

Report for ECE457B Course Project, Winter 2017 Title_Of_Project

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1 Abstract

2 Introduction

3 Background

3.1 Music Files

The files used for analysis were primarily wav files. To use another type of file required conversion into a wav file. Wav files consist of a header containing relevant information such as sample rate and the number of channels, and the sound data for each sample. This format does not compress the data and thus was chosen of the most accurate results. A parser was written to extract the sample rate and a waveform for the sound data. The sample rate is the number of samples taken per second. For CD quality (the most common type of file looked at) this value is 44,100. The waveform is the list of data for the sound data at each sample point for each channel.

3.2 Stepmania Files

3.3 File Format

asdsa

3.4 Beat Detection

Notes:

- humans have temporal masking of about 3ms
- humans hear frequency range of 20-20000Hz
- humans have frequency accuracy to 3.6Hz
- music contains sounds from 100-3200Hz (most often)

4 Solution

4.1 Feature Extraction

Three kinds of features were used in the scope of this project. There were many other potentially useful features that could be extracted from audio files for use in beat detection, but many of them required complex audio processing beyond the knowledge of the authors of this report. This project focused on power variance, bandwidth power variance, and change in peak frequency. To accommodate for audio temporal masking in human hearing the sample rate was decreased to a sample every three milliseconds. This was done by aggregating samples into a chunk and comparing that with the other aggregated samples in its neighborhood. A chunk of data is the number of samples calculated to span three milliseconds of time.

$$\text{chunk size} = \frac{\text{number of samples}}{300}$$

Each type of feature extraction generated data relative to the song it is in. This is due to the range of song genres considered in the scope of this project. Data comparisons using absolute values would confuse the training data when transitioning between songs, for example the electronic music has a much higher average frequency than dubstep. The solution to this was to compare features to a neighborhood of data to get relative values.

Since most songs go through various phases in which the pitch, tempo, and power levels can be drastically different the neighborhood of comparison was limited to one seconds worth of data. This value was chosen because it was small enough to capture the changes in features while still being large enough to contain data about the current features. One second is also the unit used when describing the tempo of a song when making a rough estimate. This allowed for a benchmark of what would be a reasonable number of beats in a second when comparing to the genre of the song.

4.1.1 Power Variance

The waveform of a sound file represents its data as energy levels within a channel at a given sample. The total power level of a sample can be calculated by summing the square over all channels in the waveform. This value is calculated as the average over a single chunk of data.

4.1.2 Bandwidth Power Variance

4.1.3 Peak Frequency Change

4.2 Multilayer Perceptron

4.3 Dataset Construction and Format

4.3.1 Dataset Format

In order to use a multilayer perceptron network, supervised learning must be used in order to let the network learn the function you are trying to represent or approximate. For our project, the network is trained on a set of timeframes corresponding to the wavelet file for an audio track in order to detect beats. A timeframe can be defined as a portion of the audio signal for a music file. Thus, a dataset that mapped different timeframes of an audio file to a beat was required. This required researching into datasets that exposed both the meta-data information for a large corpus of audio files, and the discrete times for when beats occur.

With the above requirements, we could define the necessary format of our dataset. Our dataset required pairs of files for an audio track : an uncompressed wavelet file in the .wav format and a corresponding .beats file containing comma separated times for when beats occurred in a song.

4.3.2 Music Information Retrieval Evaluation Exchange (MIREX)

Our initial dataset was a small dataset used for a 2012 audio beat tracking competition provided by the Music Information Retrieval Evaluation Exchange (MIREX). MIREX is a contest and conference organized by the graduate school of computer science at the University of Illinois Urbana-Champaign. It provides datasets for contests attempting to identify optimal algorithms for beat detection, tempo change detection and other audio analytics.

The dataset used consisted of 100 songs, where each song had a file containing the times when a human audience believe beats occurred. Each audio file was in the uncompressed wavelet format, with 1 audio channel and at a standard 44.1KHz sampling rate of timeframes per second. However each song in this dataset was less than 30 seconds in length, so it did not provide enough timeframes to train any neural network model.

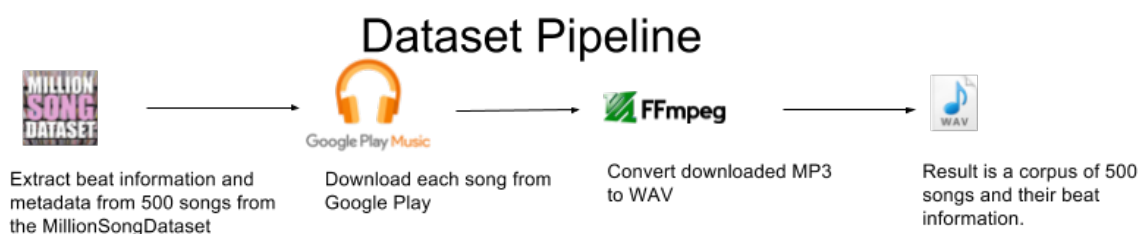
4.3.3 Million Song Dataset

The Million Song Dataset is a dataset containing audio analysis features for millions of songs. One of the features analyzed and available, is the discrete timing of beats. This dataset is openly available and was produced by the Echo Nost, an audio analytics company. This dataset provided all of the necessary beats information for an incredibly large corpus of

songs, 280GB in size. However, unlike the Mirex dataset, it did not provide any media files that would allow us to use as training inputs to our model. Thus, we had to implement our own solution.

4.3.4 Google Play Music

In order to build a corpus of media files, we used the GooglePlayMusic API to to download songs. For each song we found in a subset of the MillionSongDataset, we extracted its track title, downloaded the audio file in the MPEG-2 format (mp3), and then converted it to the uncompressed wavelet format. This conversion was performed using the popular FFMPEG utility.



5 Results

5.1 Method of Evaluation

5.2 Accuracy

5.3 Potential Sources of Errors

6 Conclusion

6.1 Future Improvements

6.1.1 Feature Extraction

6.1.2 Recurrent Networks

7 References