmul
Beatles	Devil In Her Heart	qmul
Beatles	Don't Bother Me	qmul
Beatles	Hold Me Tight	qmul
Beatles	I saw her standing there	qmul
Beatles	I Wanna Be Your Man	qmul
Beatles	It Won't Be Long	qmul
Beatles	Little Child	qmul
Beatles	Misery	qmul
Beatles	Money	qmul
Beatles	Not A Second Time	qmul
Beatles	Please Mister Postman	qmul
Beatles	Roll Over Beethoven	qmul
Beatles	Till There Was You	qmul
Beatles	You Really Got A Hold On Me	qmul
Beatles	Anna go to	qmul
Beatles	Please please me	Paulus
Björk	It's Oh So Quiet	qmul, qmul14
Black Eyed Peas	Cali To New York	qmul
Britney Spears	Hit Me Baby One More Time	qmul, qmul14
Britney Spears	Oops I Did It Again	Paulus, MUSIC
Chicago	Old Days	qmul
Chumbawamba	Thubthumping	qmul, qmul14
Coolio	The Devil Is Dope	Paulus, MUSIC
Cranberries	Zombie	qmul, qmul14
Creedence Clearwater Revival	Have You Ever Seen the Rain	Paulus, MUSIC
Depeche Mode	It's no good	Paulus, MUSIC
Desmond Dekker	You Can Get It If You Really Want	Paulus, MUSIC
Deus	Suds & Soda	qmul, qmul14
Dire Straits	Money For Nothing	Paulus, MUSIC

Artist	**Title**	**Belongs to ... corpus**
Eminem ft. Dido	Stan	Paulus, qmul, MUSIC
Faith No More	Epic	Paulus, MUSIC
Gloria Gayner	I Will Survive	qmul
KC and the Sunshine Band	That's the Way I Like It	Paulus, MUSIC
KoRn	Got The Life	Paulus, MUSIC
Lucy Pearl	Don't Mess With My Man	Paulus, MUSIC
Madonna	Like a virgin	qmul
Madonna	Into the Groove	Paulus, MUSIC
Marilyn Manson	Sweet Dreams	Paulus, MUSIC
Michael Jackson	Bad	Paulus, qmul, MUSIC
Michael Jackson	Black Or White	Paulus, qmul, MUSIC
Nick Drake	Northern Sky	qmul
Nirvana	Smells like teen spirit	qmul, qmul14
Nora Jones	Lonestar	qmul
Oasis	Wonderwall	qmul, qmul14
Pet Shop Boys	Always On My Mind	Paulus, MUSIC
Portishead	Wandering star	qmul
Prince	Kiss	qmul
Queen Yahna	Ain't It Time	Paulus, MUSIC
R.E.M.	Drive	qmul
R Kelly	I Believe I Can Fly	Paulus, MUSIC
Radiohead	Creep	qmul, qmul14
Red Hot Chili Peppers	Parallel Universe	Paulus, MUSIC
Salt N Pepa	Whatta Man	Paulus, MUSIC
Saxon	The Great White Buffalo	Paulus, MUSIC
Scooter	How Much Is The Fish	Paulus, MUSIC
Seal	Crazy	qmul, qmul14
Shania Twain	You're Still The One	Paulus, MUSIC
Simply Red	Stars	qmul
Sinhead O Connor	Nothing compares to you	qmul

Artist	**Title**	**Belongs to ... corpus**
Spice Girls	Wannabe	qmul, qmul14
Suede	Trash	Paulus, MUSIC
The Beatles	A Day In The Life	qmul
The Beatles	A Hard Days Night	Paulus
The Beatles	Being For The Benefit Of Mr. Kite	qmul
The Beatles	Fixing A Hole	qmul
The Beatles	Getting Better	qmul
The Beatles	Good Morning Good Morning	qmul
The Beatles	Help	Paulus
The Beatles	I Should Have Known Better	Paulus
The Beatles	If I Fell	Paulus
The Beatles	I'm Happy Just To Dance With You	Paulus
The Beatles	Lovely Rita	qmul
The Beatles	Lucy In The Sky With Diamonds	qmul
The Beatles	Sgt. Peppers Lonely Hearts Club Band	qmul
The Beatles	Sgt. Peppers Lonely Hearts reprise	qmul
The Beatles	She's Leaving Home	qmul
The Beatles	When I'm Sixty-Four	qmul
The Beatles	With A Little Help From My Friends	qmul
The Beatles	Within You Without You	qmul
The Clash	Combat Rock	qmul, qmul14
The Jacksons 5	Can You Feel It	Paulus, MUSIC
The Monkees	Words	qmul
The Police	Message In A Bottle	Paulus, MUSIC
The Roots	The Next Movement	Paulus, MUSIC
The Roots ft. Erykah Badu	You Got Me	Paulus, MUSIC

Artist	Title	Belongs to ... corpus / annotated by
Apollo 440	Stop The Rock	Andrei Grecu
Eav	Wo Ist Der Kaiser	Andrei Grecu
Kazuo Nishi	Eien no replica	RWC-Pop (01), Paulus
Hiromi Yoshii	Magic in your eyes	RWC-Pop (02), Paulus
Fevers	Jinsei konnamono	RWC-Pop (08), Paulus
Kazuo Nishi	Doukoku	RWC-Pop (09), Paulus
Kazuo Nishi	Kage-rou	RWC-Pop (12), Paulus
Hisayoshi Kazato	Cool Motion	RWC-Pop (19), Paulus
Rin	Feeling In My Heart	RWC-Pop (21), Paulus
Mitsuru Tanimoto	Syounen no omoi	RWC-Pop (30), Paulus
Hiromi Yoshii	Dream Magic	RWC-Pop (33), Paulus
Hiromi Yoshii	Midarana kami no moushigo	RWC-Pop (35), Paulus
The Crystal Method	Born Too Slow	Andrei Grecu
Wise Guys	Kinder	Ewald Peiszer
Wise Guys	Powerfrau	Ewald Peiszer

Table A.3: Additional songs of the corpus (“test set”)

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