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Master Thesis

# Towards Automated Retrieval of Audio Recordings based on Musical Themes

submitted by

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Erlangen, 5. November 2014

Lukas Lamprecht

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# Abstract

The research area of music information retrieval deals with the development of automated methods for analyzing, organizing and searching musical content in a robust and intelligent manner. In particular, music retrieval based on the query-by-example paradigm has received a lot of research attention: Given a music representation or a fragment of it (used as query or example), the task is to automatically retrieve documents from a music database containing parts or aspects that are similar to it.

In this thesis, we consider a cross-modal retrieval scenario, where the queries are symbolic encodings of musical themes and the database documents are audio recordings of musical performances. The task is to identify all audio recordings that contain the musical theme specified by a query. Within this scenario, we consider several challenges. First, there may be significant variations in the global and local tempo between query and the audio recordings. Second, the musical theme is monophonic, whereas the corresponding section in an audio recording may be polyphonic. Third, the audio recording may be transposed or detuned compared to the query.

The main contributions of this thesis are as follows. First, using methods from signal processing and information retrieval, we adapt an existing retrieval pipeline to cope with the various challenges. Second, we develop a large database consisting of several thousand musical themes and audio recordings of Western classical music. Third, we conduct extensive experiments by systematically adjusting parameters for the feature computation and retrieval step. As a result, we do not only improve the retrieval results, but also gain a deeper understanding of the underlying musical data.

# Contents

# Chapter 1

# Introduction

Today, we live in a world in which large music collections are omnipresent. In the last years, the demand for online music collections and services strongly increased (see Figure 1.1). Services like Spotify[1], SHAZAM[2] and the International Music Score Library Project[3] (IMSLP) became more and more popular. The services and the underlying types and formats of data which include text, symbolic data, images and audio provided by these three platforms are quite different. The IMSLP for example contains 81,547 musical works and 281,541 scores by 11,250 composers, and 30,440 audio recordings by 282 performers [15][4]. But dealing with such large collections of data also bares problems. For that reason, research groups from all over the world have considered issues in the field of *music information retrieval* (MIR), a research area that opens up new possibilities regarding the organization of large databases of music in an automated or semi-automated fashion. The organization of large music databases can be simplified by *automated retrieval* techniques. By analyzing, correlating and comparing the multimodal data, the aim is to identify the data and establish semantically meaningful relationships between different types of data, such that not only the database can be used in an intuitive fashion, but also searches lead to good results, even for non-sophisticated users.
To find data within a database, the user has to specify his information needs by means of a so called *query*. The retrieval system should then retrieve all documents from a data collection that are somehow related to the query. The retrieved *documents* are then displayed on a ranked list in a sorted fashion. For many *Information Retrieval* tasks, the query and the documents are available in the same format. An example for this scenario is to specify a keyword as query in order to search through an e-book. Using such text based retrieval systems for music collections require the audio material to be enriched with suitable metadata. In general however, the query and the documents do not necessarily have to be available in the same format. For example, someone, who only remembers a short melody, wants to find the underlying musical work without the knowledge of its composer and title. The query is then specified by singing or humming this melody into a microphone (*query-by-humming*). To cope with this task, a *content based retrieval* system is needed, that only makes use of the raw music data, rather than relying on manually generated metadata. The term *content* in this context refers to any kind of information

[1] www.spotify.com
[2] www.shazam.com
[3] www.imslp.org
[4] Retrieved on 23.07.2014

that can be directly derived from the music material to be queried, compared and retrieved. In particular, content-based retrieval strategies that follow the *query-by-example* paradigm are of great importance: Given a music representation or a fragment of it (used as query or example), the task is to automatically retrieve documents from a music collection containing parts or aspects that are similar to it.

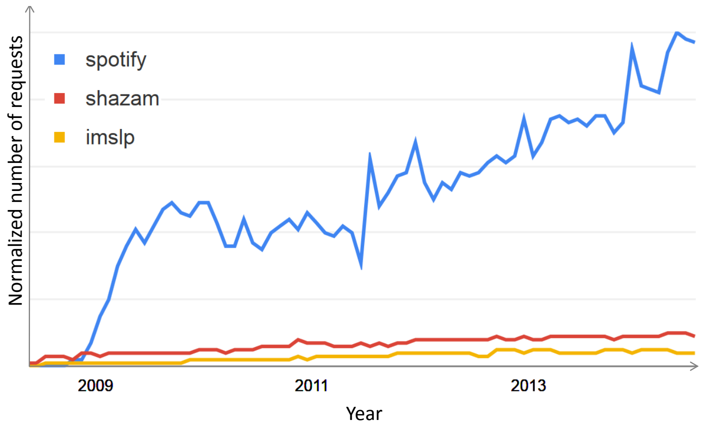



Figure 1.1: Demand on music platforms and services measured by the number of search requests on Google. Retrieved from `www.google.de/trends`.

## 1.1 Retrieval Scenario

The task of this thesis is the adaptation of a query-by-example task on datasets based on Western classical music. On the one hand, we consider musical themes given in some symbolic format, and on the other hand audio recordings of entire pieces of music. Then, given a musical theme used as query, the task is to identify the audio recording of the musical work containing this theme. The retrieved documents are then displayed on a ranked list.

In this thesis, we use three different music representations. *Sheet music* available as digital images visually represents a score or a piece of music. Furthermore, *symbolic* music data available in MIDI[5] format is used. Finally, we use *audio recordings* in WAV format that encode acoustic sound waves [10, pp.17-27]. The symbolic music data that is used in this thesis is derived from the book "A DICTIONARY OF MUSICAL THEMES" by Harold Barlow and Sam Morgenstern [1] (which we will refer to as `BM` in this thesis). This dictionary contains roughly 10,000 musical themes of mainly instrumental Western classical music which we will refer to as "`BM`-themes". The `BM` was designed as a reference book for trained musicians and professional performers. It was published in the year 1948 and is an early approach for query-by-example tasks. By playing a theme in the key of C Major or Minor (for themes in major or minor respectively), the note sequence can be looked up in the so called notation index in the `BM`. With the notation index, we can find the theme, the theme name and the corresponding composer in the `BM` [1, pp.viii-ix]. Most of the `BM`-themes are also available as MIDI-files provided by the Electronic

[5]MIDI is a standard that is used for electronic instruments and communication between electronic instruments and computers [9].

Dictionary of Musical Themes (EDM)[6] [18], which are used as queries in this thesis. We refer to these themes as "EDM-themes". Finally, a collection of audio recordings from musical works that are also listed in the BM is used as dataset for this thesis. In particular we create three datasets which we refer to as subsets. Every subset contains several audio recordings and the corresponding EDM-themes. The content of these subsets will be described in more detail in Chapter 3.2.

Our retrieval scenario offers several challenges, which are described hereafter, where the corresponding technical terms are specified in bold print.
The underlying data is **cross-modal**, as the database contains EDM-themes available in a symbolic music format as well as audio recordings in WAV file format. Furthermore, the EDM-themes are monophonic consisting of a melody without accompanying harmony. In contrast, the audio recordings are typically homophonic (music with one dominant melodic voice accompanied by chords) or polyphonic (music with two or more simultaneous lines of independent melody) (**degree of polyphony**). The EDM-themes are of very short duration and are looked up in a large database, so they may be of low **specificity** (having a low discriminative power). The audio recording may be **transposed** and thus be available in another key than the EDM-theme. The audio recordings may be **detuned**. The **tempo** of the audio recordings may differ widely from the tempo specified in the corresponding EDM-theme. There may be high local **tempo variations** in the audio recording which are not present the corresponding EDM-theme. The **dynamics** of the audio recordings may be quite high. Finally, the **quality** of some audio recordings may be quite low, especially for old recordings which are often noisy. However the task of improving audio quality and dynamics reduction is not treated in this thesis.
In this thesis we create a so called pipeline, which performs the processing of the entire matching procedure. Furthermore we systematically analyze the underlying data, which makes it possible to improve the retrieval results by adjusting parameters of the pipeline.

In the following, we will have a look at the specific steps of the pipeline needed to realize the query-by-example task. An overview of the pipeline is given in Figure 1.2. The EDM-theme corresponding to Beethoven's 5$^{\text{th}}$ Symphony, 1$^{\text{st}}$ Movement, 1$^{\text{st}}$ Theme is used as query. The database consists of several audio recordings. As these two different formats cannot be compared directly, a mid-level representation is needed. Therefore, the query as well as the database are converted into chroma-based features. These features are aligned by using a subsequence-dynamic time warping (SDTW) strategy to compensate tempo differences between the query and the database. The SDTW leads to a matching function. In case the matching process was successful, the minimum of this function indicates an excerpt of the database that is semantically related to the query. This matching function is then analyzed and a ranked list is created, which shows the retrieval results for this query. Finally, an evaluation is performed to validate the retrieval quality. To this end, evaluation measures like the Top N Match and the Mean Rank are calculated for many different queries by using ground truth data. Similar processing pipelines have already been used before, e. g, in [4] for the task of sheet music-audio identification. Related music matching tasks have been considered in [3] and [21].

[6] http://www.multimedialibrary.com/barlow/

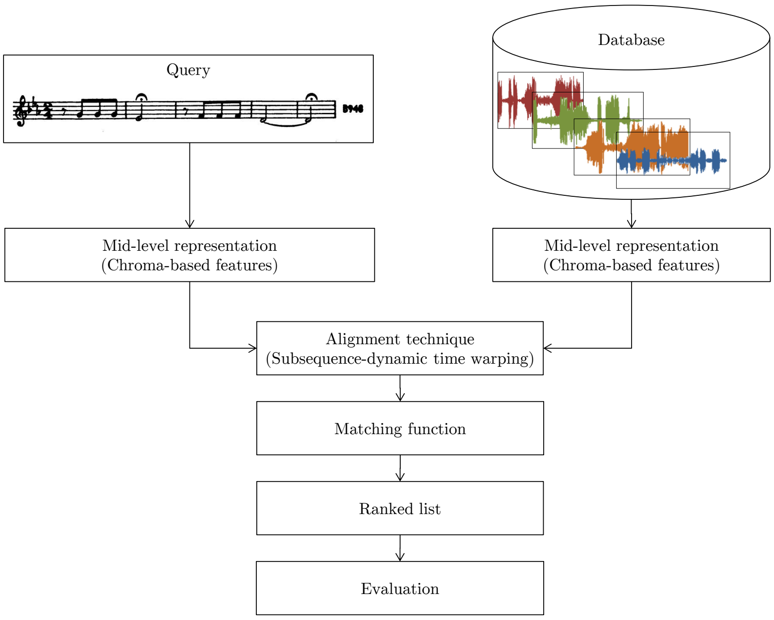



Figure 1.2: Overview of the pipeline, showing the different steps of the matching process.

## 1.2 Main Contributions

In this thesis we modify an existing pipeline to evaluate its performance depending on several parameter settings. Furthermore several intermediate steps of the pipeline are analyzed for selected data to improve the retrieval results. Therefore, we introduce an enhanced version of chroma features that takes tuning errors into account. Several strategies are implemented and evaluated to compensate great tempo differences between query and audio recording. Moreover, we adjust different parameter settings to further improve the retrieval.

In this thesis we create subsets containing `EDM`-themes from the website [18] and corresponding audio recordings. We generate ground truth data by excluding corrupted `EDM`-themes and apply a mapping between the `EDM`-themes and the corresponding audio recordings. Several exceptions in the data that occur are documented and problems are analyzed and discussed.

## 1.3 Thesis Organization

In this section, we give an overview of the structure of this thesis and briefly describe the content of each chapter.

Chapter 2 describes the intermediate steps that are essential for matching MIDI files to audio recordings like the calculation of chroma features and alignment techniques. In this Chapter we introduce an enhanced version of chroma features. Furthermore, evaluation measures are introduced.

In Chapter 3 we explain the pipeline for the matching process step by step, using the techniques we introduced in Chapter 2 as a foundation. Additionally, we introduce and describe the subsets.

In Chapter 4 we tune the parameters of our pipeline, whereas we use a database of 100 audio recordings. We then fix one parameter setting to perform and evaluate an experiment on a database of 1113 audio recordings. By analyzing several statistical measures we get insight in the underlying data. Finally, we analyze our pipeline for specific queries with respect to certain properties, like tuning, tempo variations and polyphony.

Chapter 5 concludes the thesis by recapitulating the main achievements. Besides, it provides motivations for future research in this area.

# Chapter 2

# Audio Matching

In this chapter, we introduce the intermediate steps we perform to match symbolic music data to audio recordings in a database. Symbolic music data cannot be compared to audio recordings directly, as the underlying data types are different. To resolve this issue, each of the files is converted into a mid-level representation. With this mid-level representation we can compare the content of the different data formats on an abstract level. We use chroma features as mid-level representation which are described in Section 2.1 closely following [10, pp.60-64]. Chroma features were published for the first time in [5], where they are called Pitch Class Profiles (PCP). In [6], [17] and [19] they are called Harmonic Pitch Class Profiles (HPCP). In Section 2.1.2 we introduce an enhanced version of chroma features.

To compensate tempo deviations and tempo changes between the mid-level representations of query and database we use subsequence-dynamic time warping (SDTW) as alignment technique for the audio matching which is described in Section 2.2, closely following [10, pp.69-82]. In Section 2.3 we introduce the cyclic shift operator which allows us to compensate errors in tuning and transposition. Finally, we describe evaluation measures in Section 2.4.

## 2.1 Chroma Features

Human auditory perception is similar for pitches that differ by one or more octaves [10, p. 60]. "A pitch can be separated into two components, which are referred to as *tone height* and *chroma*. The tone height refers to the octave number and the chroma to the respective pitch spelling attribute contained in the set {C,C#,D,...,B}" [10, p.60] as used in Western music notation [11, p.2]. A *chroma feature* is a twelve dimensional vector consisting of one numeric value for each chroma. This value indicates the portion of the underlying music material which can be assigned to the respective chroma. We can compute chroma features both from audio signals, as well as from MIDI files. Given an audio signal, the signal is segmented into equidistant overlapping frames of fixed length. Each of the frames is converted into a chroma feature vector, resulting in a chromagram. A MIDI file can be processed in a similar way. Figure 2.1(e) and 2.1(f) show chromagrams derived from a MIDI file and an audio recording. Both kinds of music representations are derived from Beethoven's 5$^{\text{th}}$ Symphony, 1$^{\text{st}}$ Movement, 1$^{\text{st}}$ Theme. For that reason both chromagrams are quite similar. We can see that the chromagram of the MIDI file contains almost only zeros and ones (ignoring some gray entries which occur due to smoothing effects). The reason is, that a MIDI file describes the onset and offset time, and the key velocity (which is correlated to the loudness) for each pitch. The chromagram of the audio recording shows the same dominant melody containing the pitches {G,D#,F,D}. Furthermore, we see gray entries in the chromagram that indicate that other pitches are also active. This is because the audio recording is polyphonic, whereas the MIDI file is monophonic.

Figure 2.1(a) visualizes the content of the previously mentioned MIDI file in a piano roll representation. We now compute pitch features, as shown in Figure 2.1(c). The pitch features are directly derived from the MIDI file. We use the 88 pitches on a piano keyboard as a basis for the calculation of the chroma features, which correspond to the MIDI pitches $p = 21$ to $p = 108$. A chromagram is derived by summing up all values of the same chroma, for each pitch $p$ and time instant $n \in \mathbb{Z}$, from the pitch features $\mathcal{Y}_{\mathrm{LF}} : \mathbb{Z} \times [21 : 108] \to \mathbb{R}_{\geq 0}$:

$$\mathcal{C}(n, c) := \sum_{\{p \in [21:108] \,|\, p \bmod 12 = c\}} \mathcal{Y}_{\mathrm{LF}}(n, p) \tag{2.1}$$

for $c \in [0 : 11]$.

We calculate the chromagram for the audio recording in the same way, whereas the pitch features have to be calculated first. As an audio recording encodes acoustic waves in time domain (see Figure 2.1(b)), we apply a multirate filterbank with 88 bandpass-filters and a -3dB bandwidth of one semitone per bandpass-filter. The center frequencies of the 88 frequency bands correspond to the MIDI pitches $p = 21$ to $p = 108$. This leads to a sequence of 88 dimensional pitch features where the entries correspond to the mentioned MIDI pitches [11, p.3], see Figure 2.1(d).

### 2.1.1 CENS Features

Chroma energy normalized statistics (CENS) are derived from the chroma features we introduced in Section 2.1. First of all, each chroma vector $x$ is replaced by its $l^1$-norm $x/\|x\|_1$ to express the relative distribution of the energy of the signal in the 12 chroma bands, where

$$\|x\|_1 := \sum_{i=0}^{11} |x(i)| \tag{2.2}$$

is the $l^1$-norm of $x$. This normalization step makes the features more robust to differences in sound intensity or dynamics. During passages of very low energy, we replace the chroma vector $x$ by the uniform distribution to avoid random energy distributions. Then a logarithmic quantization is applied on each of the twelve chroma values per chroma vector. This quantization step models the logarithmic sensation of the sound intensity of the human ear. Then the features are smoothed over a window of length $\omega \in \mathbb{N}$ and downsampled by a factor of $d$. Finally the resulting features are normalized with respect to the $l^2$-norm

$$\|x\| := \Big( \sum_{i=0}^{11} |x(i)|^2 \Big)^{1/2} \tag{2.3}$$

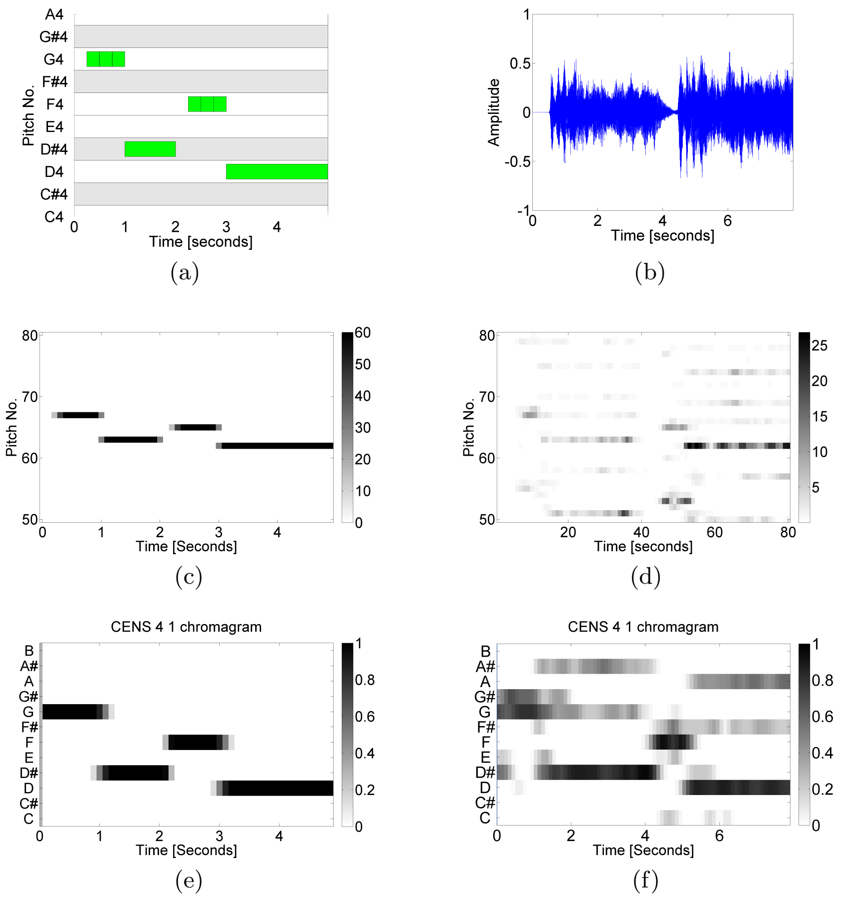


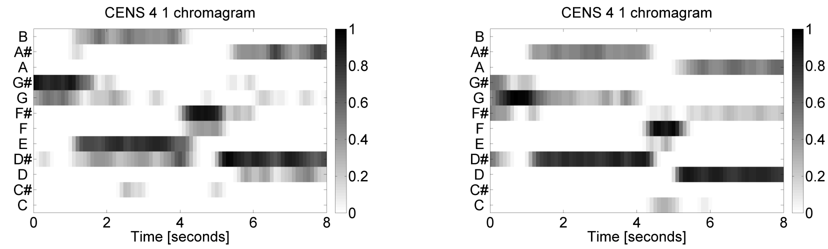

Figure 2.1: Derivation of chroma features from MIDI and audio for Beethoven's 5th Symphony. (a) MIDI (b) Audio (c) Pitch features derived from MIDI. (d) Pitch features derived from audio. (e) CENS features derived from MIDI. (f) CENS features derived from audio.

and denoted by $\text{CENS}^{\omega}_{d}$ or CENS $\omega$ $d$ where $\omega$ is the length of the smoothing window and $d$ is the downsampling factor [10, p.61], [12, pp.2-3].

### 2.1.2 36-dimensional CENS Features

A recurring problem in our concerned retrieval scenario is that audio recordings may strongly vary in their tuning. When computing chroma features for an audio recording this often leads to chroma features that are smeared between chroma bands. This is the case since chroma features are designed for a specified tuning (A4 of 440 Hz) and cannot adapt to the exact tuning of the audio recording. When computed for an audio recording having a different tuning, the energy of a certain pitch class of this recording spreads across several chroma bands in the chroma features since the range of the bandpass-filters do not match the pitch classes of the audio recording. For an example, see Figure 2.2(a).

To resolve this issue we revert to 36-dimensional chroma features. Here, the idea is to have a finer chroma resolution than one semitone, as it is the case for 12-dimensional chroma features.




(a) (b)

Figure 2.2: (a) Chromagram of an audio recording that is detuned by +1/3 semitone. (b) Chromagram of an audio recording that is detuned by +1/3 semitone using a filterbank that is also detuned by +1/3 semitone.

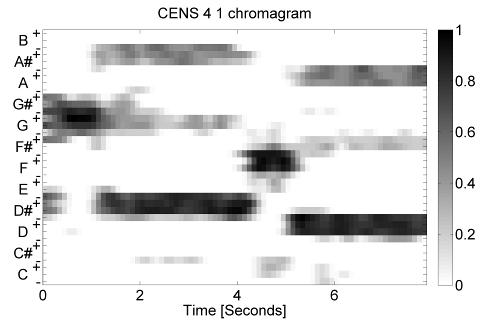



Figure 2.3: 36-dimensional CENS features derived from Beethoven's $5^{\text{th}}$ Symphony, $1^{\text{st}}$ Movement.

Instead of having one band for each of the 12 chroma, we extend this notion to three bands per chroma. These bands reflect the respective chroma for the standard tuning, a tuning of $-1/3$ semitone, and a tuning of $+1/3$ semitone. Still keeping the width of each chroma band to be equivalent to one semitone, this allows us to capture three different tunings simultaneously. To indicate the tuning we add a '-' or '+' sign to the respective chroma labels, see Figure 2.3.

In order to compute 36-dimensional chroma features we first compute the 12-dimensional chroma features. Therefore we first calculate pitch features, using the same filterbank as in Section 2.1. Then we compute two further sequences of 12-dimensional chroma features, whereas we use a filterbank for which every bandpass-filter is shifted by $-1/3$ of a semitone and $+1/3$ of a semitone, respectively. We then interleave these three sequences of 12-dimensional chroma features according to the scheme {C-,C,C+,D#-,D#,D#+,...,B-,B,B+}. In Figure 2.3 we see a 36-dimensional CENS feature sequence of an audio recording of Beethoven's $5^{\text{th}}$ Symphony. In order to compute 36-dimensional chroma features for a MIDI file, we first compute the corresponding 12-dimensional chroma feature sequence. Then we create two sequences, each of the same size containing only zero values. Then we interleave these three feature sequences according to the scheme {0,C,0,0,D#,0,...,0,B,0}. This definition yields the property that the scalar product of a 36-dimensional chroma vector derived from an audio recording and of a 36-dimensional chroma vector derived from a MIDI file results in the same value as the scalar product of the respective 12-dimensional chroma vectors.

## 2.2 Subsequence-Dynamic Time Warping

Subsequence-Dynamic Time Warping (SDTW) is an alignment technique used to find a subsequence $X$ within a longer sequence $Y$ that best fits sequence $Y$ [10, p.79]. Using SDTW, we can match a short query (for example an `EDM`-theme) with a large database of audio recordings whereas tempo changes and tempo differences can be compensated up to some extent.
In the following, we describe SDTW step by step, whereas we need a couple of definitions:
Given two *feature sequences* $X = (x_1, x_2, \ldots, x_N)$ and $Y = (y_1, y_2, \ldots, y_M)$ with $M >> N$, we calculate a *cost matrix* $\mathbf{C}(n, m) = c(x_n, y_m)$ for $n \in [1 : N]$ and $m \in [1 : M]$, see [10, p.79]. Its entries are calculated by computing a so called *cost measure* $c$. In our experiments, we use the *cosine distance* defined by

$$c(x_n, y_m) := 1 - \frac{\langle x|y\rangle}{\|x\| \cdot \|y\|} \tag{2.4}$$

for two non-zero vectors $x, y$. Furthermore we define two different step size conditions expressed by the sets

$$\Sigma_1 := (1,0), (0,1), (1,1) \tag{2.5}$$

and

$$\Sigma_2 := (2,1), (1,2), (1,1) \tag{2.6}$$

The step size condition constrains the possible warping paths by fixing the maximum tempo variations between $X$ and $Y$. $\Sigma_1$ allows infinite tempo variations. $\Sigma_2$ however allows only tempo variations of factor two. This means that SDTW can only find the subsequence $X$ in $Y$, if the length of the corresponding sequence in $Y$ is in the bounds $N/2$ and $2N$. The accumulated cost matrix $\mathbf{D}$ is derived from $\mathbf{C}$ in three steps. The first row of $\mathbf{D}$ is initialized by assigning it with the values of the first row of $\mathbf{C}$:

$$\mathbf{D}(1, m) := \mathbf{C}(1, m) \tag{2.7}$$

for $m \in [1 : M]$. With this initialization step, a subsequence can start anywhere in $m$, taking into account only the local cost of $\mathbf{C}$ at $m \in [1 : M]$.

Then, the first column of $\mathbf{D}$ is calculated by computing

$$\mathbf{D}(n, 1) = \sum_{k=1}^{n} \mathbf{C}(k, 1) \quad \text{for} \quad n \in [1 : N]. \tag{2.8}$$

All remaining entries are then calculated by using the formula

$$\mathbf{D}(n, m) \quad = \quad \mathbf{C}(n, m) + \min \begin{cases} \mathbf{D}(n-1, m-1) \\ \mathbf{D}(n-1, m) \\ \mathbf{D}(n, m-1) \end{cases} \tag{2.9}$$

for $n \in [1 : N]$ and $m \in [1 : M]$, when using the set $\Sigma_1$. For calculating the values for the first row and the first column of $\mathbf{D}$ we extend $\mathbf{D}$ by appending one row and one column each given the respective index 0. Then we initialize $\mathbf{D}(n, 0) := \infty$ for $n \in [1 : N]$ and $\mathbf{D}(0, m) := \infty$ for $m \in [1 : M]$.

When we use the set $\Sigma_2$, we use the formula

$$\mathbf{D}(n,m) \quad = \quad \mathbf{C}(n,m) + \min \begin{cases} \mathbf{D}(n-1,m-1) \\ \mathbf{D}(n-2,m-1) \\ \mathbf{D}(n-1,m-2) \end{cases} \tag{2.10}$$

with $n \in [1:N]$ and $m \in [1:M]$. For this step size condition we extend $\mathbf{D}$ by appending two rows and two columns each given the respective indices $-1$ and 0. Then we initialize $\mathbf{D}(n,-1) := \mathbf{D}(n,0) := \infty$ for $n \in [1:N]$ and $\mathbf{D}(-1,m) := \mathbf{D}(0,m) := \infty$ for $m \in [1:M]$.

We specify the weight factors $w_d, w_h, w_v \in \mathbb{R}$ to favour the diagonal, horizontal, or vertical direction in the alignment [10, p.76]. SDTW has the property that the subsequence $X$ is much shorter than $Y$. When we calculate the matrix $\mathbf{D}$, the more steps we take in $n$-direction, the earlier we reach $N$ and the less steps we need in total. So in general a path that describes a short subsequence is preferred over a longer and probably semantically more meaningful subsequence. We specify different weight factors $w_d, w_h, w_v$, to compensate this issue.

Then the accumulated cost matrix

$$\mathbf{D}(n,m) \quad = \quad \min \begin{cases} \mathbf{D}(n-1,m-1) + w_d \cdot \mathbf{C}(n,m) \\ \mathbf{D}(n-1,m) + w_v \cdot \mathbf{C}(n,m) \\ \mathbf{D}(n,m-1) + w_h \cdot \mathbf{C}(n,m) \end{cases} \tag{2.11}$$

with $n \in [1:N]$ and $m \in [1:M]$. is calculated for the step sizes $\Sigma_1$, using Equation (2.7) and (2.8) as initialization steps. Furthermore we initialize $\mathbf{D}$ in the same way as for Equation (2.9).

Using the step sizes $\Sigma_2$, the accumulated cost matrix

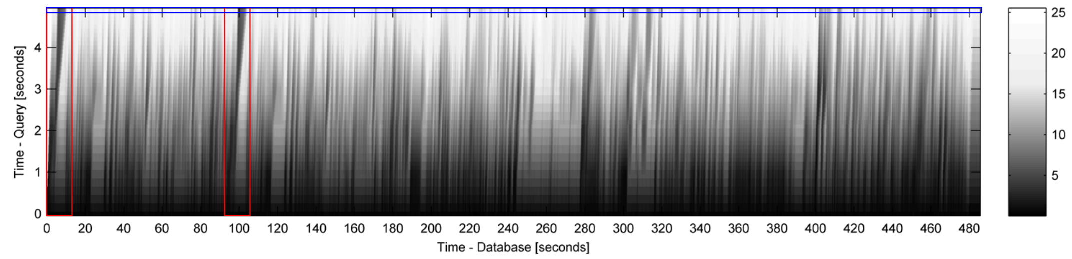
$$\mathbf{D}(n,m) \quad = \quad \min \begin{cases} \mathbf{D}(n-1,m-1) + w_d \cdot \mathbf{C}(n,m) \\ \mathbf{D}(n-2,m-1) + w_v \cdot \mathbf{C}(n,m) \\ \mathbf{D}(n-1,m-2) + w_h \cdot \mathbf{C}(n,m) \end{cases} \tag{2.12}$$

is calculated using the initialization step in Equation (2.7). Here we initialize $\mathbf{D}$ in the same way as for Equation (2.10). [10, pp.70-81].

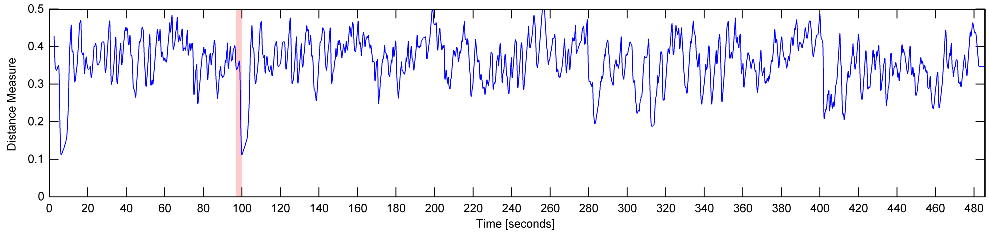
Figure 2.4(a) shows an accumulated cost matrix, derived from Beethoven's 5$^{\text{th}}$ Symphony, whereas we use Beethoven's 5$^{\text{th}}$ Symphony, 1$^{\text{st}}$ Movement, 1$^{\text{st}}$ Theme as query. A match between the query and the database is indicated by a diagonal in the matrix with low cost-values. The query occurs twice in the database. These two passages are highlighted by red frames. The two diagonals in dark gray highlighted by red frames indicate subsequences with low cost. These sequences best match the query.
The uppermost row in $\mathbf{D}$ defines a so called matching function

$$\Delta_{\text{DTW}}(m) := \frac{1}{N}\,\mathbf{D}(N,m) \tag{2.13}$$

with $\Delta_{\text{DTW}} : [1:M] \to \mathbb{R}$ and $m \in [1:M]$ to identify similar subsequences highlighted in Figure 2.4(a) by a red frame. The matching function corresponding to the accumulated cost matrix in Figure 2.4(a) is shown in Figure 2.4(b). Local minima with low cost values indicate the end position of a matching subsequence. In Figure 2.4(b) we can see two of these local minima. With a backtracking procedure the starting point of the subsequence is obtained. The




(a)




(b)

Figure 2.4: (a) Accumulated cost matrix **D**. (b) Matching function $\Delta_{\mathrm{DTW}}$. The computed subsequence is highlighted in light red color.

subsequence that matches best is highlighted in light red color [10, pp.70-81].

## 2.3 Cyclic shift

In this section we introduce the cyclic shift operator. With this operator we can take into account transposed versions of the query in the database. Therefore we shift each of the chroma vectors of the query, for example by one semitone according to the formula

$$\sigma(x) := (x(11), x(0), x(1), \ldots, x(10))^{\mathrm{T}}. \tag{2.14}$$

with $\sigma : \mathbb{R}^{12} \to \mathbb{R}^{12}$ for the 12-dimensional chroma features and we musically transpose each of the chroma vectors of the query, for example by 1/3 semitone according to the formula

$$\sigma(x) := (x(35), x(0), x(1), \ldots, x(34))^{\mathrm{T}}. \tag{2.15}$$

with $\sigma : \mathbb{R}^{36} \to \mathbb{R}^{36}$ for the 36-dimensional chroma features before performing the SDTW. Depending on the dimensionality of the chroma features, we only take into account transpositions for the 12-dimensional chroma features, or we take into account both transpositions and global tuning variations using the 36-dimensional chroma features. Figure 2.5 shows matching functions for several transpositions of the query. We can see that the query occurs in the same key as in the database twice, at time instants 30 seconds and 85 seconds. Additionally, the query occurs in a transposed version. It is transposed by +2 semitones in the audio recording occurring at time instant 130 seconds.

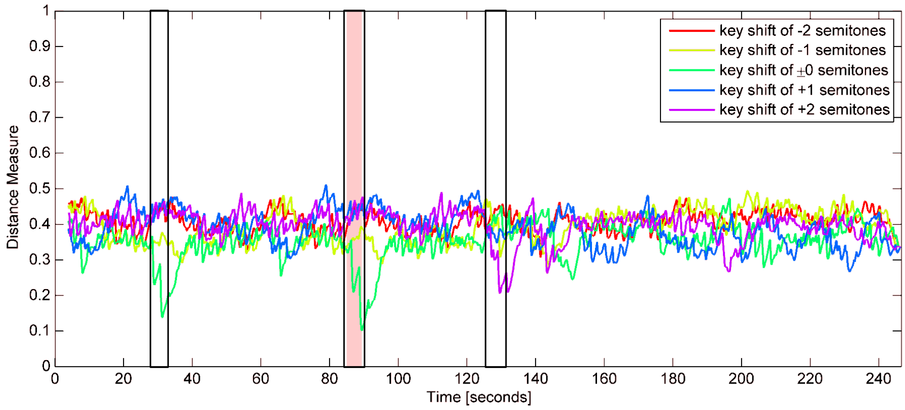



Figure 2.5: Matching functions for Beethoven Op.2 No.1 for 5 transpositions. Sequences that match the query are highlighted by a black frame. The best matching sequence is highlighted in light red color.

## 2.4 Evaluation Measures

In this section we introduce measures, that we will use for evaluation of the performance of the pipeline in Chapter 4. With these evaluation measures, we can compare the retrieval results for different parameter settings. So the parameters can be tuned to optimize results.
We use the Top N Match and the Mean Rank as evaluation measures, inspired by [17, p.55].

### 2.4.1 Top N Match

The goal of our retrieval system is, given a MIDI file (query) to identify the semantically corresponding audio recording (document) in a database. Similar to retrieval systems like Google[1], our system provides not only a single answer but a ranked list of documents. Formally, given $S$ queries to a database with $K$ documents, a retrieval system creates $S$ ranked lists with N entries, $\mathrm{N} \leq K$. We now want to quantify for how many of the $S$ queries the correct document is contained in the respective ranked list. Let $M$ be the number of queries fulfilling this condition. The Top N Match measure can be defined as:

$$\text{Top N Match} = \frac{M}{S} \cdot 100\%$$

We refer to the Top 1 Match also as Top Match. This evaluation measure is also used in [22, p.188] where it is referred to as "Top-N accuracy".

[1] www.google.com

### 2.4.2 Mean Rank

The Mean Rank specifies the rank on which the correct document occurs on a ranked list on average. This measure is related to the mean reciprocal rank used in [17]. We use the Mean Rank, because it is a semantically more meaningful measure to the user of a retrieval system. We want to know, how many entries in a ranked list we have to check on average until we find the document we are looking for. The mean reciprocal rank however only returns a number in the range of $[0, 1]$. The disadvantage of the Mean Rank is that the size of the database is not taken into account when we use this measure. For example a Mean Rank of 20 means that on average a user has to search through the top 20 entries of a ranked list to find the match. However, this measure is strongly dependent on the size of the database. For a database containing 100 documents, a Mean Rank of 20 is much better, than for a database containing only 50 documents.

The Mean Rank is calculated as follows:

$$\text{Mean Rank} = \frac{1}{S} \sum_{i=1}^{S} R_i$$

where $R_i$ is the rank for the $i^{\text{th}}$ query and $S$ is the number of queries.

Note that the Mean Rank is a measure that takes into account all $K$ entries of the retrieved ranked lists, whereas the Top N Match only takes into account the respective N entries.

# Chapter 3

# Matching Symbolic Themes to Audio

After describing the fundamental techniques, the task is to match monophonic themes to polyphonic audio recordings. In Section 3.1 we first describe the matching procedure, followed by introducing two enhancement strategies. The first strategy aims to cope with musical key shifts or different tunings and the second one with high tempo variations between the query and the database. As we will perform our following experiments based on the book by Barlow and Morgenstern (`BM`) and its digitized version from the `EDM`-website, we will further investigate in these datasets. Due to computation time and potential pitfalls when considering the entire dataset, we introduce three subsets in Section 3.2. Retrieval tasks that are similar to the matching task of this thesis can be found in [3, 14, 17].

Before we describe the structure of the pipeline for the matching process we make several assumptions about the underlying data: The used subsets contain Western classical music, so we assume an equal tempered scale containing 12 semitones per octave as a foundation for chroma features. Furthermore, we assume in general that the melody specified by the `EDM`-theme we use as query is dominant in the polyphonic audio recording. This assumption is met because of several reasons: The musical themes in the `BM` are famous themes which we would remember from listening to the audio recording and then may want to look them up. Therefore a theme must be well audible which implicates that it is the dominant melody. The theme can only be well audible if the degree of polyphony is low, or if several instruments play the theme at the same time. Furthermore, many of the themes are repeated several times in an audio recording. This also leads to a memorizing effect by the listener. It is highly possible, that the theme occurs as dominant melody at least once in the audio recording. We also assume that the queries do not contain playing errors. We assume that the audio recordings are of fair quality. Finally, we assume that every query can be mapped to one audio recording uniquely. For example we have a query $a$ which corresponds to audio recording $A$ and query $b$ corresponds to audio recording $B$. So we assume that $A$ does not contain the melody specified by $b$ and $B$ does not contain the melody specified by $a$. This also holds for transposed and detuned versions of $b$ and $a$ which may also differ in tempo.


Figure 3.1: Sheet music of the “Fate-Theme” from Beethoven’s 5$^{\text{th}}$ Symphony.

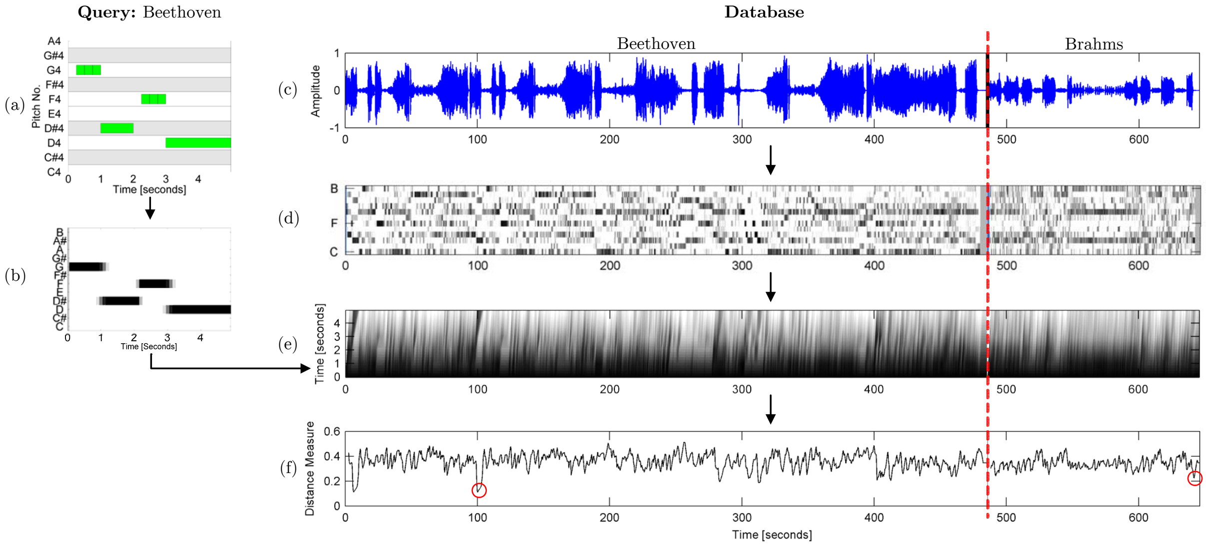



Figure 3.2: Outline of the overall pipeline of this thesis showing the matching procedure for one query with a database that contains two audio recordings. (a) Piano roll representation of the “Fate-Theme” by Beethoven. (b) Chromagram of the query. (c) Waveform of the database consisting of Beethoven’s 5$^{\text{th}}$ Symphony and Brahms’ Hungarian Dance No.5. (d) Chromagram of the database. (e) Accumulated cost-matrix. (f) Matching function for the given query in the database.

## 3.1 Matching Procedure

Following these assumptions, we present our matching procedure. Let our goal be to find the theme given in Figure 3.1 in a database of audio recordings. Figure 3.2 shows the pipeline for this particular example. The piano roll representation of the query can be seen in Figure 3.2(a). The corresponding database is shown in Figure 3.2(c), consisting of a recording from Beethoven’s 5$^{\text{th}}$ Symphony and Brahms’ Hungarian Dance No.5. The core idea of our matching procedure is to convert both modalities into a mid-level representation and then find an optimum alignment between the respective feature representations of the query and a subsequence of the database. As mid-level representation, we use chroma features, in particular CENS features, as introduced in Section 2.1.1. The implementation is given by the Chroma-Toolbox, provided by Müller et. al. [2]. The conversion result is shown in Figure 3.2(b) resp. Figure 3.2(d). We define $X \in \mathbb{R}^{\{12,36\}}$ as chroma sequence of the query and $Y \in \mathbb{R}^{\{12,36\}}$ as chroma sequence of the database. The database $Y$ is built by simply concatenating the chroma representations of the audio recordings. To prevent the algorithm which performs SDTW from aligning paths across the end of one audio

| Rank | ComposerID | WorkID | Minimum |
|---|---|---|---|
| 1 | Beethoven | Op067-01 | 0.11 |
| 2 | Brahms | HungarianDances-05 | 0.23 |

Table 3.1: Results of the matching procedure shown as a ranked list. Beethoven was used as query and correctly identified by the algorithm.

recording and the start of another audio recording in the database, the chroma sequences are separated by two infinity columns $y_\infty \in \mathbb{R}^{\{12,36\}}$. In our example, the feature sequence of the database looks like this:

$$Y = [Y_1 \; y_\infty \; y_\infty \; Y_2]. \tag{3.1}$$

The chroma sequence $Y$ of the database is visualized in Figure 3.2(d). With these two feature sequences we perform SDTW as explained in Section 2.2. The accumulated cost matrix is shown in Figure 3.2(e). To get the optimum alignment, we extract the matching function from the accumulated cost matrix, see Figure 3.2(f). To extract the best match for the given query in the database, we consider each database entry separately. In this example, we yield two minima from the matching function: One for the audio recording by Beethoven and a second one for the audio recording by Brahms, highlighted by red circles in Figure 3.2(f). The audio recordings are sorted in a ranked list, according to the respective minimum values in ascending order (see Table 3.1). For this matching procedure, the first entry of the list is the best matching candidate. In our example, the best match is at 100 seconds (see Figure 3.2(f)). This is where the theme is played for the second time in the Symphony.

In this example, the procedure is successful. This is not the case for every query, especially when there are significant time stretches or detuning of the audio recording. As we already mentioned, we therefore extend this pipeline by using two enhancement strategies.

The first strategy takes into account transposed and detuned versions of the query by using the cyclic shift operator defined in the Equations (2.14) and (2.15) to shift the feature sequence of the query. Then we derive matching functions as explained previously using all shifted versions of the query. Figure 3.3 shows matching functions for five transpositions. The black function in

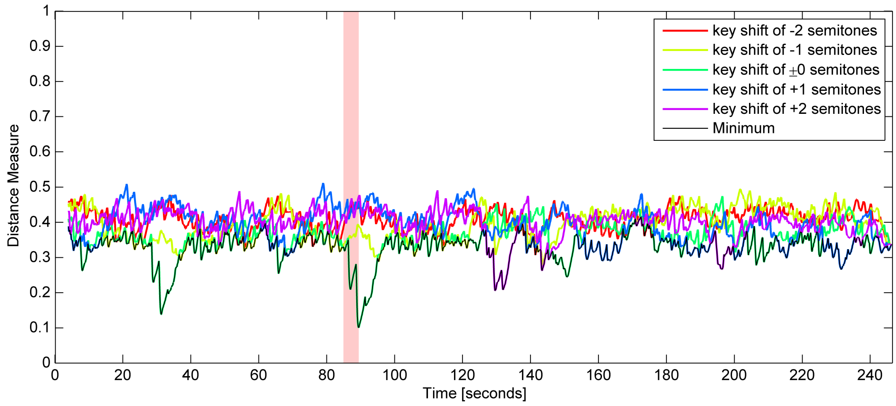



Figure 3.3: Matching functions for Beethoven's Op.2 No.1 for 5 transpositions. The sequence of lowest cost is highlighted in light red color.

this figure is derived by taking the minimum value of these five matching functions for each time instant as kind of a lower envelope. In this thesis we refer to this function as minimum function. In order to evaluate musically transposed or detuned versions of a query, we apply the cyclic shift operator to the chroma representation of the query once or several times and derive the matching functions. Then we derive the minimum function and perform the evaluation as explained in the previous paragraph. In the following, we define a parameter that denotes the number of key shifts for a certain type of chroma features. We use the parameter $\kappa_0^{12}$ or $\kappa_0^{36}$ to denote that we only use the standard tuning without any key shifts as query, using 12-dimenisonal chroma features or 36-dimensional chroma features, respectively. Furthermore we use the parameter $\kappa_2^{12}$ to denote that we use 12-dimensional chroma features including all musical key shifts from +2 semitones to −2 semitones. Accordingly, we use the parameter $\kappa_2^{36}$ to denote that we use 36-dimensional chroma features including all musical key shifts from +2.3 semitones to −2.3 semitones. Note that we compare the results for the key shifts of ±2 semitones for the 12-dimensional chroma features to the respective key shifts of ±2.3 semitones for the 36-dimensional chroma features to also consider audio recordings that are transposed by 2 semitones and additionally detuned. We also define a parameter $W := (w_d, w_h, w_v)$ that denotes the used weight factors as follows: $W_1 := (1, 1, 1)$, $W_2 := (1, 0.7, 1.4)$, $W_3 := (1, 0.5, 2)$, $W_4 := (1, 0.3, 3)$.

The second strategy is used to compensate high tempo variations between query and database. Therefore we stretch or shrink the query to a fixed duration before performing the retrieval task. Figure 3.4(a) shows the piano roll representation of the `EDM`-theme “Prelude No.1” from the “Well-tempered Clavichord Book I” by Bach. In the Figures 3.4(b) to 3.4(f) we can see chromagrams of this `EDM`-theme with different durations. Besides the original duration (denoted as $t_\delta$= orig) specified by the `EDM`-theme shown in Figure 3.4(b) we use the durations $t_\delta$= {5 s, 10 s, 15 s, 20 s} for the Figures 3.4(c) to 3.4(f), respectively. Smoothing and low duration cause blending effects between chroma vectors (see Figure 3.4(b) and 3.4(c)). This effect is undesirable, as it reduces the specificity of the query.

With the introduced strategies we make our pipeline very robust against problems in the dataset, such as detuned and transposed audio recordings, as well as high tempo variations. Using the cyclic shift operator, we take into account transposed and detuned versions of the query. Furthermore, SDTW compensates global and local tempo variations between query and database to some extent. High tempo variations are compensated by stretching or shrinking the query to a fixed duration. Finally, we can improve the specificity of a query by increasing the feature resolution for the CENS features. So we cover all the challenges described in Section 1.1 except for the degree of polyphony. Therefore we meet the assumption that the melody specified by the `EDM`-theme we use as query is dominant in the polyphonic audio recording.

As we will use many different parameter settings for our experiments in Chapter 4, we fix a notation for a parameter setting. We use the notation $\{\mathrm{CENS}_d^\omega,\ \Sigma_s,\ t_\delta,\ W\}$ to specify one parameter setting including the window-length smoothing $\omega$, down-sampling factor $d$, step size $s \in \{1, 2\}$ (see definition in Equation (2.5) and (2.6)), duration $t_\delta$ and the weight factors defined by $W$. In this thesis the default pitch feature resolution is 10 Hz. So $\mathrm{CENS}_{10}^{41}$ features have a feature resolution of 1 Hz and $\mathrm{CENS}_1^4$ features have a feature resolution of 10 Hz. If not explicitly specified for the respective experiment, we use the setting $\{\mathrm{CENS}_{10}^{41},\ \Sigma_1,\ t_\delta = \text{orig},\ W_1\}$.

Figure 3.5 gives an overview on the input and output behavior of the pipeline. It shows the dependencies between the input parameters and particular parts of the pipeline. Given a subset which contains queries and a database of audio recordings, the documents of the database are concatenated. Then we derive the database sequence $Y$, using the specified windowlength smoothing factor $\omega$ and the downsampling factor $d$ for the CENS features of the audio recordings. Furthermore we adjust the query taking into account the duration $t_\delta$ and the key shifts $\kappa$. We then calculate the CENS feature representation $X$ of the query, also taking into account $\omega$ and $d$. The SDTW is performed on the sequences $X$ and $Y$ and the step size condition defined by $\Sigma_s$. As a result we get a matching function whereas we derive a minimum value for each document of the database. Then we create a ranked list containing the documents of the database, sorted by the respective minimum in ascending order. For each query we derive a ranked list. The output of the pipeline are the evaluation measures Mean Rank and Top Match, which are derived from the ranked lists, see Section 2.4.

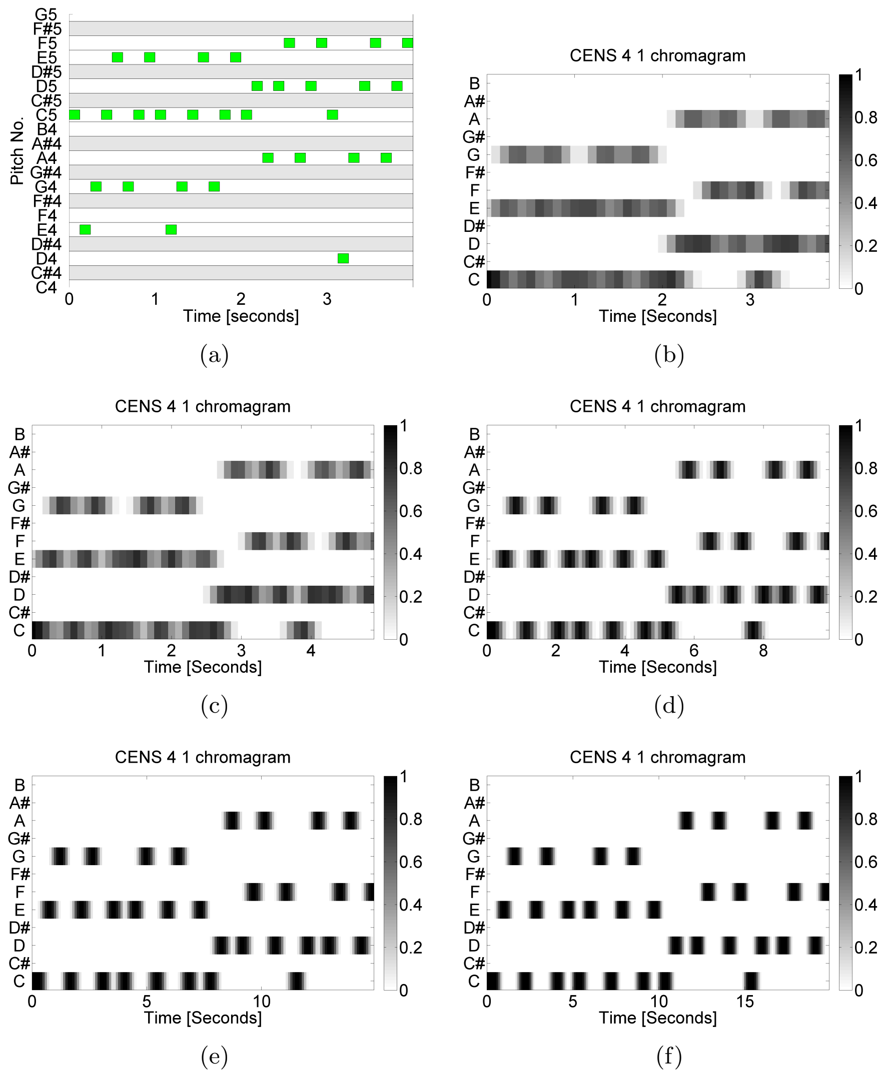



Figure 3.4: (a) Piano roll representation of the EDM-theme from the "Well-tempered Clavichord Book I", "Prelude No.1" by Bach. (b) to (f): Chromagrams of the durations $t_\delta = \{\text{orig}, 5\text{ s}, 10\text{ s}, 15\text{ s}, 20\text{ s}\}$, respectively.

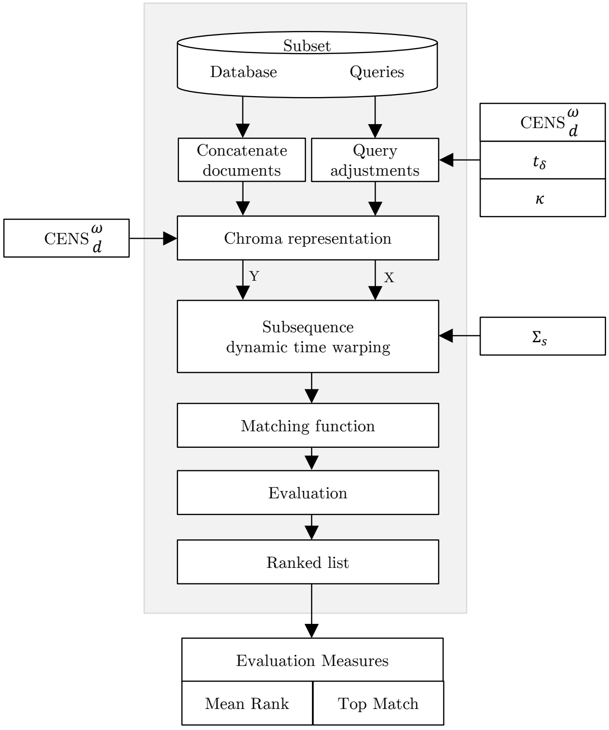



Figure 3.5: Overview of the input and output behavior of the pipeline, including the dependencies of the parameters on the appropriate parts of the pipeline.

## 3.2 Datasets

In order to do experiments on the pipeline we introduced, we need several datasets which we will refer to as subsets. We decided to create three subsets, each with a different number of audio recordings, to then compare the retrieval results for these subsets. The music data of the subsets is derived from the book "A DICTIONARY OF MUSICAL THEMES" by Harold Barlow and Sam Morgenstern. The `BM` was designed as a reference book for trained musicians and professional performers [1]. It contains roughly 10,000 musical themes from outstanding compositions in Western tradition including orchestral music, chamber music, and works for solo instruments. Each theme is specified by a visual score representation of the notes. Furthermore, the respective composer, the underlying musical work, and the movement are specified. Within the book, the themes are systematically organized and suitably indexed. Most of the `BM`-themes are also available as MIDI-files provided by the Electronic Dictionary of Musical Themes (`EDM`)[1]. In Figure 3.6 we can see one exemplary page of the `BM` containing musical works by Beethoven. The musical work "Sonata No.1, in F Minor Op.2, No.1, Pft" is highlighted by a blue frame. It contains four movements. The first movement is represented by two themes, highlighted by a red frame.
In the following, we use the term "audio recording" to refer to what one typically finds as a track of a commercial CD of Western classical music. The tracks, in turn, usually correspond to individual movements or numbers of a multi-movement musical work (such as a sonata, symphony,

[1] `http://www.multimedialibrary.com/barlow/`

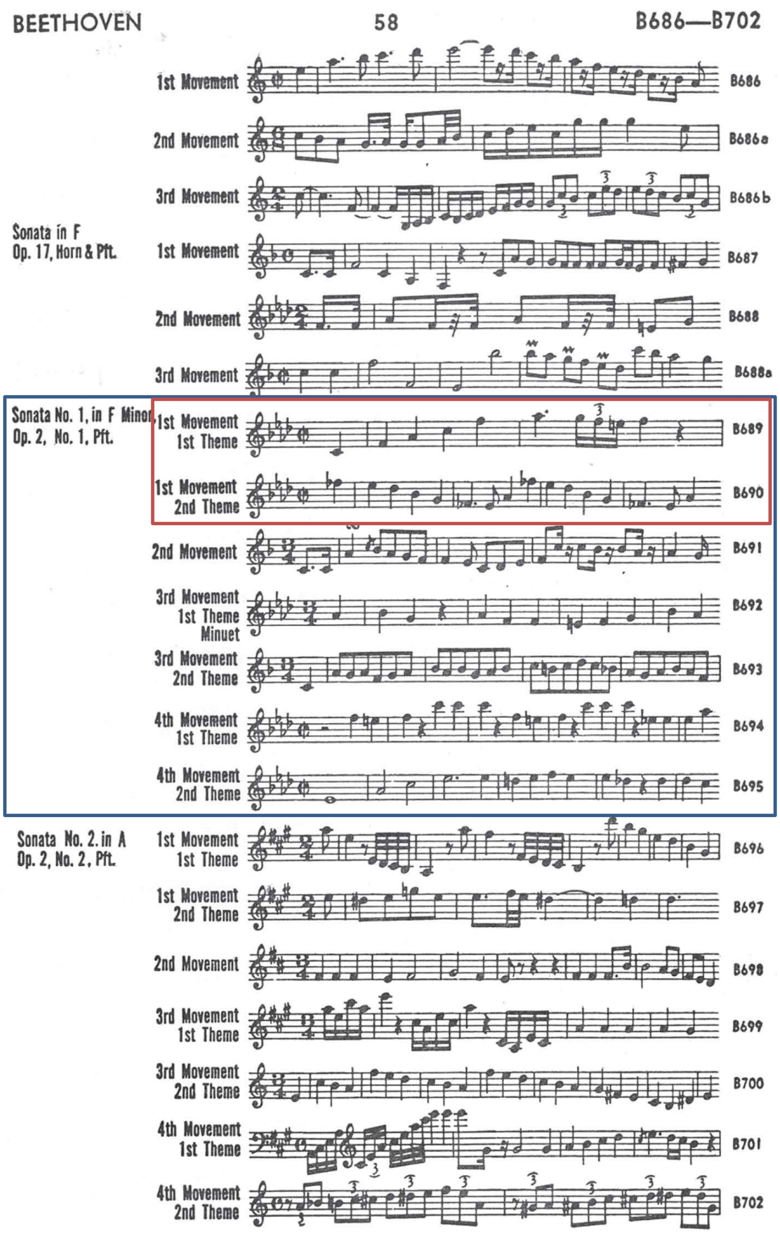
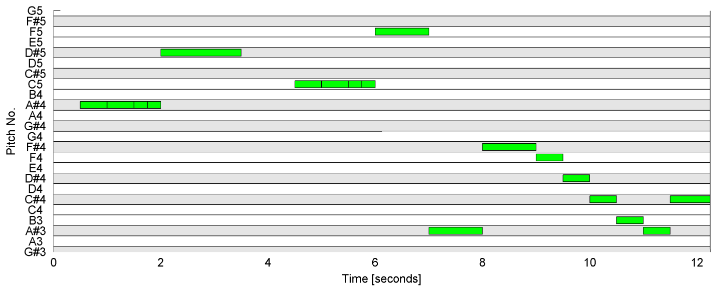



Figure 3.6: One bookpage of the BM [1], whereas one musical work and one movement are highlighted in different colors.

opera, suite), or to the entire piece of music if it consists of only a single movement. In general, a single movement may contain several BM-themes.

We create the subsets by matching data types as follows: First we choose movements from the BM. Second we add one version of a corresponding audio recording to the subset. Third we add all the corresponding EDM-themes from the EDM-website [18] to our subset. In this thesis we will refer to one movement, a corresponding audio recording and all the corresponding EDM-themes as BM *data type*. According to this procedure we create three subsets, whereas we only use data that is complete, meaning there is at least one audio recording available for the movement that contains


(a)




(b)

Figure 3.7: Example for Midi Joint Themes. (a) BM-theme of Beethoven's Quartet in B Flat, Op130-01, 1st Movement, derived by concatenating the parts 'A' and 'B'. (b) Piano roll representation of the EDM-theme.

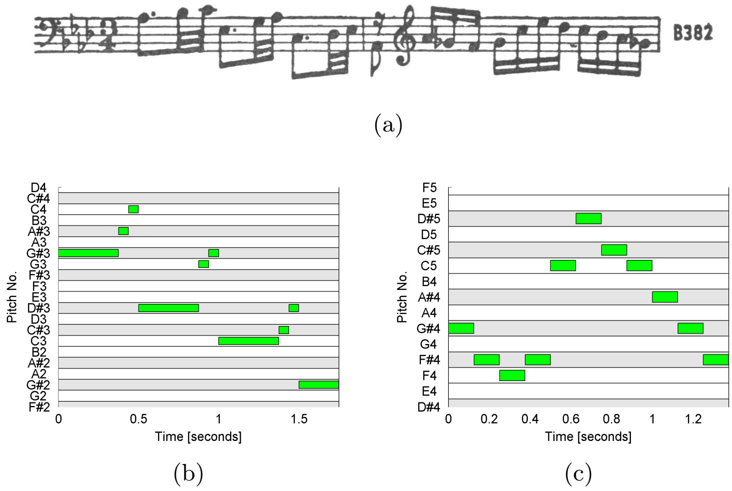
all its BM-themes and all corresponding EDM-themes are available. Table 3.2 gives an overview on the three subsets including the number of audio recordings, the number of EDM-themes and the total duration of all audio recordings.

Some of the EDM-themes are problematic with regard to the usage for our pipeline. In this thesis we will refer to these two exceptions as *Midi Joint Theme* and *Midi Part*. In the following, we explain these two irregularities. Figure 3.7 shows a BM-theme and the piano roll representation of its corresponding EDM-theme. The capital letters 'A' and 'B' in Figure 3.7(a) indicate that these 6.5 measures which we can see in the sheet music are not played consecutively in the audio recording. The first four measures which are denoted by the letter 'A' are played in the audio recording at first, followed by a second part which is not notated in the sheet music. Then the 2.5 measures are played in the audio recording which are denoted by the letter 'B'. In Figure 3.7(b) we can see that in the EDM-theme the parts 'A' and 'B' are played consecutively, whereas the second part is missing. As we use the EDM-theme as a query, we ignore the part enclosed by the parts 'A' and 'B' and thus our query is wrong, because the melody specified in the query does not occur consecutively in the audio recording.

Figure 3.8 shows another kind of exception. In this case one BM-theme corresponds to two EDM-themes, that means we have two queries for one BM-theme. Generally, these queries are not wrong compared to a Midi Joint Theme, but by splitting one query into two queries, the queries

| **Subset** | **No. Audio** | **No. EDM** | **Dur. DB [h:min:s]** | **Dur. Queries [h:min:s]** | **Mean Dur. per Audio [min:s]** | **Mean Dur. per Query [s]** | **Mean Notes per Query** |
|---|---|---|---|---|---|---|---|
| BM-Mini | 14 | 26 | 01:10:41 | 00:03:11 | 05:02 | 7.3 | 16.2 |
| BM-Small | 100 | 177 | 10:50:50 | 00:21:57 | 06:30 | 7.4 | 20.5 |
| BM-Medium | 1113 | 2039 | 119:10:44 | 04:00:45 | 06:24 | 7.1 | 19.1 |

Table 3.2: Basic information for the three created subsets including the number of audio recordings, the number of EDM-themes and the duration of the respective database.




(a)

(b) (c)

Figure 3.8: Example of Midi Parts. (a) BM-theme of Bach's "Well Tempered Clavichord Book II", Prelude No.17. (b) and (c): Visualization of the corresponding EDM-themes in a piano roll representation.

get shorter and thus loose specificity which makes the retrieval task harder. In this thesis we refer to this kind of exception as *Midi Part*.

In the following we describe each subset in more detail and explain the rules we applied to create the subsets.

The first subset BM-Mini contains 26 famous EDM-themes of Western classical music and 14 audio recordings, see Table 3.2. The mean duration of an EDM-theme in this subset is roughly 7 seconds. Figure 3.10(a) and Figure 3.10(b) show distributions of the query duration and of the number of notes, respectively. This database has a duration of roughly one hour. It is statistically not representative for doing evaluations and was created to analyze queries which represent edge cases for a specified parameter setting, and to test if our pipeline works. The advantage of this subset is that experiments require only a short time for such a small number of audio recordings. In this subset we do not use BM data types that contain a Midi Joint Theme or a Midi Part. In Appendix B.4 we provide a table containing all audio recordings of the subset BM-Mini, including Composer, WorkID[2], name of the album or CD-box, CD and track number, instrumentation and EnsembleID. Furthermore, in Appendix B.5 we provide a table containing all EDM-themes of the subset BM-Mini, including an index number for each EDM-theme, Composer, WorkID, BMID[3], ThemeID and the MidiNo[4]. In this thesis we refer to specific queries of the subset BM-Mini using this index number. For example by the term **query #1** we refer to Bach's "Well Tempered Clavichord Book I", Prelude No.1, BWV 846. Finally, Appendix B.1 provides matching functions for every query of the subset BM-Mini with specified feature settings.

The second subset BM-Small contains 177 EDM-themes and 100 audio recordings, see Table 3.2. The total duration of the database is roughly 11 hours and thus much larger than BM-Mini. The

[2] An identifier that uniquely identifies one movement in combination with the Composer.

[3] The BMID is an identifier, that uniquely identifies one BM-theme. The BMID is the number provided on the right side of each BM-theme in the BM.

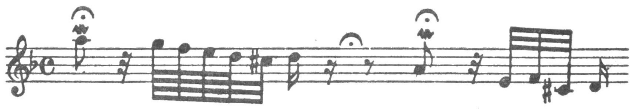
[4] A number that uniquely identifies each EDM-theme provided by the EDM-website.

mean duration of a query however, is also roughly 7 seconds. One query consists of roughly 20 notes in mean. Distributions of the query duration and of the number of notes are shown in the respective Figures 3.10(c) and 3.10(d). BM-Small contains the subset BM-Mini. Furthermore, we select many more audio recordings considering certain constraints, to make it statistically as representative for the entire BM as possible - however it contains only roughly 2% of the BM-themes. The first constraint is to choose about 100 movements in total from many different composers and different periods. The second constraint is to use movements with many different instrumentations and ensembles. In this subset we do not use BM data types that contain a Midi Joint Theme or a Midi Part. In Appendix B.6 and B.7 we provide tables containing all audio recordings and all EDM-themes of BM-Small. For most of the experiments we use this subset, as it is (assumed to be) representative for the entire BM and the runtime for most of the experiments is still acceptable.

The third subset BM-Medium contains 2039 EDM-themes and 1113 audio recordings, see Table 3.2. The total duration of the database is roughly 119 hours and thus roughly ten times larger than BM-Small. The mean duration per query is roughly 7 seconds, just like for the previous subsets. In this subset one query also consists of roughly 20 notes in mean. So from a statistical point of view, the queries in the subset BM-Small are quite similar to the subset BM-Medium. Distributions of the query duration and of the number of notes are shown in the respective Figures 3.10(c) and Figure 3.10(d). Figure 3.10(g) shows a histogram of the distribution of the query length with respect to the number of notes of the query. There is no noticeable correlation between the number of notes and the query length. In general, we would expect a correlation between the number of notes and the query length. As this is not the case, this indicates that the query length of a noticeable number of EDM-themes is wrong. BM-Medium contains the subset BM-Small. It allows us to perform evaluations on a big dataset. We create this subset by selecting several complete cycles, including all BM data types derived by the 24 preludes and fugues from “The Well-Tempered Clavichord I” and the 24 preludes and fugues from “The Well-Tempered Clavichord II” by Bach, all BM data types by Beethoven, all BM data types derived by the Symphonies and the Concertos by Brahms, all BM data types derived by the Mazurkas and by the Nocturnes by Chopin and several famous pieces by Bartók, Debussy, Dvořák, Haydn, Khachaturian, Mahler, Mozart, Schubert, Schumann, Shostakovich and Tchaikovsky. In the subset BM-Medium we allow BM data types containing Midi Joint Theme and Midi Part if they are part of a complete cycle. In Appendix B.8 we provide a statistic that shows each composer and the respective number of audio recordings that are in the subset BM-Medium.

In general, we do not exclude BM data types that have tempo errors and playing errors in some of the respective EDM-themes which are recorded in Appendix B.9. Finally, we created three subsets that we will use for our experiments on the pipeline in Chapter 4.

To this end, we discuss reasonable parameter settings for the created subsets, to then also consider these parameter settings in our experiments. Therefore we have a look at two queries which we considered to be extreme examples. In Figure 3.9 we can see two examples of BM-themes, where the according EDM-themes have a duration of only roughly two seconds. The EDM-theme corresponding to the BM-theme Bach‘s Toccata in D Minor shown in Figure 3.9(a) has a duration of 1.6 seconds. The corresponding section of the audio recording however has a duration of roughly 15 seconds. This means a tempo difference of more than factor 9. To overcome such high global tempo variations, we do the fixed duration sampling for the queries, whereas we use the durations $t_\delta$= {5 s, 10 s, 15 s, 20 s, orig}. On the one hand fixed duration sampling for short




(a) Bach's Toccata in D Minor, BWV0565-01


(b) Chopin's Fantaisie-Impromptu, 1st Theme, Op066

Figure 3.9: `BM`-themes where corresponding `EDM`-themes are of short duration

queries leads to a time stretched query. So this query which is often erroneously too short, is sampled to a duration that is closer to the duration of the corresponding `BM`-theme in the audio recording. This also prevents us from choosing an extremely high feature resolution. As the `EDM`-theme contains 20 notes[5], we would have to choose a feature resolution of at least 13 Hz[6], to ensure that every note is represented by at least one feature vector.

In the second example, the excerpt in the audio recording has a duration of only roughly 1.7 seconds, which means that it is even shorter than the corresponding `EDM`-theme with 2 seconds duration. This `BM`-theme contains 15 notes. This means, that we need a feature resolution of at least 7.5 Hz for both, the audio recordings and the `EDM`-themes. So a sufficient feature resolution is 10 Hz. To obtain this feature resolution, we use $\mathrm{CENS}_1^4$ features and $\mathrm{CENS}_1^1$ features. Due to high computational load for such a high feature resolution, we also consider lower feature resolutions of 1 Hz, 2 Hz and 5 Hz, using the respective features $\mathrm{CENS}_{10}^{41}$, $\mathrm{CENS}_5^{21}$ and $\mathrm{CENS}_2^9$. Here we also see the downside of fixed duration sampling. By sampling this `EDM`-theme to a duration of 10 seconds, we only can overcome the global tempo variation of factor 6 with the step size condition $\Sigma_1$ which lead to a high loss in specificity. So one task is to find a suitable combination of the step size condition and the duration $t_\delta$ to compensate the high global tempo variations and thus get good retrieval results. We will tune these and other parameters in Chapter 4 by analyzing selected parameter settings and evaluating the respective performance of our pipeline.

[5] In this thesis we determine the number of notes of a `BM`-theme by counting the number of MIDI events of the corresponding `EDM`-theme. This number may deviate from the actual number of notes of the `BM`-theme.

[6] Therefore we assume that the `EDM`-theme contains no rests and every note has the same duration.

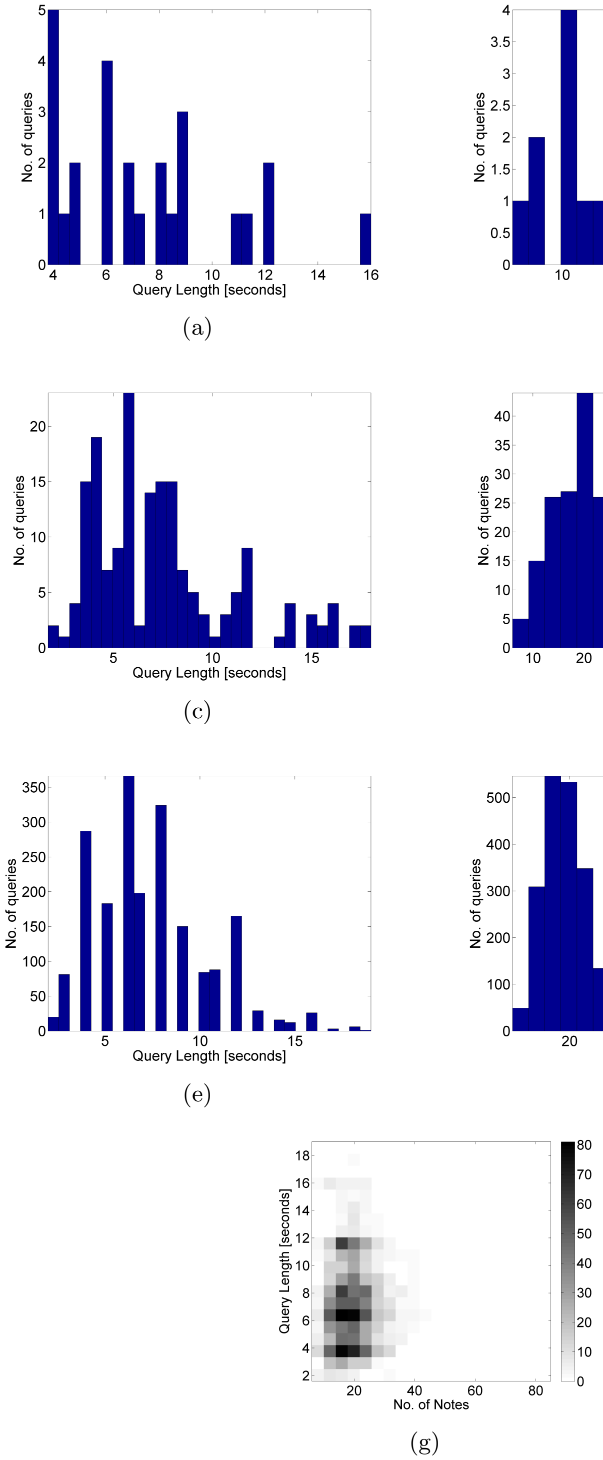



Figure 3.10: Histograms of the subsets. (a) Query lengths of BM-Mini. (b) Number of notes of BM-Mini. (c) Query lengths of BM-Small. (d) Number of notes of BM-Small. (e) Query lengths of BM-Medium. (f) Number of notes of BM-Medium. (g) Query length in dependence of the number of notes of the query for BM-Medium.

# Chapter 4

# Experiments

In this chapter, we present the results of our experiments using the pipeline and subsets which we introduced in Chapter 3. For each subset the task is to retrieve the audio recording specified by the corresponding query. As a subset has several queries, all these queries are processed. The retrieval results are then evaluated, taking into account all the queries. Therefore we use the evaluation measures Mean Rank and Top Match, as introduced in Section 2.4.

We start with the smallest subset `BM`-Mini. This subset is only used to test our algorithm and study certain behavior. We can see the matching results for each of the themes in Appendix B.1. Furthermore, retrieval results for many different parameter settings are shown in Appendix B.2. The results in this chapter are based on the subset `BM`-Small which contains 100 audio recordings and 177 queries. We will use these results to evaluate different parameters of the algorithm. We then fix a set of parameters which will be applied to the subset `BM`-Medium which contains 1113 audio recordings and 2039 queries.

Finally, we will pick some specific examples for cases where the matching procedure had problems in identifying the correct audio recording in the database to further understand the algorithm and the underlying data.

## 4.1 Parameter selection using the subset BM-Small

In this section we determine our best possible parameter setting for the subset `BM`-Small by doing experiments in the following order: First, we fix one parameter setting and evaluate the results by calculating the Mean Rank and the Top Match for this parameter setting. Second, we do this experiment again, whereas we vary one parameter according to the different settings defined in Section 3.1. Then we compare the results of these experiments, determine our best value for this parameter and fix this value for the next experiment. Then we repeat this procedure, whereas we vary the next parameter, until in the end we fixed all parameters.

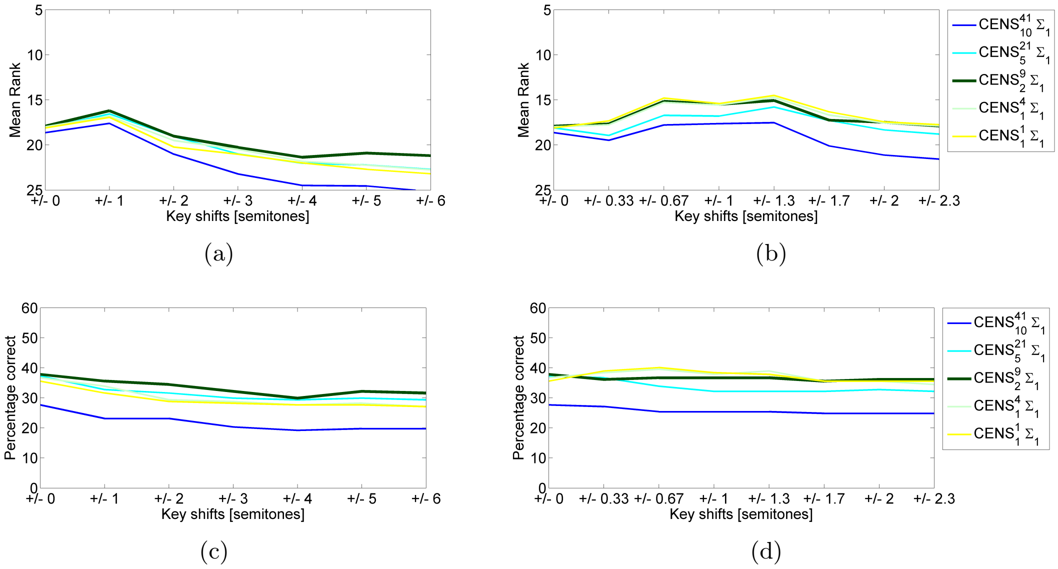
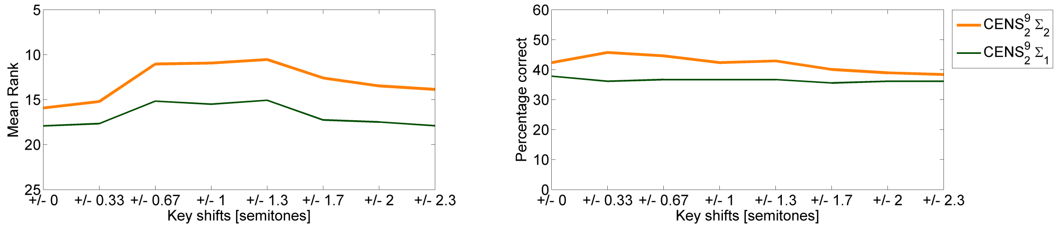



Figure 4.1: Dependency of evaluation results on the feature resolution. The evaluation was performed on the subset `BM`-Small, using the settings $\{\Sigma_1, W_1\}$. (a) Mean Rank with 12-dimensional chroma features. (b) Mean Rank with 36-dimensional chroma features. (c) Top Match with 12-dimensional chroma features. (d) Top Match with 36-dimensional chroma features.

### 4.1.1 Chroma resolution and feature resolution

In this section we determine the chroma resolution and the feature resolution that perform best for our experimental setup. First, we compare the 12-dimensional chroma features to the 36-dimensional chroma features. Figure 4.1(a) shows the Mean Rank for the 12-dimensional chromas with respect to the number of applied key shifts. The figure contains one function for several different feature resolutions. The lowest Mean Rank of 16 is achieved with the parameter setting $\mathrm{CENS}^9_2$ with the key shifts of $\pm 1$ semitone. This indicates, that several audio recordings are transposed by $\pm 1$ semitones. For the key shifts of $\pm 2$ semitones we get a Mean Rank of 19. The more number of key shifts we apply, the more unspecific our query gets and thus the Mean Rank gets worse. Figure 4.1(c) shows the Top Match for the 12-dimensional chromas. Our best Top Match is also achieved using the parameter setting $\mathrm{CENS}^9_2$. Using the key shifts of $\pm 0$ semitones we get a Top Match of 38%. For the key shifts of $\pm 1$ semitones the Top Match is still 36%. In the following, we compare these results to the 36-dimensional chromas. Using the parameter setting $\mathrm{CENS}^9_2$ we get slightly better results than for the 12-dimensional chromas (see Figure 4.1(b) and 4.1(d)). By contrast, for the 36-dimensional chromas the setting $\mathrm{CENS}^1_1$ performs better with regard to the Mean Rank and the Top Match. So it implies that for a higher feature resolution, also the tuning gets more relevant. In the following, we restrict our experiments to the 36-dimensional chromas. We achieve the lowest Mean Rank of 15 and the highest Top Match of 40% using the parameter setting $\{\mathrm{CENS}^1_1, \Sigma_1\}$ and key shifts of $\pm 1.3$ semitones and $\pm 0.67$ semitones respectively (see Figure 4.1). So the $\mathrm{CENS}^1_1$ features perform better, even though these features are not suitable for larger datasets due to the high computational cost. So the $\mathrm{CENS}^9_2$ features are a good trade-off between computational cost and retrieval performance.




(a) (b)

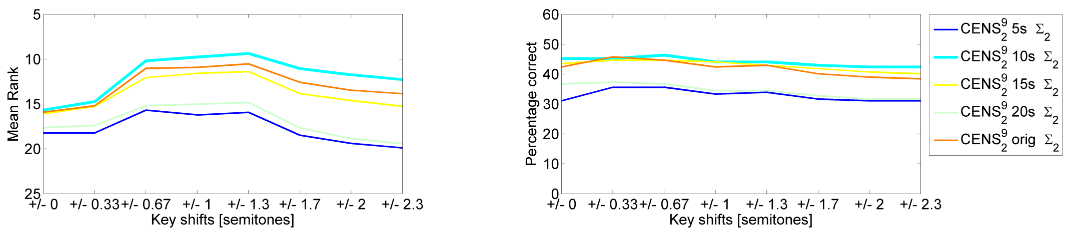
Figure 4.2: Dependency of evaluation results on the step size. The evaluation was performed on the subset BM-Small, using the settings $\{\text{CENS}_2^9$, orig, $W_1$, $\kappa^{36}\}$. (a) Mean Rank (b) Top Match

### 4.1.2 Step size condition

In the following, we compare the step sizes $\Sigma_1$ to the step sizes $\Sigma_2$ for the subset BM-Small. In Figure 4.2 we can see, that the lowest Mean Rank of 11 as well as the highest Top Match of 46% is achieved for the step sizes $\Sigma_2$. The step sizes $\Sigma_2$ leads to much better results because this parameter strongly constrains the warping path of the SDTW (see Section 2.2). This constraint in turn increases the specificity which is a very important property for a database of 100 audio recordings. Furthermore, it indicates that there are many queries that have global tempo variations of less than a factor of two.

### 4.1.3 Fixed query length

In the next step we evaluate the results for different query durations. The Mean Rank is slightly better for a fixed duration of $t_\delta$= 10 s than for the so far used original duration (see Figure 4.3). This indicates that there are several queries having a high global tempo variation which is compensated by the usage of fixed duration sampling. The queries of the length 10 seconds lead to the better results for the Mean Rank of 9 as well as for the Top Match of 46% (see Figure 4.3). To this end, we infer that the matching excerpts of the audio recordings also have a mean duration of 10 seconds. Furthermore, we infer, that many of the queries have a wrong tempo, as the mean duration of the queries is only roughly 7 seconds (see Table 3.2). Using fixed




(a) (b)

Figure 4.3: Dependency of evaluation results on the duration of the queries. The evaluation was performed on the subset BM-Small, using the settings $\{\text{CENS}_2^9$, $\Sigma_2$, $W_1$, $\kappa^{36}\}$. (a) Mean Rank (b) Top Match

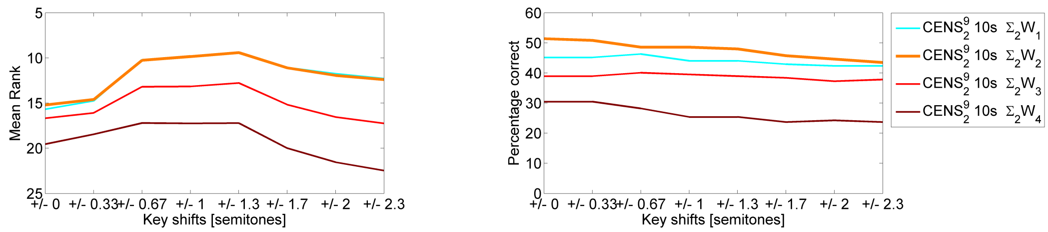



Figure 4.4: Dependency of evaluation results on the weight factor. The evaluation was performed on the subset BM-Small, using the settings $\{\text{CENS}_2^9$, 10 s, $\Sigma_2$, $\kappa^{36}\}$. (a) Mean Rank (b) Top Match

duration sampling with $t_\delta$= 10 s and the step size condition $\Sigma_2$ seems to be a good trade-off between both parameters.

### 4.1.4 Weight factors

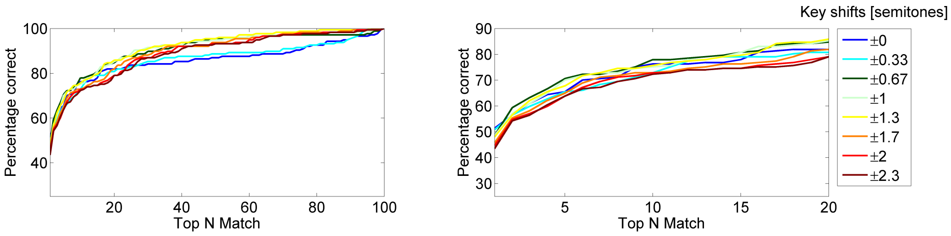
In the following, we evaluate different weight factors. Using the weight factors $W_2$ we also get a Mean Rank of 9. Furthermore we get a Top Match of 51% (see Figure 4.4), which is a high gain by comparison to the so far used weight factors $W_1$. So we finally fix the parameter setting $\{\text{CENS}_2^9$, 10 s, $\Sigma_2$, $W_2$, $\kappa^{36}\}$.

### 4.1.5 Key shifts

Finally considering several key shifts, we have a look not only on the Top Match, but also on the ranks below. Therefore, we use the previously mentioned parameter setting. Figure 4.5 shows the percentage of correct matches as a function of the Top N Match. The Top 10 Matches differ for the evaluated key shifts from 72% to 78% (see Figure 4.5). The Top 50 Matches however differ more widely from 87% to 95%. In the following, we consider the Top 50 Matches. Therefore we subdivide the different number of key shifts into three categories:

- Category I: Key shifts of $\pm 0$ semitones and $\pm 0.33$ semitones
- Category II: Key shifts of $\pm 0.67$ semitones, $\pm 1$ semitones, and $\pm 1.3$ semitones
- Category III: Key shifts of $\pm 1.7$ semitones, $\pm 2$ semitone and $\pm 2.3$ semitones

For Category I we get the lowest Top 50 Matches in the range of 87% and 89%, because several audio recordings are transposed or detuned. Thus they are not detected by the algorithm if we apply only key shifts of up to $\pm 0.33$ semitones. We get our highest Top 50 Matches of roughly 95% for Category II because these key shifts compensate transposed and detuned audio recordings and thus lead to better retrieval results for several queries. Finally, the results for Category III are slightly worse than that for Category II. Transposed and detuned audio recordings are also detected by Category III, however the higher number of key shifts also leads to a lower specificity and thus degrades the results. Our best Top 5 Match is achieved for key shifts of



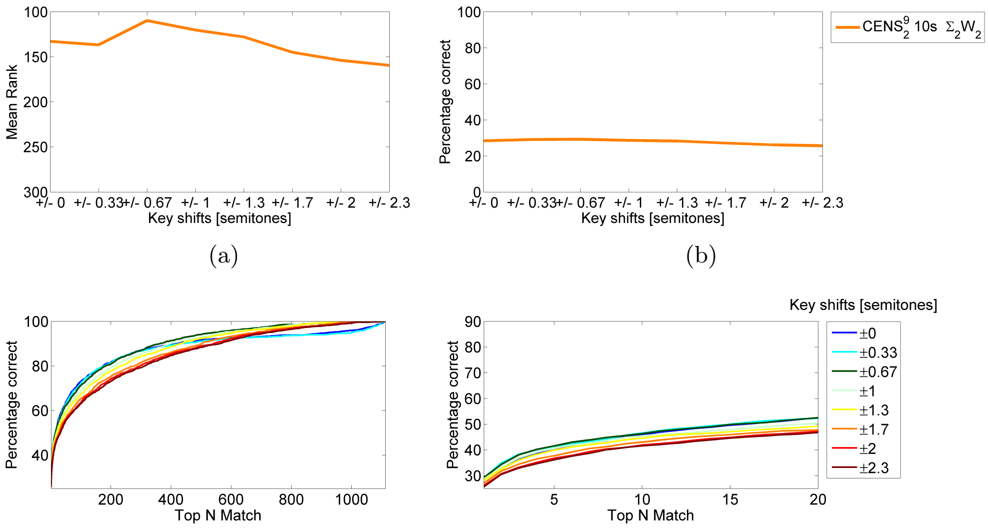

(a) (b)

Figure 4.5: Dependency of evaluation results on the number of key shifts. The evaluation was performed on the subset BM-Small, using the settings $\{\mathrm{CENS}_2^9$, 10 s, $\Sigma_2$, $W_2$, $\kappa^{36}\}$. (a) Overview of the entire database. (b) Extract showing the Top 20 Matches.

$\pm0.67$ semitones at 70% (see Figure 4.5(b)). So the Top 5 Match is much higher than the Top Match with 51% at most.

## 4.2 Evaluation of the subset BM-Medium

In this section we discuss the results for the subset BM-Medium and compare them to BM-Small. Furthermore, we consider histograms for several measures to get deeper insight into the data of BM-Medium. For BM-Medium we apply the parameter setting $\{\mathrm{CENS}_2^9$, 10 s, $\Sigma_2$, $W_2$, $\kappa^{36}\}$ which we considered to be a good trade-off for the subset BM-Small. Figure 4.6 shows the evaluation results for the subset BM-Medium. We get a Mean Rank of 110 and a Top Match of 29% when




(a) (b) (c) (d)

Figure 4.6: Dependency of evaluation results on the number of key shifts. The evaluation was performed on the subset BM-Medium, using the settings $\{\mathrm{CENS}_2^9$, 10 s, $\Sigma_2$, $W_2$, $\kappa^{36}\}$. (a) Mean Rank. (b) Top Match. (c) Overview of the entire database. (d) Extract showing the Top 20 Matches.

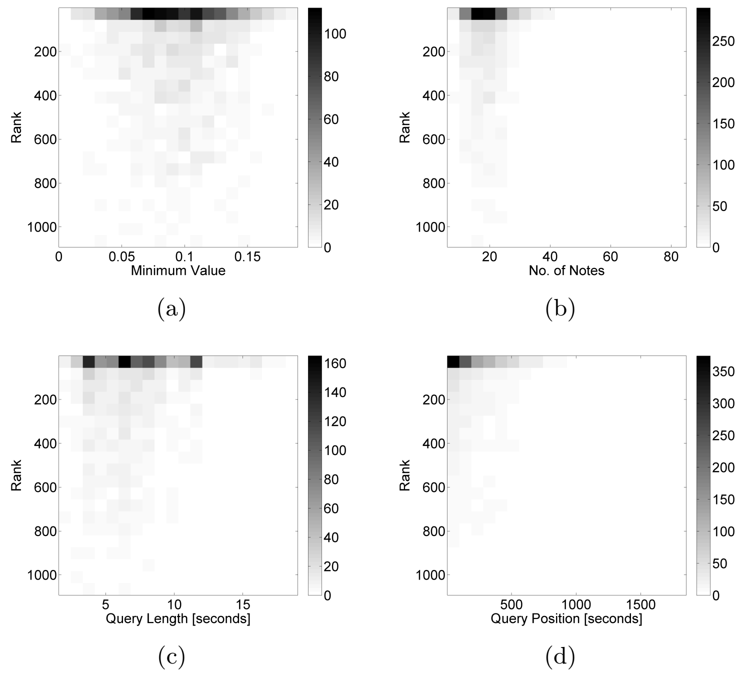



Figure 4.7: Histograms of the distribution of the Ranks in dependence of: (a) Minimum values (b) Number of notes (c) Query length (d) Position of the query within the audio. The evaluation was performed on the subset BM-Medium using the parameter setting $\{\mathrm{CENS}_2^9$, orig, $W_1$, $\kappa_2^{36}\}$.

we use the key shifts of $\pm0.67$ semitones. These results differ widely from the corresponding measures for the subset BM-Small, however the subset BM-Medium is 11 times larger than the subset BM-Small. The Mean Rank of BM-Medium is roughly 12 times higher than the Mean Rank of BM-Small. So the algorithm scales approximately to the size of the underlying subset. In the following, we compare measures for the Top Matches between both subsets. We take into account the size of the respective subset, so the Top 20 Matches of BM-Small correspond to the Top 220 Matches of BM-Medium, for instance. BM-Small has a Top 20 Match of at most 85% for key shifts of $\pm1.3$ semitones, whereas BM-Medium has a Top 220 Match of at most 83% for the key shifts of $\pm0.67$ semitones (see Figure 4.6(c)). So both subsets behave similar, with respect to their size. Considering Figure 4.6(c) more closely, we can also subdivide three categories of key shifts, as for the subset BM-Small. Category I performs better than the other categories from the Top Match to the Top 300 Match. The reason is, that specificity is more important for large databases.

In the following, we look at the correlation of different measures. Figure 4.7 shows several two-dimensional histograms, whereas every histogram shows the correlation between two measures. In Figure 4.7(a), we see the minimum value of the corresponding matching function in dependence of the rank. We can see that for most of the queries the matching document is among the ranks 1 to 50. We infer that the rank is independent of the minimum value. So in general we cannot exclude documents from a ranked list by considering the minimum value. By excluding documents in a ranked list which have a high minimum value, we would also exclude matches. Figure 4.7(b) shows the correlation between the rank and the number of notes of the query. It also shows that the rank does not depend on the number of notes. This is an unexpected observation because we would expect that the number of notes influences the specificity and thus a query that contains many notes has a better ranking result. Figure 4.7(c) shows the correlation between the rank and the length of the query. This Figure gives an unexpected result. The rank does not depend on the query length. In general we would expect, that the rank is lower for long queries, as these queries are supposed to be more specific. In Figure 4.7(d), we can see the correlation between the query position and the rank. By the term query position, we mean the time after which the query occurs in an audio recording. Here we see that for most of the audio recordings the query occurs in the beginning. So we can cut all audio recordings in the database to say 700 seconds at most and use the cut audio recordings for the retrieval system. This will save calculation time and also increases the specificity of our database. In practice however, this will either have not much effect on our database because less than 10% of the audio recordings have a duration of more than 700 seconds, or it will definitely result in a loss of Top Matches when we cut the audio recordings too much.

## 4.3 Analysis of specific queries of the subset BM-Mini

In this section, we consider several specific queries for specific parameter settings. Using the subset `BM`-Mini as foundation, we analyze several matching functions that do not result in a Top Match. This is done to get deeper insight in the limits of our algorithm and find out how the retrieval can be improved in future. The matching functions shown in this section and in Appendix B.1 stick to the following scheme: The matching function is plotted in black color. Gray vertical lines denote the ending of one audio recording and the beginning of another audio recording. The audio recording which we expect our algorithm to retrieve is highlighted in light red color (ground truth document). The global minimum of the matching function is highlighted by a horizontal and a vertical blue dotted line. The vertical dotted line shows whether the global minimum of the matching function is in the ground truth document or not. The horizontal dotted line is meant to show the distance between the global minimum and the minimum of the ground truth document. It gives a feeling of the gap between the ground truth document and the retrieved document.

### 4.3.1 Specificity

In this section we analyze the 2$^{\text{nd}}$ Theme of the Hungarian Dance No.5 by Brahms (#16). The corresponding matching function is shown in Figure 4.8(a). This matching function has no deep minimum peaks. The function has values of around 0.4 which is quite low compared to other matching functions. In the following, we compare the corresponding chromagrams. Figure 4.8(b) shows the 36-dimensional chromagram of the query, and Figure 4.8(c) shows the chromagram of the corresponding excerpt of the database. Here we see that there are mainly three active chromas G+, B+, D+ like in a chord of G Major. So the chromagram of the database is very unspecific. The reason therefore is probably that the ensemble of this audio recording is an entire orchestra. So the main melody is accompanied by deep string instruments which leads to this smoothened chromagram. By comparing it to the chromagram of the query in Figure 4.8(b), we see that they are very dissimilar. So this query will obviously not lead to good matching results. The audio recording seems to be detuned by $\pm 1.3$ semitones with respect to the query. In Appendix B.27 and B.28 we see that this query never results in a Top Match, no matter which

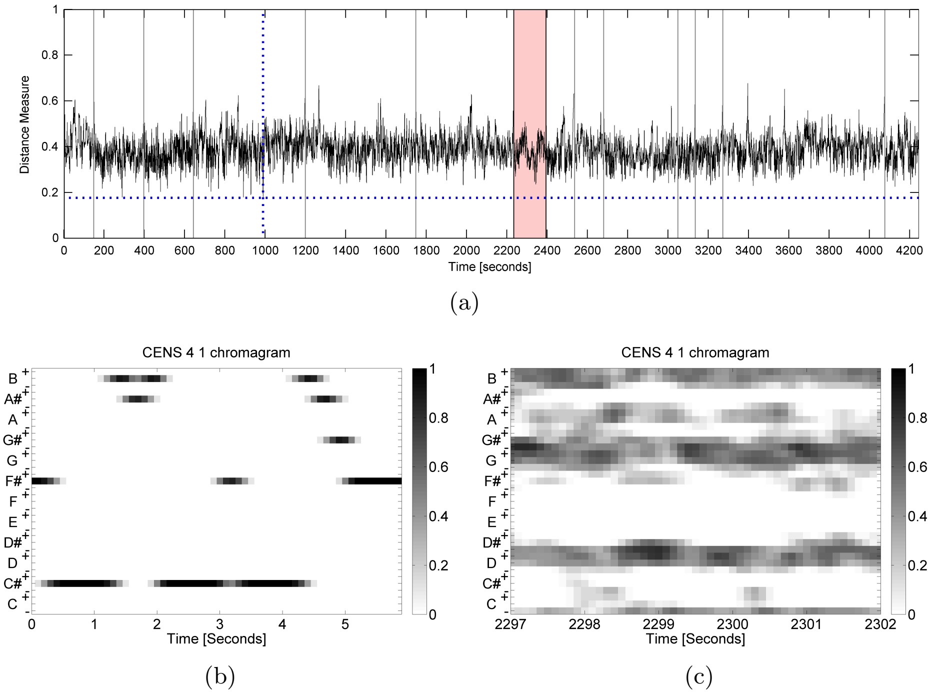
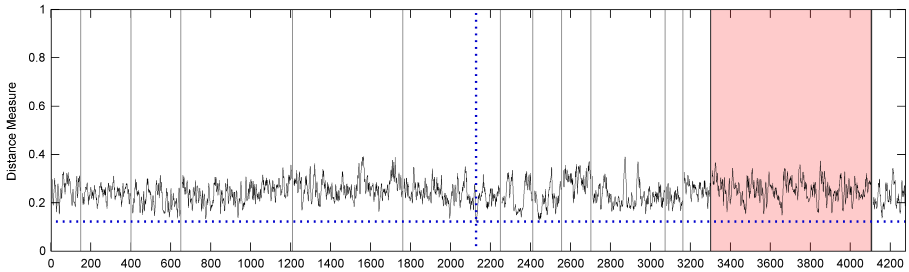



Figure 4.8: Query #16: Example for low specificity. Parameter setting: $\{\text{CENS}_1^4, \Sigma_1, \text{orig}, W_1, \kappa_2^{36}\}$. (a) Matching function. (b) Chromagram of the query. (c) Chromagram of the database corresponding to (b) (excerpt).

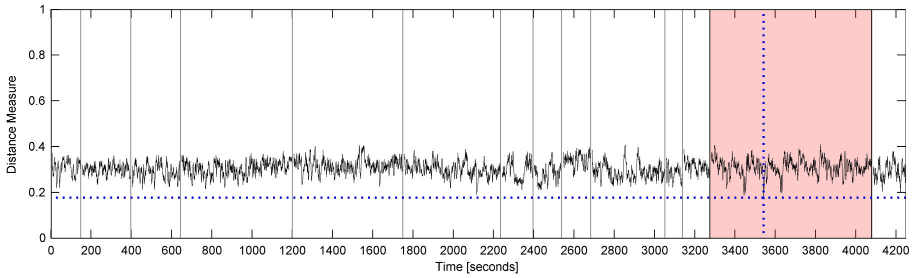
parameter setting is applied. This indicates that the features for the database are not sufficient and may be improved by filtering low frequency components.

### 4.3.2 Feature resolution

In this section we analyze different feature resolutions for Schubert‘s Symphony No.8, 1$^{\text{st}}$ Movement, 1$^{\text{st}}$ Theme (#25). In Figure 4.9 we can see similar matching functions corresponding to the query. Despite the chromagrams look quite different for different feature resolutions, this does not lead to great differences for the corresponding matching functions. So in this case, increasing the feature resolution has only a very small effect on the matching functions. Using a feature resolution of 1 Hz, the algorithm does not detect a match (see Figure 4.9(a)). However, when we use a feature resolution of 5 Hz, the algorithm detects the match (see Figure 4.9(b)). We conclude that increasing the feature resolution increases the specificity and thus improves the performance of the algorithm. On the downside, increasing the feature resolution also increases the computational cost. Furthermore, the curve shapes of both matching functions differ only slightly (see Figure 4.9(a) and Figure 4.9(b)). So increasing the feature resolution will only slightly improve the retrieval results.




(a) $\mathrm{CENS}_{10}^{41}$




(b) $\mathrm{CENS}_{2}^{9}$

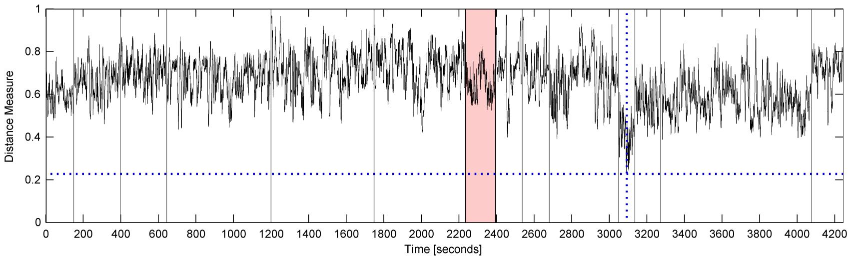
Figure 4.9: Query #25: Example for different feature resolutions. Parameter setting: $\{15$ s, $\Sigma_2$, $W_3$, $\kappa_2^{12}$ $\}$ (a) $\mathrm{CENS}_{10}^{41}$. (b) $\mathrm{CENS}_{2}^{9}$.

### 4.3.3 Tuning

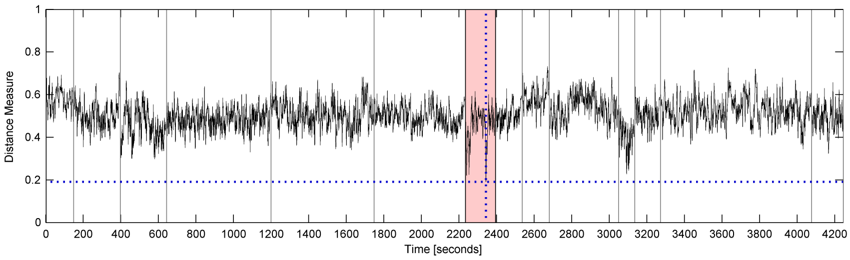
In this section we analyze Brahms' Hungarian Dance No.5 (# 15). The audio recording is detuned by +1.3 semitones as we can see by comparing the chromagrams of query and database (see Figure 4.10(c) and 4.10(d)). So if we apply key shifts of $\pm 0$ semitones, we do not retrieve a match (see Figure 4.10(a)). However if we apply key shifts of $\pm 1.3$ semitones, we retrieve the matching sequence, see Figure 4.10(b) at time 2350 seconds in the database. Having a closer look at both matching functions, we see that the mean value of the matching function in Figure 4.10(a) is roughly 0.7. However, if we apply key shifts of $\pm 1.3$ semitones, this value is roughly 0.4. Thus the gap between the minima for certain documents gets smaller. So this example shows that the specificity is greatly influenced by the number of key shifts.

### 4.3.4 Global and local tempo variations

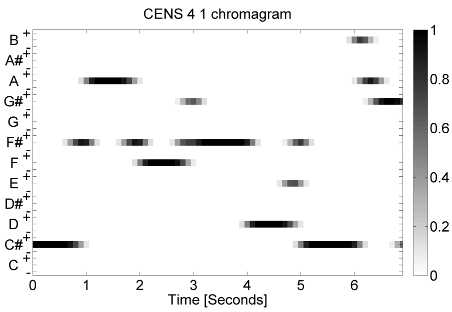
In this section we analyze several parameters which define the tolerated local and global tempo variations between query and database. There are two parameters that have influence on tempo variations, these are the step size condition and the duration of the query. So we analyze two different `EDM`-themes, each with two different step sizes and two different query durations. First of all, we consider the matching function of Beethoven‘s Op.2 No.1, $1^{\text{st}}$ Movement, $1^{\text{st}}$ Theme (#3). Using original query duration, the matching function results in a Top Match for both, the step size condition $\Sigma_2$ and $\Sigma_1$. The original duration of the matching excerpt in this audio recording is roughly 2.7 seconds, whereas the corresponding `EDM`-theme has a duration of 4 seconds, so both step sizes are convenient for this scenario. We now analyze the corresponding matching



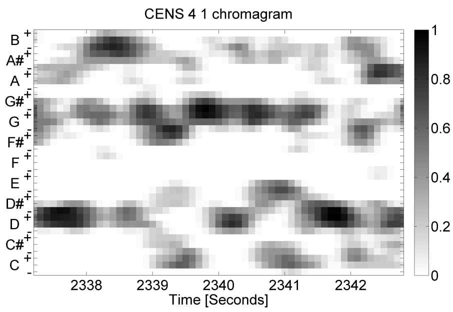

(a) Matching function using key shifts of $\pm 0$ semitones.




(b) Matching function using key shifts of $\pm 1.3$ semitones.




(c)




(d)

Figure 4.10: Query # 15: Example for a detuned audio recording. Parameter setting: $\{\mathrm{CENS}_1^4$, $\Sigma_1$, orig, $W_1$, $\kappa^{36}$ $\}$. (a) Matching function using key shifts of $\pm 0$ semitones. (b) Matching function using key shifts of $\pm 1.3$ semitones. (c) Chromagram of the query. (d) Chromagram of the database (excerpt).

function shown in Figure 4.11, where we use queries of a fixed duration of 10 seconds and the step size condition $\Sigma_2$. In this scenario, we get a matching function containing no distinctive minima and no Top Match result, because of the high global tempo variations. These high tempo variations can be compensated with the step size condition $\Sigma_1$. Then we get a Top Match. On the downside, the specificity decreases and thus this approach is not suitable for larger databases.

In the following, we analyze another `EDM`-theme which behaves quite different regarding the matching result for the specified parameter settings. Therefore we examine the matching function of Beethoven's Op.13, 1$^{\text{st}}$ Movement, 1$^{\text{st}}$ Theme (#7) for the step sizes $\Sigma_1$ and original query duration. The duration of the matching excerpt in the audio recording is roughly 4.4 seconds, the `EDM`-theme however has a duration of 12 seconds. So the matching procedure fails when we use the step size condition $\Sigma_2$, as this parameter setting can compensate tempo variations of factor two at most (see Figure 4.12). However when we use the step size condition $\Sigma_1$, we receive a Top

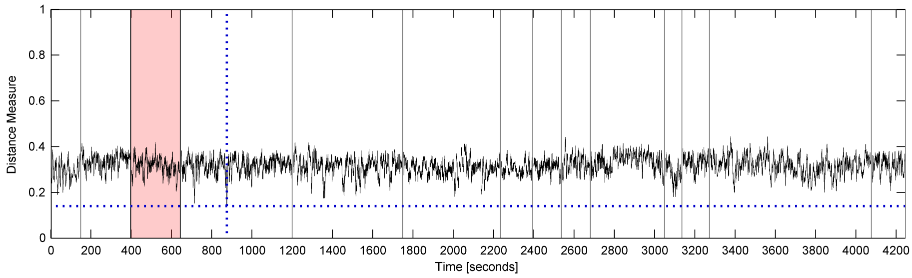



Figure 4.11: Query #3: Example for low tempo variations. Parameter setting : $\{\text{CENS}_1^4$, 10 s, $\Sigma_2$, $W_1$, $\kappa_2^{12}$ $\}$.

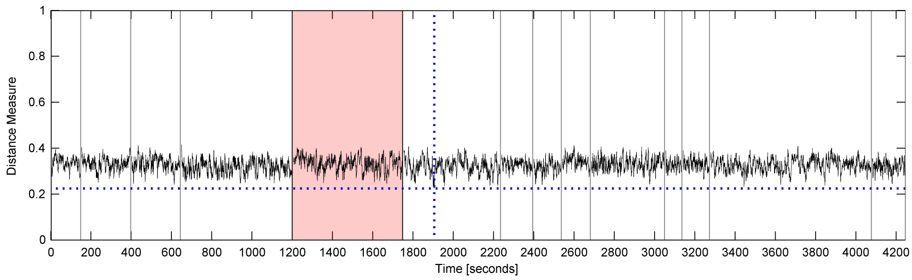


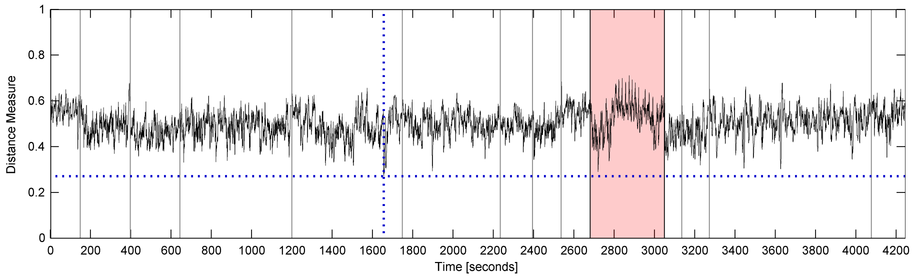

Figure 4.12: Query #7: Example for high tempo variations. Parameter setting : $\{\text{CENS}_1^4$, orig, $\Sigma_2$, $W_1$, $\kappa_2^{12}$ $\}$.

Match. When we use a fixed query duration of 10 seconds, the matching procedure is successful for both step size conditions. So this is a border case for the step size condition $\Sigma_2$ as the Top Match is still identified despite the global tempo difference is slightly higher than a factor of two.

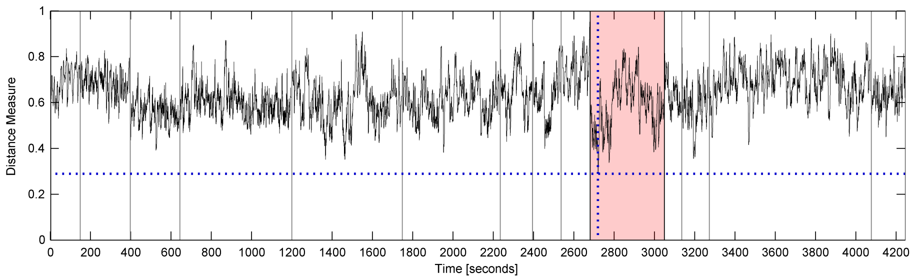
### 4.3.5 Degree of Polyphony

In the following, we show one example of a query, that corresponds to a solo piano audio recording, which is polyphonic. By comparing the chromagram of the query in Figure 4.13(c) to the chromagram of the database excerpt in Figure 4.13(d) we observe big deviations between both chromagrams. The chroma band G$^\sharp$ of the database contains noticably more energy. In order to understand this difference of both chromagrams, we examine the corresponding excerpt of the score and compare it with the `BM`-theme, see Figure 4.14(b), resp. Figure 4.14(a). The melody shown in the `BM`-theme is played by the right hand in the score. This melody is accompanied by several chords, especially by an A$^\flat$ which is played by the left hand. This is the reason why the chroma band G$^\sharp$[1] has so much energy, see Figure 4.13(d). This example shows us that even a solo piano recording can have a high degree of polyphony and thus degrades the specificity and the retrieval result. The retrieval may be improved by filtering out low frequency coefficients. However we cannot assume that this improves the retrieval results in general, as there are also queries containing low pitches. The algorithm does not retrieve the right document in this scenario when we use the parameter settting $\{\text{CENS}_1^4$, $\Sigma_1$, orig, $W_1$, $\kappa_2^{36}$ $\}$, see the matching function in Figure 4.13(a). However if we change the parameter which specifies the number of key

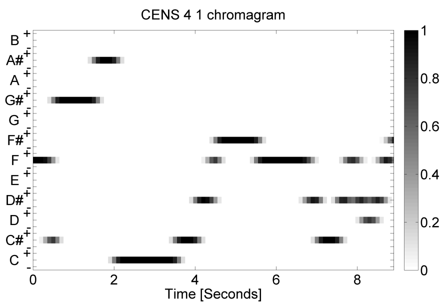
[1] The notes A$^\flat$ and G$^\sharp$ are enharmonically equivalent notes.



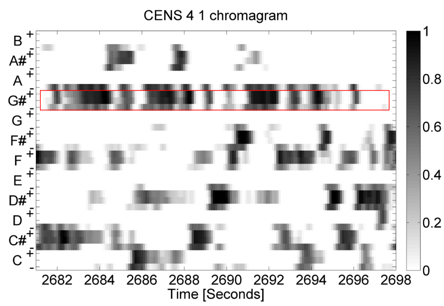

(a) Matching function using the key shifts of $\kappa_2^{36}$.




(b) Matching function using the key shifts of $\kappa_0^{36}$.




(c)



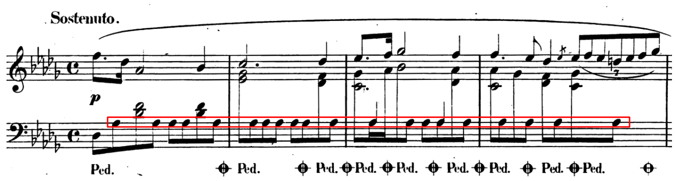

(d)

Figure 4.13: Query #19: Example for a polyphonic audio recording. Parameter setting: $\{\mathrm{CENS}_1^4$, $\Sigma_1$, orig, $W_1$ $\}$. (a) Matching function using the key shifts of $\kappa_2^{36}$. (b) Matching function using the key shifts of $\kappa_0^{36}$. (c) Chromagram of the query. (d) Chromagram of the database (excerpt).

shifts to $\kappa_0^{36}$, the algorithm finds the corresponding document in the database, see Figure 4.13(b). This however only works if the audio recording is neither transposed nor detuned. As a result, this scenario shows us that the performance of the algorithm is highly dependent on the specificity. The specificity strongly depends on the number of key shifts.

In the following, we shortly summarize the achievements of Chapter 4. Depending on the underlying datasets of Western classical music, we have to trade-off between several parameters. As the subset `BM`-Medium is a very large dataset, specificity is the most important aspect. Increasing the feature resolution leads to higher specificity. On the downside, this highly increases the computational cost. Using the step size condition $\Sigma_2$, we also gain specificity, by allowing global tempo variations of a factor of two at most. On the downside, this leads to mismatches for several queries which have much higher global tempo variations. Therefore we stretch every query to a duration of 10 seconds to compensate these high global tempo variations. Increasing


(a)




(b)

Figure 4.14: Query #19: Example for a polyphonic piano score. (a) BM-theme. (b) Score excerpt [15].

the number of key shifts decreases specificity. So we apply key shifts of ±0.67 semitones at most. Finally, polyphony also highly influences matching results of our algorithm.

# Chapter 5

# Conclusions

In this thesis, we modified an existing pipeline for a query-by-example task. We added several strategies to improve the retrieval results for the underlying data of Western classical music. Furthermore, we introduced an enhanced version of chroma features that takes tuning errors into account and thus performs better than standard chroma features. We tested our pipeline on a database of 100 audio recordings and tuned the parameters of our pipeline. Then we tested our pipeline on a large database of 1113 audio recordings using the previously tuned parameter setting. By comparing the results of both experiments, we observed that the results scale with respect to the size of the respective database. By analyzing the retrieval results and the correlation of several measures of the subset `BM`-Medium we gained further information about the underlying data. Furthermore we analyzed particular queries with respect to the properties specificity, tuning, feature resolution, global tempo variations and the degree of polyphony. To this end, we discussed the relation between these properties and the parameters of the pipeline.

The database and the pipeline which were created in this master thesis can be used in a content based search engine for Western classical music with the following properties: Given a query of 7 seconds in mean, the document we search is retrieved as Top Match in 29%. On average, it appears among the top 110 entries. The achievement of this search engine is as follows: Instead of listening through a database of 119 hours of music, we only need to listen to 6:24 min $\cdot$ 110 = 11:44 hours of audio recordings in mean. If we further restrict to listening only to the retrieved sequences (we therefore assume that the algorithm always finds the right sequence within an audio recording) and not the entire recordings, this time further decreases to roughly 18 minutes of audio excerpts.

As future work one could perform experiments on the entire `BM` collection. Therefore, strategies will be needed to decrease the running time of our algorithm. This can be done by cutting audio recordings either to a fixed duration or to a specific percentage of the original length as a preprocessing step. Furthermore, the calculation time can be improved by adding a segmentation step to our pipeline, as introduced in [13, 20]. With this segmentation every audio recording can be analyzed with regard to repeating segments. Then all repetitions can be removed so that all the remainig segments are unique. So the idea is to reduce the size of the database, by removing "redundancy" of the audio recordings. Further future work can be done to improve the retrieval performance of our pipeline. Therefore, the degree of polyphony of the audio recordings can be reduced by a preprocessing step. This can be done by filtering out low frequency coefficients.

The degree of polyphony can also be reduced by using predominant F0 estimation for the audio recordings, as in [7, 8, 16, 17]. Finally, results of chroma based and fundamental frequency based matching procedures can be combined using a descriptor fusion strategy to further improve the performance, see [17].

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# Appendix A

# Source Code

In this chapter, the headers of selected MATLAB functions created during the writing of this thesis are reproduced. The headers contain information about the name of the described function and its input/output behavior.

## Feature Extraction

The `calc_pitch_features` function is used as a wrapper for several low-level functions that perform feature extraction and storage for audio and MIDI files.

Sample usage:
```
calc_pitch_features(db_wav,db_midi,parameter);
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Name: calc_pitch_features
% Date: 2014
% Programmer: Lukas Lamprecht
%
% Description:
% Calculates and saves pitch features for all wav files and all midi files in
% specified folders, if they were not calculated so far.
%
% Input:
% db_wav:  The first column of this cell array specifies the filenames for
%          the wav files to be processed.
% db_midi: The first column of this cell array specifies the filenames for
%          the midi files to be processed.
%
%          The path for the wav files is specified in
%          parameter.directory.abs.wav
%
%          The output path for the wav features is specified in
%          parameter.directory.abs.featurewav
%
%          The path for the midi files is specified in
%          parmeter.directory.abs.midi
%
%          The output path for the midi features is specified in
%          parameter.directory.abs.featuremidi
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

## Evaluation Measures

The `eval_top_n` function calculates the Top N Match as described in Section 2.4.1.

Sample usage:

```
[ pr_match, ranks ] = eval_top_n( gt_vector, doc_matrix );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Name: eval_top_n
% Date: 2014
% Programmer: Lukas Lamprecht
%
% Description:
% Searches the values of a column vector gt_vector rowwise in all n
% columns of a matrix doc_matrix and returns the number of the column in the
% vector ranks, and the probability pr_match that the gt_vector entries
% are equal to one of the n columns in the matrix doc_matrix.
% The first dimension of both vectors must be equal.
%
% Input: gt_vector:  Column vector. The nth entry contains the index of the
%                    groundtruth document, that corresponds to query n.
%        doc_matrix: First dimension is the number of documents.
%                    Second dimension is the number of queries.
%                    Each column contains the according documents that were
%                    found for this query in a sorted fashion.
%
% Output: pr_match:  Top N Match evaluation measure.
%         ranks:     Column vector which contains the actual rank for every
%                    query.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

The `mean_rank` function calculates the mean rank as described in Section 2.4.2.

Sample usage:

```
[ m_rank ] = mean_rank(gt_vector, doc_matrix);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Name: mean_rank
% Date: 2014
% Programmer: Lukas Lamprecht
%
% Description:
% Calculates the mean rank for a given groundtruth vector gt_vector and a
% matrix doc_matrix. The n-th column of the matrix is a ranking list for
% the query n. It contains the indices of the most relevant documents in
% descending order.
%
% Input:  gt_vector:    The gt_vector is a column vector of height m. It
%                       contains the index of the ground truth document for
%                       the m-th query.
%         doc_matrix:   Matrix, that contains a ranking list for each
%                       query. Each column is a ranking list for one query.
%                       Every entry is the number of a document in the
%                       database.
% Output: m_rank:       Mean rank evaluation measure.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

## Creation of LaTeX-Code

The `cellArray2latex` function is a low-level function which generates LaTeX-code for tables provided as cell arrays. This function is called by the function `latex2file` which saves the LaTeX-code in a file.

Sample usage:

```
[ latex ] = cellArray2latex( cell_array, column_headers, entry, order );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Name: cellArray2latex
% Date: 2014
% Programmer: Lukas Lamprecht
%
% Description:
% Converts a cell array into a latex table, using the specified column headers.
%
% Input:  cell_array:     The cell array, that contains the data to be
%                         converted into a latex table.
%         column_headers: Headers of the columns, that will be shown in the
%                         latex table.
%         entry:          Specifies the name of the latex table. Has to be
%                         different for every table.
%         order:          Vector that specifies the order in which the columns
%                         are positioned.
%
% Output: latex:          Cell array, that contains the latex code.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Sample usage:

```
 latex2file( cell, headers, save_dir, filename, expr_rep );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Name: latex2file
% Date: 2014
% Programmer: Lukas Lamprecht
%
% Description:
% Converts and saves a cell array into a latex file, using the specified column
% headers.
%
% Input: cell:     Cell array with table entries
%        headers:  Table Headers provided in a cell array.
%        save_dir: Latex file is saved in this directory.
%        filename: Latex file is saved with the specified filename.
%        expr_rep: Optional - Cell array of size (N,2). Here you can pass a
%                  cell array of regular expressions, that are replaced.
%                  The content of the first row is the expression that is
%                  searched, whereas the second row specifies the replaced
%                  expression.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

# Appendix B

# BM-Subsets

In the following we provide selected data, that was created during the writing of this thesis. The data includes matching functions for all queries of the subset `BM`-Mini, whereas we use the feature settings that lead to the best matching results. Furthermore we provide an overview of the retrieval results for the subset `BM`-Mini for several parameter settings. Moreover we provide one table containing all audio recordings and another table containing all musical themes for the subset `BM`-Mini and `BM`-Small respectively. For the subset `BM`-Medium we provide statistics on the composers. Finally we provide tables that document errors in the subsets, and also in `EDM`-themes.

## B.1 BM-Mini Matching functions

In the following, we show the matching results by presenting the corresponding matching functions for the subset `BM`-Mini. Therefore we use the parameter setting: $\{\mathrm{CENS}_1^4, \Sigma_1, \text{orig}, W_1, \kappa_2^{36}\}$. The matching functions shown in this section stick to the following scheme: The matching function is plotted in black color. Gray vertical lines denote the ending of one audio recording and the beginning of another audio recording. The audio recording which we expect our algorithm to retrieve is highlighted in light red color (ground truth document). The global minimum of the matching function is highlighted by a horizontal and a vertical blue dotted line. The vertical dotted line shows wether the global minimum of the matching function is in the ground truth document or not. The horizontal dotted line is meant to show the distance between the global minimum and the minimum of the ground truth document. It gives a feeling of the gap between the ground truth document and the retrieved document.

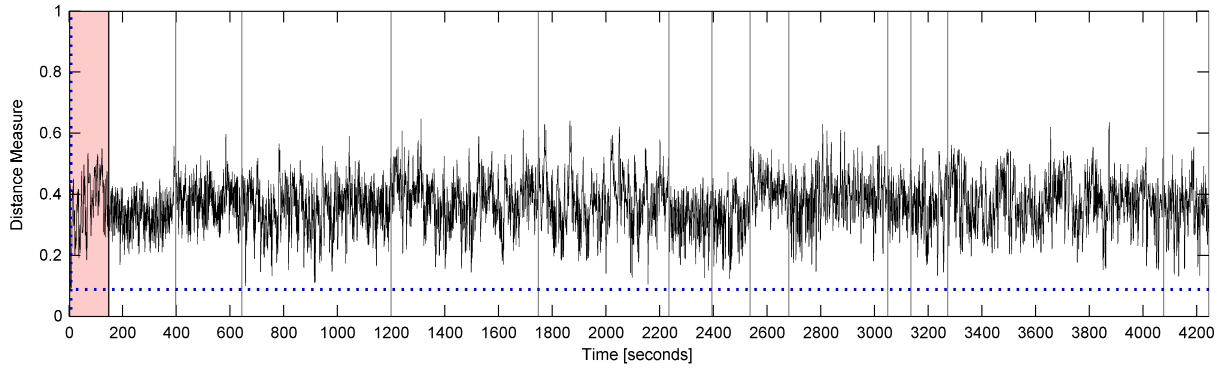


Figure B.1: Matching function for the query **Bach_BWV0846-01_EDM0394_BM0389** returns the document **Bach_BWV0846-01_Belder_BM0389-BM**.

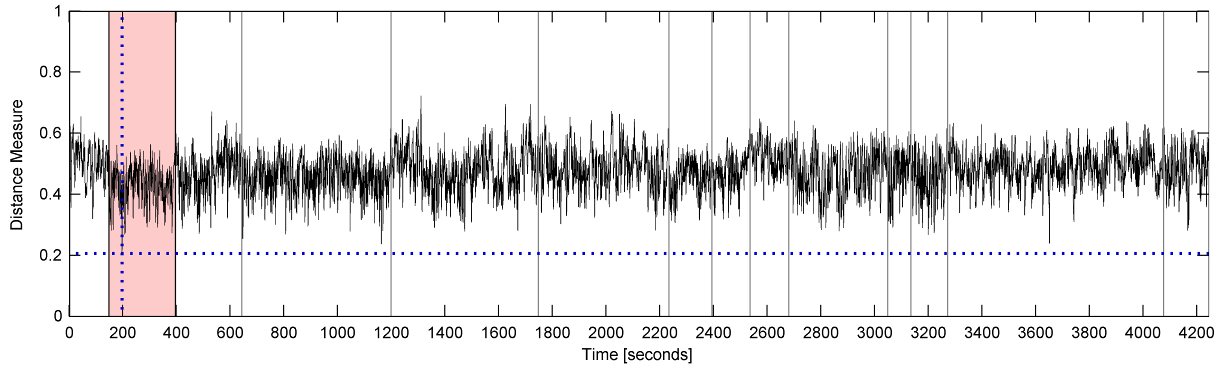


Figure B.2: Matching function for the query **Bach_BWV1041-01_EDM0174_BM0169** returns the document **Bach_BWV1041-01_Sitkovetsky_BM0169-BM**.

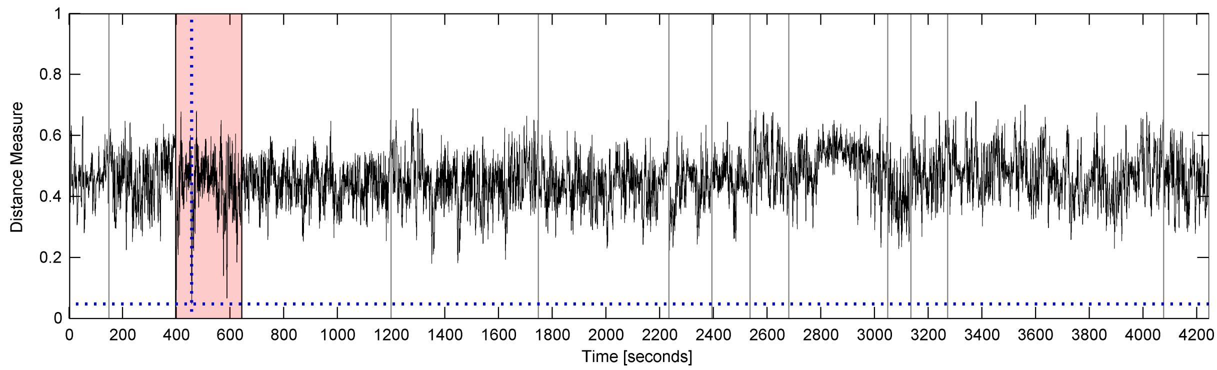


Figure B.3: Matching function for the query **Beethoven_Op002No1-01_EDM0813_BM0807** returns the document **Beethoven_Op002No1-01_Brendel_BM0807-BM**.

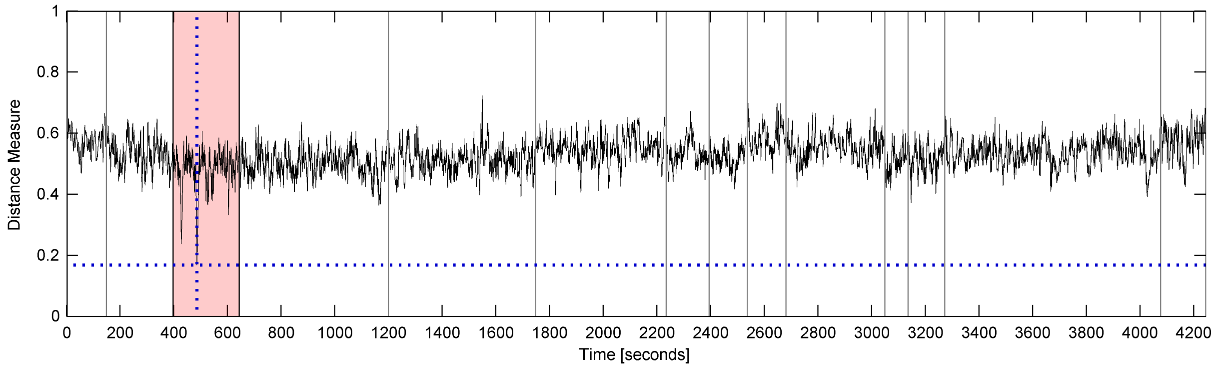


Figure B.4: Matching function for the query **Beethoven_Op002No1-01_EDM0814_BM0808** returns the document **Beethoven_Op002No1-01_Brendel_BM0807-BM**.

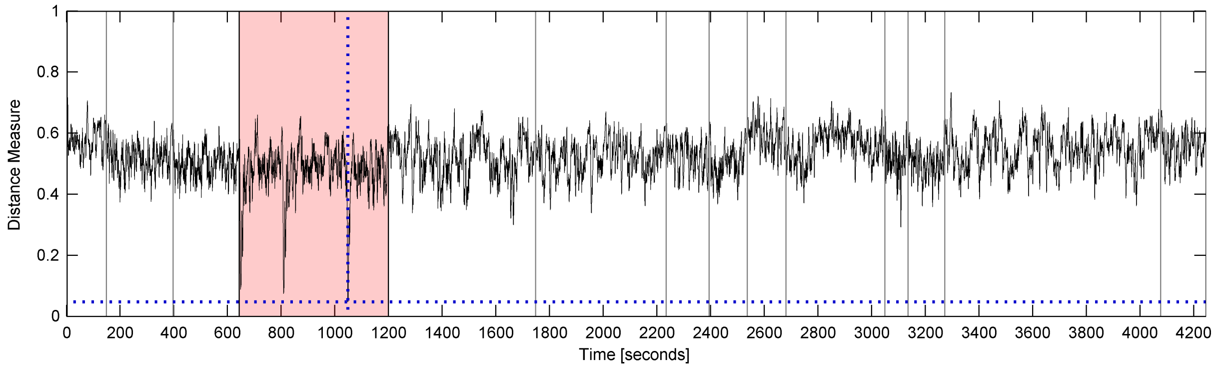


Figure B.5: Matching function for the query **Beethoven_Op011-01_EDM1156_BM1149** returns the document **Beethoven_Op011-01_Berkes_BM1149-BM**.

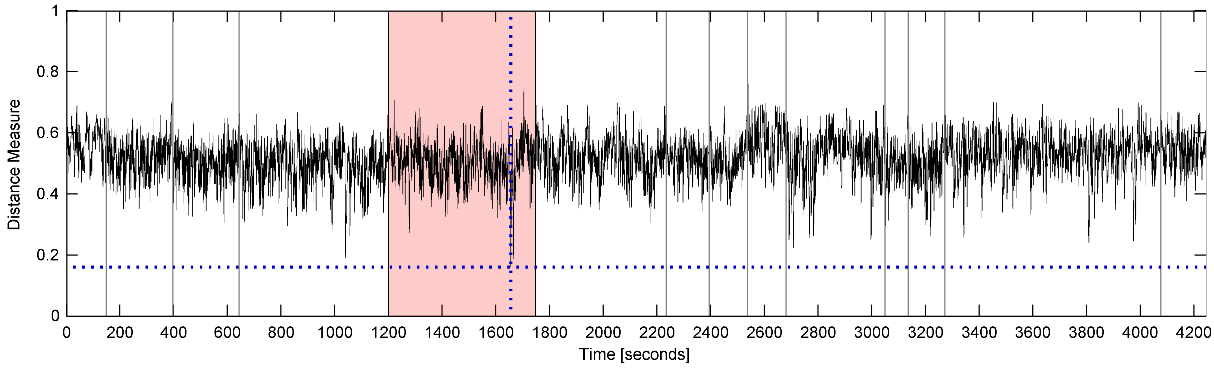


Figure B.6: Matching function for the query **Beethoven_Op013-01_EDM0852_BM0846** returns the document **Beethoven_Op013-01_Brendel_BM0846-BM**.

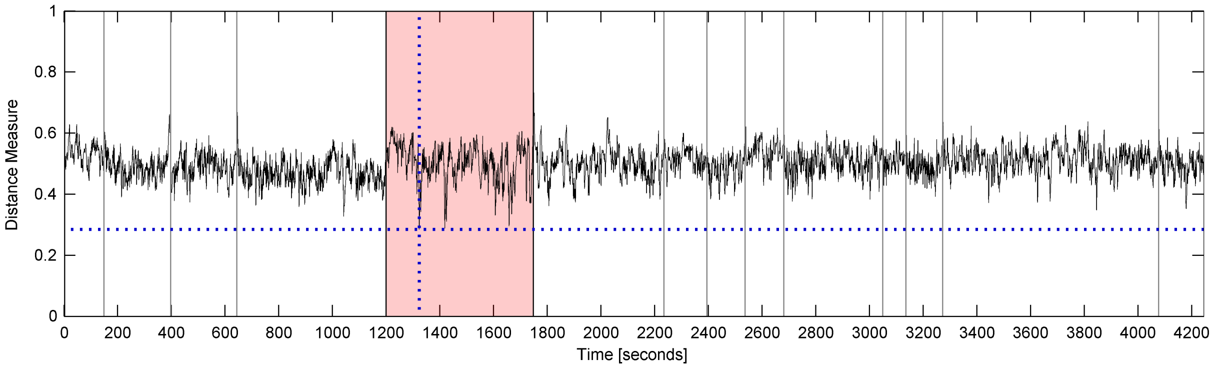


Figure B.7: Matching function for the query **Beethoven_Op013-01_EDM0853_BM0847** returns the document **Beethoven_Op013-01_Brendel_BM0846-BM**.

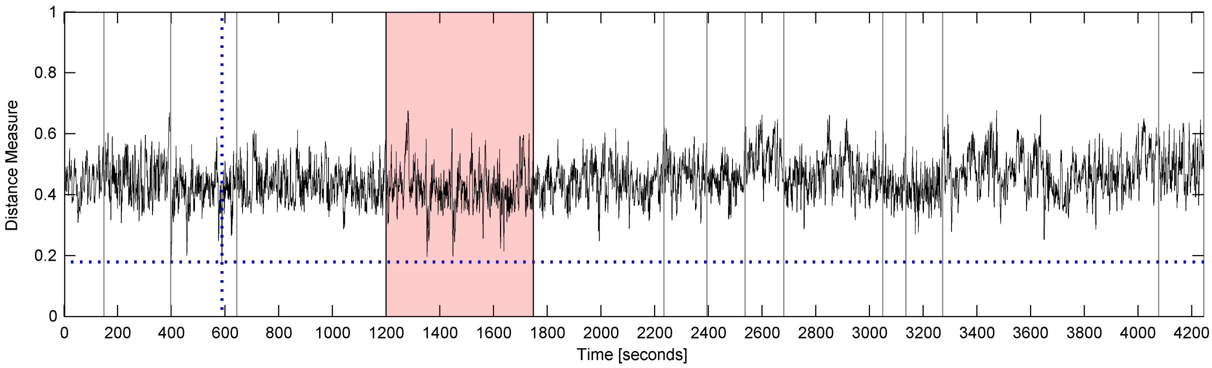


Figure B.8: Matching function for the query **Beethoven_Op013-01_EDM0854_BM0848** returns the document **Beethoven_Op002No1-01_Brendel_BM0807-BM**.

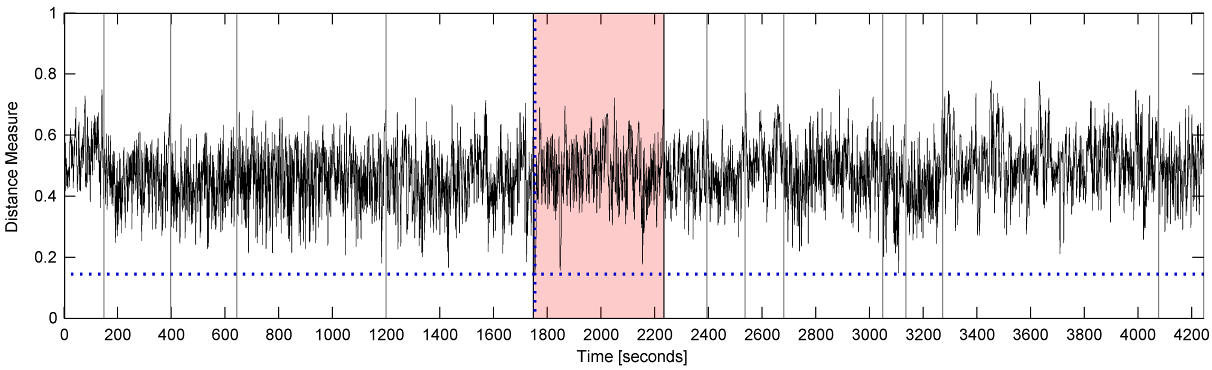


Figure B.9: Matching function for the query **Beethoven_Op067-01_EDM1072_BM1066** returns the document **Beethoven_Op067-01_Blomstedt_BM1066-BM**.

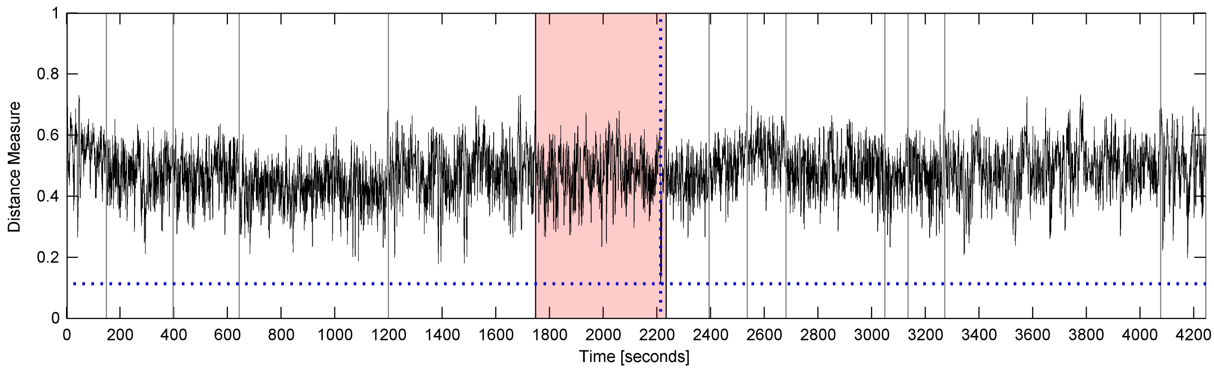


Figure B.10: Matching function for the query **Beethoven_Op067-01_EDM1073_BM1067** returns the document **Beethoven_Op067-01_Blomstedt_BM1066-BM**.

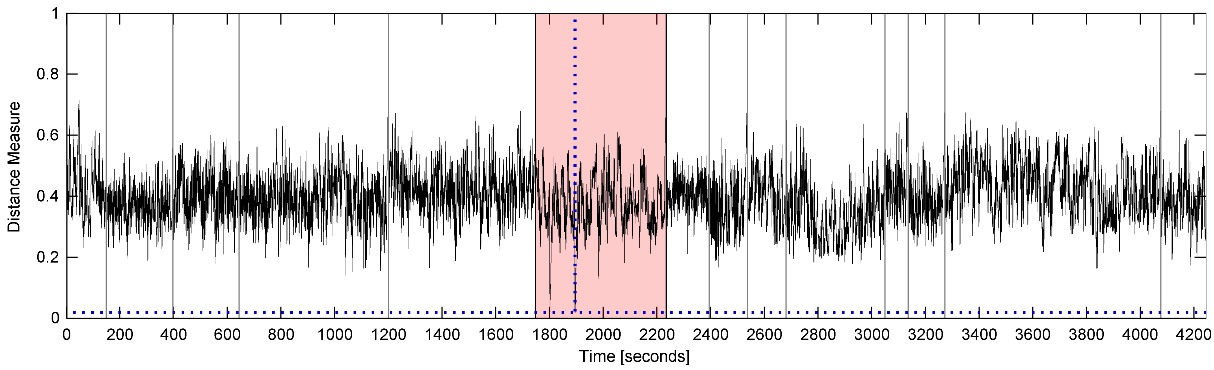


Figure B.11: Matching function for the query **Beethoven_Op067-01_EDM1074_BM1068** returns the document **Beethoven_Op067-01_Blomstedt_BM1066-BM**.

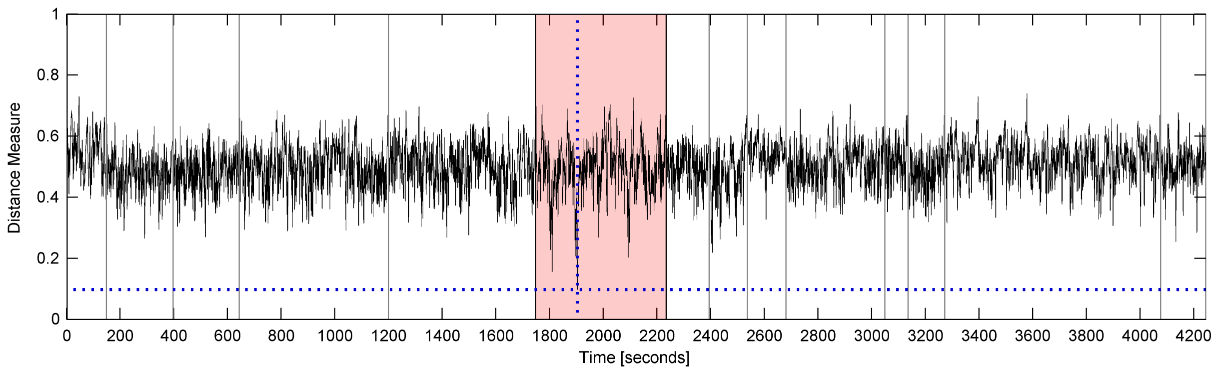


Figure B.12: Matching function for the query **Beethoven_Op067-01_EDM1075_BM1069** returns the document **Beethoven_Op067-01_Blomstedt_BM1066-BM**.

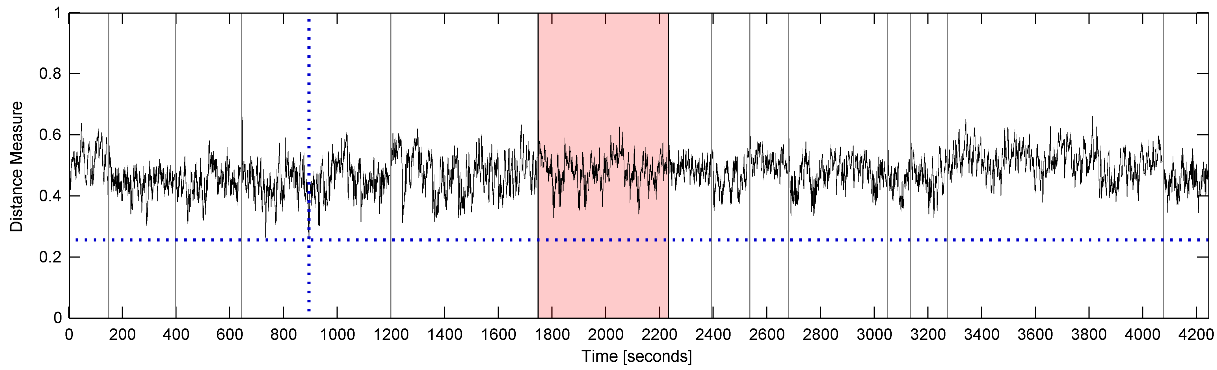


Figure B.13: Matching function for the query **Beethoven_Op067-01_EDM1076_BM1070** returns the document **Beethoven_Op011-01_Berkes_BM1149-BM**.

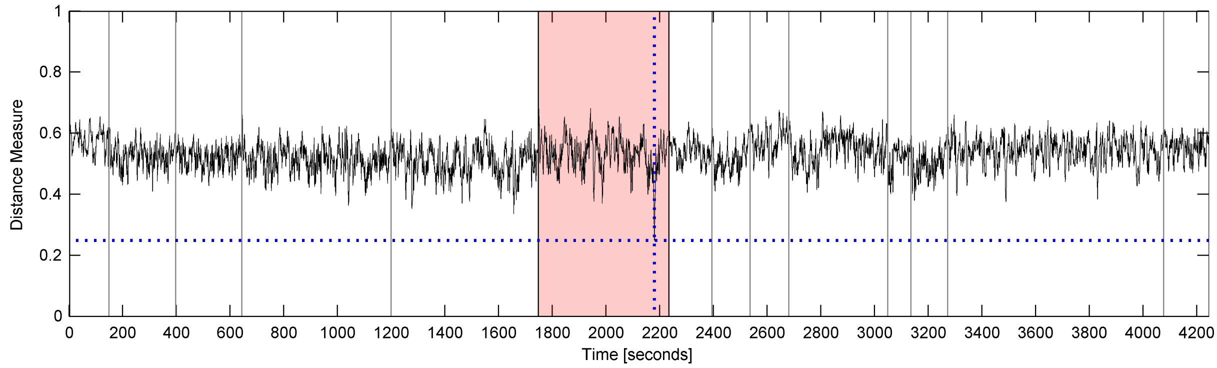


Figure B.14: Matching function for the query **Beethoven_Op067-01_EDM1077_BM1071** returns the document **Beethoven_Op067-01_Blomstedt_BM1066-BM**.

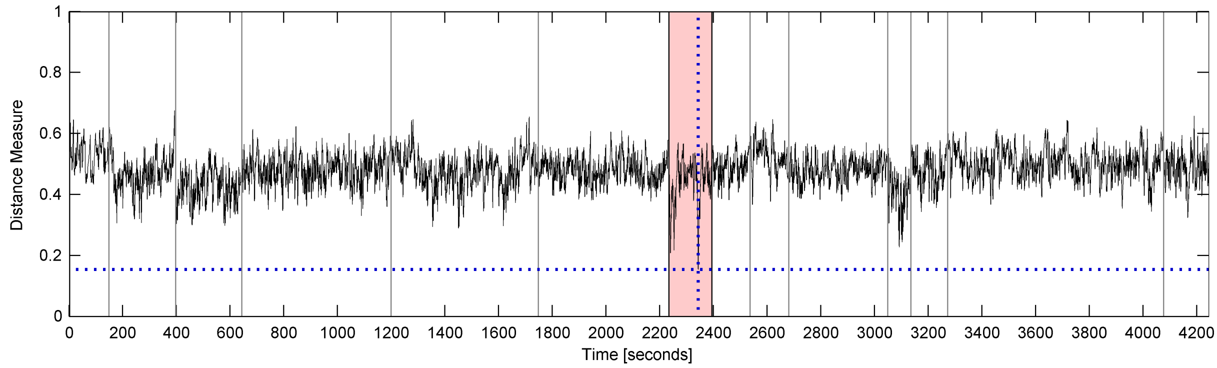


Figure B.15: Matching function for the query **Brahms_HungarianDances-05_EDM8508_BM1511** returns the document **Brahms_HungarianDances-05_SchmidtIsserstedt_BM1511-BM**.

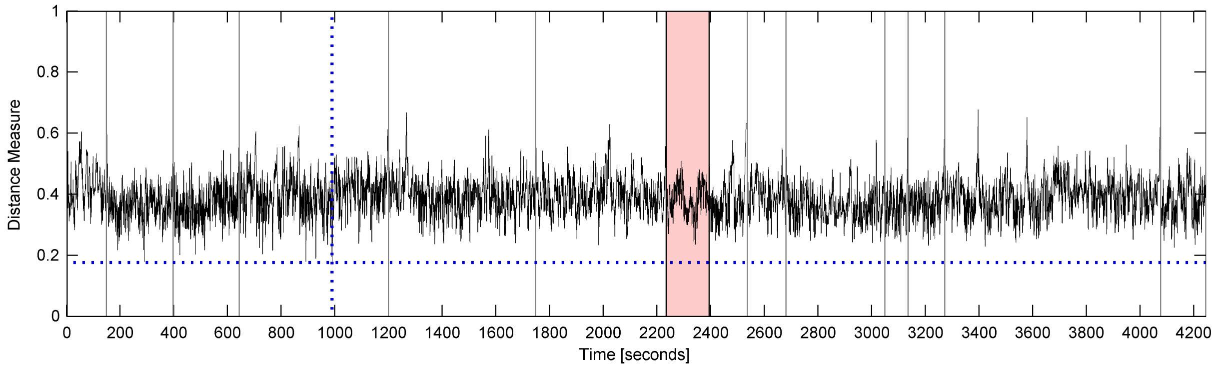


Figure B.16: Matching function for the query **Brahms_HungarianDances-05_EDM8509_BM1512** returns the document **Beethoven_Op011-01_Berkes_BM1149-BM**.

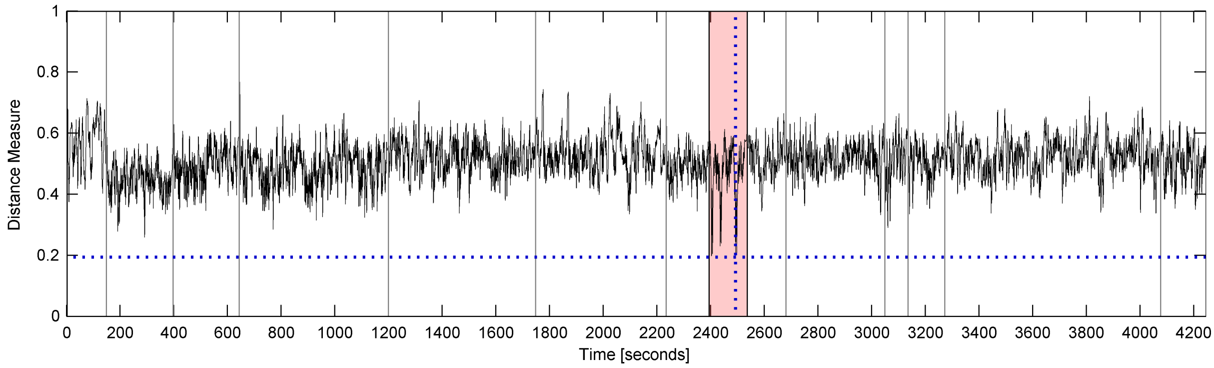


Figure B.17: Matching function for the query **Chopin_Op024-02_EDM9222_BM2219** returns the document **Chopin_Op024-02_Groot_BM2219-BM**.

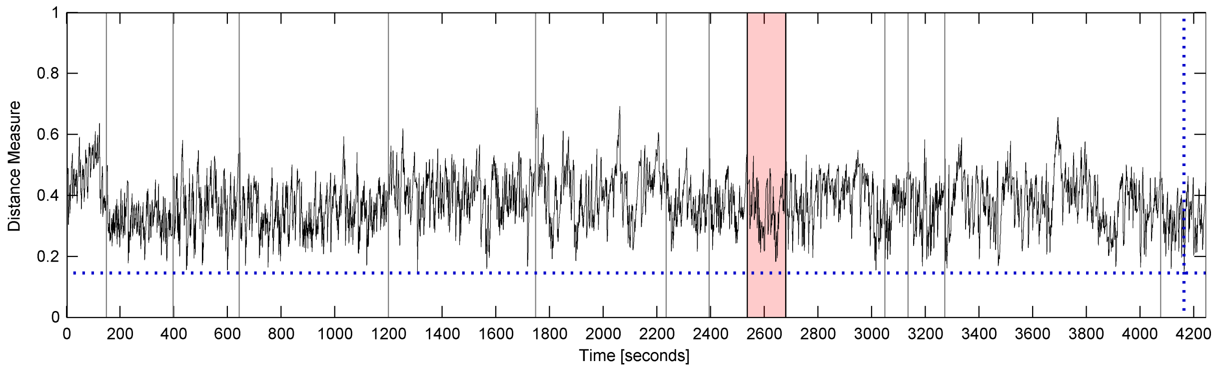


Figure B.18: Matching function for the query **Chopin_Op028-04_EDM9280_BM2276** returns the document **Schumann_Op015-07_Horowitz_BM7940-BM**.

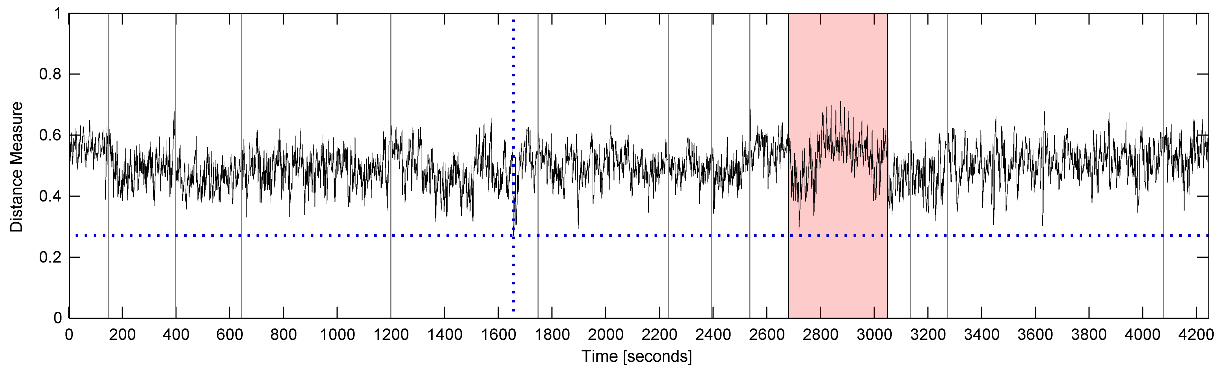


Figure B.19: Matching function for the query **Chopin_Op028-15_EDM9291_BM2287** returns the document **Beethoven_Op013-01_Brendel_BM0846-BM**.

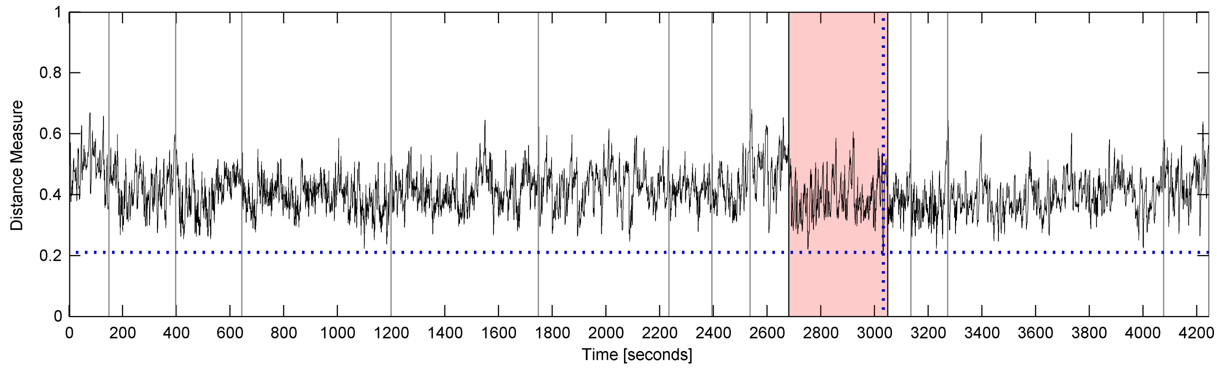


Figure B.20: Matching function for the query **Chopin_Op028-15_EDM9292_BM2288** returns the document **Chopin_Op028-15_Davidovich_BM2287-BM**.

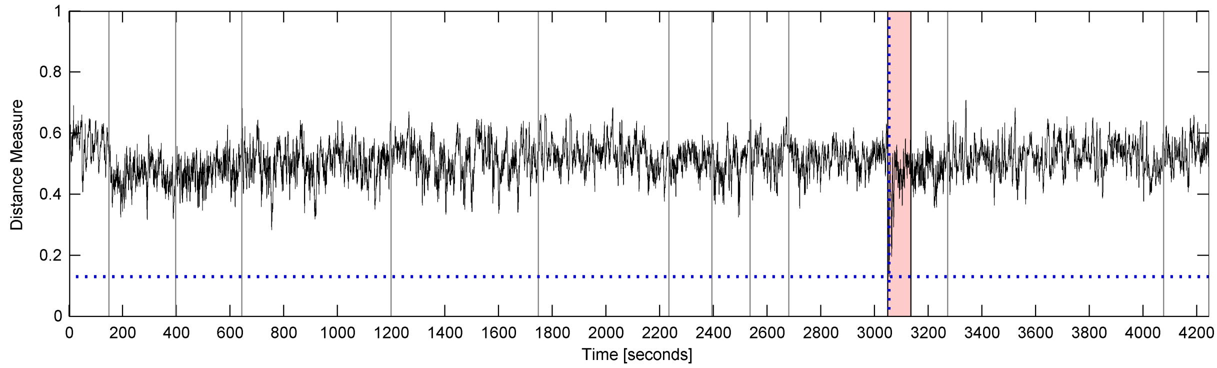


Figure B.21: Matching function for the query **Chopin_Op030-02_EDM9224_BM2221** returns the document **Chopin_Op030-02_Groot_BM2221-BM**.

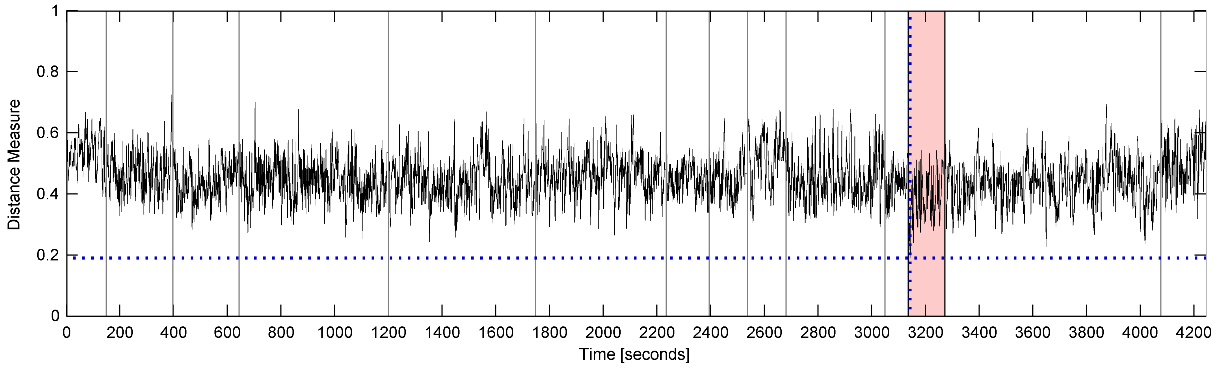


Figure B.22: Matching function for the query **Chopin_Op063-03_EDM9239_BM2236** returns the document **Chopin_Op063-03_Groot_BM2236-BM**.

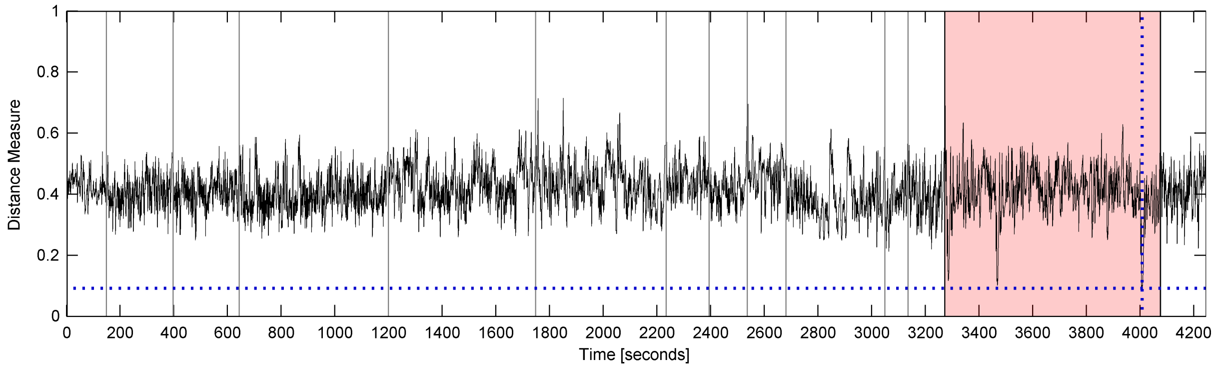


Figure B.23: Matching function for the query **Schubert_D0759-01_EDM6120_BM7752** returns the document **Schubert_D0759-01_Goodman_BM7752-BM**.

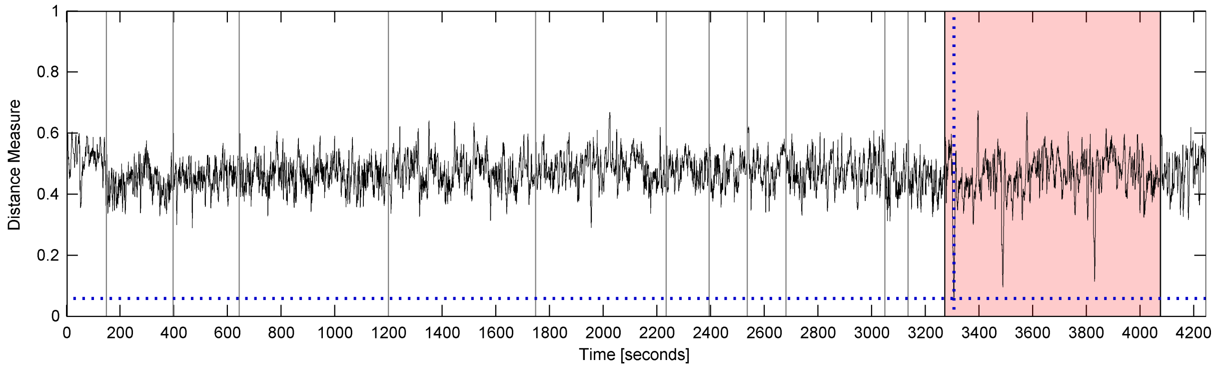


Figure B.24: Matching function for the query **Schubert_D0759-01_EDM6121_BM7753** returns the document **Schubert_D0759-01_Goodman_BM7752-BM**.

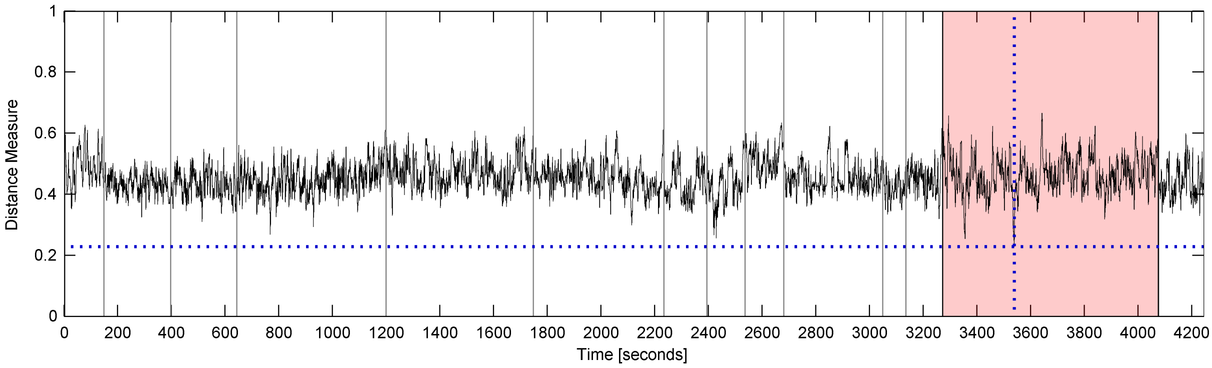


Figure B.25: Matching function for the query **Schubert_D0759-01_EDM6122_BM7754** returns the document **Schubert_D0759-01_Goodman_BM7752-BM**.

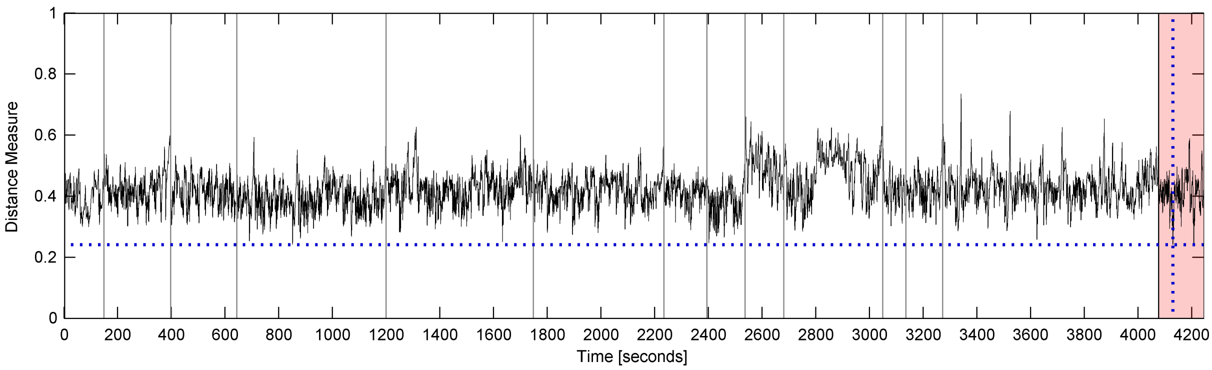


Figure B.26: Matching function for the query **Schumann_Op015-07_EDM6308_BM7940** returns the document **Schumann_Op015-07_Horowitz_BM7940-BM**.

## B.2 BM-Mini ranking results

This Appendix provides figures that give an overview of the retrieval results of the subset BM-Mini for several parameter settings. For every query of the subset, the rank on which the ground truth document appears is color coded. White spots indicate a Top Match, whereas dark spots indicate a bad matching result. With these figures many different parameter settings can be compared directly.

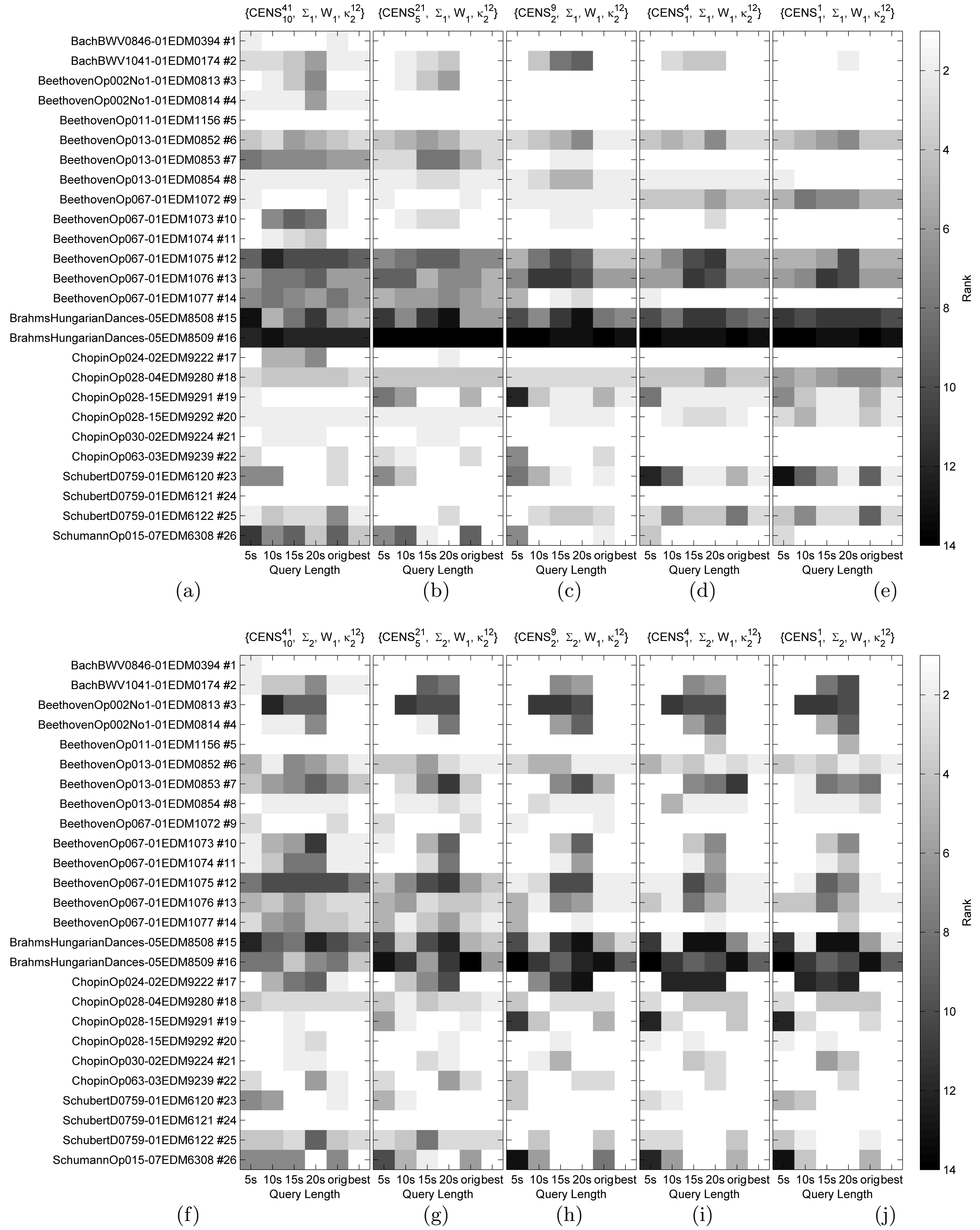

Figure B.27: Ranking results for subset BM-Small using the parameter setting $\{\kappa_2^{12}\}$.

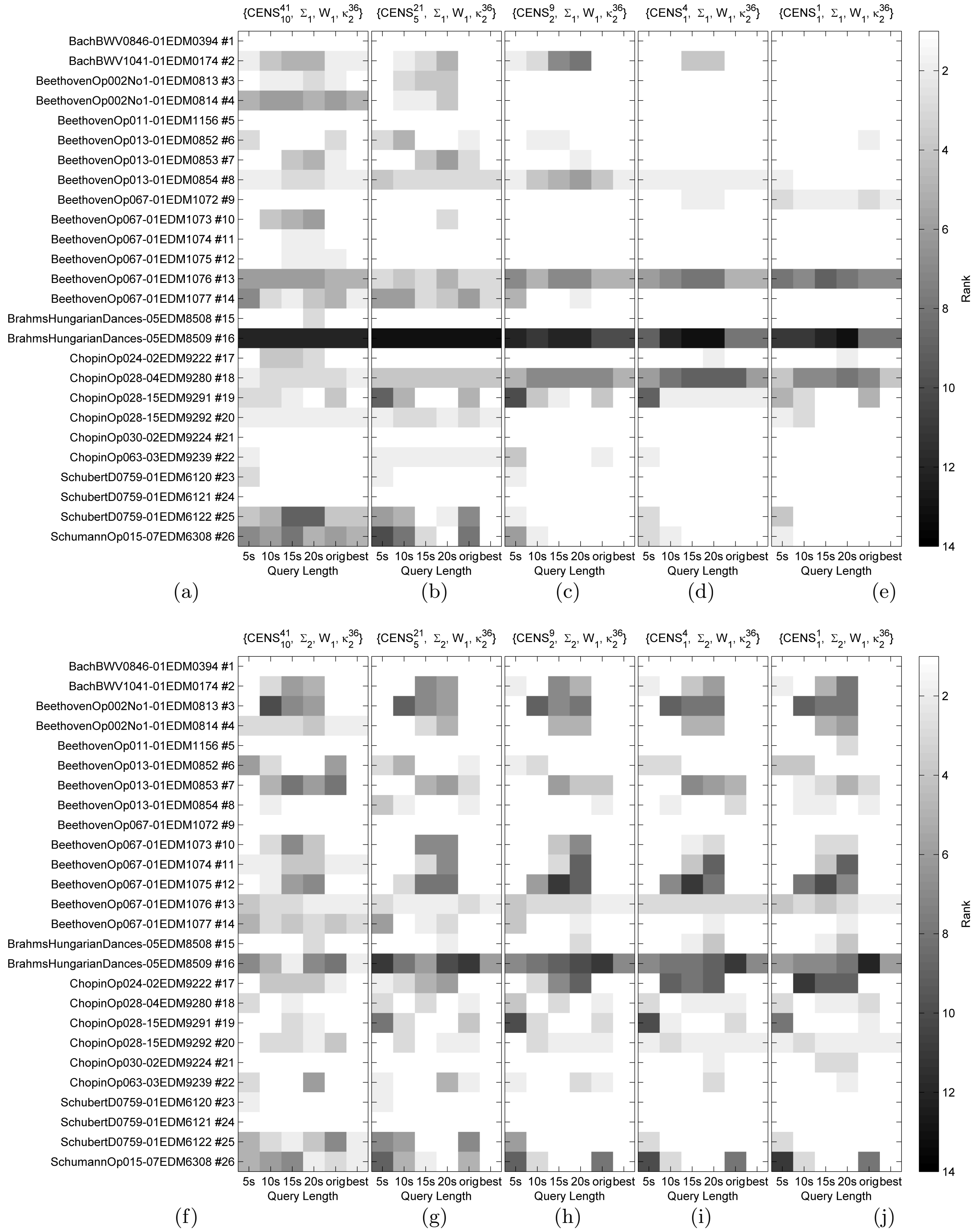


Figure B.28: Ranking results for subset BM-Small using the parameter setting $\{\kappa_2^{36}\}$.

## B.3 Ensemble and Instrumentation IDs

| EnsembleID | Number of instruments |
|---|---|
| Solo | 1 |
| Duo | 2 |
| Trio | 3 |
| Quartet | 4 |
| Quintet | 5 |
| Sextet | 6 |
| Septet | 7 |
| Octet | 8 |
| Nonet | 9 |
| Decet | 10 |
| Concerto | solo instrument and orchestra |
| Orchestra | orchestra |

| InstrumentID | Definition |
|---|---|
| altorecorder | Altorecorder |
| bassoon | Bassoon |
| cello | Cello |
| clarinet | Clarinet |
| doublebass | Doublebass |
| englishhorn | Englishhorn |
| flute | Flute |
| guitar | Guitar |
| harp | Harp |
| harpsichord | Harpsichord |
| horn | Horn |
| oboe | Oboe |
| orchestra | Orchestra |
| organ | Organ |
| piano | Piano |
| piccolotrumpet | Piccolotrumpet |
| strings | Strings or string chamber orchestra |
| timpani | Timpani |
| trumpet | Trumpet |
| viola | Viola |
| violagamba | Viola da Gamba |
| violin | Violin |
| windsection | Windsection |
| xylophone | Xylophone |

## B.4 Audio Recordings for BM-Mini

| Composer | WorkID | Folder | CD | Tr | Name | Ensemble | Instrumentation | Duration |
|---|---|---|---|---|---|---|---|---|
| Bach | BWV0846-01 | Bach Complete Edition BC | 24 | 1 | Prelude | Solo | Harpsichord | 02:28 |
| Bach | BWV1041-01 | Bach Complete Edition BC | 5 | 1 | Violin Concert in A minor | Concerto | Violin Harpsichord Strings | 04:08 |
| Beethoven | Op002No1-01 | Beethoven Complete Edition BC | 49 | 1 | Sonata no. 1 | Solo | Piano | 04:06 |
| Beethoven | Op011-01 | Beethoven Complete Edition BC | 20 | 4 | Gassenhauer-Trio | Trio | Clarinet Cello Piano | 09:16 |
| Beethoven | Op013-01 | Beethoven Complete Edition BC | 52 | 1 | Pathétique | Solo | Piano | 09:08 |
| Beethoven | Op067-01 | Beethoven Complete Edition BC | 3 | 1 | Symphony No. 5 | Orchestra | Orchestra | 08:05 |
| Brahms | Hungarian Dances-05 | Various MasterpiecesClassicalMusic MEMBRAN | 15 | 8 | | Orchestra | Orchestra | 02:40 |
| Chopin | Op024-02 | Chopin Complete Works BC | 7 | 15 | Mazurka | Solo | Piano | 02:22 |
| Chopin | Op028-04 | Chopin Complete Works BC | 16 | 4 | Prelude | Solo | Piano | 02:23 |
| Chopin | Op028-15 | Chopin Complete Works BC | 16 | 15 | Prelude Raindrop | Solo | Piano | 06:09 |
| Chopin | Op030-02 | Chopin Complete Works BC | 7 | 19 | Mazurka | Solo | Piano | 01:26 |
| Chopin | Op063-03 | Chopin Complete Works BC | 8 | 18 | Mazurka | Solo | Piano | 02:16 |
| Schubert | D0759-01 | Schubert TheMasterworks BC | 2 | 1 | Unfinished Symphony | Orchestra | Orchestra | 13:24 |
| Schumann | Op015-07 | Schumann MasterworksEdition SONY | 5 | 7 | Traeumerei | Solo | Piano | 02:50 |

## B.5 EDM-MIDIs of BM-Mini

| IDX | Composer | WorkID | BMID | ThemeID | MidiNo | Notes | Duration [$s$] |
|---|---|---|---|---|---|---|---|
| 1 | Bach | BWV0846-01 | B301 | | 394 | 32 | 4 |
| 2 | Bach | BWV1041-01 | B83 | | 174 | 15 | 3.7 |
| 3 | Beethoven | Op002No1-01 | B689 | 1st Theme | 813 | 10 | 4 |
| 4 | Beethoven | Op002No1-01 | B690 | 2nd Theme | 814 | 16 | 8 |
| 5 | Beethoven | Op011-01 | B1031 | | 1157 | 12 | 5.5 |
| 6 | Beethoven | Op013-01 | B728 | Intro | 852 | 12 | 3.7 |
| 7 | Beethoven | Op013-01 | B729 | 1st Theme | 853 | 17 | 12 |
| 8 | Beethoven | Op013-01 | B730 | 2nd Theme | 854 | 14 | 8.5 |
| 9 | Beethoven | Op067-01 | B948 | 1st Theme A | 1072 | 8 | 5 |
| 10 | Beethoven | Op067-01 | B949 | 1st Theme B | 1073 | 10 | 4.2 |
| 11 | Beethoven | Op067-01 | B950 | 1st Theme C | 1074 | 6 | 5 |
| 12 | Beethoven | Op067-01 | B951 | 2nd Theme | 1075 | 8 | 4 |
| 13 | Beethoven | Op067-01 | B952 | 3rd Theme | 1076 | 25 | 7.2 |
| 14 | Beethoven | Op067-01 | B953 | 4th Theme | 1077 | 17 | 9 |
| 15 | Brahms | Hungarian Dances-05 | B1375 | 1st Theme | 8508 | 18 | 7 |
| 16 | Brahms | Hungarian Dances-05 | B1376 | 2nd Theme | 8509 | 20 | 6 |
| 17 | Chopin | Op024-02 | C232 | | 9222 | 24 | 6 |
| 18 | Chopin | Op028-04 | C289 | | 9280 | 18 | 16 |
| 19 | Chopin | Op028-15 | C300 | 1st Theme | 9291 | 21 | 9 |
| 20 | Chopin | Op028-15 | C301 | 2nd Theme | 9292 | 19 | 11.5 |
| 21 | Chopin | Op030-02 | C234 | | 9224 | 18 | 6 |
| 22 | Chopin | Op063-03 | C249 | | 9239 | 13 | 6 |
| 23 | Schubert | D0759-01 | S533 | Intro | 6120 | 10 | 12 |
| 24 | Schubert | D0759-01 | S534 | 1st Theme | 6121 | 17 | 11 |
| 25 | Schubert | D0759-01 | S535 | 2nd Theme | 6122 | 21 | 8.7 |
| 26 | Schumann | Op015-07 | S713 | Träumerei | 6308 | 21 | 8 |

## B.6 Audio Recordings for BM-Small

| Composer | WorkID | Folder | CD | Tr | Name | Ensemble | Instrumentation | Duration |
|---|---|---|---|---|---|---|---|---|
| Bach | BMW1048-01 | Bach Complete Edition BC | 1 | 8 | Brandenburg Concerto no. 3 | Concerto | Violin Viola Cello Harpsichord Strings | 05:19 |
| Bach | BWV0543-01 | Bach Complete Edition BC | 157 | 16 | Prelude | Solo | Organ | 03:29 |
| Bach | BWV0565-01 | Bach Complete Edition BC | 152 | 1 | Toccata | Solo | Organ | 02:49 |
| Bach | BWV0565-02 | Bach Complete Edition BC | 152 | 2 | Fugue | Solo | Organ | 06:17 |
| Bach | BWV0808-01 | Bach Complete Edition BC | 35 | 20 | English Suite No 3 | Solo | Harpsichord | 03:22 |
| Bach | BWV0846-01 | Bach Complete Edition BC | 24 | 1 | Prelude | Solo | Harpsichord | 02:28 |
| Bach | BWV0846-02 | Bach Complete Edition BC | 24 | 2 | fugue | Solo | Harpsichord | 01:59 |
| Bach | BWV0847-01 | Bach Complete Edition BC | 24 | 3 | WTC: prelude | Solo | Harpsichord | 01:28 |
| Bach | BWV0847-02 | Bach Complete Edition BC | 24 | 4 | fugue | Solo | Harpsichord | 01:31 |
| Bach | BWV1001-01 | Bach Complete Edition BC | 10 | 1 | Sonata: Adagio | Solo | Violin | 04:56 |
| Bach | BWV1002-03 | Bach Complete Edition BC | 10 | 9 | Partita: Sarabande | Solo | Violin | 02:53 |
| Bach | BWV1009-05 | Bach Complete Edition BC | 12 | 11 | Cello Suite | Solo | Cello | 03:44 |
| Bach | BWV1030-01 | Bach Complete Edition BC | 14 | 16 | Sonata | Duo | Flute Harpsichord | 07:19 |
| Bach | BWV1041-01 | Bach Complete Edition BC | 5 | 1 | Violin Concert in A minor | Concerto | Violin Harpsichord Strings | 04:08 |
| Bach | BWV1046-01 | Bach Complete Edition BC | 1 | 1 | Brandenburg Concerto no 1 | Concerto | Oboe Violin Horn Harpsichord Strings | 03:54 |
| Bach | BWV1065-01 | Bach Complete Edition BC | 7 | 13 | Concerto | Concerto | Harpsichord Strings | 04:00 |
| Bartok | Sz112-01 | Bartok OrchestralWorks EMI | 3 | 1 | Concerto | Concerto | Violin Orchestra | 16:09 |
| Beethoven | Op002No1-01 | Beethoven Complete Edition BC | 49 | 1 | Sonata no. 1 | Solo | Piano | 04:06 |
| Beethoven | Op011-01 | Beethoven Complete Edition BC | 20 | 4 | Gassenhauer-Trio | Trio | Clarinet Cello Piano | 09:16 |
| Beethoven | Op013-01 | Beethoven Complete Edition BC | 52 | 1 | Pathétique | Solo | Piano | 09:08 |
| Beethoven | Op017-01 | Beethoven Complete Edition BC | 20 | 7 | | Duo | Horn Piano | 08:06 |
| Beethoven | Op018No4-01 | Various Master-worksHeritage SONY | 15 | 1 | | Quartet | Violin Viola Cello | 06:32 |
| Beethoven | Op027No2-01 | Beethoven Complete Edition BC | 50 | 8 | Moonlight Sonata | Solo | Piano | 06:02 |
| Beethoven | Op067-01 | Beethoven Complete Edition BC | 3 | 1 | Symphony No. 5 | Orchestra | Orchestra | 08:05 |
| Beethoven | WoO059 | Beethoven Complete Edition BC | 56 | 8 | Für Elise | Solo | Piano | 02:48 |
| Brahms | Hungarian Dances-05 | Various MasterpiecesClas-sicalMusic MEMBRAN | 15 | 8 | | Orchestra | Orchestra | 02:40 |
| Brahms | Op015-01 | Various Master-worksHeritage SONY | 23 | 1 | | Concerto | Piano Orchestra | 21:20 |
| Brahms | Op025-04 | Brahms Complete Works BC | 10 | 4 | Rondo alla Zingarese | Quartet | Piano Violin Viola Cello | 08:09 |
| Britten | Op002 | Britten TheCollec-torsEdition EMI | 10 | 1 | Phantasy-Quartet | Quartet | Oboe Violin Viola Cello | 13:18 |
| Chopin | Op009-02 | Chopin Complete Works BC | 3 | 2 | | Solo | Piano | 04:56 |
| Chopin | Op010-12 | Chopin Complete Works BC | 2 | 12 | Etude Revolu-tionnary | Solo | Piano | 02:49 |
| Chopin | Op024-02 | Chopin Complete Works BC | 7 | 15 | Mazurka | Solo | Piano | 02:22 |

| Composer | WorkID | Folder | CD | Tr | Name | Ensemble | Instrumentation | Duration |
|---|---|---|---|---|---|---|---|---|
| Chopin | Op028-04 | Chopin Complete Works BC | 16 | 4 | Prelude | Solo | Piano | 02:23 |
| Chopin | Op028-15 | Chopin Complete Works BC | 16 | 15 | Prelude Raindrop | Solo | Piano | 06:09 |
| Chopin | Op030-02 | Chopin Complete Works BC | 7 | 19 | Mazurka | Solo | Piano | 01:26 |
| Chopin | Op063-03 | Chopin Complete Works BC | 8 | 18 | Mazurka | Solo | Piano | 02:16 |
| Chopin | Op066 | Chopin Complete Works BC | 1 | 8 | Fantasie-Impromptu | Solo | Piano | 05:05 |
| Debussy | L075-03 | Debussy TheDebussyEdition DG | 8 | 3 | Suite Bergamasque: Clair de Lune | Solo | Piano | 05:52 |
| Debussy | L095-01 | Debussy TheDebussyEdition DG | 8 | 8 | Pour le Piano | Solo | Piano | 04:12 |
| Debussy | L103-01 | Debussy TheDebussyEdition DG | 3 | 3 | | Concerto | Harp Strings | 04:38 |
| Dukas | ApprentiSorcier | Various MasterpiecesClassicalMusic MEMBRAN | 51 | 2 | Zauberlehrling | Orchestra | Orchestra | 09:26 |
| Dvorak | B078-08 | Dvorak Complete Symphonies BC | 9 | 8 | Slav. Dances | Orchestra | Orchestra | 04:08 |
| Dvorak | B178-01 | Various MasterworksHeritage SONY | 22 | 5 | Aus der neuen Welt | Orchestra | Orchestra | 08:41 |
| Dvorak | B178-04 | Various MasterworksHeritage SONY | 22 | 8 | | Orchestra | Orchestra | 10:55 |
| Gershwin | AmericanParis | Gershwin GeorgeGershwin TIM | 2 | 6 | | Orchestra | Orchestra | 15:48 |
| Granados | Op037-02 | Bream Complete RCACollection SONY | 29 | 21 | Spanish Dance | Solo | Guitar | 05:02 |
| Grieg | Op036-01 | Grieg Edition BC | 7 | 1 | | Duo | Cello Piano | 09:46 |
| Handel | HWV-368a-01 | Handel Portrait BC | 15 | 1 | Sonata | Quartet | Flute Violin Cello Harpsichord | 10:54 |
| Handel | HWV287-01 | Handel Portrait BC | 2 | 6 | Concerto | Concerto | Oboe Strings Harpsichord | 02:37 |
| Handel | HWV289-01 | Handel Portrait BC | 8 | 1 | Concerto | Concerto | Organ Strings Windsection Harpsichord | 05:14 |
| Handel | HWV361-01 | Handel Portrait BC | 14 | 1 | | Trio | Violin Cello Harpsichord | 07:20 |
| Handel | HWV365-01 | Handel Portrait BC | 18 | 1 | | Duo | Altorecorder Harpsichord | 02:35 |
| Haydn | Hob03No006-01 | Haydn Edition BC | 93 | 6 | Quartet | Quartet | Violin Viola Cello | 01:54 |
| Haydn | Hob03No031-01 | Haydn Edition BC | 91 | 9 | Streichquartett | Quartet | Violin Viola Cello | 06:25 |
| Haydn | Hob07bNo002-01 | Haydn Edition BC | 39 | 4 | Concerto | Concerto | Cello Strings Windsection Harpsichord | 13:30 |
| Haydn | Hob15No027-01 | Haydn Edition BC | 111 | 1 | Trio | Trio | Piano Violin Cello | 07:51 |
| Khachaturian | ConcertoViolin DMinor-01 | Khachaturian ComposerConductorPianist SUP | 1 | 1 | Concerto | Concerto | Violin Orchestra | 13:08 |
| Kodaly | GalantaDances | Kodaly OrchestralWorks BC | 2 | 3 | | Orchestra | Orchestra | 15:34 |
| Liszt | S541-03 | Liszt TheComplete PianoMusic HYP | 24 | 3 | Liebestraum | Solo | Piano | 04:14 |
| Mendelssohn | Op030-03 | Mendelssohn Portrait BC | 22 | 9 | Lied ohne Worte | Solo | Piano | 02:39 |
| Mozart | KV145 | Mozart Complete Edition BC | 68 | 5 | | Concerto | Violin Strings | 02:55 |
| Mozart | KV186-02 | Mozart Complete Edition BC | 43 | 7 | | Decet | Clarinet Oboe Englishhorn Bassoon Horn | 02:05 |
| Mozart | KV188-01 | Mozart Complete Edition BC | 45 | 21 | | Septet | Trumpet Piccolotrumpet Timpani | 01:46 |
| Mozart | KV219-01 | Mozart Complete Edition BC | 28 | 4 | turkish | Concerto | Violin Strings Windsection | 09:37 |

| Composer | WorkID | Folder | CD | Tr | Name | Ensemble | Instrumentation | Duration |
|---|---|---|---|---|---|---|---|---|
| Mozart | KV298-01 | Mozart Complete Edition BC | 58 | 8 | | Quartet | Flute Violin Viola Cello | 05:56 |
| Mozart | KV315 | Mozart Complete Edition BC | 24 | 4 | Andante | Concerto | Flute Strings Windsection | 06:26 |
| Mozart | KV334-01 | Mozart Complete Edition BC | 30 | 10 | | Concerto | Violin Strings Windsection | 06:38 |
| Mozart | KV361-01 | Mozart Complete Edition BC | 46 | 1 | | Orchestra | Windsection | 09:58 |
| Mozart | KV370-01 | Mozart Complete Edition BC | 53 | 4 | | Quintet | Oboe Violin Viola Cello | 07:17 |
| Mozart | KV378-01 | Mozart Complete Edition BC | 66 | 1 | | Duo | Violin Piano | 12:34 |
| Mozart | KV447-01 | Mozart Complete Edition BC | 26 | 4 | | Concerto | Horn Strings Windsection Harpsichord | 06:40 |
| Mozart | KV452-01 | Mozart Complete Edition BC | 54 | 1 | | Quintet | Piano Clarinet Oboe Horn Bassoon | 09:29 |
| Mozart | KV550-01 | Mozart Complete Edition BC | 11 | 1 | Symphony No 40 | Orchestra | Orchestra | 07:29 |
| Mozart | KV581-01 | Mozart Complete Edition BC | 53 | 7 | | Quintet | Clarinet Violin Viola Cello | 09:03 |
| Mozart | KV622-01 | Mozart Complete Edition BC | 23 | 1 | Klarinetten-konzert | Concerto | Clarinet Orchestra | 12:00 |
| Paganini | MS025-24 | Paganini Accardo-PlaysPaganini DG | 5 | 24 | Caprice: Vn. | Solo | Violin | 04:23 |
| Piston | IncredibleFlutist-01 | Various Collec-torsEdition2 MERCURY | 35 | 4 | | Orchestra | Flute Orchestra | 01:09 |
| Rachmaninoff | Op019-01 | Rachmaninoff Edition BC | 19 | 7 | | Duo | Cello Piano | 13:02 |
| Ravel | MR081 | Various MasterpiecesClas-sicalMusic MEMBRAN | 26 | 3 | Bolero | Orchestra | Orchestra | 15:30 |
| Saint | CarnavalAnimaux-12 | Saint KlarheitUn-dRaffinesse MEMBRAN | 4 | 12 | | Orchestra | Clarinet Xylophone Piano Violin Viola Cello Doublebass | 01:28 |
| Saint | Op028 | Saint KlarheitUn-dRaffinesse MEMBRAN | 7 | 5 | introduction rondo Capriccioso | Concerto | Violin Orchestra | 08:42 |
| Saint | Op033-01 | Various MasterpiecesClas-sicalMusic MEMBRAN | 40 | 4 | Cello concert | Concerto | Cello Orchestra | 05:29 |
| Saint | Op040 | Saint KlarheitUn-dRaffinesse MEMBRAN | 3 | 4 | Danse Macabre | Orchestra | Orchestra | 07:28 |
| Saint | Op065-01 | Various Classical-Masterworks SONY | 20 | 17 | | Septet | Trumpet Strings Piano | 04:49 |
| Scarlatti | K009 | Scarlatti Complete KeyboardSonatas BC | 1 | 9 | | Solo | Harpsichord | 03:23 |
| Schubert | D0667-04 | Schubert TheMasterworks BC | 13 | 4 | | Quintet | Piano Violin Viola Cello doublebass | 07:59 |
| Schubert | D0759-01 | Schubert TheMasterworks BC | 2 | 1 | Unfinished Symphony | Orchestra | Orchestra | 13:24 |
| Schubert | D0780-03 | Schubert TheMasterworks BC | 19 | 7 | Moments musicaux | Solo | Piano | 02:08 |
| Schubert | D0810-01 | Schubert TheMasterworks BC | 10 | 5 | der Tod und das Mädchen | Quartet | Violin Viola Cello | 16:12 |
| Schubert | D0899-03 | Schubert TheMasterworks BC | 26 | 3 | Impromptu | Solo | Piano | 05:38 |
| Schumann | Op015-07 | Schumann Master-worksEdition SONY | 5 | 7 | Traeumerei | Solo | Piano | 02:50 |
| Schumann | Op094-01 | Schumann Master-worksEdition SONY | 20 | 14 | Three Romances | Duo | Oboe Piano | 03:29 |
| Shostakovich | Op040-01 | Shostakovich Edition BC | 24 | 1 | | Duo | Cello Piano | 11:23 |
| Smetana | MyCountry-02 | Smetana BedrichSmetana DOC | 1 | 2 | Moldau | Orchestra | Orchestra | 11:30 |
| Stravinsky | DumbartonOaks-01 | Stravinsky Work-sOfIgorStravinsky SONY | 11 | 10 | | Orchestra | Strings Windsection | 04:22 |

| Composer | WorkID | Folder | CD | Tr | Name | Ensemble | Instrumentation | Duration |
|---|---|---|---|---|---|---|---|---|
| Stravinsky | OctetWinds-01 | Stravinsky WorksOfIgorStravinsky SONY | 12 | 3 | | Orchestra | Windsection | 03:57 |
| Telemann | TWV043-e4-01 | Telemann Edition BC | 23 | 13 | | Quintet | Flute Violin Violagamba Cello Harpsichord | 05:08 |
| Tschaikovsky | Op071-13 | Tschaikovsky Edition BC | 16 | 19 | Blumenwaltzer (Nussknacker-suite) | Orchestra | Orchestra | 06:26 |
| Turina | Op036 | Bream Complete RCACollection SONY | 5 | 11 | Fandanguillo | Solo | Guitar | 05:13 |
| Visee | SuiteDMinor-01 | Bream Complete RCACollection SONY | 9 | 9 | Petites Suite | Solo | Guitar | 00:51 |

## B.7 EDM-MIDIs of BM-Small

| IDX | Composer | WorkID | BMID | ThemeID | MidiNo | Notes | Duration [$s$] |
|---|---|---|---|---|---|---|---|
| 1 | Bach | BMW1048-01 | B40 | | 131 | 25 | 4 |
| 2 | Bach | BWV0543-01 | B93 | | 184 | 20 | 2.6 |
| 3 | Bach | BWV0565-01 | B298 | | 391 | 20 | 1.6 |
| 4 | Bach | BWV0565-02 | B299 | | 392 | 28 | 3.5 |
| 5 | Bach | BWV0808-01 | B245 | | 338 | 24 | 3.9 |
| 6 | Bach | BWV0846-01 | B301 | | 394 | 32 | 4 |
| 7 | Bach | BWV0846-02 | B302 | | 395 | 18 | 3.6 |
| 8 | Bach | BWV0847-01 | B303 | | 396 | 24 | 3 |
| 9 | Bach | BWV0847-02 | B304 | | 397 | 20 | 4.1 |
| 10 | Bach | BWV1001-01 | B175 | | 266 | 20 | 3.5 |
| 11 | Bach | BWV1002-03 | B156 | | 247 | 15 | 5.2 |
| 12 | Bach | BWV1009-05 | B209 | | 302 | 23 | 8 |
| 13 | Bach | BWV1030-01 | B171 | | 262 | 19 | 4.2 |
| 14 | Bach | BWV1041-01 | B83 | | 174 | 15 | 3.7 |
| 15 | Bach | BWV1046-01 | B30 | | 121 | 25 | 4.1 |
| 16 | Bach | BWV1065-01 | B81 | | 172 | 31 | 7.5 |
| 17 | Bartok | Sz112-01 | B461 | 1st Theme | 563 | 20 | 7.2 |
| 18 | Bartok | Sz112-01 | B462 | 2nd Theme | 564 | 19 | 4 |
| 19 | Beethoven | Op002No1-01 | B689 | 1st Theme | 813 | 10 | 4 |
| 20 | Beethoven | Op002No1-01 | B690 | 2nd Theme | 814 | 16 | 8 |
| 21 | Beethoven | Op011-01 | B1031 | | 1157 | 12 | 5.5 |
| 22 | Beethoven | Op013-01 | B728 | Intro | 852 | 12 | 3.7 |
| 23 | Beethoven | Op013-01 | B729 | 1st Theme | 853 | 17 | 12 |
| 24 | Beethoven | Op013-01 | B730 | 2nd Theme | 854 | 14 | 8.5 |
| 25 | Beethoven | Op017-01 | B687 | | 810 | 20 | 7.5 |
| 26 | Beethoven | Op018No4-01 | B592 | 1st Theme | 694 | 12 | 5.5 |
| 27 | Beethoven | Op018No4-01 | B593 | 2nd Theme | 695 | 17 | 8 |
| 28 | Beethoven | Op027No2-01 | B762 | Intro. | 886 | 12 | 3 |
| 29 | Beethoven | Op027No2-01 | B763 | | 887 | 11 | 7 |
| 30 | Beethoven | Op067-01 | B948 | 1st Theme A | 1072 | 8 | 5 |
| 31 | Beethoven | Op067-01 | B949 | 1st Theme B | 1073 | 10 | 4.2 |
| 32 | Beethoven | Op067-01 | B950 | 1st Theme C | 1074 | 6 | 5 |
| 33 | Beethoven | Op067-01 | B951 | 2nd Theme | 1075 | 8 | 4 |
| 34 | Beethoven | Op067-01 | B952 | 3rd Theme | 1076 | 25 | 7.2 |
| 35 | Beethoven | Op067-01 | B953 | 4th Theme | 1077 | 17 | 9 |
| 36 | Beethoven | WoO059 | B554 | | 656 | 17 | 2.7 |
| 37 | Brahms | Hungarian Dances-05 | B1375 | 1st Theme | 8508 | 18 | 7 |
| 38 | Brahms | Hungarian Dances-05 | B1376 | 2nd Theme | 8509 | 20 | 6 |
| 39 | Brahms | Op015-01 | B1337 | 1st Theme | 8470 | 69 | 15.5 |
| 40 | Brahms | Op015-01 | B1338 | 2nd Theme | 8471 | 14 | 17.5 |
| 41 | Brahms | Op015-01 | B1339 | 3rd Theme | 8472 | 21 | 7.5 |
| 42 | Brahms | Op015-01 | B1340 | 4th Theme | 8473 | 21 | 12 |
| 43 | Brahms | Op025-04 | B1415 | 1st Theme | 8548 | 22 | 6 |
| 44 | Brahms | Op025-04 | B1416 | 2nd Theme | 8549 | 32 | 4 |
| 45 | Brahms | Op025-04 | B1417 | 3rd Theme | 8550 | 32 | 6 |
| 46 | Britten | Op002 | B1711j | 1st Theme | 8854 | 24 | 8 |
| 47 | Britten | Op002 | B1711k | 2nd Theme | 8855 | 18 | 17 |
| 48 | Britten | Op002 | B1711l | 3rd Theme | 8856 | 25 | 17.2 |
| 49 | Britten | Op002 | B1711m | 4th Theme | 8857 | 29 | 8.5 |
| 50 | Chopin | Op009-02 | C258 | | 9248 | 17 | 6 |
| 51 | Chopin | Op010-12 | C198 | | 9186 | 17 | 8.6 |
| 52 | Chopin | Op024-02 | C232 | | 9222 | 24 | 6 |
| 53 | Chopin | Op028-04 | C289 | | 9280 | 18 | 16 |
| 54 | Chopin | Op028-15 | C300 | 1st Theme | 9291 | 21 | 9 |
| 55 | Chopin | Op028-15 | C301 | 2nd Theme | 9292 | 19 | 11.5 |
| 56 | Chopin | Op030-02 | C234 | | 9224 | 18 | 6 |
| 57 | Chopin | Op063-03 | C249 | | 9239 | 13 | 6 |
| 58 | Chopin | Op066 | C223 | | 9213 | 15 | 2 |
| 59 | Chopin | Op066 | C224 | | 9214 | 16 | 7 |
| 60 | Debussy | L075-03 | D144 | Clair de Lune 1st Theme | 9721 | 22 | 11.2 |
| 61 | Debussy | L075-03 | D145 | Clair de Lune 2nd Theme | 9722 | 15 | 8.2 |
| 62 | Debussy | L095-01 | D97 | Prelude 1st Theme | 9674 | 23 | 6.5 |
| 63 | Debussy | L095-01 | D98 | 2nd Theme | 9675 | 19 | 9.5 |
| 64 | Debussy | L103-01 | D30 | | 9607 | 9 | 15 |
| 65 | Dukas | ApprentiSorcier | D262 | Intro | 9850 | 10 | 2.9 |
| 66 | Dukas | ApprentiSorcier | D263 | 1st Theme | 9851 | 19 | 6.7 |
| 67 | Dukas | ApprentiSorcier | D264 | 2nd Theme | 9852 | 25 | 6 |
| 68 | Dvorak | B078-08 | D372 | 1st Theme | 1296 | 21 | 11 |

| IDX | Composer | WorkID | BMID | ThemeID | MidiNo | Notes | Duration [$s$] |
|---|---|---|---|---|---|---|---|
| 69 | Dvorak | B078-08 | D373 | 2nd Theme | 1297 | 13 | 18 |
| 70 | Dvorak | B178-01 | D434 | 1st Theme | 1358 | 23 | 7.2 |
| 71 | Dvorak | B178-01 | D435 | 2nd Theme | 1359 | 20 | 4 |
| 72 | Dvorak | B178-01 | D436 | 3rd Theme | 1360 | 22 | 8 |
| 73 | Dvorak | B178-04 | D443 | 1st Theme | 1367 | 11 | 7 |
| 74 | Dvorak | B178-04 | D444 | 2nd Theme | 1368 | 21 | 4 |
| 75 | Dvorak | B178-04 | D445 | 3rd Theme | 1369 | 19 | 14 |
| 76 | Gershwin | AmericanParis | G39 | 1st Theme | 1777 | 33 | 8 |
| 77 | Gershwin | AmericanParis | G40 | 2nd Theme | 1778 | 16 | 7 |
| 78 | Gershwin | AmericanParis | G41 | 3rd Theme Blues Theme | 1779 | 22 | 14 |
| 79 | Gershwin | AmericanParis | G42 | 4th Theme | 1780 | 21 | 8 |
| 80 | Granados | Op037-02 | G206 | 1st Theme | 1955 | 34 | 10.5 |
| 81 | Granados | Op037-02 | G207 | 2nd Theme | 1956 | 21 | 6 |
| 82 | Grieg | Op036-01 | G310 | 1st Theme | 2060 | 20 | 13.5 |
| 83 | Grieg | Op036-01 | G311 | 2nd Theme | 2061 | 12 | 16 |
| 84 | Handel | HWV-368a-01 | H163 | | 2282 | 18 | 3.5 |
| 85 | Handel | HWV287-01 | H9 | | 2128 | 21 | 4.2 |
| 86 | Handel | HWV289-01 | H13 | 1st Theme | 2132 | 37 | 6 |
| 87 | Handel | HWV289-01 | H14 | 2nd Theme | 2133 | 19 | 5 |
| 88 | Handel | HWV361-01 | H183 | | 2302 | 20 | 4.7 |
| 89 | Handel | HWV365-01 | H147 | | 2266 | 14 | 3.5 |
| 90 | Haydn | Hob03No006-01 | H320 | | 2439 | 17 | 5.2 |
| 91 | Haydn | Hob03No031-01 | H336 | | 2455 | 34 | 7.5 |
| 92 | Haydn | Hob07bNo002-01 | H300 | 1st Theme | 2420 | 30 | 5.7 |
| 93 | Haydn | Hob07bNo002-01 | H301 | 2nd Theme | 2421 | 17 | 3.7 |
| 94 | Haydn | Hob15No027-01 | H703 | 1st Theme | 2824 | 21 | 3.5 |
| 95 | Haydn | Hob15No027-01 | H704 | 2nd Theme | 2825 | 23 | 3.7 |
| 96 | Khachaturian | ConcertoViolin DMinor-01 | K30 | 1st Theme A | 3201 | 58 | 11.5 |
| 97 | Khachaturian | ConcertoViolin DMinor-01 | K31 | 1st Theme B | 3202 | 32 | 6 |
| 98 | Khachaturian | ConcertoViolin DMinor-01 | K32 | 2nd Theme | 3203 | 25 | 7.7 |
| 99 | Kodaly | GalantaDances | K63 | Intro | 3234 | 15 | 6 |
| 100 | Kodaly | GalantaDances | K64 | | 3235 | 27 | 6.5 |
| 101 | Kodaly | GalantaDances | K65 | | 3236 | 21 | 5.1 |
| 102 | Kodaly | GalantaDances | K66 | | 3237 | 23 | 4 |
| 103 | Kodaly | GalantaDances | K67 | 1st Theme | 3238 | 16 | 6 |
| 104 | Kodaly | GalantaDances | K68 | 2nd Theme | 3239 | 21 | 4 |
| 105 | Kodaly | GalantaDances | K69 | 1st Theme | 3240 | 29 | 8 |
| 106 | Kodaly | GalantaDances | K70 | 2nd Theme | 3241 | 20 | 3.7 |
| 107 | Liszt | S541-03 | L189 | | 3483 | 11 | 11.5 |
| 108 | Mendelssohn | Op030-03 | M289 | | 3899 | 22 | 7.5 |
| 109 | Mozart | KV145 | M822 | | 4448 | 14 | 8.5 |
| 110 | Mozart | KV186-02 | M557 | | 4181 | 16 | 11.5 |
| 111 | Mozart | KV188-01 | M561 | | 4185 | 22 | 6 |
| 112 | Mozart | KV219-01 | M522a | | 4145 | 15 | 3.5 |
| 113 | Mozart | KV219-01 | M523 | | 4146 | 21 | 6 |
| 114 | Mozart | KV219-01 | M524 | | 4147 | 22 | 8 |
| 115 | Mozart | KV298-01 | M615 | | 4240 | 23 | 7 |
| 116 | Mozart | KV315 | M429 | | 4051 | 24 | 4.5 |
| 117 | Mozart | KV334-01 | M579 | | 4203 | 19 | 4.5 |
| 118 | Mozart | KV361-01 | M736 | | 4362 | 16 | 11.5 |
| 119 | Mozart | KV370-01 | M619 | | 4244 | 20 | 5.7 |
| 120 | Mozart | KV378-01 | M840 | | 4466 | 21 | 7 |
| 121 | Mozart | KV447-01 | M445 | | 4067 | 18 | 7.5 |
| 122 | Mozart | KV447-01 | M446 | | 4068 | 23 | 7 |
| 123 | Mozart | KV452-01 | M687 | | 4312 | 17 | 4.5 |
| 124 | Mozart | KV452-01 | M688 | | 4313 | 14 | 3.7 |
| 125 | Mozart | KV550-01 | M972 | | 4598 | 20 | 9 |
| 126 | Mozart | KV550-01 | M973 | | 4599 | 14 | 7.5 |
| 127 | Mozart | KV581-01 | M682 | | 4307 | 15 | 11 |
| 128 | Mozart | KV622-01 | M434 | | 4056 | 14 | 7.2 |
| 129 | Paganini | MS025-24 | P37 | | 4772 | 20 | 3.7 |
| 130 | Piston | IncredibleFlutist-01 | P114 | Intro | 4854 | 21 | 14.7 |
| 131 | Rachmaninoff | Op019-01 | R53 | | 5181 | 22 | 14 |
| 132 | Rachmaninoff | Op019-01 | R54 | | 5182 | 15 | 8 |
| 133 | Ravel | MR081 | R125 | Theme A | 5254 | 36 | 8 |
| 134 | Ravel | MR081 | R126 | Theme B | 5255 | 28 | 7.5 |
| 135 | Saint | CarnavalAnimaux-12 | S14 | Fossiles | 5598 | 20 | 8.5 |
| 136 | Saint | Op028 | S63 | Intro | 5648 | 26 | 5.5 |
| 137 | Saint | Op028 | S64 | 1st Theme | 5649 | 22 | 7 |
| 138 | Saint | Op028 | S65 | 2nd Theme | 5650 | 41 | 5.7 |
| 139 | Saint | Op028 | S66 | 3rd Theme | 5651 | 30 | 6 |
| 140 | Saint | Op033-01 | S17 | 1st Theme | 5601 | 19 | 7 |
| 141 | Saint | Op033-01 | S18 | 2nd Theme | 5602 | 20 | 14 |

| IDX | Composer | WorkID | BMID | ThemeID | MidiNo | Notes | Duration $[s]$ |
|---|---|---|---|---|---|---|---|
| 142 | Saint | Op040 | S47 | 1st Theme | 5632 | 40 | 9.5 |
| 143 | Saint | Op040 | S48 | 2nd Theme | 5633 | 18 | 11.5 |
| 144 | Saint | Op065-01 | S89 | Preambule | 5674 | 15 | 8.5 |
| 145 | Scarlatti | K009 | S214 | Pastorale | 5800 | 33 | 6 |
| 146 | Schubert | D0667-04 | S387 | Theme and Variation on Die Forelle | 5974 | 14 | 4 |
| 147 | Schubert | D0759-01 | S533 | Intro | 6120 | 10 | 12 |
| 148 | Schubert | D0759-01 | S534 | 1st Theme | 6121 | 17 | 11 |
| 149 | Schubert | D0759-01 | S535 | 2nd Theme | 6122 | 21 | 8.7 |
| 150 | Schubert | D0780-03 | S319 | | 5906 | 20 | 4 |
| 151 | Schubert | D0810-01 | S370 | 1st Theme | 5957 | 12 | 8 |
| 152 | Schubert | D0810-01 | S371 | 2nd Theme | 5958 | 22 | 8.1 |
| 153 | Schubert | D0899-03 | S301 | | 5888 | 13 | 15.5 |
| 154 | Schumann | Op015-07 | S713 | Träumerei | 6308 | 21 | 8 |
| 155 | Schumann | Op094-01 | S802 | | 6398 | 22 | 7.5 |
| 156 | Shostakovich | Op040-01 | S870a | 1st Theme | 6467 | 21 | 10 |
| 157 | Shostakovich | Op040-01 | S870b | 2nd Theme | 6468 | 15 | 16 |
| 158 | Smetana | MyCountry-02 | S1114 | 1st Theme | 6723 | 23 | 11.2 |
| 159 | Smetana | MyCountry-02 | S1115 | 2nd Theme | 6724 | 21 | 3.7 |
| 160 | Smetana | MyCountry-02 | S1116 | 3rd Theme | 6725 | 12 | 16 |
| 161 | Smetana | MyCountry-02 | S1117 | 4th Theme | 6726 | 10 | 15 |
| 162 | Stravinsky | DumbartonOaks-01 | S1534a | 1st Theme | 7154 | 29 | 4 |
| 163 | Stravinsky | DumbartonOaks-01 | S1534b | 2nd Theme | 7155 | 16 | 5.5 |
| 164 | Stravinsky | DumbartonOaks-01 | S1534c | 3rd Theme | 7156 | 18 | 4.5 |
| 165 | Stravinsky | OctetWinds-01 | S1541 | Intro. | 7167 | 15 | 5.6 |
| 166 | Stravinsky | OctetWinds-01 | S1542 | 1st Theme | 7168 | 23 | 7.2 |
| 167 | Stravinsky | OctetWinds-01 | S1543 | 2nd Theme | 7169 | 9 | 7.5 |
| 168 | Telemann | TWV043-e4-01 | T58 | Prelude | 7362 | 28 | 9 |
| 169 | Telemann | TWV043-e4-01 | T59 | 1st Theme | 7363 | 38 | 7 |
| 170 | Telemann | TWV043-e4-01 | T60 | 2nd Theme | 7364 | 40 | 4.7 |
| 171 | Tschaikovsky | Op071-13 | T198 | 1st Theme | 7541 | 14 | 10.5 |
| 172 | Tschaikovsky | Op071-13 | T199 | 2nd Theme | 7542 | 13 | 5.7 |
| 173 | Tschaikovsky | Op071-13 | T200 | 3rd Theme | 7543 | 13 | 9.5 |
| 174 | Tschaikovsky | Op071-13 | T201 | 4th Theme | 7544 | 14 | 10.5 |
| 175 | Turina | Op036 | T301 | 1st Theme | 7645 | 30 | 7 |
| 176 | Turina | Op036 | T302 | 2nd Theme | 7646 | 22 | 6 |
| 177 | Visee | SuiteDMinor-01 | V123 | Prelude | 7787 | 16 | 4.7 |

## B.8 BM-Medium

In the following we provide a statistic that shows each composer and the respective number of audio recordings that are in the subset BM-Medium.

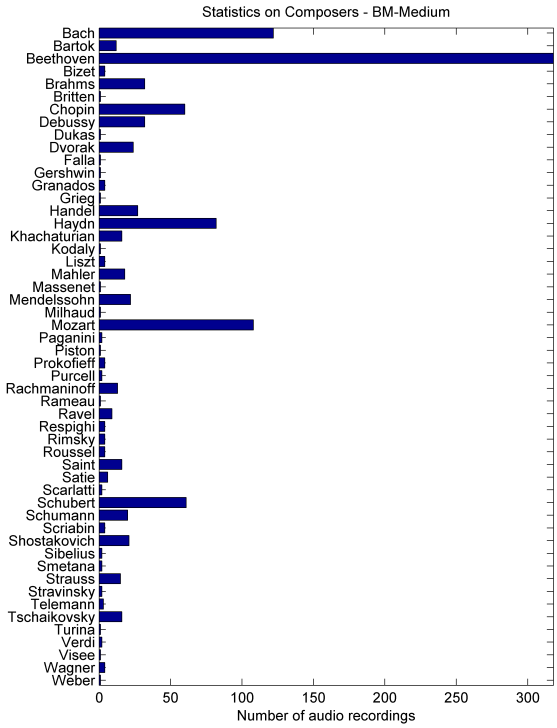


Figure B.29: Number of audio recordings by composer for the subset BM-Medium

## B.9 Errors

In the following we provide a table that contains errors which affect the subset BM-Medium. For each of the entries, there is one audio recording per theme and two themes per movement. Due to the naming conventions for the audio recordings this leads to an error which causes that one of the two audio recordings is overwritten by the other one.

| Composer | WorkID | Folder | CD | Tr | ErrorType |
|---|---|---|---|---|---|
| Beethoven | Op130-04 | Beethoven CompleteEdition BC | 42 | 4 | Movement |
| Beethoven | Op130-04 | Beethoven CompleteEdition BC | 42 | 5 | Movement |
| Beethoven | Op005No2-01 | Beethoven CompleteEdition BC | 28 | 3 | Movement |
| Beethoven | Op005No2-01 | Beethoven CompleteEdition BC | 28 | 4 | Movement |
| Beethoven | Op110-03 | Beethoven CompleteEdition BC | 46 | 8 | Movement |
| Beethoven | Op110-03 | Beethoven CompleteEdition BC | 46 | 9 | Movement |

In the following we provide a table that contains EDM-themes that are not within the subset BM-Medium, despite the corresponding audio recordings are in the subset. These EDM-themes were either found after the creation of the subset BM-Medium, or they are not available on the EDM-website.

| Composer | WorkID | BMID | ThemeID | MidiNo | ErrorType |
|---|---|---|---|---|---|
| Bach | BWV0886-01 | B382 | | 476 | EDM-Theme not in subset |
| Beethoven | Op002No1-04 | B694 | 1st Theme | 818 | EDM-Theme not in subset |
| Beethoven | Op084-00 | B561 | 2nd Theme | 663 | EDM-Theme not in subset |
| Chopin | Op034-02 | C344 | | 9338 | EDM-Theme not in subset |
| Chopin | Op037-02 | C268 | | 9259 | EDM-Theme not in subset |
| Wagner | WWV086C-02-02-02 | W47 | 5th Theme | 7893 | EDM-Theme not in subset |
| Beethoven | Op092-01 | B988 | 1st Theme | | No EDM-Theme on EDM Website |

In the following we provide a table that contains errors regarding EDM-themes. The specific error is specified by a keyword in the column 'ErrorType'. For some of the errors, we provide a more detailed description in the column 'ErrorDescription'. For large tempo differences between the EDM-theme and the audio recording we use the keyword 'MidiErrTempo'. Playing errors in the EDM-theme are stated by the keyword 'MidiErr'. The keywords 'MidiJointThemes' and 'MidiPart' are explained in Section 3.2.

| Composer | WorkID | BMID | ThemeID | MidiNo | ErrorType | ErrorDescription |
|---|---|---|---|---|---|---|
| Bach | BWV0846-01 | B301 | | 394 | MidiErrTempo | |
| Bach | BWV0543-01 | B93 | | 184 | MidiErrTempo | |
| Bach | BWV1001-01 | B175 | | 266 | MidiErrTempo | |
| Bach | BWV0565-01 | B298 | | 391 | MidiErrTempo | |
| Beethoven | WoO059 | B554 | | 656 | MidiErrTempo | |
| Beethoven | Op018No4-01 | B593 | 2nd Theme | 695 | MidiErr | |
| Brahms | Op025-04 | B1415 | 1st Theme | 8548 | MidiErr | |
| Chopin | Op010-12 | C198 | | 9186 | MidiErr | |
| Chopin | Op009-02 | C258 | | 9248 | MidiErr | |
| Gershwin | AmericanParis | G39 | 1st Theme | 1777 | MidiErr | |
| Handel | HWV361-01 | H183 | | 2302 | MidiErrTempo | |
| Mozart | KV315 | M429 | | 4051 | MidiErrTempo | |
| Scarlatti | K009 | S214 | Pastorale | 5800 | MidiErr | |
| Schubert | D0780-03 | S319 | | 5906 | MidiErr | |
| Stravinsky | OctetWinds-01 | S1541 | Intro | 7167 | MidiErr | |
| Bach | BWV0851-01 | B311 | | 404 | MidiErrTempo | |
| Bach | BWV0855-01 | B319 | | 412 | MidiErr<br>MidiErrTempo | missing trill |
| Bach | BWV0857-01 | B323 | | 416 | MidiErrTempo | |
| Bach | BWV0861-01 | B331 | | 424 | MidiErrTempo | |
| Bach | BWV0862-02 | B334 | | 427 | MidiErrTempo | |
| Bach | BWV0863-02 | B336 | | 429 | MidiErr | double sharp |
| Bach | BWV0865-02 | B340 | | 433 | MidiErrTempo | |
| Bach | BWV0866-01 | B341 | | 434 | MidiErrTempo | |
| Bach | BWV0872-01 | B354 | | 447 | MidiErr | |
| Bach | BWV0877-01 | B364 | | 457 | MidiErr | double sharp |
| Bach | BWV0877-02 | B365 | | 458 | MidiErr | double sharp |
| Bach | BWV0882-01 | B374 | | 467 | MidiErrTempo | |
| Bach | BWV0883-01 | B376 | | 469 | MidiErrTempo | |
| Bach | BWV0885-01 | B380 | | 473 | MidiErrTempo | |
| Bach | BWV0886-01 | B382 | | 475476 | MidiPart | |
| Bach | BWV0887-01 | B384 | | 478 | MidiErr | double sharp |
| Bach | BWV0889-02 | B389 | | 483 | MidiErr | wrong note |
| Bartok | Sz040-02 | B484 | 1st Theme | 586 | MidiErr | wrong note |
| Bartok | Sz067-01 | B489 | | 591 | MidiErr | wrong notes |
| Bartok | Sz087-01 | B495 | 1st Theme | 597 | MidiErrTempo | |

| Composer | WorkID | BMID | ThemeID | MidiNo | ErrorType | ErrorDescription |
|---|---|---|---|---|---|---|
| Bartok | Sz087-02 | B498 | 2nd Theme | 600 | MidiErr | missing ornaments |
| Beethoven | Op019-03 | B532 | | 634 | MidiErr | |
| Beethoven | Op037-02 | B535 | | 637 | MidiErrTempo | |
| Beethoven | Op058-02 | B539 | | 641 | MidiErrTempo | |
| Beethoven | Op073-03 | B546 | 1st Theme | 648 | MidiErr | wrong note |
| Beethoven | Op073-03 | B547 | 2nd Theme | 649 | MidiErr | missing ornament |
| Beethoven | Op138 | B566 | 2nd Theme | 668 | MidiErr | missing grace note |
| Beethoven | Op018No2-01 | B579 | 1st Theme | 681 | MidiErrTempo MidiErr | missing grace note |
| Beethoven | Op018No2-02 | B581 | 1st Theme | 683 | MidiErr | missing notes |
| Beethoven | Op018No4-04 | B597 | 1st Theme | 699 | MidiErr | missing grace note |
| Beethoven | Op018No6-02 | B606 | | 709 | MidiErrTempo MidiErr | missing notes |
| Beethoven | Op059No1-03 | B612 | | 715 | MidiErrTempo MidiErr | missing notes |
| Beethoven | Op095-04 | B633 | Intro | 736 | MidiErrTempo | |
| Beethoven | Op130-01 | B642 | | 745 | MidiJointThemes | A B |
| Beethoven | Op131-06 | B654 | | 758 | MidiErr | wrong note |
| Beethoven | Op132-01 | B657 | Intro and 1st Theme | 761 | MidiJointThemes | Intro1st Theme |
| Beethoven | Op135-01 | B663a | 1st Theme | 770 | MidiErrTempo MidiErr | wrong notes |
| Beethoven | Op135-04 | B666 | Intro | 774 | MidiJointThemes | |
| Beethoven | Op016-01 | B667a | Intro | 776 | MidiErrTempo | |
| Beethoven | Op016-02 | B667c | | 778 | MidiErrTempo | |
| Beethoven | Op020-06 | B678 | | 790 | MidiErrTempo | |
| Beethoven | Op008-02 | B679b | | 793 | MidiErrTempo | |
| Beethoven | Op005No2-02 | B680a | | 801 | MidiErrTempo | |
| Beethoven | Op102No1-02 | B686a | | 808 | MidiErrTempo MidiErr | wrong note |
| Beethoven | Op017-03 | B688a | | 812 | MidiErrTempo | |
| Beethoven | Op002No1-02 | B691 | | 815 | MidiErr MidiErrTempo | missing grace note |
| Beethoven | Op002No2-04 | B701 | 1st Theme | 825 | MidiErr | missing grace note |
| Beethoven | Op002No3-02 | B706 | | 830 | MidiErrTempo | |
| Beethoven | Op007-04 | B713 | | 837 | MidiErrTempo | |
| Beethoven | Op010No1-02 | B716 | | 840 | MidiErr | missing ornament |
| Beethoven | Op014No1-01 | B737 | 2nd Theme | 861 | MidiErr | double sharp |
| Beethoven | Op027No1-02 | B759 | 2nd Theme | 883 | MidiErr | wrong note |
| Beethoven | Op028-02 | B772 | 2nd Theme | 896 | MidiErrTempo | |
| Beethoven | Op081a-02 | B823 | l'absence | 947 | MidiErrTempo | |
| Beethoven | Op101-03 | B829 | | 953 | MidiErrTempo | |
| Beethoven | Op110-01 | B842 | 1st Theme A | 966 | MidiErr | missing note |
| Beethoven | Op111-01 | B847 | Intro | 971 | MidiErrTempo | |
| Beethoven | Op012No3-02 | B859 | | 983 | MidiErr | missing grace note missing ornament |
| Beethoven | Op023-01 | B861 | | 985 | MidiErr | missing grace notes |
| Beethoven | Op030No1-01 | B869 | 2nd Theme | 993 | MidiErr | missing grace notes |
| Beethoven | Op030No2-03 | B875 | 1st Theme | 999 | MidiErr | missing grace notes |
| Beethoven | Op036-02 | B912 | 4th Theme | 1036 | MidiErrTempo | |
| Beethoven | Op055-02 | B924 | 1st Theme | 1048 | MidiErrTempo | |
| Beethoven | Op067-02 | B954 | 1st Theme | 1078 | MidiErrTempo | |
| Beethoven | Op068-03 | B975 | 1st Theme A | 1099 | MidiErr | missing grace note |
| Beethoven | Op093-02 | B1007 | 1st Theme | 1132 | MidiErrTempo | |
| Beethoven | Op093-02 | B1008 | 2nd Theme | 1133 | MidiErrTempo MidiErr | missing trills |
| Beethoven | Op125-01 | B1016 | 1st Theme | 1141 | MidiErrTempo | |
| Beethoven | Op001No3-01 | B1034 | 1st Theme A | 1159 | MidiErr | Missing ornament |
| Beethoven | Op070No1-02 | B1044 | | 1169 | MidiErrTempo | |
| Brahms | HungarianDances-07 | B1378 | | 8511 | MidiErrTempo | |
| Brahms | Op073-01 | B1604 | 5th Theme | 8737 | MidiErr | double sharp |
| Brahms | Op073-03 | B1612 | 2nd Theme | 8745 | MidiErr | missing bar |
| Chopin | Op050-02 | C243 | | 9233 | MidiErr | missing grace note |
| Chopin | Op009-03 | C259 | | 9249 | MidiErr | wrong notes |
| Chopin | Op037-02 | C268 | | 92589259 | MidiPart | |
| Chopin | Op053 | C284 | | 9275 | MidiErr | missing grace notes |
| Chopin | Op034-02 | C344 | | 93379338 | MidiPart MidiErr | B C double sharp |
| Chopin | Op064-02 | C350 | | 93449345 | MidiPart | |
| Debussy | L066-02 | D18 | 1st Theme | 9595 | MidiErr | missing repetition |

| Composer | WorkID | BMID | ThemeID | MidiNo | ErrorType | ErrorDescription |
|---|---|---|---|---|---|---|
| Debussy | L113-03 | D24 | Serenade of the Doll | 9601 | MidiErr | missing grace notes |
| Debussy | L113-06 | D28 | 2nd Theme | 9605 | MidiErr | missing grace note |
| Debussy | L100-03 | D38 | Jardins sous la Pluie 1st Theme | 9615 | MidiErr | wrong note |
| Debussy | L122No2-01 | D51 | 5th Theme | 9628 | MidiErrTempo | |
| Debussy | L110-01 | D63 | 1st Theme | 9640 | MidiJointThemes | A B |
| Debussy | L109-01 | D69 | 1st Theme | 9646 | MidiErr | missing tie |
| Debussy | L109-02 | D75 | 1st Theme | 9652 | MidiErrTempo | |
| Debussy | L109-02 | D76 | 2nd Theme | 9653 | MidiErr | missing grace note |
| Dvorak | B191-01 | D278 | 1st Theme | 1193 | MidiErr | wrong note |
| Dvorak | B147-04 | D384 | 1st Theme | 1308 | MidiErrTempo | |
| Dvorak | B147-04 | D385 | 2nd Theme | 1309 | MidiErrTempo | |
| Dvorak | B147-06 | D389 | 2nd Theme | 1313 | MidiErr | wrong note |
| Granados | Op037-04 | G208 | 1st Theme | 1957 | MidiErr | missing grace notes |
| Haydn | Hob17No006 | H294 | 1st Theme | 2414 | MidiErrTempo | |
| Haydn | Hob03No032-02 | H342 | 2nd Theme | 2461 | MidiErr MidiErrTempo | missing grace note |
| Haydn | Hob03No034-02 | H346 | | 2465 | MidiErr MidiErrTempo | missing grace note |
| Haydn | Hob03No039-02 | H362 | 2nd Theme | 2481 | MidiErr | wrong note |
| Haydn | Hob16No023-01 | H508 | | 2628 | MidiErrTempo | |
| Haydn | Hob16No034-02 | H513 | | 2633 | MidiErrTempo | |
| Haydn | Hob16No036-01 | H520 | | 2640 | MidiErrTempo | |
| Haydn | Hob16No036-03 | H523 | 1st Theme | 2643 | MidiErr | wrong note |
| Haydn | Hob16No037-02 | H526 | | 2646 | MidiErrTempo | |
| Haydn | Hob15No025-01 | H689 | | 2809 | MidiErr | wrong grace note |
| Haydn | Hob15No025-02 | H690 | 1st Theme | 2810 | MidiErr | missing grace note |
| Haydn | Hob15No026-02 | H700 | | 2820 | MidiErrTempo MidiErr | wrong grace note |
| Haydn | Hob15No029-02 | H708 | | 2829 | MidiErr | double sharp |
| Khachaturian | ConcertoPianoDFlat-01 | K23 | 1st Theme | 3194 | MidiErr | double b |
| Khachaturian | ConcertoPianoDFlat-01 | K24 | 2nd Theme | 3195 | MidiErr | missing grace notes |
| Khachaturian | ConcertoPianoDFlat-02 | K25 | Intro | 3196 | MidiErr | missing grace notes |
| Khachaturian | GayaneBalett-09 | K41 | Lullaby | 3212 | MidiErr | missing grace notes |
| Liszt | S244-02 | L149 | 1st Theme | 3443 | MidiErrTempo | |
| Liszt | S244-02 | L155 | 7th Theme | 3449 | MidiErr | wrong note |
| Mahler | SymphonyNo02-01 | M59 | 2nd Theme | 3667 | MidiErr | wrong note |
| Mahler | SymphonyNo04-02 | M80 | 2nd Theme | 3688 | MidiErrTempo | midi much faster |
| Mahler | SymphonyNo05-04 | M90 | Adagietto | 3698 | MidiErrTempo | midi much faster |
| Mahler | SymphonyNo09-01 | M93 | 3rd Theme | 3701 | MidiErr | wrong note |
| Mahler | SymphonyNo09-03 | M102 | 2nd Theme | 3710 | MidiErrTempo | audio much faster |
| Mahler | SymphonyNo09-04 | M106 | Intro | 3714 | MidiErrTempo | midi much faster |
| Mozart | KV320-03 | M731 | | 4357 | MidiErr | wrong note |
| Mozart | KV525-02 | M755 | | 4381 | MidiErr | wrong note |
| Mozart | KV543-02 | M968 | | 4594 | MidiErr | missing note |
| Mozart | KV550-04 | M980 | | 4606 | MidiErr | one note too much |
| Mozart | KV551-01 | M981 | | 4607 | MidiErr | wrong note |
| Paganini | MS025-05 | P23 | | 4758 | MidiErr | wrong note |
| Ravel | MR072 | R208 | 7th Theme | 53385339 | MidiPart | |
| Schubert | D0667-02 | S384 | | 5971 | MidiErrTempo | audio much slower |
| Schubert | D0667-03 | S385 | 1st Theme | 5972 | MidiErrTempo | audio much faster |
| Schubert | D0894-02 | S414 | 1st Theme | 6001 | MidiErrTempo | |
| Schubert | D0894-02 | S415 | 2nd Theme | 6002 | MidiErrTempo | |
| Schubert | D0960-03 | S438 | | 6025 | MidiErrTempo | audio much faster |
| Schubert | D0574-02 | S455 | | 6042 | MidiErrTempo | audio much faster |
| Schubert | D0574-03 | S456 | | 6043 | MidiErrTempo | missing grace note midi much faster |
| Schubert | D0485-01 | S499 | | 6086 | MidiErrTempo | audio much faster |
| Shostakovich | Op010-01 | S873 | 2nd Theme | 6476 | MidiErr | |
| Shostakovich | Op047-03 | S891 | 1st Theme | 6494 | MidiErrTempo | audio much slower |
| Shostakovich | Op047-03 | S893 | 3rd Theme | 6496 | MidiErr | |
| Shostakovich | Op054-01 | S897 | 2nd Theme | 6500 | MidiErrTempo | |
| Shostakovich | Op054-03 | S900 | 1st Theme | 6503 | MidiErrTempo | audio much faster |
| Shostakovich | Op070-01 | S914 | 1st Theme | 6517 | MidiErrTempo | audio much faster |
| Shostakovich | Op070-01 | S915 | 2nd Theme | 6518 | MidiErrTempo | audio much faster |
| Shostakovich | Op070-03 | S918 | 1st Theme | 6521 | MidiErrTempo | audio much faster |
| Shostakovich | Op070-04 | S920 | | 6523 | MidiErrTempo | audio much slower |

| Composer | WorkID | BMID | ThemeID | MidiNo | ErrorType | ErrorDescription |
|---|---|---|---|---|---|---|
| Strauss | Op418 | S1308 | No. 4 2nd Theme | 6917 | MidiErr | |
| Tschaikovsky | Op071-12b | T195 | | 7538 | MidiJointThemes | |
| Wagner | WWV086C-02-02-02 | W47 | 5th Theme | 78927893 | MidiPart | |

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