1 Summary of articles

1.1 Folk Music Classification

Chai begins by explaining how it would be useful for computers to be able to classify musical works, and by doing so we could learn how a human can identify a musical work quickly. They then explain the goals of their research being ": (1) to explore whether there exists significant statistical difference among folk music from different countries based on their melodies; (2) to compare the classification performances using different melody representations; (3) to study how HMMs perform for music classification as a time series analysis problem."

They used German and Irish folk music pieces for their data. They chose folk songs because of their clear monophonic melody line. They chose German and Irish because of the availability of data.

For the representation of the melody line they used four different methods.

- Absolute Pitch: where they have a value for each note in an octave.
- Absolute Pitch with Duration Representation: Same as absolute pitch but each note is repeated relative to the length of the smallest rhythmical note.
- Interval Representation: The melody is converted to a sequence of intervals.
- Contour Representation: The melody is converted to a sequence of contours, instead of using intervals it just states +/- for small change and ++/−− for large change in the melody.

They used 16 different Hidden Markov Models to test how varying structures and number of states for the HMM's performed in the melody classification. For the HMM's they used the Baum-Welch reestimation method for training the markov model for each country. For the identification they used the Viterbi algorithm to decode the sequence and compute its log probabilities.

The data was split 70%/30% training/testing. After training the HMM's the best representation achieved 63%-77% correctness in identifying the origin of the folk melody.

The results they concluded include that different melodic origins can have varying degrees of similarity making it more difficult to differentiate them. Additionally they discovered that although absolute pitch is a more objective way to represent the melodic line, interval representation performed better, which is consistent with how humans perceive melody lines.

Finally they conclude with stating how HMM's can be used for melody classification for folk music and how folk music does have significant statistical difference between countries of origin. Ending with stating that melody is an important feature but calssification can be greatly improved if other significant features (harmony, instrumentation, performance style etc.) are included in the features used.

1.2 Classification of Musical Genre: A Machine Learning Approach

This paper starts by describing musical genre and how it exists as a terms that define recurrences and similarities between two works of music that the community uses to identify musical events. Thus their analysis is focused on symbolic musical aspects to gain as much information about the dynamic genres, without additional noise. They used six different musical genres with 300 midi songs.

They used 5 different features of the musical work in their research:

- Melodic Intervals
- Instruments
- Instrument Classes and Drumkits
- Meter/Time Changes
- Note Extension

The experiments performed were all run within The Waikato Environment for Knowledge Analysis. They used 6 different Machine Learning Algorithms for their analysis which include:

- The Naive Bayes
- The Voting Feature Intervals
- J48
- The PART algorithm
- NNge
- RIPPER

They separated the data into training and testing portions with three different proportions of training data 90%, 75%, and 66%. They found that for multiclass categorization the Bayesian classifier performed the best, additionally that classical music is the easiest for their algorithms to recognize followed by Jazz. The binary classifiers outperformed the multiclass in accuracy.

The paper ends with stating that simple musical features can provide enough information to successfully categorize a first level of musical genre but classification of closer genres such as Jazz and Blues would require more complex features.

1.3 Melody Recognition: The Experimental Application of Musical Rules

Cuddy's paper begins by explaining how melodies are recognized even when transposed to different keys despite the fact that the absolute pitches are altered. It then goes on to speculate on the importance of diatonicism, the tones of the diatonic scale, and cadence, a particular order of tones at the end of a melody. The paper then went on to discuss testing of transposed melodies, melodies with errors that fell inside the diatonic scale and errors that fell outside the diatonic scale, in addition to testing melodies in the context of a cadence. Their results showed that when the error in the melody included a non-diatonic tone performance deteriorated, but when inside a diatonic and cadence context performance improved.

1.4 Automatic Identification of Music Works through Audio Matching

This paper begins by explaining a need for automated identification of musical works, then goes on to explain different current types of identification, namely, audio fingerprint, and audio watermarking. It then goes on to begin it's discussion on its main work of music identification using audio matching. There research utilizes Hidden Markov Models, and aims to be able to identify live performances of musical works with diverse instrumentation.

Their approach is based on an *audio to audio* matching process, retrieving all the audio recordings from a database that in some sense represent the same musical content of the query. This is done with the idea that two different performances of the same musical work, even though they could differ greatly, can be generalized to model the features of other performances of the same musical work.

With the goal of analyzing a performance to create a statistical model of the score, they followed the following steps:

1. Segmentation: Extraction of audio sub sequences with a coherent acoustic content

2. Parameter Extraction: Analyzation of the segments to compute a set of acoustic parameters general enough to be matched varying performances of the same musical work

3. Modeling: Automatically building a HMM from the segmentation and parameter extraction to model music production as a stochastic process.

Finally at matching time an unknown recording of a performance is preprocessed to extract the features modeled by the HMMs, and then all the models are ranked based on their probability of creating the same features of the unknown performance.

2 References

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