# A Study on Music Genre Recognition and Classification Techniques

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## Abstract

Automatic classification of music genre is widely studied topic in music information retrieval (MIR) as it is an efficient method to structure and organize the large numbers of music files available on the Internet. Generally, the genre classification process of music has two main steps: feature extraction and classification. The first step obtains audio signal information, while the second one classifies the music into various genres according to extracted features. In this paper, we present a study on techniques for automatic music genre recognition and classification. We first describe machine learning based chord recognition methods, such as hidden Markov models, neural networks, dynamic Bayesian network and rule-based methods, and template matching methods. We then explain supervised, unsupervised and semi-supervised classification methods classifying music genres. Finally, we briefly describe the proposed method for automatic classification of music genres, which consists of three steps: chord labeling, genre matching and classification.

Keywords: chord recognition, genre classification, subsequence matching, decision tree

## 1. Introduction

The rapid development of Internet together with the growth of the bandwidth availability have resulted in the widespread of large amounts of digital multimedia contents in Internet [1]. One of the most important types of multimedia content distributed over the Internet is a high volume of digital music in MP3 format. This has motivated researchers to develop music information retrieval (MIR) techniques that would be helpful for Internet music search engines, musicologist and listeners to find music from numerous options. Among these techniques, automatic classification of music pieces into categories such as mood, artist or genre is widely studied topic in MIR as it is an efficient method to structure and organize the large numbers of music files available on the Internet.

A music genre describes a style of music that has similar characteristics shared by its members and can be distinguished from other types of music. These characteristics are usually related to the instrumentation, rhythm, harmony, and melody of the music [2]. Generally, the genre classification process of music has two main steps: feature extraction and classification. The first step obtains audio signal information, while the second one classifies the music into various genres according to extracted features. Chord recognition methods are used for feature extraction from an audio signal. The

chord recognition task constructs a chord label from a specific music-related feature. On the other hand, different data-mining algorithms, including supervised, unsupervised and semi-supervised classification, are proposed to classifying music genres.

In this paper, we present a study on techniques for automatic music genre recognition and classification. We first describe machine learning based chord recognition methods, such as hidden Markov models, neural networks, dynamic Bayesian network and rule-based methods, and template matching methods. We then explain supervised, unsupervised and semi-supervised classification methods classifying music genres. Finally, we briefly describe the proposed method for automatic classification of music genres, which consists of three steps: chord labeling, genre matching and classification.

The rest of the paper is organized as follows. In Section 2, we discuss techniques on music genre classification. In Section 3, we briefly describe the proposed method. In Section 4, we highlight conclusions and future work.

## 2. Techniques on Music Genre Classification

Generally, the genre classification process of music has two main steps: feature extraction and classification. The first step obtains audio signal information, while the second one classifies the music into various genres according to extracted features. Chord recognition methods are used for feature extraction from an audio signal. Thus, in Section 2.1, we discuss chord recognition methods. In Section 2.2, we explain music genre classification methods.

### 2.1. Chord Recognition

The chord recognition task constructs a chord label from a specific music-related feature. Typically, chord recognition techniques use a chromagram as an input to the system and output a chord label for each chromagram frame. Various methods have been used for this task. In this subsection, we discuss machine-learning methods and template matching methods.

**2.1.1. Machine-learning based cord recognition:** Hidden Markov models are the most popular methods used in chord recognition. One of the earliest implementation of such a method is described in [3]. In [3], the authors proposed to construct a system for automatic chord transcription using speech recognition tools. In the proposed method, input signal is first segmented to the frequency domain. Then, it is mapped to the Pitch Class Profile domain, where vectors are used as features to train a hidden Markov model with one state for each chord. These features are then used to construct chord models via Expectation-Maximization algorithm. Finally, chord recognition is carried out with the Viterbi algorithm. The experimental results with a small set of 20 songs demonstrate that the proposed method has a frame-level accuracy of around 75% on forced-alignment task.

In [4], the authors proposed a method for semantically describing harmonic content directly from music signals. In the proposed method, the audio signal is first transformed into tactus window and pitch chroma tuning process is done. Then, cord labeling is accomplished where a lexicon of 24 triads is used in order to describe harmonic movement in a piece. The hidden Markov model algorithm is then initialized that keeps dependency between tonic, mediant, and dominant pitches in a triad, along with the consonance between neighboring triads in a sequence. Finally, the updates to models parameters of hidden Markov model algorithm is performed in order to maintain the relationship between pitches in a chord.

In [5, 6], the authors proposed an automatic chord recognition method from audio using an hidden Markov model with supervised learning. For this, the authors used symbolic data to

make label files and create audio files. For feature vectors, the authors used 12-bin tune chrome vectors. Each state in hidden Markov models was designed by a multivariate, single Gaussian completely represented by its mean vector and a diagonal covariance matrix. In their model, the authors used 36 chord types that include three distinct sonorities, such major, minor and diminished, for each pitch type. Once the model parameters, such as initial state probabilities, state transition probabilities, and mean vector and covariance matrix for each state, are estimated from the training data, the Viterbi algorithm is applied to the model to find the chord sequence from input signal. The proposed system is demonstrated in Figure 1. The results of experiments demonstrate that the proposed method has a higher performance in frame-level chord recognition than existing methods.

In [7], the authors proposed a simultaneous estimation of chord progression and downbeats from an audio file. In the proposed method, to extract chord progression and the downbeats from the audio signal, a set of meter-related feature vectors that describe the signal is extracted. The chord progression is described using a hidden Markov model that considers global dependencies on meter. In order to extract the tactus/tatum positions, the authors used the method introduced in [8]. The proposed method is evaluated on a dataset of 66 popular music songs from the Beatles and shows improvement over the existing methods.

In [9], the authors proposed a method for automatic chord recognition using hidden Markov models. The applicability of standard factored languages to the chord recognition are also studied. In the proposed method, pitch type profile vectors are first extracted from the given audio signal. Then, in order to capture chord sequence, Viterbi decoder on trained hidden Markov models and subsequent lattice rescoring, applying the language model weight is used. The experiment results with 175 manually-labelled songs demonstrate that the proposed method provided an increase in accuracy of about 2%.

In [10], the authors proposed a chord recognition method using duration-explicit hidden Markov models. The model break up the duration constraints from the transition matrix. Then, the method constructs distinct models for duration distributions that demonstrate time signatures to improve the duration constraint in each model. The proposed method is experimented using Uspop dataset and demonstrates that it recognizes chords with accuracy to 84.23%.

In [11], the authors argue that traditional hidden Markov model, with Vitebri algorithm, is not suitable for real-time chord recognition, and proposed a system of buffers and a modified decoding process that approximates offline results while minimizing the system's latency. The authors used two different types, such as an audio input buffer and an observation buffer. The audio input buffer estimates block size of audio samples from incoming audio signals. Each time new hop size of samples comes into the buffer, chroma features are extracted from audio input buffer. For local decoding process, the observation buffer saves $L$ number of the extracted chroma vectors. The experiment results show that the real-time system can be as efficient as offline systems.
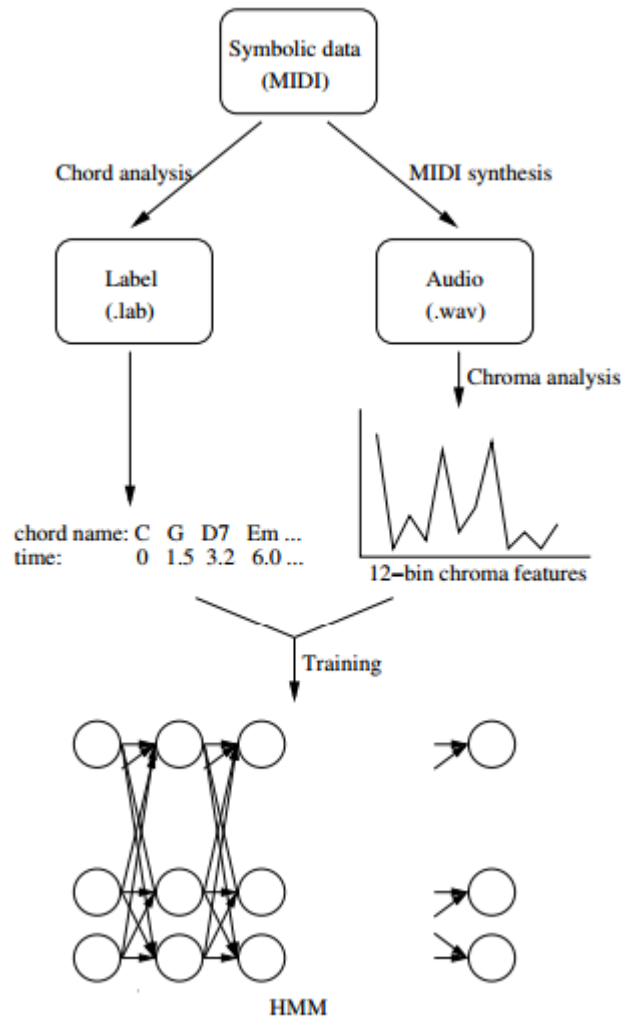
**Figure 1. Automatic chord recognition from audio using hidden Markov model [5]**

In order to speed up the process of chord recognition compared to hidden Markov model, some of the studies used neural networks. For example, in [12], the authors proposed a feed forward neural network method for chord recognition. Through various experiments, the authors demonstrate that using 12-dimensional Pitch Class Profile vectors are effective representation method of chords. Specifically, the experiment result demonstrate that the Pitch Class Profile is well-suited for describing chords in a machine learning context, and the algorithm is capable to recognize chords played with other instruments. In [13], the authors proposed an audio chord recognition system based on a recurrent neural network. The proposed model can learn fundamental musical properties, such as temporal continuity, temporal dynamics and harmony. The authors propose an algorithm that is able to search for the chord sequences when the audio signal is ambiguous, noisy or weakly discriminative. Through various experiments with MIREX dataset, the authors demonstrate that the proposed method is competitive with existing approaches.

Another body of the literature used dynamic Bayesian network to recognize chords of the music. For example, in [14], the authors present dynamic Bayesian network, which integrates models of metric position, key, chord, bass note and two beat-synchronous audio features (bass and treble chroma) into a single high-level musical context model. With 109 chord types, the model provides a higher level of detail than existing approaches while maintain a high level of accuracy. In [15, 16], the authors proposed a modification to [14], which integrates in a single probabilistic model the hidden states of metric position, key, chord, and bass node, along with two observed variables: chroma and bass chroma.

Rule-based recognition methods are presented in [17, 18]. In [17], the authors proposed a framework to analyze a musical audio signal sampled from a popular music, and define its key, offer usable chord transcriptions, and extract the hierarchical rhythms structure representation including the quarter-note, half-note, and whole note levels. In chord accuracy enhancement phase, the authors perform a rule-based analysis of the detected chord to check if it exists in the key of the song. In [18], the authors proposed a signal based approach to obtain chords from a music files. Information about chords are obtained from spectral representations of the audio data. Then, for each frequency bub in the desired frequency range, the amplitudes of all hypothetic harmonics are summarized. To extract the most salient pitches, the eight strongest local maxima in the resulting sum spectrum are chose as candidates. From this set of chord candidates, the most plausible sequence of chords sequence of chords is obtained using the following criteria: maximization of amplitude, maximization of duration and fitness to the detected key.

**2.1.2. Template-based cord recognition:** There are several methods that used different techniques to machine learning techniques to recognize chords of the music. Template based techniques are one of them and use pre-defined chord models to recognize the cord type. For example, in [19, 20, 21], instead of using hidden Markov models, the authors proposed a chord recognition method using measures of fit, chord templates and filtering methods. In the proposed method, they first calculate chrome vectors from input audio signal. A set of chord templates for several types of chords are also proposed. A scale parameter is then calculated in order to fit the chroma vectors to the chord templates. The detected chord is the one minimizing the measure of fit between a rescaled chroma vector and the chord templates. In order to consider the time-persistence, the authors performed a post-processing filtering that can smooth the results and correct the errors.

In [22, 23], the authors proposed a probabilistic template-based chord recognition. The key distinction of the proposed method to the existing template-based approach is that the authors proposed chord probabilities, learned from the song. The result of the proposed method demonstrate that there is no probability of spurious chords, which smoothed out the transcription produced with deterministic approach. The method is tested on dataset consists of the 180 pop-rock songs and the other one that is composed of 20 songs from various artists and music genres. The results of experiments show that the proposed method has better performance in chord recognition comparing to existing work.

In [24], the authors proposed a method for automatic chord recognition from audio files using enhanced pitch class profile. In order to do so, the authors introduced a feature vector called the Enhanced Pitch Class Profile (EPCP). In the proposed method, first, the Harmonic Product Spectrum is extracted from the Discrete Fourier transform of the input audio signal. An algorithm for calculating a 12-dimensional pitch class

profile is then used to it to provide the EPCP feature vector. The EPCP vector is correlated with pre-determined templates for 24 major/minor triads, and the template with maximum correlation is identified as the chord of the input audio signal. The experiment results demonstrate that the EPCP is error-prone compared to the traditional PCP in frame-rate chord recognition.

### 2.2. Genre Classification

One of the most important types of multimedia data distributed over the Web is a high volume of digital music in MP3 format. Music genre classification is effective way to structure and organize the large numbers of music files on the Web. Several methods have been used for this task. In this subsection, we discuss the supervised, unsupervised and semi-supervised classification methods.

**2.2.1. The supervised classification method:** In supervised methods, the model is first trained by manually labeled data, i.e., supervised classification knows the genres of songs. In [25], the authors proposed a music genre classification method using multi-layer support vector machine learning. In this method, to characterize music content, beat spectrum, linear prediction coefficients, zero crossing rates, short time energy and mel-frequency cepstral coefficients are used as features. Support vector machines are developed to obtain optimal class boundaries between different kinds of music genres by learning from training data. Through various experiments, the authors demonstrated that multi-layer support vector machines have better performance compared to traditional Euclidean distance based methods and statistical learning methods.

In [26], the authors explore automatic classification of audio signals into a hierarchy of musical genres. The main focus of the proposed method is to discover three feature sets for representing timbral texture, rhythmic content and pitch content. Gaussian mixture model (GMM) and K-nearest neighbor (KNN) classifiers are used based on the extracted features. Through experiments, the authors show that the proposed method has accuracy of 61% (non-real time) and 44% (real time) when there are ten musical genres present.

**2.2.2. The unsupervised classification method:** In contrast to supervised classification methods, unsupervised classification methods classify data based on no knowledge about the genre clusters. In [2], the authors argue that supervised classification methods may not be appropriate for personal music management as manually labeling music for each individual-defined genres can be difficult and inconsistent. They proposed to partition a music genres into several clusters by measuring the similarities between music based on cross likelihood ratio, inverse Euclidean norm, and cosine measure. Next, the authors used hierarchical agglomerative clustering in order to group music of one genre. A method based on Rand index is also proposed to define the optimal number of clusters automatically according to the number of genres. The experiment results show the feasibility of proposed method in music genre classification.

In [27], the authors proposed an unsupervised learning method of local features. In the proposed method, local patches from the time-frequency transformed audio signal is obtained. It is then pre-processed by normalizing all patches and applying whitening transformation to the patches. Furthermore, unsupervised learning of an overcomplete dictionary of local features is used. For learning, the authors used earthier bootstrapped *k*-means algorithm or select features randomly. Feature responses are obtained in a convolutional manner and trained using a linear support vector machine for

classification. Through various experiments, it is demonstrated that the proposed method is competitive with existing classification methods.

In [28], the authors proposed a method to classify music genres using hidden Markov models. The proposed method contains two steps. In the first step, to characterize music content, segmentation scheme is used based on music intrinsic rhythmic structure analysis as features. Then, based on these features, hidden Markov model is trained for the music piece. In the second step, a distance matrix is constructed of the distance between every pair of music pieces (hidden Markov models) and clustering to make desired clusters are performed. The authors experimentally show that the proposed method performs as good as supervised classification methods.

**2.2.3. The semi-supervised classification method:** The semi-supervised classification methods make use of both supervised and unsupervised classification methods. That is a small amount of labeled data with a large amount of unlabeled data are used for training. In [29], the authors proposed a semi-supervised classification method for musical genres using multi-view features. The method proposes to combine different feature sets, such as Short Time Fourier Transform (STFT) based features, Mel Frequency Ceptral Coefficients (MFCC) features, and Discrete Wavelet Transform (DWT) based features, and split it into several feature subsets. Co-Training algorithm is then applied to classify music pieces with only few annotations compared to traditional supervised classification methods that need large amount of annotations. Through various experiments, the authors prove the validity and effectiveness of the proposed method.

In [30], the authors proposed a framework for hierarchical music classification of music pieces into a genre taxonomy. A music piece is described by a set of feature vectors, where number of instances can be from tens to hundreds per song. Thus, in the proposed method, the authors first introduce hierarchical semi-supervised technique for instance reduction. This reductions are then used for hierarchical classification music pieces with support vector machines. Furthermore, the authors use object adjusted weighting in order to take advantage from multiple representations. Experiment results with real data set demonstrate that the proposed method is efficient has high classification accuracy.

## 3. Proposed Method

In this section, we briefly describe the proposed method. Our method consists of three main steps. In Section 3.1, we describe the chord labeling scheme. In Section 3.2, we explain the genre matching process. In Section 3.3, we introduce the genre classification.

### 3.1. Chord Labeling Scheme

In the proposed method, we first annotate the music sequence using the binary sequence. Figure 1 demonstrates the example of chord labeling scheme, where a "1" is used to denote a sound that is going up in the music sequence, and a "0" is used to represent a sound that is going down. Note that a sound that does not change it is state in the music sequence is denotes as "0". Thus, the chord labeling scheme for a music sequence presented in Figure 2 is as following: [11010101].
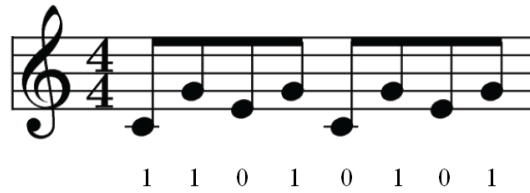
**Figure 2. Representation of music sequence using the binary sequence.**

### 3.2. Genre Matching

Once the music sequence is demoted with binary sequence, we can consider it as time sequence and find the subsequence matching to the genre. Given two time sequence $S$ and $Q$ which may have different length, the goal is to find all similar subsequence pairs between two time sequences with a specified threshold [31]. A $k$-windowSubsequenceMatching algorithm, described in [31], is used in order to find subsequence matching in music sequence.

We formally describe the problem of subsequence matching. We describe some relevant definitions for the targeted problem as follows.

**Definition 1** *(Time Sequence)* [32]: A time sequence $S$, $S(s_1, s_2, s_3, \ldots, s_{l(S)})$, is an ordered set of real values, where $s_i$ is the $i^{th}$ element of $S$, and $l(S)$ is sequence length of $S$.

**Definition 2** *(Time Subsequence)* [32]: A time subsequence is and ordered sequence. $S_{i,j} = s_i, s_{i+1}, s_{i+2}, \ldots, s_j$ denotes the time subsequence of a time sequence $S$, which contains the elements of $S$ in positions $i$ through $j$, and the length of $S_{i,j}$ is $(l)S_{i,j} = i + j - 1$.

**Definition 3** *(Similar Time Sequence)* [32]: Two time $S$ and $Q$ are called similar if and only if $W(S, Q) \geq \Delta$, where $W()$ is a function for calculating similarity between $S$ and $Q$, and $\Delta$ is a specified threshold value.

**Definition 4** *(Similar Subsequence)* [32]: Given two time sequence $S$ and $Q$, the sequences $S'$ and $Q'$ are called a similar subsequences of $S$ and $Q$ if and only if $S'$ and $Q'$ are similar and they subsequences of $S$ and $Q$, respectively.

**Definition 5** *(Distance of Similar Subsequence)* [32]: If $S$ and $Q$ have similar subsequences $S_{i,j}$ and $Q_{x,y}$, then the distance between $S_{i,j}$ and $Q_{x,y}$ is $D(S_{i,j}, Q_{x,y}) = |i - x|$.

Notice that any kind of measure could be used for the similarity function $W()$ in Definition 3. Based on the above definitions, the shape or trend of two subsequences should be very close if they are similar subsequences.

### 3.3. Genre Classification

Once the genre matching process is performed, we classify the matched music sequence according to music genres. We restrict ourselves to four genres: prehistoric time, middle age, renaissance, baroque, classic and modern, although the approach we use can possibly be extended to much larger classification set. In this paper, we used the decision tree algorithm presented in [33] in order to classify music genres.

Decision trees are one of the well-known classification techniques. They are widely used due to comparatively rapid to compute, simple to understand by humans, and they can reach accuracies similar to other well-known classification techniques. A decision tree is a tree consisting of a root node, child nodes and edges. Each internal node is a test node that indicates the attribute; the edges indicate the possible values taken on by that attribute. Each non-leaf node consists of a splitting point, and the main task for building the decision tree is to identify the test attribute for each splitting point. The ID3 algorithm uses the information gain to select the test attribute. Information gain can be computed using entropy. In the following, we assume there are m classes in the whole training data set. We know

$$Entropy(S) = -\sum_{j=1}^{m} Q_j(S) \log Q_j(S), \qquad (1)$$

where $Q_j(S)$ is the relative frequency of class $j$ in $S$. We can compute the information gain for any candidate attribute $A$ being used to partition $S$:

$$Gain(S, A) - Entropy(S) - \sum_{v \in A}\left(\frac{|S_v|}{|S|} Entropy(S_v)\right) \qquad (2)$$

where $v$ represents any possible values of attributes $A$; $S_v$ is the subset of $S$ for which attributes $A$ has value $v$; $|S|$ is the number of elements in $S$.

## 4. Conclusion

In this paper, we have introduced a study on techniques for automatic music genre recognition and classification. We first explained machine learning based chord recognition methods, such as hidden Markov models, neural networks, dynamic Bayesian network and rule-based methods, and template matching methods. We then described supervised, unsupervised and semi-supervised classification methods classifying music genres. Finally, we briefly introduced the proposed method for automatic classification of music genres, which consists of three steps: chord labeling using the binary sequence, genre matching using the subsequent match technique and classification of music genres using decision tree.

As for the future work, we plan to implement and describe the proposed method in details. Effectiveness of the proposed method will be compared with various machine learning classification algorithms, including Support Vector Machines and k-nearest neighbor. Through various experiments, we will demonstrate that the proposed method is both fast and accurate comparing to the previously studied methods.

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