


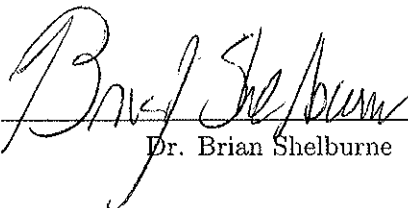
This thesis entitled:

Automated Identification of Chondrocytes in Classical Media

written by Peiqian Li
has been approved for the Department of Computer Science



Dr. Steven Bogaerts



Dr. Brian Shelburne

Abstract

1. Introduction 2. Related Work 3. System Description 4. Experimental Results 5. Conclusion

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

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

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.

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-

chroma-log-pitch (CLP) features CLP features

Synthesized Wave

4000



Chapter 4

III: L L M L M L L

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

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

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

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

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

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

c_i at time n :

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

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

$$\phi_n(i) = \arg \max_{q_1, q_2, \dots, q_{n-1}} P(q_1, q_2, \dots, q_{n-1}, q_n = c_i, f_1, f_2, \dots, f_n | \Theta) \quad (4.13)$$

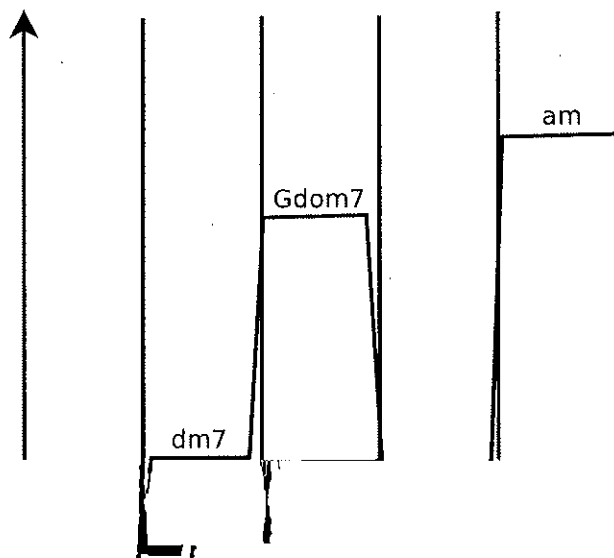
Chapter 5

Test Results and Conclusion

5.1 Testing

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

... ..



Time (s)

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.

Figure 5.2: A frame-level chord sequence with the ground truth state path used in our system. A variable

[REDACTED]

[REDACTED]

[REDACTED]

[1, 2, 3, 4] [1, 2, 3, 4] (A least-mid-level representation for harmonic content in

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