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A Survey of Automated Harmonic Analysis Techniques

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Abstract

The problem of using the computer for automated harmonic analysis has been approached from several different directions with varied degree of success. Techniques from artificial intelligence such as machine learning and pattern recognition have been used. The division of a given piece in harmonic significant segments is a crucial problem in the area of automated harmonic analysis, although it is still underrepresented in the literature. Also, most algorithms ignore relevant contextual clues and little has been done towards establishing standard benchmarks. This paper presents a comprehensive survey of the existing literature on the subject.

1 Introduction

Music information retrieval has received increasing attention recently. Some research focus on music retrieval by polyphonic query-by-audio [12, 27], development of tools for digital libraries [4, 20, 7], detection of musical patterns [15, 5, 14] that may help, among other things, to identify musical styles [6, 22, 30], and in problems related to musical representation [9, 8, 31].

While the main goal in music information retrieval " is not an understanding of music. It is not to develop a better theory of music, or even to analyze music. The goal is retrieval" [26], other researchers seek a better understanding of elements and music processes through automatic analysis by computer. We agree with Mouton et al that "only automatic analysis of a large corpus of tonal music may eventually provide us (the human) with insights on the very nature of tonal music" [17]. Computer-based musical analysis is important because it can bring new insights in music theory, in the same way as use of computer in vision and problem solving has brought new insights in these areas [36].

There are many practical applications for automatic music analysis, among them arranging, detection of possible logical mistakes in scores, database search, automatic accompaniment generation, and statistical analysis of musical styles for automated composition [25, 36].

Functional harmonic analysis is a specific kind of musical analysis, in which a musical passage is represented as a sequence of chords. By definition, automated harmonic analysis must be done completely by computer programs without human intervention. Typically the system accepts musical data in a format such as MIDI or scores in symbolic or numeric format, and returns information such as chord roots, chord types, or symbols in roman numerals indicating tonal function.

This paper gives an overview of the current status of automated harmonic analysis. To our knowledge, there is no comprehensive survey on this subject. Scholz et al. [32] offer a brief survey of the state of the art until 2001. Mouton et al. [17] and Barthèlemy et al. [1] have general but informative surveys on the topic. This paper focuses on the main problems and solutions of automated harmonic analysis with a discussion of their effectiveness. Harmonic analysis from audio sources will be not approached.

2 The problem of automated harmonic analysis

The problem of automated harmonic analysis might be understood by dividing it into three sub-problems. The first problem is to divide a given piece into segments with harmonic significance. The second is to label each segment with a chord name. The last problem is to assign a tonal function to each chord.

A few additional sub-problems might arise from the input format, such as determining meter or a correct pitch spelling depending on its suitability.

3 Music representation in harmonic analysis

A musical piece must be represented in a form suitable to automated analysis before making any attempt to extract information. There is a broad number of codifications in existence, focusing on performance, sound synthesis, computer games, musical notation, braille notation, folk songs, musical bibliography, and many others [33].

Interestingly, the choice of a proper codification influences the results obtainable from analysis. For example, chords that sound the same but have different tonal function and spelling might not be told apart using an algorithm that does not consider enharmonic difference. For instance, in [25] a German augmented sixth chord is mistakenly identified as a dominant seventh chord.

Most systems [28, 25, 23, 36] represent notes as pitch classes, ignoring enharmonic information. This is somewhat emphasized by the fact that MIDI or MIDI-like input is used [23, 25, 40, 29]. Pardo et al. [25, 23] also ignore meter and all forms of contextual information with the intention to provide a basis for study of better algorithms.

A few numeric representations for pitch [11, 19] were developed to highlight tonal information in music. The one developed by Oliveira [19] is particularly elegant. This representation is not only capable of differentiating enharmonic notes (for instance, D$\sharp$ is represented by 7 and D$\flat$ by 91) but allows operations like calculation of tonal intervals, transposition, inversion, and so on. It is modulo 96 based and can be easily converted to the more common module 12 based representation.

The systems described in literature usually return information such as keys [3, 18], chords [36, 25], figured bass [1], or tonal function [21, 39]. Most systems, as those from [25, 24, 36], use notation like A$\flat$7 for chords. The system described in [21] outputs not only the chord names but some functions used in jazz harmony like "modal borrowing" and "tritone substitution". Ulrich [39] also performs a functional analysis of chords, indicating information such as "tonic of G" or "substitute for x+2".

Since the usual notation for chords is ambiguous some alternatives were proposed. Harte et al. notation [10] has tuples of chord intervals, like `c:(3,5)` for C major or `d#:(b3,5,b7,9)/5` for D$\sharp$m$^{7}_{9}$/A$\sharp$. Since this notation is too verbose Harte et al. use shorthands such as `d#:min9/5`. Kroger et. al [13] use a list with chord information in the format:
(<name> <type> <intervals> <inversion>)
For instance, G7/B would be `(g major 7 1)`.

4 Harmonic Context

In harmony some structures like non-chord notes are better understood in a particular context. For instance, a passing note is a non-chord note that only can be identified if it is approached and left by step in the same direction, so it is only identifiable by considering contextual information. Proper use of harmonic context helps to solve problems such as ambiguities in chord analysis, identification of non-chord notes, suspensions, and retardations.

The NUSO system [17] uses harmonic context to define tonality through rules considering non-chord notes in accompanied melody, Alberti bass, and baroque style. The MusES system [17] uses relations between adjacent chords to define the best possible tonality for a chord. Finally, the automated harmonic analysis method developed by [1] has a simple algorithm to process non-chord notes, often producing errors. It assumes that every non-chord note is followed by a conjunct movement. This assumption is not true, and may lead to errors.

Some projects don't take harmonic context into account. Harte et al. [10] ignores key context in their model for chord labels. Pardo et al. [23, 25] developed a set of algorithms for automated chordal analysis making minimal use of harmonic context.

Barthèlemy et al. [1] raise four issues related to harmonic context. Ornamental notes and incomplete harmony, ambiguities, non-regularity of harmony, and non-universality of harmony rules. Pardo et al. [23] classify errors from their approach, most of them related to harmonic context, specifically non-chord notes and cadence recognition. They agree that a deeper understanding of voice leading and knowledge about neighbor chords would help adjusting chord-label weights.

5 Proposed Solutions

Many techniques from artificial intelligence, such as machine learning and pattern recognition have been used in automated harmonic analysis. These can be classified as either expert-systems or statistical models.

5.1 Expert Systems

Since expert systems abound in the field of artificial intelligence it is only natural that they should be the first attempt at codifying music theory in a format proper for automated analysis.

Pattern matching over chord templates is used in [28], [25], and [23]. Barthèlemy et al. [1] use a somewhat more complex model, that can ignore ornamental notes. Wang et al. [40] use pattern matching in three passes and assumes that no modulation happens. Temperley et al. [36] use a sophisticated preference-rule system to identify the roots of the chords in a piece, but it avoids the problems of tonality detection and harmonic function identification.

Barthèlemy et al. [1] and Mouton et al. [17] use a greedy algorithm for tonality recognition that is based on the fact that every chord can be only part of a few keys.

5.2 Statistical Models

While not specifically addressing the problem of musical context, statistical models differ from their rule-based counterparts by considering harmonic information implicitly. This is accomplished by inference of this information from already harmonized scores during training. Too much sensitivity to the training data might be problematic, since it may lead the algorithm to make errors when analyzing a piece. For instance, after being trained on Bach chorales if the system is exposed to an arpeggiated melody it might classify each note of the arpeggio as a different chord [38].

Back-propagating neural networks are used by T'sui [38] with good results, analyzing bach chorales with over 90% efficiency. A hidden markov model is employed by Raphael et al. [29] and Noland and Sandler [18], with over 91% accuracy for key estimation. A Bayesian model is used by Temperley et al. [37] for key estimation with 86.5% accuracy.

6 Segmentation

The division of a given piece in harmonic significant segments - groups of notes within chord boundaries - is a crucial problem in the area of automated harmonic analysis, although underrepresented in the literature [25, 2].

The task of designing an effective algorithmic solution for the problem of segmentation is difficult because the segmentation problem isn't clearly formalized in the music theory literature.

This problem is of high computational complexity, since the number of possible partition points in a given piece is proportional to the number of notes. The number of possible segmentations is approximately two to the power of the number of partition points. To reduce the space of possible partitions one must consider the harmonic context of each segment, which is difficult. Most systems make little use of proper context, according to Barthèlemy et al. [1].

Prather [28] approaches the problem in a simplified fashion, segmenting only inside measures. Therefore a chord is split if it spans more than a bar. Barthèlemy et al. [1] segment bottom-up, starting from minimal segments and merging them in a larger segment if possible. Pardo et al. [23, 25] perform segmentation backwards, by comparing all possible segmentations and choosing the ones that better match chord templates.

7 Tests and benchmarks

Pardo et al. state that "no researchers have published statistical performance results on a system designed to analyze tonal music" [25] before their paper. This lack of data in literature makes it difficult to compare different systems. Also, there aren't standard benchmarks to compare different algorithms and results. In fact, only Pardo et al. [24] and Barthèlemy et al. [1] published specific comparisons between theirs and other's results. Pardo compares his results with [36] while Barthèlemy compares his model against [16], [23] and [35]. However, they are based on the results published in papers and not on results from direct implementations, which means that only the examples published by the authors can be compared.

8 Conclusion and discussion

This paper presented a comprehensive overview of the current status of automated harmonic analysis, focusing on the main problems with a discussion of their effectiveness.

The problems of harmonic segmentation and harmonic analysis are not fully solved. A more systematic approach to segmentation might yield considerably better results. Musical theory lacks precise formalisms, so developing effective algorithms based on it is non-trivial. The lack of standard benchmarks contributes to this problem and makes the comparison of existent methods difficult.

Although many aspects of music can be understood using mathematical models such as set theory (or post-tonal theory), it is not clear in literature if a mathematical approach would help in harmonic analysis. Taneyev [34] has used mathematics extensively in his counterpoint treatise with a good degree of success. As far as we know, meaningful works do not exist in the literature of automatic harmonic analysis where a mathematical model such as set theory is used extensively.

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