Automated Identification of Chord Progression in Classical Music

This thesis entitled:

[redacted]

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Abstract

sequence recognition from synthesized audio of Classical music phrases. A hidden Markov model-based system achieves 67.7% accuracy on an independent set of

Chapter 1

Introduction

Chord progression - the succession of chords over time - defines the harmonic structure in of a seventh chord. For instance, a half-diminished seventh chord consists of a diminished triad

and a minor seventh note above the root; a dominant seventh chord (or major-minor seventh chord) is made up of a major triad with a minor seventh note.

major and minor triads.

music, there has been little research on the application of statistical learning methods on chord

Chapter 2

Overview

[illegible]

recording is converted into a series of features that represent the audio spectrum. Then, a trained HMM is used to perform chord pattern matching, i.e. mapping the chroma features to chord labels that correspond to the various chords under consideration.

[illegible]

2.1 Music Selections and Synthesis

synthesized from MIDI symbolic data. The artificially synthesized audio clips can feature the enharmonic spectrum of musical instruments, making them comparable to recordings in the

HMM.

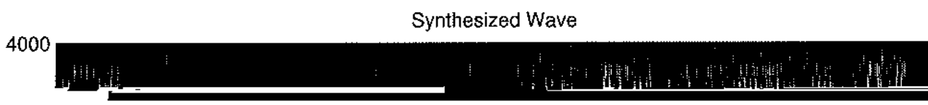
Chapter 3

Chroma Features

Chroma features, also known as pitch class profiles, are well established in music audio

3.2 Chroma-Log-Pitch Features

Since sound intensity is perceived logarithmically rather than linearly, a logarithmic com-


Synthesized Wave
4000

Chapter 4

Hidden Markov Models

Before we discuss HMMs, let us first look at Markov Models in the context of chord pro-

[redacted]

$$P(c_1, c_2, ..., c_n) = \prod_{i=1}^{n} P(c_i|c_{i-1}). \tag{4.4}$$

[redacted]

nificantly reduced. Instead of an exponentially growing numbers of statistics, we only need $3 \times 3 = 9$ observations to infer the probabilities of all possible sequences. $P(c_n|c_{n-1})$ is the same

[redacted]

Exercise: [illegible] (either true or false)

Of course, actual feature vectors are much more complicated, capturing acoustic signals (like

4.2 Formal Definition of HMMs

Before moving on to discussions of optimal pattern matching in HMMs, we need to speci fy terminology about various probabilities involved.

- The *set of states* $S = \{s_1, s_2, ..., s_{N_s}\}$, where each s_i corresponds to one of the possible

c_i at time n:

$$\delta_n(i) = \max_{q_1, q_2, \dots, q_{n-1}} P(q_1, q_2, \dots, q_{n-1}, q_n = c_i, f_1, f_2, \dots, f_n | \Theta) \tag{4.12}$$

- $\phi_n(i)$, helping us keep track of the "optimal" path ending in chord c_i at time n:

Chapter 5

Test Results and Conclusion

5.1 Testing

Test data consist of fifty selections. They went through the same chroma analysis as the

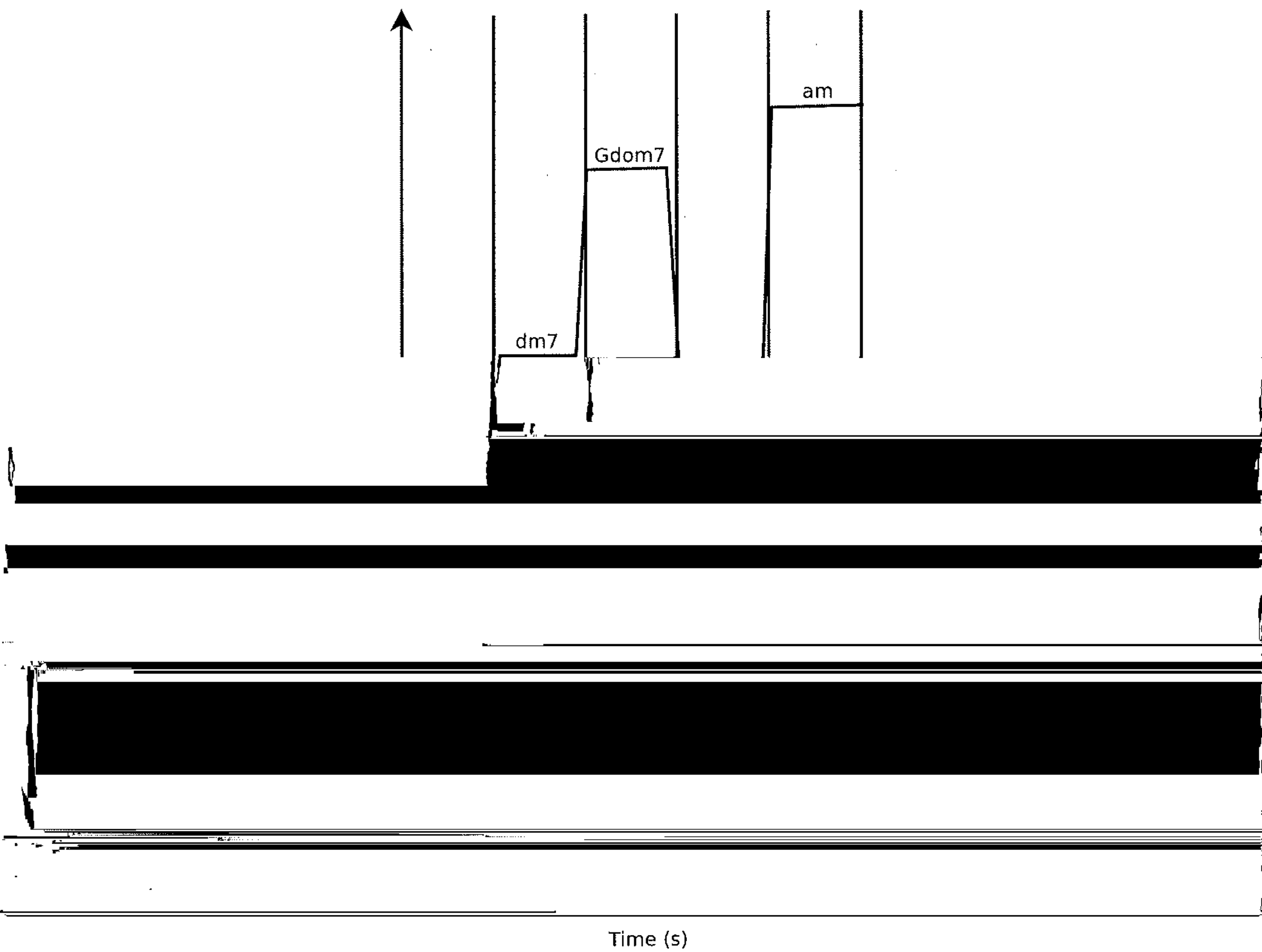


Figure 5.1: Frame-level chord sequence (state path) of a selection from Bach's *Prelude in C Major (BWV 846)*. The vertical lines correspond to ground-truth boundaries.

or even two individual chords, are included in the same frame window. In these cases, the system has a much harder time figuring out the chords when many notes are clustered in a single frame.

[redacted]

[redacted]

[redacted]

B and D. Three of the [illegible] C, B, and D also form C [illegible] triad. The system

[illegible] E [illegible] C [illegible] if the note E does not appear

[illegible] J. P. Bello and J. Pickens, "A robust mid-level representation for harmonic content in

[14] "Classical piano midi page," http://www.piano-midi.de/midicoll.htm.