

Analysis and evaluation of audio-similarity algorithms for cover and live song identification



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Acknowledgements

Write here your acknowledgements...

Abstract

The abstract goes here. The abstract should be self-contained and:

- clearly state the problem dealt with by the thesis;
- give a synthetic description of the proposed solution;
- highlight the sense in which the proposed solution enhances the state of the art.

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Chapter 1

Introduction

1.1 Project overview

Music information retrieval (MIR) is an area of analysis dedicated to extracting information from music. It combines many different disciplines of science including psychology, psychoacoustics, signal processing and computer science. One of the main aims when applying MIR techniques solving the task of song identification, i.e. matching an audio stream to a particular song [1]. This is usually achieved through a form of hashing applied on the digital signal and comparing the resulting representation to a reference fingerprint [2], [3]. This approach returns good results for the task, since we can easily quantify a good match between both fingerprints.

We can further modify the original song identification task to apply to cover songs. A cover song is a very creative reinterpretation of a released song usually performed by an artist different than the original. The cover can therefore differ significantly from the origin in tempo, pitch or song structure (*add more*). The amount of variation in a cover strongly depends on the genre of the primary track - Western popular music pieces are for example more likely to be transformed than ones from classical music [4]. Therefore the only remaining common feature between the cover song and the original is the underlying fundamental melody of the piece and potentially the lyrics.

Because of these potential disparities between two versions of a single song, the problem of identifying covers of songs is much more difficult than determining an identical match with the original. The above fingerprinting approach has been attempted [5] and the results are insignificant [6]. Direct comparison between the fingerprints of the song is unable to capture the remaining similarity within two audio files. Other MIR methods need to be considered in order to measure similarity when attempting cover song recognition.

The general advances of technology have allowed companies such as Spotify

[7], Apple [8], SoundCloud [9] and more to create large-scale music databases and offer them as commercial services. Proportionally to the increasing availability of large music collections grows the need for managing the volumes of audio information through MIR techniques, with cover song identification being one of them. As a consequence most modern mechanisms to cover song recognition work by comparing an audio track called *query song* against a large database of songs, a *reference database*. Each mechanism is evaluated based on its similarity estimation performance, as well as its scalability as we increase the database size.

This project analyses the principles of a set of non-hashing based cover song identification algorithms and evaluates their performance. Most of the examined algorithms are designed to work with large-scale databases and follow the workflow model described above. The evaluation considers only their similarity estimation results and does not account for scalability. After analysis of the results a hypothesis on the best performing audio similarity technique is established (*or maybe devised?*).

1.2 Report structure

The sections of this report are as follows:

- *Chapter 2* offers a summary of the background information required to understand and implement the audio similarity algorithms
- *Chapter 3* explores other state of the art methods of measuring similarity not examined in detail by the project
- *Chapter 4* provides a description of the evaluation task through which each algorithm is analysed
- *Chapter 5* contains detailed descriptions of each algorithm
- *Chapter 6* expands on implementation details related to the benchmark tool
- *Chapter 7* outlines the best results achieved and offers an analysis on them
- *Chapter 8* summarises potential further contributions to the project
- *Chapter 9* discusses the main challenges related to the project and the task of cover song identification
- *Chapter 10* is a summary of the project management techniques utilised during the project

Chapter 2

Background theory

Each type of information extracted from an audio stream is referred to as an *audio feature*. Audio features are mainly derived using various transformations on the signal based on some basic properties of sound. This section presents low-level theory required to understand the high-level description of how each feature is obtained further in the report. At this level of the project description we only require an understanding of general principles related to audio and signal processing, therefore the explanations are kept concise without going deeper into technical details.

2.1 Basic properties of audio signal

A *digital audio signal* is a representation of the continuous sound wave as a series of binary numbers. This representation helps preserve the *frequency* (the speed of the vibrations), as well as the *amplitude* (the fluctuations of the vibrations) of the sound. The energy that each sound wave emits through vibrations is called *sound energy* and its rate is measured through *sound power*. The majority of audio features use frequency or power as a primary audio property used to define the feature (*modify/change*).

2.1.1 Sampling and sample rate

The process of converting an analogue sound wave to a digital one involves a process of extracting points (samples) from the continuous signal and using them to describe the signal into a discrete form. This method is called *sampling* and the amount of samples collected per time frame is *sample rate*. The representation of a song used during feature extraction is a sequence of samples extracted from the digital signal of the song based on its sample rate.

2.1.2 Tones

In order to understand how properties of a digital signal could form audio features we first need to examine how they relate to the ways of how people perceive music and sound. Western music is described using *tones*, steady periodic sounds [10]. They can be pure if the sound has sinusoidal waveform, or complex if they are a combination of pure tones with a periodic repetition pattern. A half tone is called a *semitone* and it is the smallest measure of period between sounds. Semitones are grouped into *octaves* where each octave contains 12 semitones. The acoustic opposite of tone is noise, a disordered sound which is unpleasant to the human brain and is disruptive to hearing [11].

2.1.3 Psychoacoustic properties

Tones are distinguished by several basic perceptual properties of sound - pitch, loudness, timbre and duration [12]. Consequently these properties are also regularly used to describe what is accurately captured by each audio feature. Klapuri et al. [13] form good definitions of the psychoacoustical terms outlined. They define *pitch* as a perceptual attribute which offers ordering of tones on a frequency-related scale. Different pitches could be labelled through the Helmholtz pitch notation [14] using letters, through scientific pitch notation [15] utilising letters and numbers, or directly using numbers representing the closest frequency in hertz (hz). Despite being determined by clear and stable frequencies in sound, pitch is more importantly a subjective auditory sensation, so a strict mathematical relationship between frequency and pitch does not exist [16]. As a standard it is accepted the musical note of A above C (Helmholtz notation) or A4 (scientific notation) has a frequency of 440 Hz [17]. The human ear perceives musical intervals on an approximately logarithmic scale with respect to a *fundamental frequency*, the lowest frequency available in a tone and therefore determining the overall pitch of the tone. Using this notion of logarithmic perception there are various mappings of pitches to frequencies, the most famous of which is the MIDI tuning standard [18].

Loudness is another subjective psychoacoustical attribute of sound [13]. Similar to how pitch is related to frequency, loudness is a perception of sound pressure. *Sound pressure* is a measurement of the pressure divergence caused by a sound wave to the ambient atmospheric pressure [19]. Loudness orders sounds on a scale ranging from quiet to loud [16].

Tones also have a "colour" attribute attached to them through the introduction of *timbre*. Timbre allows distinguishing sounds with potentially identical pitch, loudness and duration, but produced by different musical instruments [13]. It is a complex concept which cannot be defined by a single property of

sound. There are many attempts at breaking down the attribute into components. Robert Erickson [20] offers one of the most accepted decompositions where timbre relates to the following acoustic parameters of sound:

1. Tonal and noise characters
2. Time envelope - A *time envelope* describes how sounds changes over time [21]. It measures how much time it takes for the sound to reach an amplitude level when a musical instrument is activated (a key on the piano is pressed, for example) and subsequently how long it takes for the sound to go back to its initial level.
3. Spectral envelope and any changes to it - when only the curve of the amplitude out of a time envelope is taken into consideration then a *spectral envelope* is used. Figures 2.1 and 2.2 illustrate the difference of between both envelopes.
4. Changes in the fundamental frequency
5. Onset dissimilar to the dominant vibration - with *onset* being the start of a musical note we look for 'anomalies' in the vibration of the wave compared to the vibrations following the anomaly.

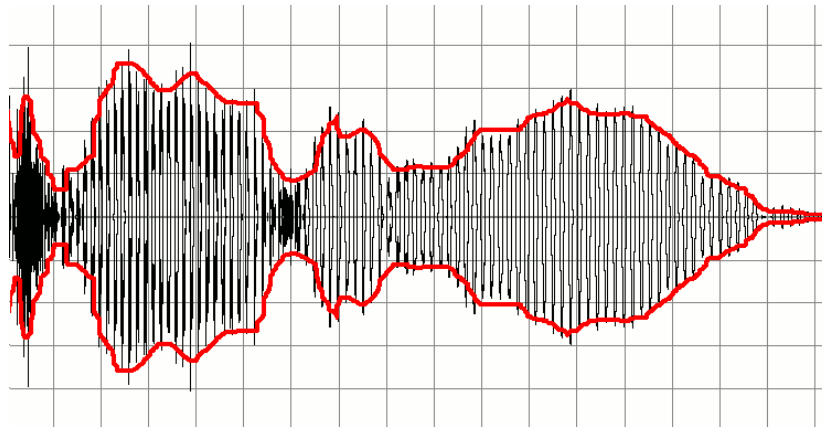


Figure 2.1: Time envelope *add citations and description*

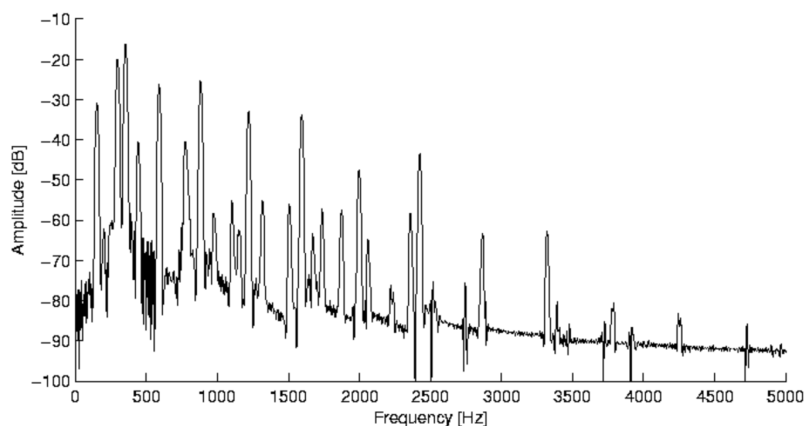


Figure 2.2: Spectral envelope *add citations and description*

Out of all psychoacoustical properties introduced *duration* is the one which is the easiest to directly measure. It is an indicator of a length of any part of a musical composition - tone, pitch, the whole piece, etc [22]. The measurement is expressed using a base unit of time.

2.1.4 Beat

One final basic concept that we need to introduce is the *beat*. It signifies repeating portions in a song which define the overall rhythm of a music piece. Rhythm is formed of "strong" and "weak" beats, with the former signifying a suitable moment for melody change.

2.2 Audio transformation techniques

2.2.1 Fourier transform

Any waveform including the audio ones could be presented as a sum of sinusoids of different frequencies [23]. In music each of the constituting frequencies represents a pure tone. In order to be able to work with the tonal representation of a song we need to find a way to separate the different frequencies within the audio signal. We achieve that using *Fourier transform* - one of the most widely used audio transformations.

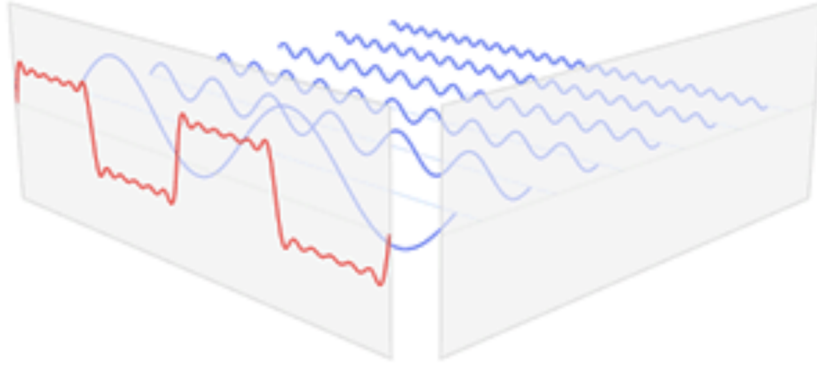


Figure 2.3: Fourier transform applied on a periodical function (in red). The transform distinguishes six sine functions (in blue) represented as an amplitude-frequency relationship [24]

Fourier transform could be applied to either periodic (resulting in *Fourier series*) or non-periodic functions. As we are working in the domain of music we are focussed on the Fourier workings on functions with periodicity. Using the transform our goal is finding an approximation for function $f(t)$ with period $T = 2L$ using a sinusoid functions each with period a multiple of T [24]. Figure 2.3 shows the destructuring that a Fourier transformation performs on a function. The resulting function $g(t)$ which is the transform of $f(t)$ takes the form of:

$$g(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} \left(a_n \cos \frac{n\pi x}{L} + b_n \sin \frac{n\pi x}{L} \right) \quad (2.1)$$

Figure 2.4: Fourier series representation of a periodic function [25].

The coefficients a_n and b_n determine the relative weights of each of the sinusoids [24]. They are calculated using sine and cosine integrals over the function period:

$$a_n = \frac{1}{L} \int_{-L}^L f(x) \cos \frac{n\pi x}{L} dx, \quad n = 1, 2, 3, \dots \quad (2.2)$$

$$b_n = \frac{1}{L} \int_{-L}^L f(x) \sin \frac{n\pi x}{L} dx, \quad n = 1, 2, 3, \dots \quad (2.3)$$

Figure 2.5: Derivation of the parameters for the Fourier transform [25].

From a frequency spectrum perspective the relative weights of the sinusoids also represents the amount of frequency present in the original function at a point of time [26].

The result of a Fourier transform is represented in a spectrogram (figure 2.6). The information contained in it is very valuable when determining sound properties such as pitch, power, timbre and more.

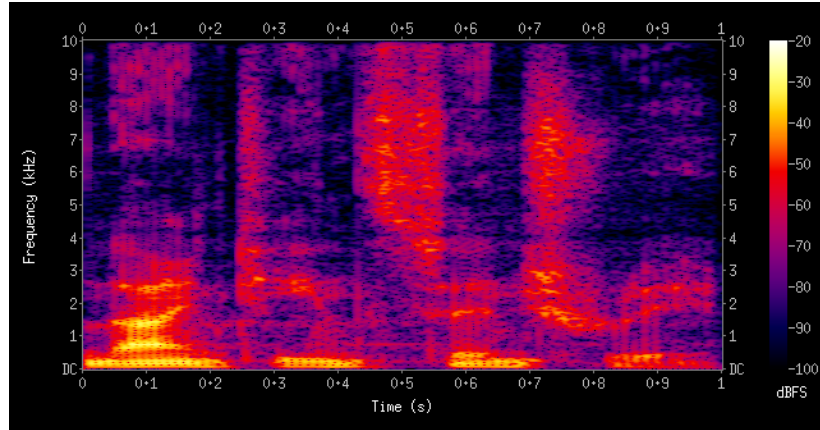


Figure 2.6: Spectrogram of a spoken word phrase. It shows the time versus frequency relationship produced by the Fourier transform, as well as the intensity (amount) of each frequency for a time frame [27].

2.2.2 Filters

During the processing of the audio signal we want to detect the frequency maxima and minima of the wave, or possibly attenuate certain frequencies. In order to do that we use *audio filters* - tools that pass certain frequencies and blocks others [28]. Filters are defined in terms of *bands*, the range of frequencies they pass. A combination of filters which helps us produce the required frequency cut-off is called a *filter bank*.

2.2.3 Scales

Earlier we mentioned that an octave contains 12 semitones. This is an established standard - the semitones are equal on a logarithmic scale and form the *twelve-tone equal temperament scale*. It is the ordering that most Western music compositions employ and therefore the ordering we use to determine relative positions in tones of audio signals.

Another scale which is widely used to arrange values of a psychoacoustic variable is the mel scale. It presents a perceptual ordering of pitches which are determined to be equally far away from each other [29]. The scale introduces a unit of perceptual pitch called *mel*, where $1000\text{ mel} = 1000\text{ Hz}$. The rest of the mel-frequency mapping is displayed in figure 2.7.

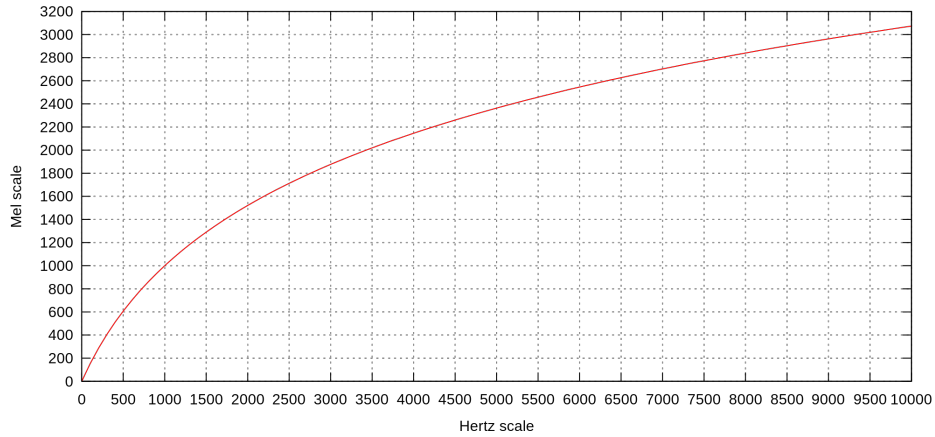


Figure 2.7: Perceived pitches on a Mel scale versus the Hertz frequency scale [30]

2.3 Machine learning techniques

Some cover song identification algorithms create machine learning models based on which they measure similarity when a query song is provided. This section outlines the principles of each method used later in the algorithms.

2.3.1 Random forests

Random forests are a form of ensemble learning for classification and regression [31]. Ensemble methods train multiple learners in an attempt to solve the same problem [32], and in the case of random forests the type of learner is a decision tree. The method works by building a predefined number of decision trees during training, and return a result combining their individual outcomes. In the case of

classification the mode of all returned class predictions is taken, while the mean of the predictions is used during regression. Random trees help avoid the tendency of individual decision trees to overfit to their training data [33].

2.3.2 K-means clustering

K-means clustering is an unsupervised machine learning approach which aggregates a collection of data points together because of some similarity between them. The end result is a separation of the points into k distinct clusters. The outcome of the clustering is evaluated through the sum of squares defined as:

$$\text{Sum of squares} = \sum_{i=1}^n (x_i - \bar{x})^2 \quad (2.4)$$

Figure 2.8: The sum of squares for n items where x_i is the value of the i -th item and \bar{x} is the mean of the set n .

The intent is to reduce the sum of squares as much as possible. Clustering is complete when either the sum of squares does not significantly change any more, or the algorithm runs a pre-determined number of iterations.

In the area of digital signal processing K-means clustering is used to perform *quantisation* - mapping a large (possibly continuous) set of values to a countable smaller set which is easier to work with [34].

Chapter 3

Related work

Cover song identification has been a very active topic of research in the last 10 years. The task has spawned many solutions, so for the scope of this project it is infeasible for each technique to be analysed in detail - from technical implementation details to results on datasets. To fully cover the active developments in the research area should also examine related research which is not the direct focus of the project.

The chapter presents an analysis of the algorithms submitted in the *Cover song identification* task, part of the Music Information Retrieval Evaluation eXchange (MIREX) conference [35]. The format is similar to a competition, where participating researchers submit potential solutions to a task and each proposal is evaluated under equal conditions. The evaluation environment is preserved throughout the MIREX editions, so results from different years are comparable between each other.

The study of the conference was conducted before the selection of the main audio similarity algorithms for the project and their implementation in a benchmark. This allowed for an informed decision on what audio features are performing best and also ensured that algorithms not included in MIREX are picked, to potentially present a contribution to the field.

3.1 Cover song identification in MIREX 2005-2018

In 2006 the MIREX conference created the *Cover Song Identification* task. The datasets used for evaluation are the MIREX 2006 US Pop Music Cover Song dataset (1000 tracks, each track is 16-bit monophonic, 22.05 kHz sampling rate, wav format). The dataset has 30 cover songs each represented by 11 different versions for a total of 330 files. Each of the files are then individually run as

3.1 Cover song identification in MIREX 2005-2018

queries for the algorithms. Each algorithm then attempts to return the other 10 versions of the same song. The only output the submitted algorithms should return is a *number of queries* \times *number of candidates* distance matrix.

Out of the 40 submissions related to the cover song task in the MIREX conference 25 were considered.

3.1.1 Results evaluation

In order to determine which algorithms perform best we need to look at the results achieved each year. From them we would then be able to determine what audio similarity techniques have worked best so far and examine them further in depth.

The results outlined here are based on the statistics provided by MIREX each year for the results of the cover song identification task. Each year MIREX publishes the total number of covers identified (TNCI), the mean number of covers identified (MNCI), the mean of average precisions (MAP) and the mean rank for first correctly identified cover (MRFCIC) for each algorithm.

Let us look at the best THCI results plotted over the years for the MIREX cover song identification task:

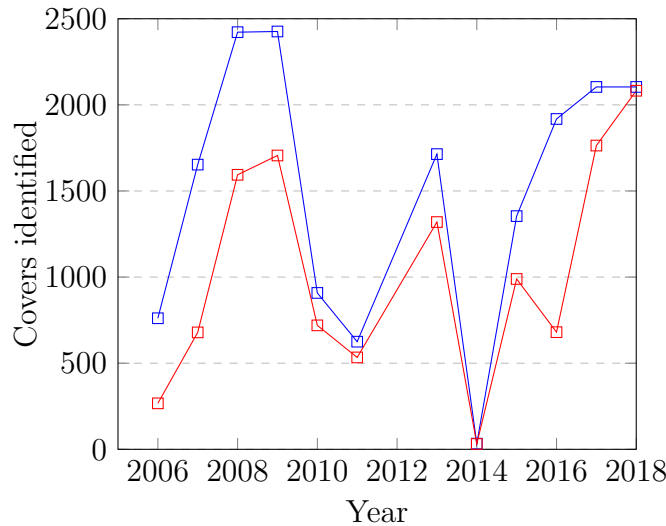


Figure 3.1: Results of the winning submissions in the period 2005-2018. The blue line represents the max THCI achieved for each year (i.e. the challenge winners). The red line outlines the average THCI for each year the task has taken place. The challenge did not run in 2005 and 2012.

We could see that the best performing submissions are the ones published in 2008, 2009 and 2018.

3.1 Cover song identification in MIREX 2005-2018

To determine if there is a tendency into what type of audio feature is used, a table comprising of all audio features used is compiled from the available submissions:

Audio feature	Times used	Winner
Chroma features	12	2006, 2018
Harmonic Pitch Class Profiles (HPCPs)	5	2007, 2008, 2009, 2016
Mel-frequency cepstral coefficients (MFCCs)	2	
HPCP, MFCC and MFCC SSM combined	1	
Basic Pitch Class Profiles (PCP)	1	
Custom technique	1	2014
Relationship (distance) to other songs in set	1	
Statistical Spectrum Descriptors	1	
Pitch line estimation	1	

Figure 3.2: Number of times a type of audio feature is used in MIREX 2005-2018. The *Winner* column indicates whether the best algorithm for the year utilises the feature.

Based on this evaluation we could see that the best audio features for measuring song similarity are chroma features and HPCPs. Unfortunately only 7 out of the 13 winning papers were available online, so it is unclear whether they are also using any of the features for information extraction. The *custom technique* mentioned in the table refers to an algorithm implementing a non-conventional audio feature which achieves the worst winning result in the MIREX competition so far - only 33 covers identified (out of 3300 possible).

Some of the main audio similarity algorithms explored in the project use chroma features and MFCCs as audio features. Therefore in this section we only explore the structure of HPCPs.

3.1.2 Harmonic Pitch Class Profiles

For each pitch representing a semitone part of an equal temperament scale a *pitch class* is the set of all pitches which are all separated by an octave from each other. Knowing that we can create a *pitch class profile (PCP)* - a vector which represents the intensities of all twelve pitch classes [36]. PCPs become *harmonic* when they represent the relative intensities of the pitch classes within an analysis frame in a signal [37]. Straying from the general definition of a PCP they could also be extracted over a 24 or 36-bin pitch spectrum, representing the relative intensity of every 1/2 or 1/3 semitones respectively.

HPCPs are generally extracted using a Fourier transform to determine the constituting frequencies in the audio stream. The resulting spectrogram is then

filtered to include only an audible spectrum of frequencies, which are then mapped to their pitch classes. Each time frame is then normalised to obtain the HPCP audio feature representation of a song.

3.1.3 Similarity methods

Besides introducing the audio features which provide a song representation, a majority of the MIREX submissions also outline the processes of measuring similarity between songs. A set of notable similarity techniques is of interest to background of the task.

Dynamic time warping (DTW) is an algorithm for measuring similarity between two temporal sequences, which may vary in speed [38]. The algorithm performs a sequence alignment method, which 'bends' the sequences non-linearly in the time dimension in order to determine the similarity independent of other non-linear variations in the time dimension. After sequences are aligned a rule-based matching is applied which determines the final similarity score. Dynamic time warping has been very successful when creating automatic speech recognition systems. The algorithm achieves great results when used in a voice recognition system with MFCC audio features [39], a task not too dissimilar to cover song identification.

Because a digital audio signal is essentially a binary stream some submissions appropriate classic information theory techniques such as *Normalised compression distance (NCD)* to establish whether two songs are covers. The origins of NCD come from the notion of information distance, a metric that represents the size of the shortest program required to convert one binary object into another. We apply normalisation to the result to obtain similarity based on the object lengths. If objects a and b are of length 1000000 bits and their distance is 1000 bits, then this should be a more significant result than having objects c and d of length 1000 bits with the same distance [40]. Given this outcome a normalised information distance (NID) indicates that a and b are more similar than c and d .

NID however is proven to not be computable or semicomputable [41]. It is therefore approximated using a compressor algorithm applied on the objects, with the NID applied to the compressed results.

Chapter 4

The task

An evaluation task must be set based on which the algorithms are analysed, evaluated and compared.

4.1 Design

The design of the evaluation task follows the general structure for an algorithm targeted towards utilising a large-scale database. It includes taking a query song and creating pairwise comparisons of it with any song from a song database. The similarity score of each pair is then calculated using a cover song identification algorithm and an ordering is created. The pair with the highest similarity includes the database song that the algorithm has identified to be most similar to the query song (and potentially its cover version).

As a song database the evaluation task uses several music datasets. Each dataset contains sets of different versions of a song. The unique identifier that combines all versions of a single song is called a *clique*. For instance, the original version song 'Take On Me' by the Norwegian band A-ha and its cover version created by the American punk rock artist MxPx are in the same clique named *Take On Me*. Each dataset is split into a symbolical *train* and *test* sets. The train portion of the songs is initialised as a song database, while each of the tracks in the test set is used as a query song. During the split it is ensured that there is at least one song from each clique in both the train and test set, so that for every query song a cover ready to be identified is found in the song database.

The task results are produced through a benchmark written using Python [42] and storing the song database into a MongoDB [43] instance. Figure 4.1 shows a high-level architecture diagram of the benchmark, which could help understand the general design of the evaluation task.

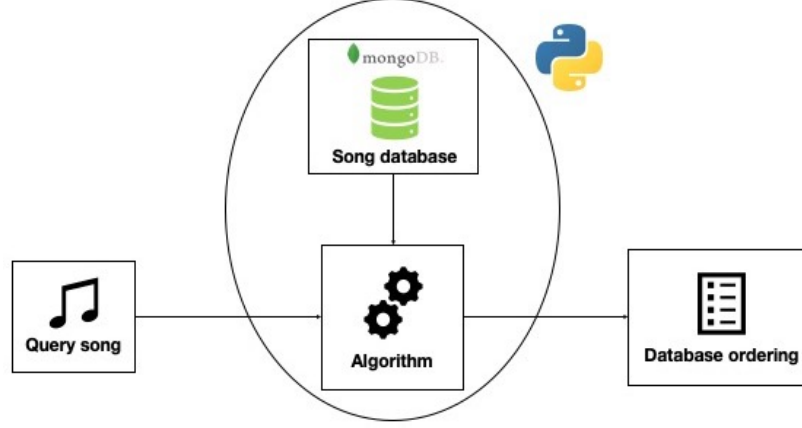


Figure 4.1: Benchmark architecture diagram

4.2 Evaluation methods and metrics

All algorithms are evaluated using metrics adapted from the MIREX *Cover Song Identification* competition format. The benchmark implements the following measurements:

- *mean rank (MR)* of the position of a true cover (a song from the same clique as the query song) in the database ordering produced by an algorithm
- *mean reciprocal rank (MRR)* of the position of a true cover in the database ordering produced by an algorithm
- covers identified in the *Top-K* positions of the database orderings for all songs, where K is a number
- covers identified in the *Top-P* percentile of the database orderings for all songs, where P is a number

4.3 Datasets used for evaluation

One of the main challenges in the project was the lack of appropriate datasets, therefore some of the datasets are self-curated using my personal music collection. The algorithms were evaluated using the following datasets:

- *covers80* - a widely used by MIR researchers consisting of 80 cliques and 164 songs [44]. Contains original compositions and cover versions of them.

4.3 Datasets used for evaluation

- *live_dataset* - a self-curated dataset consisting of 70 cliques and 145 songs. Contains original compositions and professionally recorded, mixed and mastered live performances of them.
- *yt_dataset* - a self-curated dataset consisting of 16 cliques and 32 songs. Contains original compositions and live performances of them recorded from an audience perspective using a smartphone.

TODO: Mention if the songs in a dataset is included in the appendix

Chapter 5

The algorithms

Summary

Details all the results of your study here (exploits graphics for results visualization). This chapter should also contain a full discussion, interpretation and evaluation of the results.

5.1 Osmalskyj big algorithm

5.2 Osmalskyj weak features

5.3 Ellis cross-correlation algorithm

5.4 Osmalskyj quantisation algorithm

5.5 Tralie timbre algorithm

5.6 Rank aggregation techniques

5.7 Rafii audio fingerprinting algorithm

Chapter 6

The benchmark

Summary

Details all the results of your study here (exploits graphics for results visualisation). This chapter should also contain a full discussion, interpretation and evaluation of the results.

6.1 Implementation details

6.2 Brief usage information

6.3 Algorithm structure in the benchmark

6.4 Result format produced by benchmark

Chapter 7

Results

Summary

Details all the results of your study here (exploits graphics for results visualisation). This chapter should also contain a full discussion, interpretation and evaluation of the results.

7.1 Best results

7.2 Comparison to results from papers

7.3 Result analysis

Chapter 8

Further work

Details all the results of your study here (exploits graphics for results visualisation). This chapter should also contain a full discussion, interpretation and evaluation of the results.

Chapter 9

Challenges

Summary

Details all the results of your study here (exploits graphics for results visualisation). This chapter should also contain a full discussion, interpretation and evaluation of the results.

9.1 Lack of datasets

9.2 Lack of universal comparison metric?

9.3 Academic papers algorithm description

Chapter 10

Project management

Summary

Details all the results of your study here (exploits graphics for results visualisation). This chapter should also contain a full discussion, interpretation and evaluation of the results.

10.1 Using GitLab

10.2 Canvas logs

10.3 other? Gantt chart?

Chapter 11

Conclusion

Conclusions should summarize the problem, the solution and its main innovative features, outlining future work on the topic or application scenarios of the proposed solution.

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