Stellenbosch University

Honours project

Music identification tool: Stelhound

Project report

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1 Introduction

Music is a daily part of every person's life. With so much music around and new songs being created every single day it is impossible to identify every song you might hear. Having the ability to determine what song is playing at any given moment is a valuable service with wide commercial appeal. Giving a user the ability to discover new music that they otherwise would never have identified is the ultimate goal of Stelhound, an open source music identification tool. The aim of this project is to create an open-source music identification tool using technologies and algorithms with other potential audio processing applications such as voice recognition.

Stelhound uses the basic principles of spectral analysis to identify and classify important points in an audio files information. These points are used to create custom song fingerprints which allow the program to search for matches between two different audio files. The specifics of the algorithm will be described in more detail in the Overview and Design sections.

There are currently music identification tools available such as Shazam and Sound Hound, however the techniques these companies use are proprietary and shrouded in ambiguity. The project aims to shed some light on the mystery surrounding these applications and to open the door to some great open source projects using similar algorithms.

This project does not intend to improve on the accuracy or efficiency of existing music identification tools, but to act as a proof of concept for small scale audio pattern matching.

2 Overview

Stelhound is an application designed to allow a user to record sound from their environment with their device and have it identified. Once a song has been identified its information is stored on the device and the user is able to see the last 5 matches made by the program.

The program was created in Java 8 with the intent that if it were ever to be converted into an Android application the conversion process would be relatively straightforward.

The initial design and requirements documents written for this project were altered significantly and so no longer accurately reflect the final program. Midway through the projects implementation it became apparent that certain design choices had to be altered and this in turn affected the scope.

2.1 Initial approach

The initial plan for this project was to generate Parsons code [1] from an audio recording and use it to search through the Musipedia webservice. After spending some time on the project and working with the webservice it quickly became apparent that Musipedia could not be used. The main reasons for this are listed below.

1. Parsons code has no specificity:
   Parsons code is a good representation of a song's melody and can provide a good understanding of the melodic pattern. However in popular music, melodies are often replicated across multiple songs. This means that if two songs share the same melody they will generate the same Parsons code. This problem becomes even more prevalent when looking at small recordings which only contain part of a melody. This increases the likelihood of generating false positives and makes it almost impossible to ensure accuracy.

[1] Parsons code is a compact way to represent the melody in a piece of music, where each note is given a value of U,D or R (Up, Down or Repeat) depending on the note that came before it.

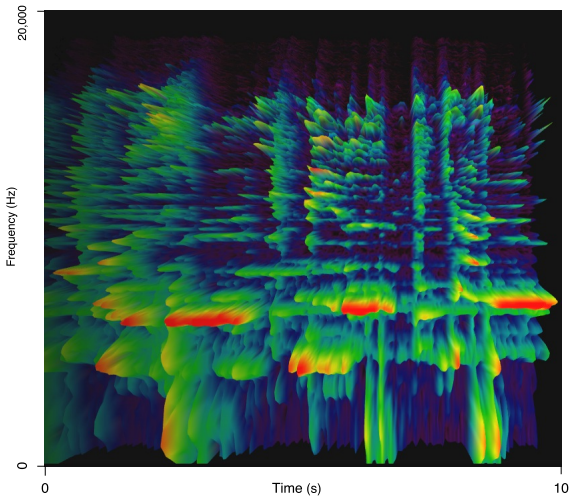


Figure 1: Spectrogram of a 10 second audio recording

2. The Musipedia database is not transparent:
   The webservice has a large but incomplete database with no way of knowing its exact contents and reliability. Only partial Parsons codes are stored and there is no indication as to where in the song the Parsons code is from. This makes it very difficult to do any testing with accuracy. Not knowing the structure and contents of the database creates a layer of complexity that this project does not need.

3. There is no way to do any kind of search optimisation:
   The Musipedia webservice uses SOAP to do its API calls and an unknown searching algorithm to search through the database. In a program such as this one where search speeds are critical the programmer needs as much control as possible over the data. Without having direct access to the database the program can never be efficient.

Once it was clear that the approach needed to be altered a new system was devised. After some reading and research it was decided that the most accurate way to determine song matches was to create a custom fingerprinting algorithm.

2.2 Modified approach

The modified approach needed to combat the three main issues highlighted above: specificity, database transparency and searching optimisation. To do this a custom fingerprinting algorithm needed to be created which could consistently reproduce fingerprints in noisy environments. Having read through both Wang [1] and Kurth's [2] papers it was decided that the most effective way to generate reproducible fingerprints was through the principles of spectral analysis.

Spectral analysis is the process of analysing data which falls within a spectrum, in this case audio frequencies between 0 and 20,000 Hz. The best known example of this is the spectrogram which is a visual representation of the time, frequency and intensity data in an audio file. An example is given in Figure 1. Full spectrograms contain too much information for rapid comparison so key information is picked and used to generate a much smaller fingerprint. By using all this information to create a fingerprint we eliminate the problem of specificity in the matching criteria, a major issue in the initial solution. This is discussed in the Design section.

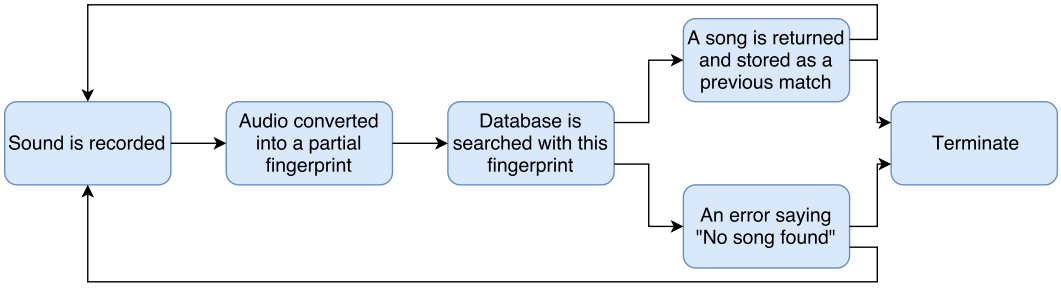


Figure 2: User pipeline

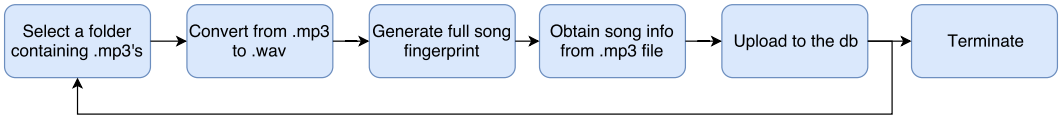


Figure 3: Administrator pipeline

Fixing the other two problems is done by creating a custom database which contains all the information a user might want. This provides database transparency and allows for a custom searching algorithm, both of which will be explained in depth later on.

With the addition of a database a second application needs to be made which allows an administrator to easily upload audio files. This application will follow a similar process to the main application but will act on larger pieces of audio. Both the user and administrator pipelines are given in Figure 2 and Figure 3 respectively.

Once a song has been matched by the algorithm it is stored on the device as a previous results. This allows the user to go back and view previous matches found using the program. This feature only remembers the last 5 matches found.

With the modified approach the goal was not to reproduce the performance and accuracy of Shazam. This is reflected in the non-functional requirements. It was expected that the program would have an accuracy of close to 75%, matching 3 out of every 4 songs correctly. The program was also expected to find matches within 25 seconds and display a message letting the user know if the recorded audio is not in the database.

2.3 The final requirements simplified

2.3.1 Functional requirements

- The system shall record audio through the devices built-in microphone.
- The system shall convert audio into search-able values using a custom fingerprinting algorithm.
- The system shall search through a local database checking for substrings and storing the offsets of any it may find.
- The system shall attempt to match audio recordings to database entries and will return a result when confident.

- The system shall store the 5 most recent matches locally allowing the user to see their previous matches.

2.3.2 Non-functional requirements

- The system shall be able to determine whether there is or is not a match in the database within 25 seconds of starting a recording.
- The system shall have an accuracy of approximately 75%, allowing 1 false positive in 4 matching attempts.

This project has a simple concept which requires some intensive and complex algorithms. These algorithms and their implementations will be discussed thoroughly in the Design and Implementation section.

3 Design/Implementation

The design of this system, as outlined in the Overview section, can be split into two applications: one for the Client and one for the Administrator. Both applications utilise the same underlying fingerprinting system, but the Client searches and returns results where as the Administrator uploads songs to the database. By using the same fingerprinting algorithm for both systems we ensure that fingerprints are consistent.

The main components of this program can be broken down as follows:

1. Client
   (a) Audio recording
   (b) Audio preprocessing
   (c) Fingerprint construction
   (d) Database searching
   (e) Returning results
2. Administrator
   (a) Reading in audio files
   (b) Audio preprocessing
   (c) Fingerprint construction
   (d) .mp3 information extraction
   (e) Database updating

The following sections will contain a full description of each of these components and their interactions with one another. Thereafter the implications of each component will be explored.

Before getting into the specifics of the program this document will explore some of the theory related to the fundamentals of sound, audio recordings and the Fourier transform.

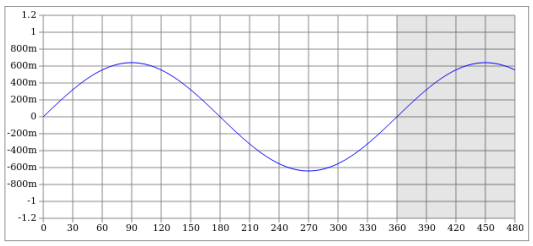


Figure 4: Pure sine wave

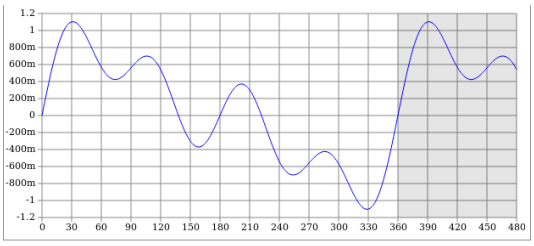


Figure 5: Typical sound wave

3.1 The fundamental properties of sound

To understand this project fully we first need to learn about what makes a sound or song unique. Once we know that we can design a program which looks for these unique features.

Sound can be defined as a series of vibrations which propagates as an audible wave of pressure through a medium. In people and animals these pressure waves are picked up by the ears and interpreted by the brain into meaningful information. The number of times a pressure wave repeats itself is called the frequency of that wave and the higher the frequency of the wave, the higher the pitch of the sound. It is important to note that the pitch of a sound is not the same as the "loudness" of a sound. Loudness is determined by the amplitude of the pressure wave and not by its frequency. Sounds can occur at any frequency but humans generally only have the ability to hear between 20 Hz and 20,000 Hz.

Sounds which only have a single frequency are produced by *sine* waves with varying wave lengths and are almost never found in nature. Sounds almost always consist of multiple frequencies with differing amplitudes and can be thought of as a combination of multiple pure tone sine waves [3]. This distinction can be seen in Figures 4 and 5.

The important things to remember moving forward are that:

- Most sounds are made up of multiple frequencies which can span across a broad range;
- Sound waves can contain multiple frequencies but only those that lie between 20 Hz and 20,000 Hz are relevant to humans;
- Frequency relates to pitch;
- and Amplitude relates to loudness.

3.2 Audio recordings

Audio recording is the process of converting an analogue sound (a sound produced in the real world) into a digital one. This is not as intuitive as one might think because of how computers handle information.

When a sound is created and the sound wave propagates through the atmosphere the wave is continuous. In other words the sound wave can be divided into an infinite number of parts and each will still contain some information relating to the sound. This is a problem when using computers as they do not contain an infinite amount of memory to store this information. We thus need to limit the number of times per second a recording device will *sample* the sound whilst keeping all of the frequency information which makes the sound unique. We do not want this rate to be too high as it will waste space and computation time but we also do not want it to be too low and miss important sound information. To solve this problem we use the *Nyquist-Shannon sampling theorem*.

The Nyquist-Shannon theorem states that the sampling frequency must be greater than twice the maximum frequency one wishes to reproduce [4]. So in order to get every frequency within the audible human spectrum we need a sampling rate of at least 40,000 samples per second (Hz). The sampling rate for our recording device is thus chosen as 44.1 kHz in accordance with industry standards.

If we were to sample at a lower rate our recording would not contain any of the higher frequencies in the human hearing range. This can be useful when very high quality audio is not a priority but can cause *aliasing* which gives the audio a "stutter" effect.

3.3 Fourier transform

After the program has made a recording through the microphone the information is stored as a byte array. This byte array represents the recording in the time domain, meaning every entry in the array directly correlates to a sample. Unfortunately this byte information is almost useless when it comes to audio matching. In order to get usable information we need to convert this data from the time domain into the frequency domain. To do this we use a *Fourier transform*.

An example of how a Fourier transform changes a signal is given in Figure 6. The problem with using a Fourier transformation on the microphone data is that all time information would be lost. For this reason a sliding window only performs the transformation on small chunks of each recording. This allows the program to keep the time information of the recording and extract the frequency data. Keeping the time information creates a new problem regarding performance. A Fourier transform now takes place many times a second instead of just once, increasing our computation time drastically. The solution to this problem is to use a modified version of the Fourier transform known as the *Fast Fourier transform* (FFT) [5].

The FFT gives exactly the same results as a normal Fourier transform but at a fraction of the computation time. Where a normal Fourier transform takes approximately $\mathcal{O}(N^2)$ time, the FFT only takes $\mathcal{O}(NlogN)$ time, where N is the number of samples being converted. It is important to note that from this point forward any mention of a Fourier transformation is in fact referring to the FFT.

The discussed theory will now be used to explain the design decisions and algorithms used in this project.

3.4 Client side

3.4.1 Recording

Recording sound is the first steps in the matching process and it is important that the recorded sound contains all the fundamental frequencies needed for matching. There are several parameters that can be tweaked and changed in this area and testing was done to ensure that the ones which produced the best results were chosen.

As discussed previously in this document a recording needs to be sampled at least 40,000 times per second in order to contain all of the frequencies audible to the human ear. The sample rate is one of the parameters used by the system to determine the quality and clarity of the recording which will later be converted into a fingerprint. Any change to the parameters in the audio format will have a direct impact on the generation of the fingerprint. Another important parameter to consider is the *sampleSizeInBits*. This is the number of bits recorded per sample and in most recordings is standardised with a size of 16. In this application a size of 16 is used to reduce the amount of noise created by the recording and improve the similarity between the recording and songs in the database.

For consistency sake the same audio format is used on the server side when adding songs into the database. The audio format used can be found in Listing 1.

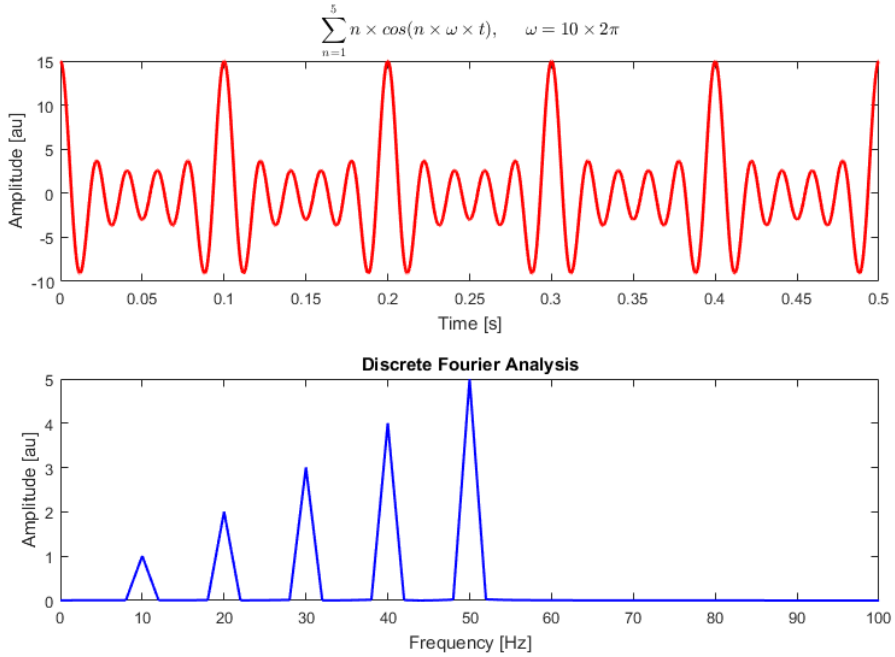


Figure 6: Fourier transform on a cosine summation function [7]

```
protected static AudioFormat audioFormating () {
      final float sampleRate = 44100.0f;
      final int sampleSizeInBits = 16;
      final int channels = 1;
      final boolean signed = true;
      final boolean bigEndian = false;
      AudioFormat format = new AudioFormat(sampleRate, sampleSizeInBits, channels, signed,
          bigEndian);

      return format;
}
```

Listing 1: Audio formatting for recordings

Recoding sound in Java is a fairly simple process which involves opening a line to a recording device and reading the information received into a byte array. This is all made possible with the `javax.sound.sampled` library. All audio recording is done in a separate thread from the main program so that sound can be recorded and searched for concurrently. After every second of recording the program generates 20 partial fingerprints, henceforth know as *fingerprint fraction*, based on the audio. Each fingerprint fraction will then be used to search through the database. The fingerprinting and searching processes are described in more detail below.

3.4.2 Preprocessing

The audio data needs to be preprocessed before the frequency information can be extracted and turned into a fingerprint. The raw sound data first needs to be converted from an array of `bytes` to an array of `doubles`. This conversion is necessary for when we change the recording information from the time domain into the frequency domain using the FFT discussed earlier.

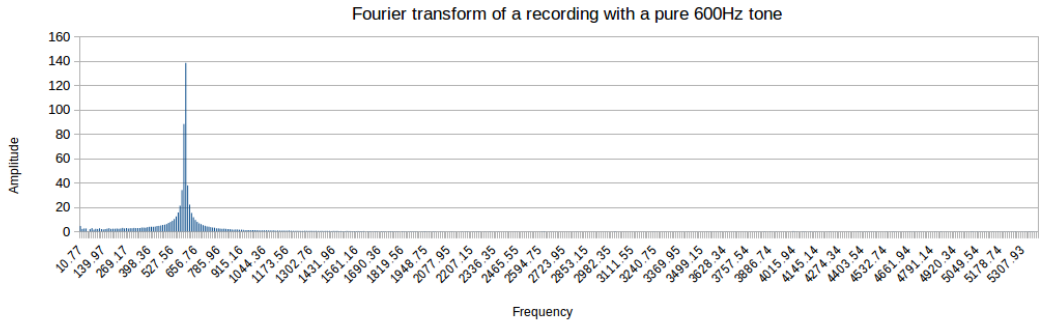


Figure 7: Fourier transform of a pure 600Hz tone

Converting the byte array is not as simple as parsing each value as a double and storing it in a new array. In order to preserve all of the sound information stored, the conversion needs to take into account what audio parameters were used in its storage, for example if the audio was recorded using a `sampleSizeInBits` of 8, then the original byte array needs to be split up into segments of 8 bits each and then converted. Neglecting to do this will result in erroneous, inconsistent data.

After the conversion the new array is split up into chunks to preserve the time information of the recording. After testing with chunk sizes of 2, 4 and 8KB it was found that the best size was 2KB. The chunk size in combination with the sample rate determines how many fingerprint fractions are produced per second. From the parameters used it can be calculated as $44,100/2046 = 21.55$ chunks per second. This value gets rounded down to 21 which means a small amount of information is cut off at the end of each second. This provides extra time for FFT computation.

On each chunk of data a FFT is applied and the result is returned as two arrays, one real and one imaginary. The imaginary array given by the FFT can be used to determine the phase of the audio wave, however in this application the phase is not considered as part of the fingerprint and so the imaginary array is dropped. Each value in the array of real numbers is an amplitude associated with a frequency calculated by $(1 + i) \times 21.55$, where i is the index of the value in the array. So for example if the maximum value in the array is 140 at position 27 then the frequency can be calculated as $(27 + 1) \times 21.55 = 603.4$Hz. This example is visualised in Figure 7.

The values are multiplied by 21.55 because of a feature in Fourier transforms called *spectral resolution*. Spectral resolution is the degree of accuracy to which a Fourier transform can get a frequency and is calculated as $sampleRate/windowSize$. This effectively bins all of the frequencies we might get and provides a 21.6Hz margin of error. It does also mean however that frequencies obtained may not be exact but are rounded down to the nearest bin.

3.4.3 Fingerprint generation

The task is to now use the frequency, amplitude and time information gathered from the recording and preprocessing to generate a fingerprint fraction for each chunk of data. This fraction will then be used to search through the database and potentially find a match. The algorithm used to create the fingerprint fractions, and on the server side full fingerprints, is simple and efficient using the amplitude information to determine which frequencies to store and which to ignore.

As discussed earlier most sounds found in the real world do not consist of just single tones, often having several peaks and valleys in the sound wave. This translates into the frequency domain as well, meaning that most sounds have several peak frequencies used in their construction. Generating fingerprint fractions from just the frequency with the highest amplitude would be too general and

produce too many false positives in the searching and matching phases. At the same time, using too many of the top frequencies would produce results which could not be repeatable if these peak frequencies were not much louder than the average. Looking at the full audio spectrum for loud frequencies also takes too much computation time. In general songs exist in several frequency bands such as the baseline being 10-100 Hz, the low range being 100-200Hz, the mid range being 200-800Hz and the high range being anything above this. Using similar principles a fingerprint fraction can be generated by getting the highest frequencies between certain ranges and then combining them together. This is the logic behind the fingerprinting algorithm.

After testing several different sets of frequency ranges it was found that 107-214, 214-418, 418-836 and 836-1672Hz gave the best results. These ranges represent the octave distance between each A note on a typical musical scale. The testing methodology can be seen in the testing section: Parameters.

Below is the algorithm used in generating song and recording fingerprints.

1. The array of amplitudes received from the Fourier transform is iterated through.
2. Each item in the array gets checked against the current maximum amplitude in the current range. If the amplitude is higher both it and its related frequency are stored. If not the next value is checked.
3. Once every value has been checked we now have the frequencies with the highest amplitudes in each of the four ranges. Every value which is not above 70% of the maximum is rounded down to the lower bound of the range, effectively zeroing it out. This is done to prevent weak, erroneous tones from being used.
4. The dominant frequencies all go into a function which concatenates them together, forming the fingerprint fraction.
5. Steps 1-4 happen for each chunk of the recording and get added into an `arrayList`. Once every chunk has been utilised the algorithm completes.
6. The final fingerprint is created by doing a `toString()` operation on the `arrayList` of fingerprint fractions. An example output for 0.25 of a second would be `[0946430300214, 0946624322214, 1270624322214, 1270624418214, 1270624322214]`

An example of how the fingerprinting process is done can be seen in Figure 8. Each of the cyan coloured rectangles represents a frequency range and each of the red x's represents the dominant frequency in that range. From there the algorithm would determine that the frequency in the fourth range is below 70% of the maximum and so is converted to the lower bound of its range. The other three would keep their frequencies as they are above the zeroing threshold.

3.4.4 Searching

During the fingerprinting process 21 fingerprint fractions will be generated per second. Over the course of 25 seconds of recording this amounts to 525 fractions being created. These fractions need to be used to search through the database quickly and accurately whilst remembering that there is a good chance individual fingerprint fractions may occur in multiple songs as well as at multiple positions in a single song. While this is happening the search also needs to be robust, accounting for noise during recordings.

The first step in accomplishing all of the goals set out is determining the matching algorithm. Fingerprints are stored as strings in the database meaning that the searching algorithm needs to be substring based. The best algorithm for this task is Boyer-Moore with a time complexity of $\mathcal{O}(nm)$ in the worst case and $\Omega(n/m)$ in the best case, where m is the length of the fingerprint and n is the

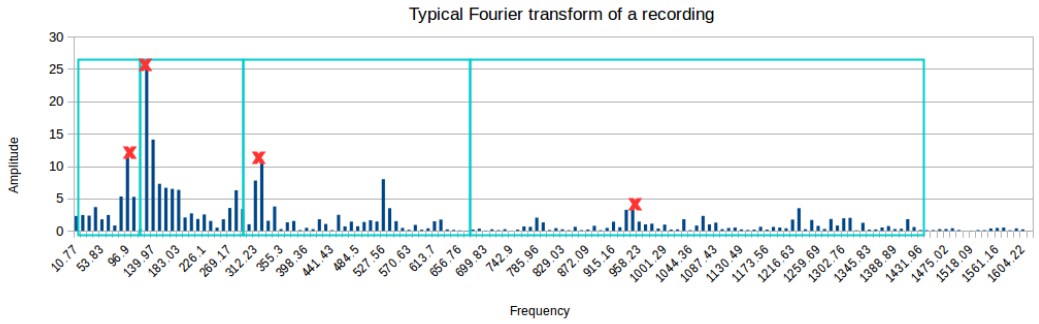


Figure 8: Visualisation of the fingerprint fraction algorithm

length of the fraction. The Boyer-Moore algorithm is perfect for this application as it specialises in finding matches where the substring is much shorter than the full string. The algorithm works by going back to front, checking if the current character is the same as the last character in the search and if not, skipping forward [8]. This makes the algorithm very efficient. A small modification is made so that once a match is found its offset in the fingerprint is stored and the algorithm continues. The pseudo code for the algorithm can be found in Algorithm 1 [9].

Algorithm 1 Pseudo code for the Boyer Moore algorithm

```
1:  procedure COMPUTE FUNCTION LAST
2:  arrayList a
3:  i ← m − 1
4:  j ← m − 1
5:  Repeat:
6:      if P[j] = T[i] then
7:          if j = 0 then a.add (i)
8:          else
9:              i ← i − 1
10:             j ← j − 1
11:     else
12:         i ← i + m − min(j, 1 + last[T[i]]
13:         j ← m − 1
14: until i > n − 1
15: return a
```

For each fingerprint fraction the Boyer-Moore algorithm needs to search through every song in the database. This means that the larger the database, the longer it takes to search through every entry making this solution non-scalable. The program's solution to this problem is to apply concurrency. The database can be divided into sections with each section performing its own search on a subset of the data. This makes the solution more scalable but potentially very expensive. This is an area for further research in the project.

After running the searching algorithm through every song with each fingerprint fraction the result is a list of songs with positions in their fingerprints that had matches. These positions, or *offsets*, represent potential matching locations where the recording could be taking place. This information

is used when determining whether a song is a match or not.

3.4.5 Matching

The first instinct when searching for correct matches is to pick the song that gets the most fingerprint fraction matches over the course of the recording. This can give a good indication of which song might be correct but is a poor metric for determining exact matches. Part of the reason for this is because of how repetitive most songs are. In popular music a song will often have the same baseline and chorus in multiple positions and these areas have a high chance of containing similar fingerprint fractions. This would then cause issues for songs of varying lengths. For example if the song the user is trying to match is only one minute long but there is a similar song in the database that is five minutes long the program is more likely to pick the longer song and produce an incorrect match. It is for this reason that timing needs to be taken into account.

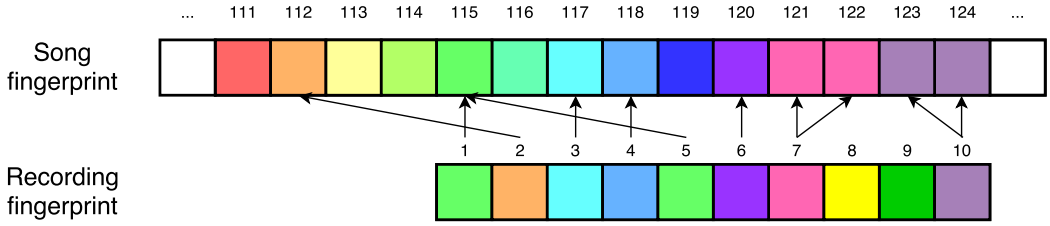
Offsets retrieved from the searching algorithm are in terms of character positions in the string and are hard to read and use accurately. For this reason the first step towards getting matches is converting the character offsets into fingerprint fraction offsets. The below equation represents the conversion where h is the character offset in the fingerprint, $cPerSec$ is the number of characters generated per second of audio and $fPerSec$ is the number of fingerprint fractions generated per second of audio.

$$\text{fracOffset} = (h/cPerSec \times fPerSec) + ((h \mod cPerSec)/cPerSec \times fPerSec) + 1$$

For every second of runtime fingerprint fractions are generated and searched for, giving a list of offset values. The easiest way to incorporate timing information into this data is to subtract the time in the recording from the suspected time in the matched fingerprint. This is done by subtracting the number of fractions recorded from the offset of the matched fraction. The value is then stored in a `HashMap` where the key is the result and the value is a counter. Every time the same key is made by subtracting these values the counter is incremented. By subtracting the values and storing this number the algorithm is effectively running a side-by-side comparison between the song's fingerprint and the recording's fingerprint, incrementing a counter every time that the values are the same. The algorithm can then find a match by seeing which song has a key with the largest counter value. If there is not a conclusively large counter then the algorithm will continue running until either the time limit is reached or a significantly large value is found. To get a better understanding of how this algorithm works Figure 9 has been given as an example:

The figure shows two arrays of coloured blocks where each colour is representative of a unique fingerprint fraction. The large array represents the full fingerprint of the song being matched against and the small array represents the fingerprint generated from one second of recording. The position chosen in the songs fingerprint is arbitrary. The example is explained step-by-step below.

1. A search for the fraction at position 1 in the recording is conducted through the song's fingerprint.
2. A match for this fraction is found in the song's fingerprint at position 115.
3. The offset value is calculated ($115 - 1 = 114$).
4. There are currently no stored values so a new `HashMap` entry is made with 114 as the `key` and 1 as the `value`.
5. The rest of the fingerprint is searched for another instance of the fraction, but none is found. The algorithm then resets and does the same process used on the fraction at position 2.
6. A match is found at position 112.
7. The offset is now calculated as $112 - 2 = 110$ and stored.



Resulting map:

110: 2

113: 1

114: 6

115: 1

Figure 9: Visual example of the time inclusion matching process

8. This algorithm continues until the end of recording and produces the resulting map which shows 114 to have the highest counter.

After running this algorithm for at least ten seconds each song should have a large `HashMap` of keys and values. Each song's maximum counter is compared and the song with the highest maximum is then checked against the second highest. The algorithm decides if a song is a good enough match when the next closest song is less than 80% of the maximum. Once a definite match is found the algorithm completes and sends the top ten matches to get displayed to the user.

3.5 Server side

The Server side application has many similarities to the Client in how it generates song fingerprints. In cases where there is a function overlap between the two applications the reader will be directed towards sections in the Client documentation in order to reduce repetition.

The server application was a late but necessary addition to the program's requirements which allows an Administrator to add songs to the database individually or in large groups. This application follows the pipeline displayed in Figure 3. Each step in the pipeline will be fully explained in the sections below.

3.5.1 Reading in files

The first step in the administrator process is selecting a file or folder to upload. To do this the user is given a simple *GUI* (Graphical User Interface) which uses `JFileChooser` to select a file location on the users device. If a folder is chosen the application will go through every .mp3 file in that location and upload them one by one. If the user just selects a single .mp3 file the application will remain open in case the user wishes to upload a file from a different location.

For each file uploaded a process of conversion needs to take place from .mp3 to .wav. This needs to happen for a couple reasons:

1. .mp3 files are encoded as stereo files and the program requires files in mono, [2]

[2]Stereo sound means that the audio was recorded with multiple microphones on different tracks whilst mono means that the audio is only on a single track.

2. Extracting the sound information from a .mp3 file is much harder than extracting the information from a .wav file because there is no standard .mp3 encoding type.

The process of converting an .mp3 file to a .wav file is fairly simple, using the `javax.sound.sampled` library and the audio format discussed in listing 1 to change the data in the file from its native format to the new format. This conversion effectively makes it so that there is no audio difference between sound read in from a file and sound recorded through the microphone.

The generated .wav file is now converted into an array of bytes which is the same format as the raw microphone recording. The byte array is now converted into a full song fingerprint in the same way as the raw microphone recording. For clarification on this process please read section **3.4.3 Fingerprint generation**.

3.5.2 DB storage and management

The database was designed to store all the information the user might want in conjunction with the audio's fingerprint. For these reasons the database stores the song title, artist, duration, album art and fingerprint for each song. Inputting all of these fields manually would take too much time and would prevent the quick uploading of files needed for testing. This is the reason why the administrator is only allowed to upload .mp3 files.

.mp3's are special in that they are highly compressed and can contain information about the song in the header, the first few bytes of information. Unfortunately there is no standard encoding for .mp3 files, meaning that the song information can be stored in different parts of each individual header. In order to reliably get song information from each file the program uses a Java library called "MP3agic" [10]. This library has the ability to determine the kind of encoding an .mp3 has and then extract the desired information. Filling the database is then as easy as using this library to retrieve the desired fields from the song and then using a query to upload the values.

In the event that a song does not have the desired information stored in the header the system automatically rejects it. If there is no album artwork available the system assigns a default image.

The database system used to store all the information is MongoDB, a NoSql based database which uses a document-oriented data model. MongoDB is optimized for systems which contain non-relational data and provides quick access to the database on reads and writes. In order to get MongoDB working with Java the MongoDB Java Driver [11] is required. This driver allows the Java program to access the local MongoDB installation as well as create, update and query collections and documents. This makes it easy to set-up the database and removes the need for any external database management software.

The database is initialised as a single collection which contains multiple documents. The collection acts as the table and each document acts as a row. Each document is given an auto-incrementing id number which is used to identify it when querying the database. Queries have almost no time impact on the system as the database is hosted locally and not over a network.

3.6 Code and version control

Throughout this project code was written and removed as requirements changed, leading to more efficient and economical code design. This program was more algorithmically than functionally intensive and this is reflected in the projects final code base.

The program can be broken down into three areas: program function, program testing and the user interface's. These three combined use in excess of 2000 lines of code, with program testing accounting for just under half of all the code written. The program needed as much testing as possible due to the nature of the project's variable inputs. Every time the program runs it receives a different input

in the form of an audio recording and testing needed to be done to ensure results were as consistent as possible. By thoroughly testing we ensure the program functions optimally.

To keep code safe during the development process the version control system GitLab was used. By using version control, programmers are able to go back to any previous code they may have changed in order to fix new bugs that were accidentally introduced. This system also means that code is backed up externally, so any corruption or loss of data on the programmers machine will not mean the loss of a project.

The program and all its supporting documentation can be found at the link below.
`https://git.cs.sun.ac.za/18516009/18516009-hons-project`

4 Testing

In testing this program there were two main objectives: (1) Testing to make sure that the program functioned as it should without errors and (2) Testing all of the parameters to get an optimal solution. In effect the first kind of testing is to make sure that the program has no computation errors or interface bugs and the second type of testing is to try optimise the searching and matching potential of the program. Both of these testing methods are explained in their own sections.

4.1 Program Correctness

There are many complex functions in this program, all of which need to be thoroughly tested to make sure there are no programming errors. The easiest way to do this in Java is to create a JUnit test suite. JUnit tests allow the programmer to specify expected output from functions within the program, failing a test if the expected output does not match the actual output.

A JUnit test suite should ideally cover 100% of a program's code. Code coverage is measured by how many lines in each of the program's files are executed versus how many are not, thus if all the lines in the program are executed then coverage is 100%. To measure the coverage in this program the tool EclEmma [12] is used. EclEmma is an Eclipse plug-in which has the ability to highlight lines of code in different colours depending on whether they were executed or not.

Unfortunately there are some functions in the program which cannot be automatically tested, such as the correctness of the audio recording. The correctness of functions like this can however be inferred further along in the program's pipeline as well as with manual testing. In this case a function was created which plays back the audio recorded to listen for audio artefacts. This is not an ideal situation, but will still give a reasonable estimation of the functions correctness.

After executing all of the JUnit tests the code coverage report came back having covered 80% of all branches related to the user experience. The parameter tester files were not considered in the coverage report as they were only used as a reference for program editing and have no direct impact on the user experience.

The tests conducted covered all aspects of the program in an effort to prevent any possible unexpected errors. These include accessing and uploading to the database, creating song fingerprints and ensuring consistent and persistent data across the entire system.

The tests successfully brought to light three errors which would have crashed the program had they not been discovered: (1) a variable which was not cleared that could cause false matches, (2) an error with retrieving album artworks that was not handled and (3) a programming error in the song matching. The third error was the most significant as it greatly reduced the likelihood of finding a correct match and would have produced erroneous results.

The JUnit tests were designed to execute the program both typically and atypically. The typical tests attempted to run the program with the average user experience in mind, executing the program as it was designed to run. The atypical tests aim to provide inputs that the system would not expect. One benefit of this program is that it requires minimal user interaction, preventing possible user generated errors and making test design straightforward.

After creating and passing all all of the tests we can be confident that the program will not break in the hands of a user.

4.2 Parameters

Once the correctness of the program was tested the next step was to test to see how to improve the accuracy of the program i.e. trying to reduce the number of false positives and false negatives. There are several programmatic parameters which directly affect the way fingerprints are created and they all need to be tested against one another. The parameters included things like how many fingerprint fractions to make per second, which frequency ranges to use when creating each fingerprint fraction and the number of bits used to store recordings. When changing any of these parameters the fingerprint generator produces a different output making manual testing very difficult and time consuming. Because of this a brute force testing function was created which goes through every combination of parameters available. Each time a parameter changes the function creates a new set of fingerprints for 12 different songs. It then attempts to match snippets from each back to the original. The results of this are then saved to a file to be later examined. Once every combination of parameters has been used the program terminates.

The songs used for this process were chosen from different genres to make sure that a specific set of parameters did not produce biased data. These genres included rock, metal, pop, indie and acapella. The snippets used in the searching part of this function are each 10 seconds long and chosen at random from within 14 different songs. Two additional snippets where included which should not match in order to determine whether a set of parameters produced false positives or not. Every time a parameter changes the test outputs are stored in a text file with the test number, parameters used and matching results obtained.

The testing function took 10.5 hours to run and produced 720 result outputs with varying degrees of accuracy. For the comparison of test results accuracy was measured by (1) how many false positives were produced, (2) how many false negatives were produced and (3) the degree of error.

After completing the test, the parameters which were chosen as the best were placed into the program and tested with the microphone recording. The results of this were that no songs would match at all. It became apparent that the chosen parameters worked well on very high quality inputs, but poorly on low quality recordings with noise. This realisation meant that the testing information became irrelevant and so the tests needed to be re-conducted with low quality recordings.

Each snippet was recreated but with microphone recordings instead of being cut out of the original song. The tests were then re-run and a new set of parameters were created. When placed in the program matching results were far better. A subset of the test output can be found in Appendix A.

By doing testing like this we guarantee that the program will get the best parameters possible. The full list of parameters tested and their final decisions is given below:

Table 1: Parameter options

Zeroing rule	**Frequency ranges (Hz)**	**No. of ranges**	**Chunk size**	**Bit depth**
No zeroing	110,220,440,880,1760	2	2048	8
plus 10% max	107,214,418,836,1672	3	4096	16
plus 20% max	80,120,180,300,600	4	8192	
plus 30% max		5		
plus 40% max				
plus 50% max				
plus 60% max				
plus 70% max				
plus 80% max				
plus 90% max				
>= mean				
70% max	**214,418,836,1672,5467**	**4**	**2048**	**16**

By having the zeroing rule set to 70% the program is able to filter out some of the noise whilst keeping the uniqueness of each fraction. This reduces the chances of false positives significantly. The chosen frequency range further improves the accuracy by finding a balance between including low end and high end frequencies.

The bit depth and chunk size both improve accuracy by adding audio quality to the inputs. By chunking 21 times a second the program makes sure that most changes in song frequencies are recorded, whilst the bit depth of 16 ensures audio recordings have high clarity and better matching results.

Overall these parameters make sense and provide a good amount of accuracy, whilst keeping the information compact enough for searching.

5 Discussion

Some of the solutions implemented in this project are not as optimised as they could have been, namely the searching and storing off song information in the database. The main issue with the searching is that it is effectively linear, checking each song individually for matches. Because of this the solution will not scale well with a much larger database. I attempted to circumvent this problem by using parallelism, but this solution does not fix the underlying issue. After doing some research I discovered a potential method to correct this problem which involved hashing. The general principle behind this was to group fingerprint fractions together which would compress the size of the fingerprint. The data would then be stored as an inverted lookup table which could be searched far quicker than the solution implemented in this program. Unfortunately, this solution was only discovered late in the projects cycle and there was no time to implement it. This is something that could be attempted in the future. If the initial scope of the project had not been so different from the final result there may have been time to implement this solution. This was due to a misunderstanding of the intended project resources and this used up a large amount of time.

The design decision to create this program using Java 8 was slightly misguided and in hindsight I would have done this project in Python 3. The initial reason for using Java was so that the completed program could be adapted into an Android application with relative ease. Having not converted the program into an application it would have been far easier to do some of the computations in Python with Numpy's built in FFT functions. It would have also been much easier to visualise some of the diagrams used in the documentation of this project.

When attempting to match recordings to songs the program tends to have a much higher accuracy rate when the recording is over a chorus. I believe that this is because the chorus of a song normally contains frequencies with higher amplitudes and specificity than the rest of the song and this makes the partial fingerprints more accurate. Therefore in order to increase the likelihood of finding a match with this program a user should attempt to record over a songs chorus. This does not seem to be the case with either Shazam or Soundhound.

Compared to these other solutions this piece of software does not outperform them, however this was never the aim. Shazam was founded in 1999 with the first working version of the service available in 2002. Since then there have been many improvements to the service and there was no way that my own service could outperform theirs in just a year. The aim was to alleviate some of the mystery surrounding these applications and I believe that this program has done that.

6 Future Work

There are many things that could be done to improve the services accuracy and usability. The ones I believe to be the most useful have been listed below.

- Implement the better storage and searching solution mentioned in the Discussion section.
  The bottleneck of this entire application is based on searching through the database. By doing more research in this area the application could be sped up greatly. Any improvement here could also be of great use to other applications which require speed in searching through very large databases.

- Host the database online:
  Having access to the database from any location is not a hard task but would be useful if this application were to ever be deployed. It was not implemented in this project as it fell out of the immediate scope.

- Create an equivalent mobile application:
  A mobile application would greatly improve the program's accessibility and usefulness.

- Create a partner application which using song lyrics to search through a database instead of sound frequencies:
  This would be an interesting way to compare the accuracy of matching music based on frequencies to that of lyrics and could provide some kind of middle ground for higher matching accuracy in general.

- More research into different identification techniques:
  Finding an alternative approach which had higher accuracy would be beneficial in many areas of computer and data science. The results of this research could be used in applications like voice recognition and audio information extraction.

There are many more areas for future work on this application as it extends far beyond the realm of music recognition. With another year or two this program could be an open source all purpose audio matching program which was not limited to music.

Glossary

.mp3 An audio file format for compressed data. 6

.wav An audio file format for uncompressed data. 14

Array A datatype used in programming which stores a series of objects all of which are the same size and type . 8

EclEmma A plug-in for the eclipse IDE which displays and highlights code coverage. 16

Eclipse An IDE used in writing, compiling and running Java code. 16

Fingerprint The unique identifier created for each audio recording and audio file. 4

Fingerprint fraction A small subset inside a fingerprint which represents the frequency information of 0.1 seconds of recording. 9

HashMap A datatype built into the Java.util package which allows the storage of data as key and value pairs. 13

Java A programming language which supports Object Orientated Programming. 3

JFileChooser A function built into the java.io.file library which allows the selection of files on the system. 14

JUnit A method of testing specific to Java. 16

Musipedia An online webservice containing songs and their Parsons codes stored in a database. The API can be accessed through the SOAP protocol. 3

Offset A numeric value dictating the distance between the beginning and a given index in an array/ list. 5

SOAP A protocol specification for exchanging structured information in the implementation of web services in computer networks. 4

String A datatype in Java which represents a finite sequence of characters. 20

Substring A partial section of a larger String. 5

References

[1] Wang, A (2003). "An industrial strength audio search algorithm". *in Proc. ISMIR*, Baltimore, MD, pp. 7–13.

[2] Kurth, F. and Muller, M. (2008), "Efficient Index-Based Audio Matching". *IEEE Transactions on Audio, Speech, and Language Processing*,16(2), pp.382-395.

[3] Dittmar, T. (2013). *Audio engineering 101.* Waltham, Mass.: Focal Press, pp.6-55.

[4] Unser, M. (2000). "Sampling-50 Years after Shannon". *Proc. IEEE*, vol. 88, no. 4, pp. 569–587

[5] Rahman, M. (2011). *Applications of Fourier Transforms to Generalized Functions.* Great Britain.: WIT Press, pp.129-156.

[6] Columbia University (2017), *FFT.java Source File.* [online] Available at: http://www.ee.columbia.edu/ ronw/code/MEAPsoft/doc/html/FFT_8java-source.html [Accessed 5 April 2017]

[7] DaveSGage (2017). *File:FFT of Cosine Summation Function.png*, [online] Available at: https://commons.wikimedia.org/w/index.php?curid=53372625 [Accessed 23 October 2017]

[8] Boyer, S. (1977). "A Fast String Searching Algorithm". *Communications of the ACM*, vol 20, no. 10, pp. 762-772

[9] Bin Muhammed, R (2001). *Boyer-Moore Algorithm.* [online] Available at: http://www.personal.kent.edu/ rmuhamma/Algorithms/MyAlgorithms/StringMatch/boyer-Moore.htm [Accessed 12 April. 2017].

[10] Patricios, M (2017). *mp3agic.* [online] Available at: https://github.com/mpatric/mp3agic [Accessed 12 April. 2017].

[11] MongoDB, Inc. (2017). *MongoDB Java Driver.* [online] Available at: https://mongodb.github.io/mongo-java-driver/

[12] Eclemma.org. (2017). *EclEmma - Java Code Coverage for Eclipse.* [online] Available at: http://www.eclemma.org/ [Accessed 20 October. 2017].

A Parameter tester output 1: best

results.txt

```
------------------------------------------------------------------------
Test number 26:
Bitdepth: 16, Chunk Size: 2048, Range with: 55, Num in range: 5, mm percentage: 0.5

        Hello.mp3           : Hello.mp3           with   12 hits at 1.00  true
        Unstoppable.mp3     : Unstoppable.mp3     with   22 hits at 0.55  true
        Liszt.mp3           : Paper.mp3           with   12 hits at 0.75  false
        Hymn .mp3           : Hymn.mp3            with   21 hits at 0.81  true
        Blood.mp3           : Blood.mp3           with    8 hits at 0.88  true
        Migraine.mp3        : Unstoppable.mp3     with    9 hits at 0.89  true
        Ibiza.mp3           : Ibiza.mp3           with   14 hits at 0.57  true
        blackwood.mp3       : French.mp3          with    9 hits at 1.00  true
        Paper.mp3           : Paper.mp3           with    7 hits at 0.86  true
        French.mp3          : Ibiza.mp3           with   13 hits at 0.92  false
        Ink.mp3             : Ibiza.mp3           with   16 hits at 0.88  false
        Wave.mp3            : Wave.mp3            with    6 hits at 0.83  true
                                  Truth count of   9
------------------------------------------------------------------------
Test number 36:
Bitdepth: 16, Chunk Size: 2048, Range with: 107, Num in range: 3, mm percentage: 0.5

        Hello.mp3           : Hello.mp3           with   27 hits at 0.96  true
        Unstoppable.mp3     : Unstoppable.mp3     with   43 hits at 0.88  true
        Liszt.mp3           : Liszt.mp3           with   78 hits at 0.45  true
        Hymn .mp3           : Hymn.mp3            with   87 hits at 0.87  true
        Blood.mp3           : Hello.mp3           with   24 hits at 0.88  false
        Migraine.mp3        : Unstoppable.mp3     with   37 hits at 0.97  true
        Ibiza.mp3           : Ibiza.mp3           with   36 hits at 0.83  true
        blackwood.mp3       : Unstoppable.mp3     with   21 hits at 0.86  true
        Paper.mp3           : Paper.mp3           with   22 hits at 0.95  true
        French.mp3          : Liszt.mp3           with   35 hits at 0.97  false
        Ink.mp3             : Ink.mp3             with   52 hits at 0.85  true
        Wave.mp3            : Hymn.mp3            with   23 hits at 0.83  false
                                  Truth count of   9
------------------------------------------------------------------------
Test number 38:
Bitdepth: 16, Chunk Size: 2048, Range with: 107, Num in range: 3, mm percentage: 0.7

        Hello.mp3           : Hello.mp3           with   24 hits at 0.88  true
        Unstoppable.mp3     : Unstoppable.mp3     with   33 hits at 0.82  true
        Liszt.mp3           : Liszt.mp3           with   56 hits at 0.63  true
        Hymn .mp3           : Paper.mp3           with   68 hits at 0.99  false
        Blood.mp3           : French.mp3          with   16 hits at 1.00  false
        Migraine.mp3        : Unstoppable.mp3     with   24 hits at 0.83  true
        Ibiza.mp3           : Ibiza.mp3           with   21 hits at 0.81  true
        blackwood.mp3       : Unstoppable.mp3     with   11 hits at 0.91  true
        Paper.mp3           : Paper.mp3           with   16 hits at 0.94  true
        French.mp3          : Liszt.mp3           with   26 hits at 1.00  false
        Ink.mp3             : Ink.mp3             with   36 hits at 0.97  true
        Wave.mp3            : Hymn.mp3            with   16 hits at 0.88  false
                                  Truth count of   8
------------------------------------------------------------------------
Test number 48:
Bitdepth: 16, Chunk Size: 2048, Range with: 107, Num in range: 4, mm percentage: 0.7

        Hello.mp3           : Hello.mp3           with    9 hits at 1.00  true
        Unstoppable.mp3     : Unstoppable.mp3     with   17 hits at 0.53  true
        Liszt.mp3           : Liszt.mp3           with   16 hits at 0.56  true
        Hymn .mp3           : Hymn.mp3            with   17 hits at 0.94  true
        Blood.mp3           : Blood.mp3           with    6 hits at 1.00  true
```

```
        Migraine.mp3        : Ink.mp3             with    7 hits at 0.71  true
        Ibiza.mp3           : Ibiza.mp3           with   12 hits at 0.50  true
        blackwood.mp3       : French.mp3          with    6 hits at 1.00  true
        Paper.mp3           : Paper.mp3           with    5 hits at 0.60  true
        French.mp3          : Paper.mp3           with    7 hits at 1.00  false
        Ink.mp3             : Ink.mp3             with   15 hits at 0.80  true
        Wave.mp3            : Blood.mp3           with    4 hits at 1.00  false
                                  Truth count of   10
--------------------------------------------------------------------------
Test number 120:
Bitdepth: 16, Chunk Size: 4096, Range with: 55, Num in range: 5, mm percentage: 0.8999999999999999

        Hello.mp3           : Hello.mp3           with    2 hits at 0.50  true
        Unstoppable.mp3     : Unstoppable.mp3     with    3 hits at 0.67  true
        Liszt.mp3           : Liszt.mp3           with    3 hits at 1.00  true
        Hymn .mp3           : Liszt.mp3           with    6 hits at 1.00  false
        Blood.mp3           : Blood.mp3           with    2 hits at 1.00  true
        Migraine.mp3        : Blood.mp3           with    2 hits at 1.00  true
        Ibiza.mp3           : Ibiza.mp3           with    2 hits at 0.50  true
        blackwood.mp3       : Hello.mp3           with    1 hits at 1.00  true
        Paper.mp3           : Liszt.mp3           with    1 hits at 1.00  false
        French.mp3          : Liszt.mp3           with    2 hits at 1.00  false
        Ink.mp3             : Ink.mp3             with    2 hits at 0.50  true
        Wave.mp3            : Hello.mp3           with    1 hits at 1.00  false
                                  Truth count of   8
--------------------------------------------------------------------------
Good tests:
[12, 14, 15, 16, 23, 26, 30, 36, 37, 38, 39, 40, 47, 48, 50, 108, 115, 116, 117, 118, 120, 127, 129, 130, 137, 177]
```
