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 determing 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. They allow for music data to be comparable and algorithmically accessible [10]. 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

Western music is described using *tones*, steady periodic sounds [11]. 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. Tones are distinguished by several basic perceptual properties of sound - pitch, loudness, timbre and duration [12]. 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 [13].

2.1.3 Psychoacoustic properties

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.

Several basic perceptual properties of sound are regularly used to describe what is captured by each audio feature. They are pitch, loudness, timbre and duration. Klapuri et al. [14] 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. The term is very closely related to tone and sometimes both definitions are used interchangeably. Different pitches could be labelled through the Helmholz pitch notation [15] using letters, through scientific pitch notation [16] 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 [17]. As a standard it is accepted the musical note of A above C (Helmholz notation) or A4 (scientific notation) has a frequency of 440 Hz [18]. 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 [19].

Similar to tones, pitches are also ordered in octaves, where an octave is an interval between one pitch and another with double its frequency [20]. The set of all pitches which are within one octave of each other is called a *pitch class*.

Loudness is another subjective psychoacoustical attribute of sound [14]. 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 [21]. Loudness orders sounds on a scale ranging from quiet to loud [17].

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 [14]. 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 [22] 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 [23]. 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.

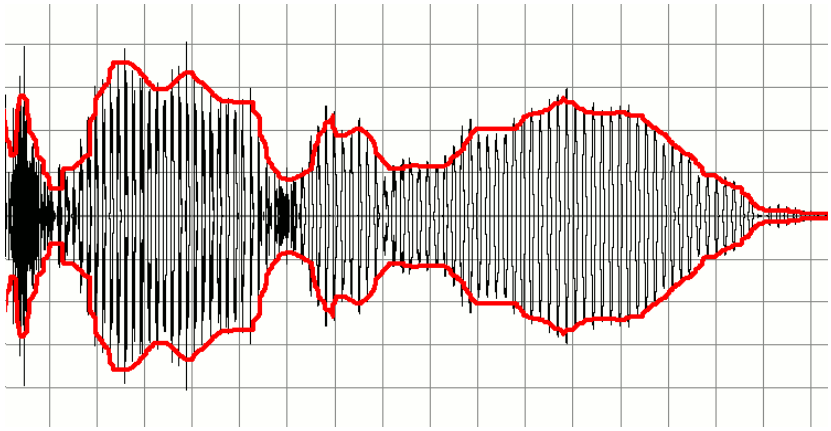

Figure 2.1: Time envelope *add citations and description*

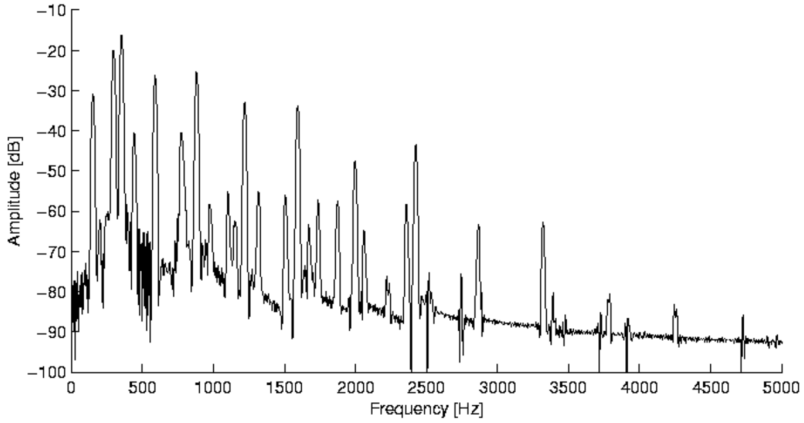

Figure 2.2: Spectral envelope *add citations and description*

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 [24]. 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 [25]. 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 perform *Fourier analysis*, that is, find a way to separate the different frequencies within the audio signal. We achieve that using a decomposition called *Fourier transform* - one of the most widely used audio transformations.

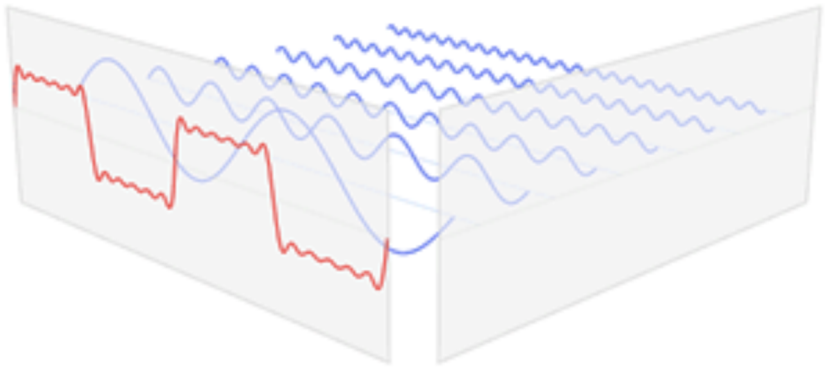

Figure 2.3: Fourier transform applied on a periodical function (in red). The transform distinguishes six sine functions (in blue) represented as an amplitude-frequency relationship [26]

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 [26]. 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:

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

Figure 2.4: Fourier series representation of a periodic function [27].

The coefficients a_n and b_n determine the relative weights of each of the sinusoids [26]. They are calculated using sine and cosine integrals over the function period:

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

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

Figure 2.5: Derivation of the parameters for the Fourier transform [27].

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 [28].

There are different forms of Fourier analysis. In the area of MIR one of the most frequently used is the *discrete-time Fourier transform (DTFT)*. It works on discrete uniformly spaced samples from a continuous function. The result produced is a periodic summation of the Fourier transform of the function [29]. To obtain DTFT we need to run *discrete Fourier transform (DFT)*, a type of Fourier transform, on the function samples.

Computing DFT directly is an operation on a sequence of complex numbers converting it into a new sequence of complex numbers. The computational complexity of the transformation is $\mathcal{O}(n^2)$. A class of algorithms called *fast Fourier transform (FFT)* has been created to compute DFT more efficiently with complexity of $\mathcal{O}(n \log n)$ [30]. This is achieved by representing the DFT as a transformation matrix - a matrix which when multiplied with the input signal achieves the same result as normal DFT. To optimise the matrix multiplication process FFT algorithms factorise the transformation matrix into a product of several sparse factors [31]. In practice FFT is the main way to compute DFT and therefore both terms are used interchangeably.

The result of a Fourier analysis 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.

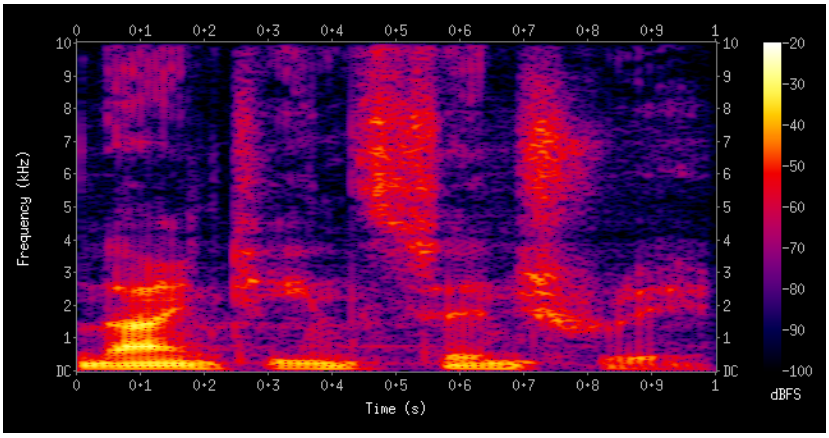

Figure 2.6: Spectrogram of a spoken word phrase. It shows the time versus frequency relationship produced by the Fourier transform, as well as the intensity (amount) of each frequency for a time frame [32].

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 [33]. 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 or *chromatic 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. It is also the scale which musical instruments often utilise. A good example of this are the keys of a piano, which are ordered based on an equal temperament scale.

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 [34]. The scale introduces a unit of perceptual pitch called *mel*, where $1000\,mel = 1000\,Hz$. The rest of the mel-frequency mapping is displayed in figure 2.7.

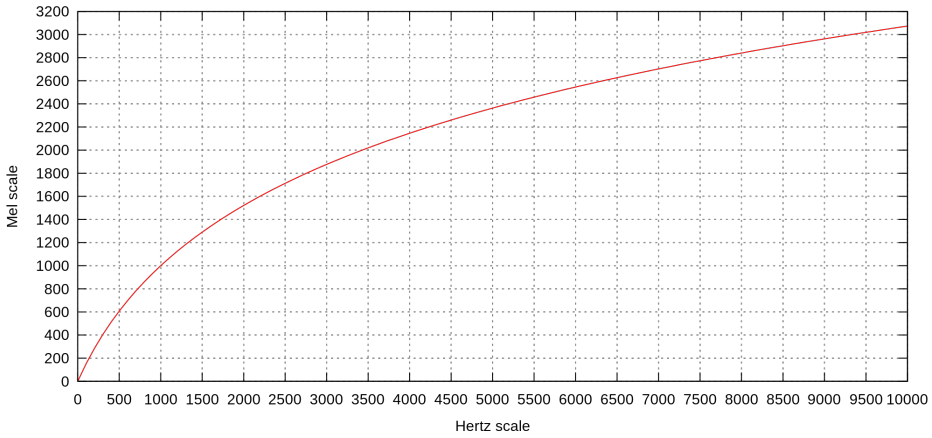

Figure 2.7: Perceived pitches on a Mel scale versus the Hertz frequency scale [35]

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 [36]. Ensemble methods train multiple learners in an attempt to solve the same problem [37], 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 learning generally builds upon the idea of recursive partitioning used in decision tree learning. Partitioning builds a decision tree from the training data based by asking questions related to the independent variables (attributes) formed by the data samples. The 'answer' or split points for the tree are called cut points. They are calculated to be the local optima values which best split the data into homogenous sets based on the attribute. This principle fails to create generalised models, since as the tree becomes deeper and deeper the more it tends to overfit on their training data [38].

Random trees help avoid the overfitting tendency of individual decision trees by implementing bootstrap aggregating, also known as bagging. The learning algorithm creates several small sets of uniformly sampled observations from the

training set and constructs trees using them. Depending on the configuration some samples can be picked in more than one set. The end result is achieved through the voting approaches explained above.

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:

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

Figure 2.8: The sum of squares for n items where x_i is the value of the i-th item and $\overline{x}$ 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 [39].

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 [40]. 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

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:

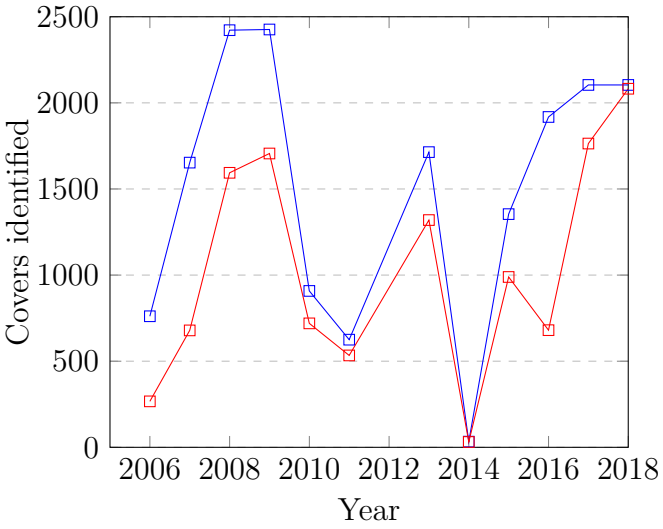

Figure 3.1: Results of the winning submissions in the period 2005-2018. The blue line represents the max THCI achieved for each year (i.e. the challenge winners). The red line outlines the average THCI for each year the task has taken place. The challenge did not run in 2005 and 2012.

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

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 [41]. PCPs become *harmonic* when they represent the relative intensities of the pitch classes within an analysis frame in a signal [42]. 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 [43]. 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 [44], 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 [45]. 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 [46]. 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. In 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 [47] and storing the song database into a MongoDB [48] instance. Figure 4.1 shows a high-level architecture diagram of the benchmark, which could help understand the general design of the evaluation task.

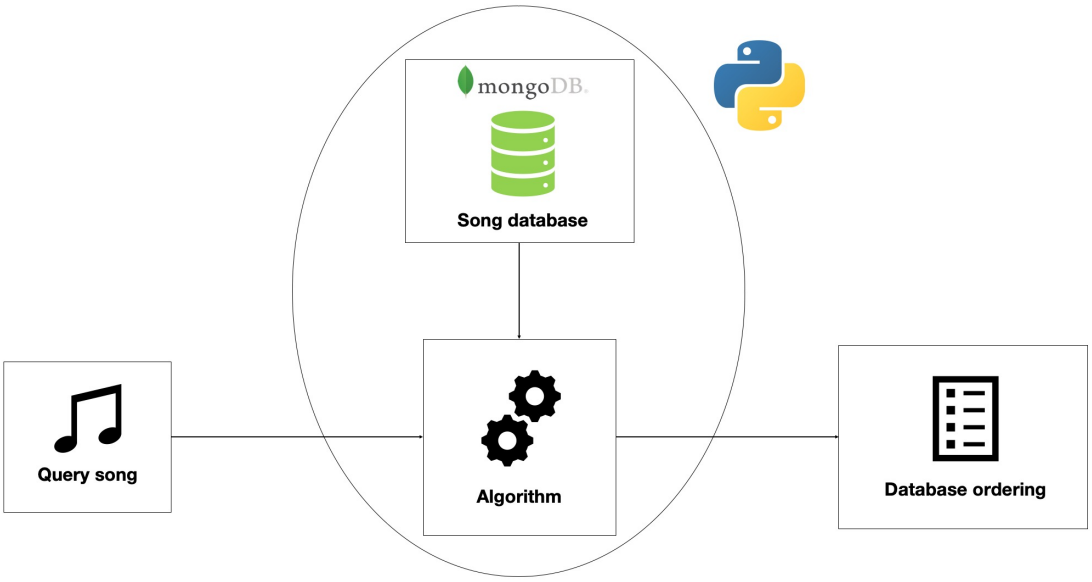

Figure 4.1: Benchmark architecture diagram

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 [49]. Contains original compositions and cover versions of them.
- *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

The main algorithms analysed in the project are attempted to be as different as possible from each other. This allows covering as many audio features and similarity measuring techniques as possible. My motivations of the choice of algorithms were influenced by the study on MIREX submissions, as well as the overall scope of features they encompass.

Julien Osmalsky coins the term *rejector* to define a pairwise comparison function that given two audio tracks it returns a score ranking of similarity between both tracks [50]. This term was adopted by the project to refer to each of the algorithms examined. The relation between an algorithm paper and its rejector term is outlined in section 5.1.

The final selection includes 5 individual algorithms and an algorithm aggregating results from 4 of them. Each of the algorithms is examined individually, with the results from some of them combined through the rank aggregation algorithm.

5.1 Algorithms list

The analysis if performed on the following algorithm:

- **Weak rejector** - Osmalskyj, Julien, Marc Van Droogenbroeck, and Jean-Jacques Embrechts. *Enhancing cover song identification with hierarchical rank aggregation* [51]
- **Cross-correlation rejector** - Ellis, Daniel PW, Courtenay V. Cotton, and Michael I. Mandel. *Cross-correlation of beat-synchronous representations for music similarity* [52]
- **Quantisation rejector** - Osmalskyj, Julien, et al. *Combining features for cover song identification* [50]

- **Timbre rejector** - Tralie, Christopher J., and Paul Bendich. *Cover song identification with timbral shape sequences* [53]
- **Aggregated rank rejector** - Osmalskyj, Julien, Marc Van Droogenbroeck, and Jean-Jacques Embrechts. *Enhancing cover song identification with hierarchical rank aggregation* [51]
- **Fingerprint rejector** - Rafii, Zafar, Bob Coover, and Jinyu Han. *An audio fingerprinting system for live version identification using image processing techniques* [54]

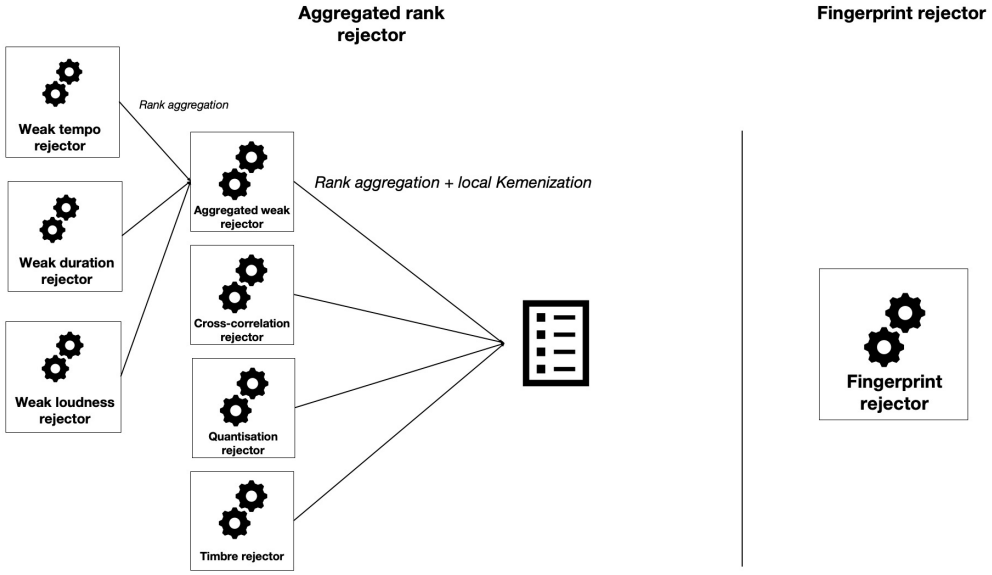

Figure 5.1: Diagram of chosen algorithms and the relationships between them. The aggregated rank rejector combines the results of 3 types of weak rejectors, as well as the quantisation, cross-correlation and timbre rejectors

5.2 Weak rejector

The weak rejector takes its name from the fact that it uses global single-valued features of sound to calculate a similarity score. Weak features include tempo, duration, loudness, average number of beats, etc. Those audio properties are considered 'weak' since by themselves they cannot uniquely describe a song - the majority of pop tracks from a certain era are composed with the same tempo, for example [55]. As a consequence the results from weak rejectors are inherently

insignificant are usually not considered individually, but as part of an aggregation with other results.

Each weak rejector takes a single audio feature as song representation. The algorithm extracts the feature from each song in a dataset and from them it creates a training set by combining each pair of songs in different ways. For songs A and B with weak feature values of $f1$ and $f2$ respectively the minimum ($min(f1, f2)$), maximum ($max(f1, f2)$), sum ($f1 + f2$), quotient ($\frac{f1}{f2}$) and absolute value of quotient of the difference divided by the sum ($abs(\frac{f1-f2}{f1+f2})$) are taken. The generated data is used as attributes to train an ExtraTrees classifier model. Extra randomised trees or ExtraTrees classification is a form of random forest classification. In contrast to the regular random forest implementation, ExtraTrees uses the whole training data for each decision tree. Rather than calculating an optimal cut-point, it also uses a random one. The direct benefits of using this variation of random trees are higher computational efficiency while achieving similar perfomance on average, in addition to better results on some specific problems [56].

The evaluation datasets used in this project are too small to generate an ExtraTrees model which performs even adequate classification of songs. To gather sufficient training data the weak features of 12,104 songs are extracted from the music streaming service Spotify [7]. The tracks are chosen based on clique groupings from the SecondHandSongs (SHS) [57] dataset - the largest dataset of covers songs aimed at academic research. While the full dataset is difficult to obtain, information about the cliques structure within it is easy to find. The extracted data is then combined into pairs using the procedure outlined in the previous paragraph. A binary class is then assigned to each pair entry depending on whether the pair of songs are covers or not. Afterwards the training data is further split into a training set of 3773 cliques (8653 songs) and validation set containing 1573 cliques (3451 songs). The metric used to validate the model performance is the area under the receiver operating characteristic (ROC) curve - a curve resulting from the plot of the true positive against the false positive rate of the validation results. ROC analysis of such form is suitable as a validation metric for the selection of an optimal model because it is independent of any potential cost function or cost distribution [58]. Because we are solely working with weak feature information the we can only validate based on correct and incorrect produced results.

After the training phase is complete each of the evaluation datasets is converted into the training set format and passed to the model for class prediction. The output result is a probability of every pair of songs being covers. Grouping the results per song produces a database ordering that is required by the evaluation task.

5.3 Cross-correlation rejector

The cross-correlation rejector uses chroma features as the main audio feature describing each song. Chroma is another name for pitch class profiles, i.e. a 12-dimensional representation of the intensity distribution in each of the twelve pitch classes part of the chromatic scale [41]. Any feature that at its core uses chroma to represent a song is a chroma feature. That is why the terms harmonic pitch class profiles (HPCP) and chroma features have a very similar definition, in fact HPCP is a type of chroma feature. The main difference between chroma features is their method of extraction. Using chroma features produces a chromagram - a pitch class versus time plot showing the intensity of each pitch class at any time point (Figure 5.2).

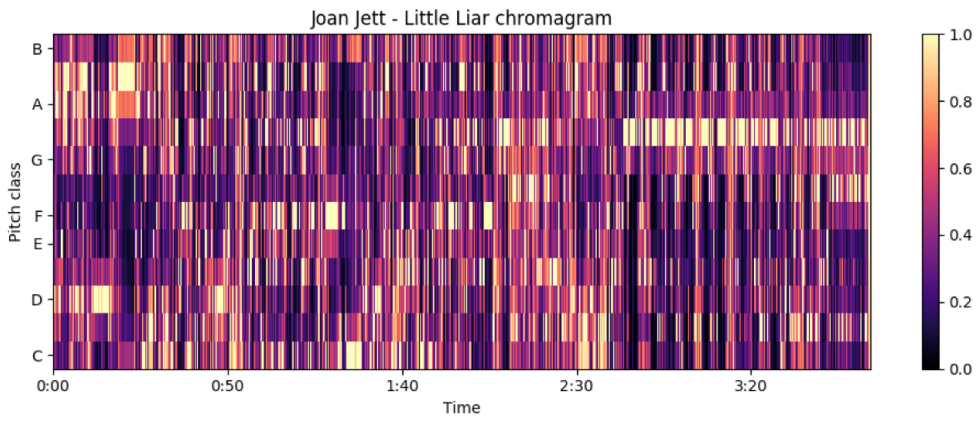

Figure 5.2: Chromagram of the song *Little Liar* by Joan Jett

The chroma features in the cross-correlation rejector are extracted by performing short-time Fourier transform (STFT) analysis. It consists of running Fourier transform on short segments of a signal to determine how the frequency content changes over time [59]. STFT improves upon the concepts of regular Fourier transform by not only telling us what frequencies are contained within the audio stream, but also at what time intervals does each frequency appear.

The transformations are applied using the fast Fourier transform (FFT) algorithm. The short segments are calculated over sliding overlapping windows as illustrated on figure 5.3. The size of the sliding window is determined by *FFT window size* and the overlap between each window depends on a parameter called *hop length*. The actual window overlap is calculated as the difference between the window size and the hop length.

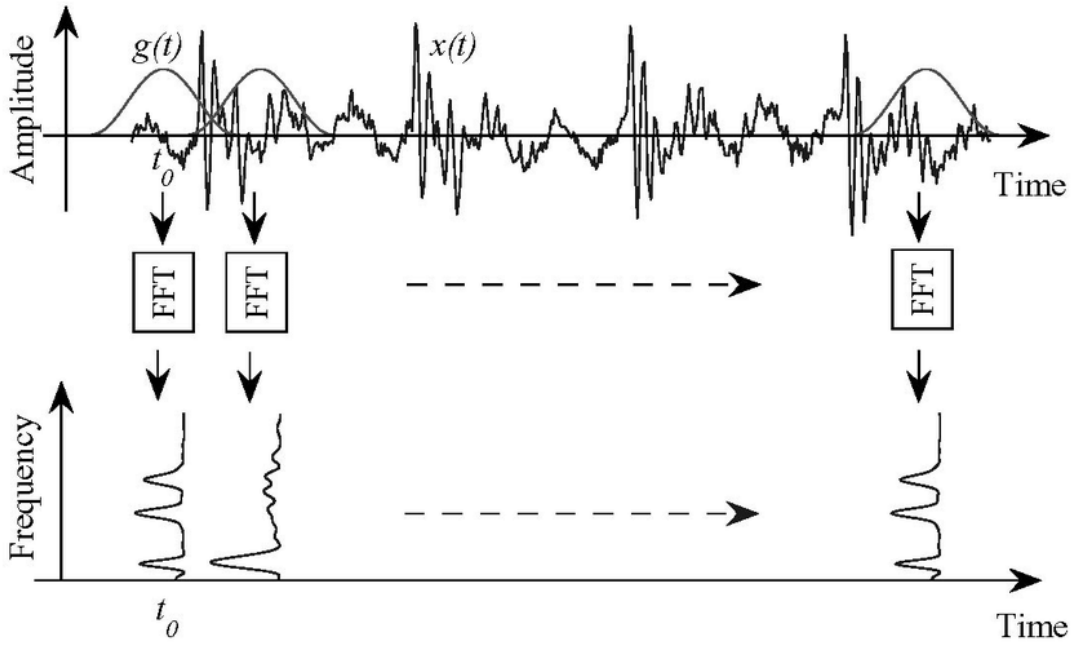

Figure 5.3: Workings of STFT on an audio signal $x(t)$. $g(t)$ is a function defined using the FFT window size and the hop length. The result of each FFT transformation is the amplitude and phase of frequency over the time period. [59]

The next step into obtaining chroma features for the cross-correlation rejector is converting the spectrogram resulting from the STFT into a chromagram. Using the standard mapping of pitch $A4 = 440Hz$ and knowing that pitches in music lay on an equal-tempered scale we can calculate the remaining pitches (relative to A4) from the frequency spectrum. We then aggregate all pitches belonging to the same pitch class and that gives us the chroma value of the chroma value corresponding to the class.

The conversion from frequency to pitch is regulated using a specification defining a function to be used when the pitches relative to $A4$ are calculated. This standardisation is commonly referred to as *tuning standard*. The paper describing the cross-correlation rejector does not specify what tuning was used to generate the chroma features, so a library implementation of chroma feature extraction was used in the benchmark. To further explain the conversion of frequency to chroma an example using the *MIDI tuning standard* is presented. Figure 5.5 follows each stage of the procedure.

The MIDI tuning covers a range of 128 frequencies enumerated from 0 to 127. A4 (which again corresponds to $440Hz$) is assigned number 69 and all other pitches are calculated using the equation:

$$d = 69 + 12\log_2(\frac{f}{440Hz}) \tag{5.1}$$

Figure 5.4: Calculating pitch from frequency f based on MIDI tuning standard [19].

This gives us a song representation similar to the one from 5.5 c). The final step is to sum all MIDI pitch coefficients into their corresponding pitch classes and obtain the chromagram from 5.5 d).

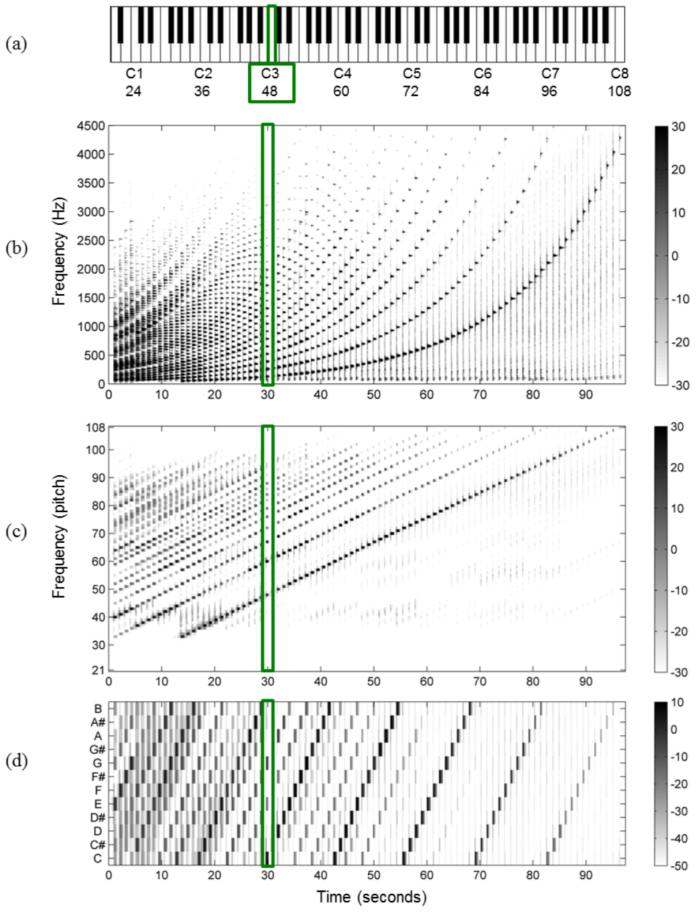

Figure 5.5: The separate stages of a spectrogram to chromagram conversion of a piano recording of the chromatic scale from A0 to C8 using MIDI tuning. [10]. a) The equal-tempered scale represented by the keys of a piano, with the pitch C3 mapped to 48 according to MIDI Tuning b) A spectrogram of the song, with the time frame where C3 was played marked in red c) Pitch log-frequency representation of the spectrogram d) Resulting chromagram

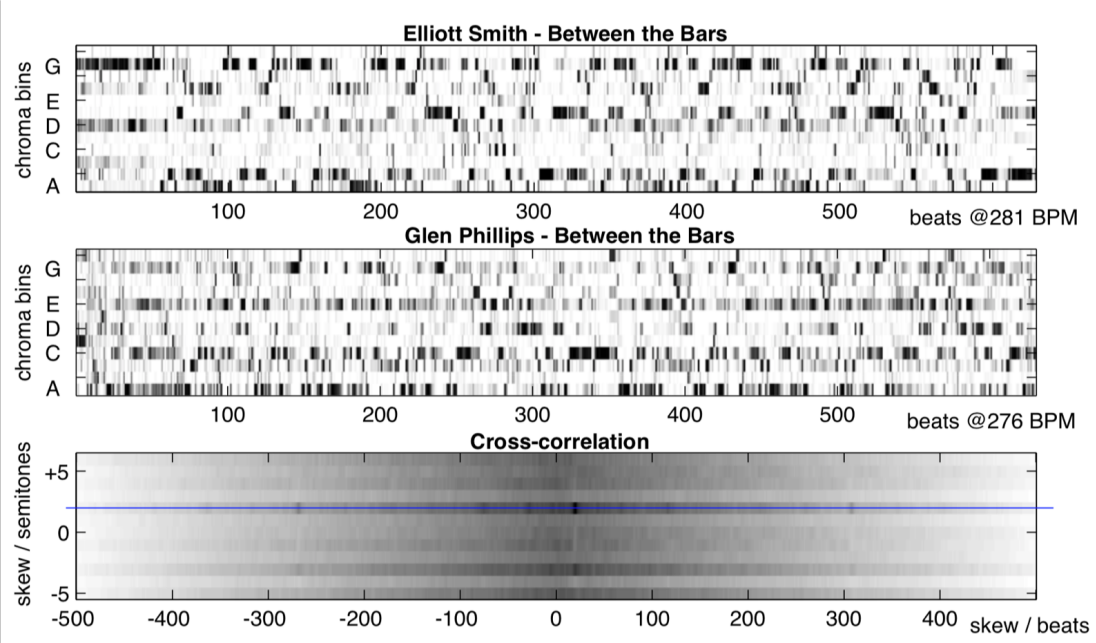

Figure 5.6: Extracted chromagrams of two cover songs and the resulting cross-correlation [4]

The chroma features in the cross-correlation rejector are *beat-synchronous*. This means that the period over which a chroma feature is obtained is every beat of the song, rather than a shorter time segment. Understanding beat detection in detail was beyond my abilities and a library implementation of a beat tracker created by the algorithm creators is directly used to obtain a result [60].

The resulting chromagrams for two songs are then scaled to unit length, so that the sum of all dimensions of the chroma vector has a sum of 1. The representation of the longer song is also shortened to be equal to the one of the shorter song. The chromagram matrices are then cross-correlated. To account for variations in the structure or pitch of the cover songs the shifts of the chromagrams between -500...500 beats are considered. The resulting intervals of peak values of peaks in the resulting cross-correlation matrix indicate a strong match between both tracks. Figure 5.6 shows the correlation process of two chromagrams. The blue line in the cross-correlation matrix indicates the strong similarity detected.

The similarity score that the rejector returns is the reciprocal value of the highest peak value in the cross correlation matrix.

5.4 Quantisation rejector

The dominant audio feature in the quantisation rejector is again chroma vectors which are beat-synchronous and unit normalised. The extraction implementation is the same, with some modifications to the FFT window size and hop length parameters. The general idea of the rejector is to represent songs using *codewords* which are generated using K-means clustering of a large number of chroma vectors. The resulting cluster centers are the codewords. Each song is then represented using a histogram showing the codewords frequency for each track. As illustrated in figure 5.7 the approach leads to visible similarity between cover songs.

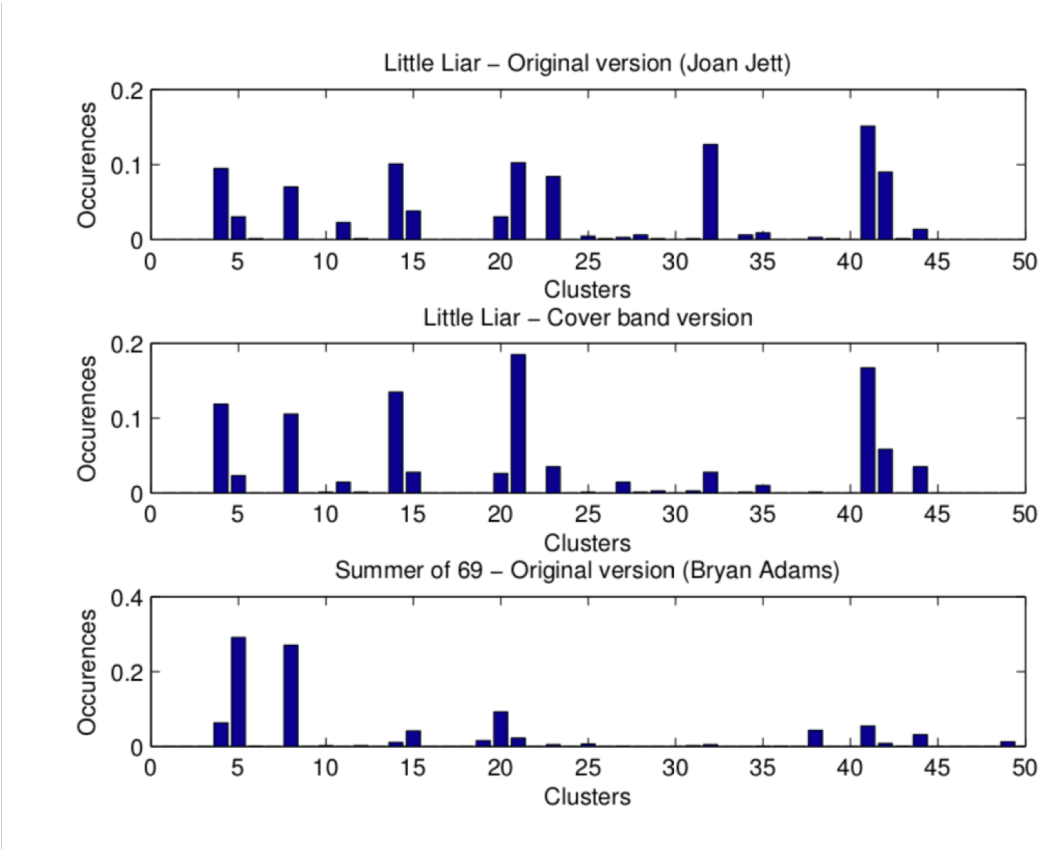

Figure 5.7: Histogram representations of songs utilising codewords. The first two histograms illustrate the visual similarity occurring between two cover, in comparison to the third song which is not related to the first two [61]

Sometimes a cover song can shift up or down the overall pitches of the original by a fixed interval. This technique is called *key transpositions*. To take possible

transpositions into consideration the quantisation rejector implements *Optimal Transposition Index (OTI)* [62]. It is a calculation on the number of positions one of the histograms needs to be shifted in order to achieve best possible alignment with the other. For two histograms represented as n-dimensional vectors $\vec{A}$ and $\vec{B}$, where n is the number of codewords used, the OTI is derived from:

$$OTI(\vec{A}, \vec{B}) = \underset{0 \leq m \leq n-1}{\operatorname{argmax}} \{\vec{A} \cdot circshift_R(\vec{B}, m)\} \tag{5.2}$$

Figure 5.8: OTI equation

$circshift_R$ is a function shifting the vector $\vec{B}$ m positions to the right. The shift is circular, which means that the last element of the vector becomes the first one after every position shift. The operator $\cdot$ specify a dot product operation between both vectors. The OTI is used to shift one of the vectors to achieve best alignment between both songs:

$$\vec{A^{Tr}} = circshift_R(\vec{A}, OTI(\vec{A}, \vec{B})) \tag{5.3}$$

Figure 5.9: Shifting $\vec{A}$ to best align with $\vec{B}$

The final similarity metric returned by the quantisation rejector is the cosine similarity between both histograms.

5.5 Timbre rejector

5.6 Aggregated rank rejector

5.7 Fingerprint rejector

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 and experimentation

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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