

Real Time Tempo Analysis of Drum Beats

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Abstract

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Abbreviations

| | |
|-------------|--------------------------------|
| BPM | Beats Per Minute |
| DFT | Discrete Fourier Transform |
| DWT | Discrete Wavelet Transform |
| FFT | Fast Fourier Transform |
| JSON | JavaScript Object Notification |
| SBT | Simple Build Tool |
| TDD | Test Driven Development |

Definitions

| | |
|----------------------------|--|
| Acoustic Drum Kit | A collection of drums and cymbals which do not have electronic amplification. Typically made up of a bass drum, snare drum, tom-toms, hi-hat and 1 or more cymbals. |
| Beat | For the purpose of this project a beat is defined as the sequence of equally spaced pulses used to calculate the tempo being played by the drummer. |
| Drum Module | The device which serves as a central processing unit for an electronic drum kit, responsible for producing the sounds of the drum kit. |
| Electronic Drum Kit | An electrical device which is played like an acoustic drum kit, producing sounds from a stored library of instruments and samples. |
| MIDI | Musical Instrument Digital Interface is a protocol developed in the 1980's to allow electronic instruments and other digital musical tools to communicate with each other [1]. |
| Tempo | The speed at which a piece of music is played [2] and counted in beats per minute (bpm). |

1 Introduction and Background

This project report details the aim to develop a real-time drum beat tempo analysis system using different beat detection algorithms which is able to record the performance of each method when an extensive set of drum samples, representing a real drummer's performance, is processed through the system.

1.1 Drumming Training Tools Background

Timing is the fundamental skill any good drummer should possess and is the staple by which they are judged. For many years the only training tool available to a drummer to improve their timing was the metronome, which is an instrument used to mark musical tempo. The metronome was erroneously attributed to Johann Nepomuk Maelzel in 1815 but was invented by a Dutchman, Dietrich Nikolaus Winkel a year earlier. The traditional metronome, based on Winkel's original design is a hand-wound clockwork instrument that uses a pendulum swung on a pivot to generate the ticking which depicts the desired tempo [3] is still used today by musicians, as seen in Figure 1.



Figure 1: Traditional Metronome

For drummers however the electronic versions of the metronome are much more widely used, to the point that metronomes are now developed with functions specifically tailored to a drummers training requirements. The Tama Rhythm Watch (Figure 2) was the first metronome designed specifically for drummers, providing enough volume to be used with real drums as well as allowing for the use of different time signatures¹ and preset set rhythm patterns to help improve performance.

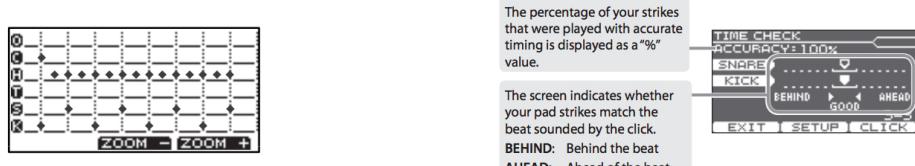
Following the development of the MIDI driven electronic drum kit came the development of more advanced training tools that were able to provide live feedback to drummer during any given performance. Today the leaders in this field are Roland. Their V-Drums line provide a variety of tuition packages including the SCOPE and more recently the COACH system

¹A details explanation of time signatures can be found in section 1.2.2



Figure 2: Tama Rhythm Watch

provided in the drum modules. The SCOPE system provides live feedback to the drummer by plotting their performance on a grid representing the elements of the drum kit, Figure 3a. The COACH system offers an improved user experience by providing an accuracy figure relating to the number of hits that the drummer has played in time, Figure 3b.



(a) Screen shot of the SCOPE system

(b) Screen shot of the COACH system

Figure 3: SCOPE and COACH training tools

The Roland catalogue also includes the DT-1 tutor software package, which provides drummers with an interactive experience helping to improve their rhythm, coordination and sight reading (Figure 4). Roland have even started to design games within this field, their latest release, the V-Drums Friend Jam app. The application itself provides the player with live feedback and evaluates each performance to provide the player with a score which they can share over social media. See Figure 5 for a screen shot of the Friend Jam App.

Despite these developments there have been a limited number of tools available to be used with acoustic drums. A look at the the App Store² and Google Play³, reveals a small number of general live bpm detectors an no applications which are focused towards a drummers training needs.

²Apple's application store - itunes.apple.com/uk/appstore

³Google's application store for Android devices - play.google.com/store

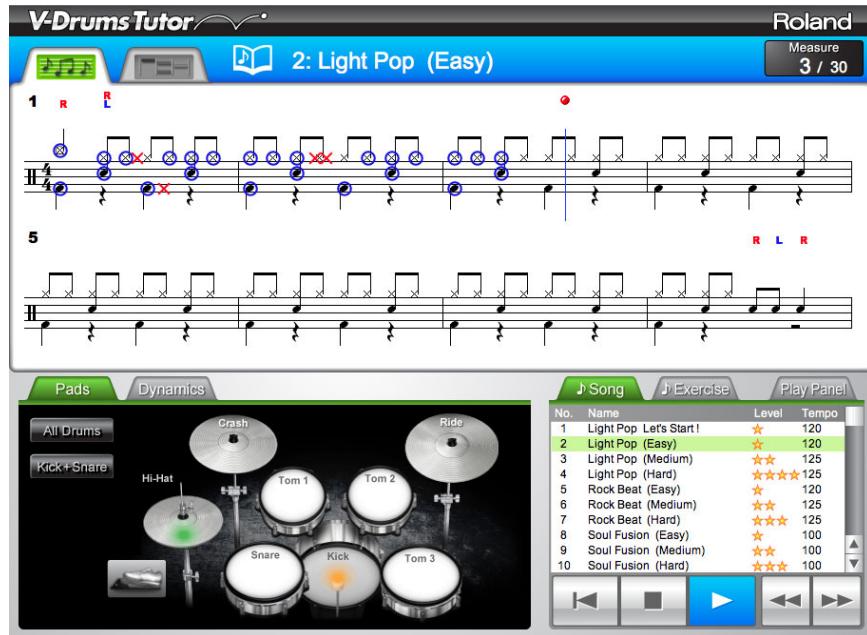


Figure 4: Screen shot of the DT-1 V-Drums Tutor

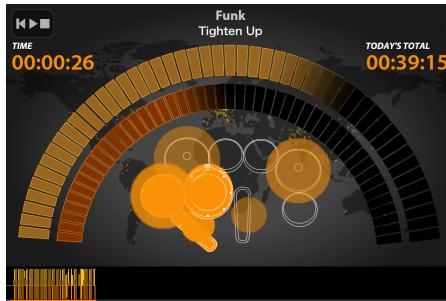


Figure 5: Example of the Roland Friend Jam software package

1.2 Drum Musical Theory

In order to understand the fundamentals of musical timing some theory needs to be examined but beforehand the concept of a drummer playing time must be considered. Time, in a drumming sense is an informal term used to describe the consistent rhythmic pattern that a drummer will play on the hi-hat or ride cymbal [4] and it can be considered one of the most important components of any drum beat.

1.2.1 Notation

Drum music notation is written on staff, which is made up of five individual lines (Figure 6). The clef found on the far left of the staff indicates the pitch of the notes [2] and as percussion



Figure 6: Example of a staff used in musical notation

instruments are non-pitched they use the percussion-clef. On traditional musical notation, the lines and spaces between them represent a tone to be played. However, as drums are not considered tonal, the notes written on lines or spaces indicate a certain drum or cymbal. The staff is separated into individual measures which are known as bars [5] and it is these bars that are the basis of musical time. A bar of drum music typically consists of different notes representing which instruments to be played and when. The number of notes within a bar may also vary depending on their length.

1.2.2 Notes

The notes used in drum notation not only represent the percussive instrument to be played but also the duration it should be played for. Notes come in different lengths and the key values are the whole (1/1), half (1/2), quarter (1/4), eighth (1/8) and sixteenth (1/16). For example two eighth notes represent the same time value as a single quarter note. It is also possible to divide note values by three instead of two, these notes are known as triplets. An eighth note triplet is played fifty percent faster than a normal eighth note, therefore for every two eighth notes there are three eighth note triplets [5]. An example of the eighth-note triplets being used is in a twelve eight (12/8) jazz shuffle, the time element played on the ride cymbal or hi-hat is characterised by playing the first and third triplet of an eighth-note triplet grouping [4].

For the purpose of this project it is the count of these beats that are used to calculate the tempo of a certain drum beat.

add figure?

1.2.3 Time Signatures

Time signatures appear on the staff just after the clef and are written as a fraction where the top number indicates the number of beats that there are in a bar, as seen in Figure 6. With the bottom number representing the size of the note that makes up the duration of one beat. For example the straight time four four (4/4) or common time signature indicates four beats in each bar or measure where each beat is made up of one quarter note [5]. Within these

bar lines beats can be further divided by using a technique known as subdivision, which is a method for reducing the pulse or rhythm pattern into smaller parts than those originally written, for example counting a four four (4/4) measure in eighth (1/8) or sixteenth (1/16) notes.

1.2.4 Playing Basics

With the basics of drum theory covered it is now possible to discuss the key elements of a drum beat, typically for a straight four four (4/4) beat, the bass drum is played on the first and third beat and the snare drum is played on the second and fourth beat both as quarter notes. This is more commonly known as a back beat [4]. This just leaves the time element which will usually be played on the ride cymbal or hi-hat, this too could be played using quarter notes on the first, second, third and forth beats. However, in order to make the drum pattern more dynamic the time element will usually be played using subdivisions, typically using eighth note subdivisions. The ride cymbal or hi-hat will therefore be played on the first, second, third and forth beats as well as the eighth notes in-between each quarter note. This can be demonstrated by counting the one-and-two-and-three-and-four-and, where the “and” represents the subdivided eighth note. Playing time on the “and” note is also known as playing on the off beat. Additionally to this technique a drummer will usually ensure that there is difference in the volume of the eighth notes being played on the quarter notes and those being played on the “and”. This technique of emphasising certain beats is known as accenting.

1.3 Beat Detection Background

Most of the early work on beat detection was a by-product of research directed at other areas of musical understanding. Some of the first work in this field can be attributed to H. C. Longuet-Higgins. Who in 1976 while studying the psychological theory of how Western musicians perceive rhythmic and tonal relationships between musical notes, produced an algorithm capable of following the beat of a performance and adjust the perceived tempo accordingly[6]. Longuet-Higgins’ work was built on the premise that in order to perceive the rhythmic structure of a melody it is first necessary to identify the time at which each beat occurs [7], otherwise known as onset detection. The onset of a note is the instant which marks the start of the variation in the frequency of a signal, a visualisation of this can be seen in Figure 7. Once detected it can then be used to measure the onset times of sonic events⁴ within a piece of music [11]. These onset times are then used within a beat detection algorithm in order to calculate a piece of music’s tempo.

⁴A sonic event is a singular feature of a piece of music which can be made up of one source or many [12], e.g. the hitting of a drum

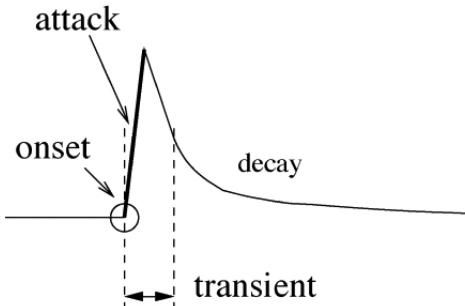


Figure 7: The onset of a note is the instant which marks start of the variation in the frequency of a signal (Image Source: [13])

Since Longuet-Higgins' first work the area of beat detection has expanded rapidly, in 2005 the first annual Music Information Retrieval Evaluation eXchange (MIREX) was held in 2005. MIREX includes a contest with the goal of comparing state-of-the-art algorithms for music information retrieval [14]. The topics to be evaluated are proposed by the participants. In the first year, three of the nine topics concerned beat detection, including audio onset detection and since it's first inclusion it has been an evaluated topic of all but one of the last twelve contests [11]. The beat detection algorithms proposed to perform the tempo analysis for this project, the Beatroot system developed by Simon Dixon [8] and a development on the original audio analysis using the Discrete Wavelet Transform (DWT) by Tzanetakis, Essel and Cook [15]. Are both former entrants to the MIREX contest, with the Beatroot system receiving the highest score in the 2006 Audio Beat Tracking task [16]

1.4 Project Aims

The primary aim of this project is to investigation whether some of the currently available beat detection algorithms are accurate enough to form the basis for a training tool to be used by drummers practicing on an acoustic drum kit. In order to achieve this the developed software package, hereafter referred to as RTT_Analyser⁵, will need to process enough live audio in form of sampled drum beats and record each of the chosen beat detection algorithms accuracy.

The original core features of the RTT_Analyser developed for this project are:

1. A live audio tempo analysis tool, that compares and records the performance of selected beat detection algorithms
2. The RTT_Analyser implements an adapted version of the beat tracking system Beatroot and Discrete Wavelet Transform algorithm described by Tzanetakis *et al*'s [15] which process live audio as opposed to originally designed off-line audio files.

⁵Where RTT stands for Real Time Tempo

3. RTT_Analyser implements a system capable of parallel processing, allowing for the same captured live audio data to be sent to the chosen beat detection algorithms in order for the tempo to be calculated simultaneously.
4. While processing live audio the RTT_Analyser stores a predetermined data set in order to allow for performance analysis of the beat detection algorithms.
5. The RTT_Analyser will provide the user with real time feedback of the most recent tempo calculation returned
6. An extensive sample set of drum beats will need to be created to ensure the system is tested sufficiently

2 RTT_Analyser Beat Detection Algorithms

The original proposed solution incorporated two beat detection algorithms, Beatroot system [8] and the DWT method [15]. However, the adaptation of the Beatroot system to be used with live audio took longer than the proposed time-frame. This meant that an alternative system needed to be found in order to mitigate this issue, conveniently the Beatroot software package also contained another beat detection system, the Performance Worm [10]. In order to ensure the project remained on track it was decided to substitute the Performance Worm for the Beatroot system. The intention was, if time allowed, to resume the adaptation of the Beatroot system to work with live audio once the project was ahead of schedule and this was successfully completed prior to the development of the user interface.

The project report will now discuss the beat detection algorithms incorporated in the RTT_Analyser as well as the system used to allow for simultaneous tempo calculation.

2.1 Beatroot

Beatroot is a beat detection software package created by Simon Dixon [8], designed to extract musical expression information from musical recordings [10]. The algorithm designed by Simon Dixon is ideal for the RTT_Analyser as it is considered to be sufficiently fast enough to be implemented as part of a real-time system [17].

Beatroot is comprised of two major components, the tempo induction and the beat tracking subsystems. Before tempo induction can take place, first a list of onsets needs to be retrieved[17]. This is achieved by obtaining a time-frequency representation with a Short Time Fourier Transform (STFT). The STFT is based on the Discrete Fourier Transform (DFT), which can be used to determine how much of a frequency exists within a signal. However, the DFT is unable to provide any details of when a frequency component occurs

in time for non-stationary signals⁶. A solution to this is to split a non-stationary signal into a number of smaller segments using a window function, which effectively creates a series of stationary⁷ signals which the DFT can then be applied to. By splitting the signal into smaller segments the STFT is able to apply the DFT to these segments and essentially express a signal as a linear combination of elementary signals that are easily manipulated. The DFT returns a spectrum that contains information about how the energy held within the signal is distributed in the time and frequency domains [20].

The window function used by Beatroot within the STFT is the Hamming window, which can help to reduce the amount of additional frequencies appearing in the returned DFT spectrum, known as spectral leakage. This is caused when the steep slope of a rectangular window (Figure 8a) causes the frequencies to become distorted. The Hamming window counteracts this by using a bell shape, which reduces the amplitudes of its sidelobes [19] and ensures the spectrum returned is less spread out and closer to the ideal theoretical result [20]. A visualisation of a Hamming window can be seen in Figure 8b.



Figure 8: (Image Source: [19])

Beatroot uses the STFT as follows:

$$X(n, k) = \sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} x(hn + m) w(m) e^{-\frac{2jmk}{N}} \quad (1)$$

Where a Hamming window $w(m)$ is calculated at a frame rate of 100 Hz, N is the size of the window, n represents the frame number being processed, k is the index of frequency-domain component, and h is the hop-size or number of samples between the start times of adjacent frames.

The spectral flux function is then used as a method for measuring the change in magnitude of each returned frequency-domain sample [9] and is provided by:

⁶Non-stationary signals are signals whose frequency contents changes over time [18]

⁷The frequency contents of a stationary signal does not change over time

$$SF(n) = \sum_{k=-\frac{N}{2}}^{\frac{N}{2}-1} H(|X(n, k)| - |X(n - 1, k)|) \quad (2)$$

Where SF is the spectral flux and H is the half-wave rectifier function given by the $H = \frac{x+|x|}{2}$, which is used to remove any negative values representing a falling signal. An example of the peaks returned by a spectral flux function can be seen in Figure 9.

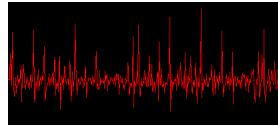


Figure 9: (Image Source: [57])

The onsets detected are then selected by a peak-picking algorithm which finds local maxima within the detection function. The tempo induction algorithm is then used to compute clusters of inter-onset intervals (IOI) by using the calculated onset times. Each cluster represents a hypothetical tempo, in seconds per beat [8]. The clustering algorithm works by assigning an IOI to a cluster if its difference from the cluster is less than 25ms. The cluster information is then combined by recognising the approximate integer relationships between clusters. An example of this can be seen in Figure 10 where cluster C2 is twice as long as C1 and C4 is twice that of C2. This information along with the number of IOIs within a cluster is then used to weight each cluster which is then returned as a ranked list of tempo hypotheses [17].

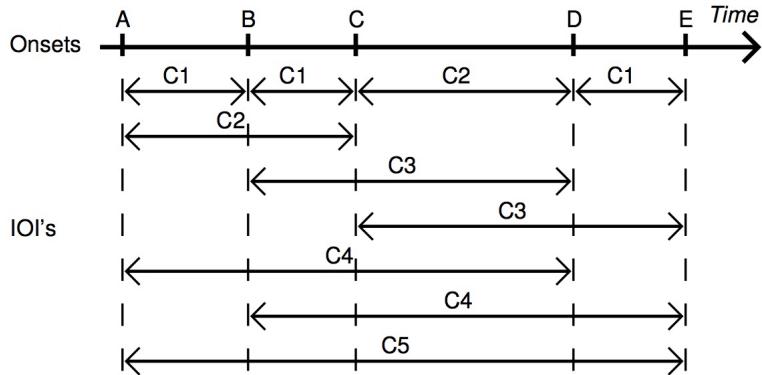


Figure 10: (Image Source: [17])

The multiple agent architecture of Beatroot's beat tracking subsystem is then employed to find the sequences of events that closest match the original tempo hypotheses, each of these sequences are rated and the most likely set of beat times is determined. Each of the agents

are initialised with a tempo or beat rate hypothesis and an onset time. Further beats are then predicted by the agent based on these parameters. Any onsets corresponding with the predicted beat times are taken as a beat time, those falling outside are not considered to be a beat time, although the possibility that the onset is not on the beat is considered. The agents then rate themselves based on how evenly spaced the beat times are, the number of predicted beats which relate to actual events, and the salience⁸ of the matched onsets. The agent with the highest score is then returned as the sequence of beats corresponding to the processed audio [17], which is then used to determine the overall tempo of the audio by using the “inter-beat intervals, measured in beats per second” [8] to calculate beats per minute (bpm) of the audio.

2.2 Discrete Wavelet Transform and Beat Detection Method

The first literature about wavelets was provided by the mathematician Albert Haar in 1909 [18]. The wavelet transform is a technique for analysing signals which was developed as an alternative to the STFT [15]. Like the STFT, the DWT is able to provide time and frequency information, however, unlike the STFT the DWT is able to do this without the need for a window function. The DWT can essentially be considered to be a filter-bank, where a filter-bank is a system used to separate sub-bands by using an array or bank of filters. Where each of the filters corresponds to half frequency range of the closest centre higher frequency. Thus each filter will have half or twice the bandwidth of any of its adjacent filters.

In 2001, Tzanetakis *et al* described how the Discrete Wavelet Transform (DWT) could be used to extract information from non-speech audio [15]. Their beat detection algorithm was based on the detecting the most prominent signals which are repeated over a period of time within the analysed audio. The first stage is to split the signal into a number of octave⁹ frequency bands with the DWT. This allows for the time domain amplitude envelopes of each frequency band to be extracted separately. The extraction of these envelopes is completed in the following three steps:

1. Full Wave Rectification - process of converting the amplitude of each frequency band to one polarity [23], which can be either positive or negative. A visual representation can be seen in Figure 11.
2. Low Pass Filtering - Low pass filtering is a signal processing technique which is designed to allow frequencies below a cutoff frequency through but blocks any frequencies above the cutoff frequency [22].

⁸The salience is a measure of the note duration, density, pitch and density [8], which is calculated from the spectral flux of the onset [17]

⁹Acoustically, an octave above a note is the note which has twice the frequency of the original [2].

3. Down-sampling - Due to the large periodicities that can occur in beat analysis, down-sampling the signal reduces the computation time of the autocorrelation stage without causing any negative effects on the performance or the algorithm [21]

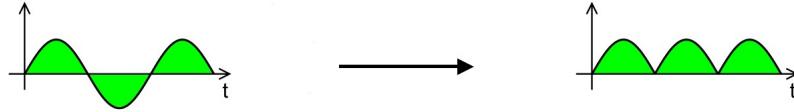


Figure 11: Visual representation of Full Wave Rectification (diagram adapted from <https://en.wikipedia.org/wiki/Rectifier>)

After these steps each frequency band is normalised through a method of mean removal in order to ensure the signal is centred at zero for the autocorrelation stage. The autocorrelation function is then applied to each frequency band and its peaks correspond to the various periodicities of that signal's envelope. The first five peaks of the function and their corresponding periodicities are then calculated in beats per minute and added to a histogram, this process is repeated while iterating over the signal. The estimated tempo of the audio signal is then retrieved from the periodicity that corresponds to the highest peak within the histogram [15]. The DWT beat histogram flow diagram can be seen in Figure 12.

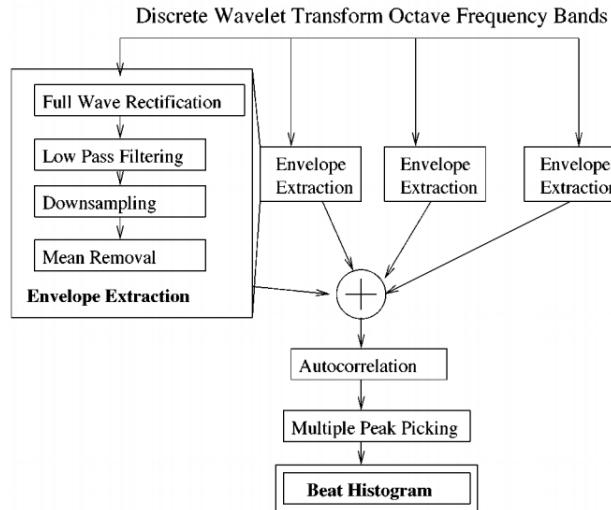


Figure 12: Flow diagram of the beat histogram method described by Tzanetakis *et al* [21]

Originally, it was intended that Discrete Wavelet Transform beat detection component of the RTT_Analyser would be implemented by the author. It was recognised in the project proposal that this could result in the rest of the project being delayed and with the alternative solution being to adapt the Matlab implementation of the Tzanetakis *et al* [15] algorithm by Eng Eder de Souza [32]. Due to the time spent in investigating how to adapt

the Beatroot system to work with live audio a different solution was needed, this was provided by the Scala implementation by Marco Ziccardi [33].

2.3 Performance Worm

The final beat detection algorithm employed in the RTT-Analyser is the Performance Worm (PW) system, designed by Simon Dixon, Werner Goebel and Gerhard Widmer [24]. The PW is based on a real time algorithm which is able to determine the tempo of the input raw audio, while keeping track of other possible tempo hypotheses that are rated and updated dynamically. Allowing for the most recently highest ranked tempo hypothesis to be returned to the user [24].

First the PW processes the raw audio which can either be extracted from a static recording or directly from a live input with a smoothing filter¹⁰ in order to obtain the RMS amplitude¹¹ of the signal taken from a 40ms window. The note onsets are then calculated by the event detection module that finds the slope of the smoothed amplitude and then calculates the set of local peaks which are taken as the note onset times [24].

The signal is then processed by the multiple tempo tracking subsystem which uses a similar approach to the Beatroot system. A clustering algorithm (Figure 13), first calculates the time intervals (inter-onset intervals or IOIs) between the pairs of onsets, which it holds in memory (approximately five seconds of audio). The intervals are then weighted by the mean of the amplitudes and each interval's IOIs are clustered using the best-first part of Figure 13 is then applied in order to determine the significant clusters of IOIs, which are subsequently assumed to be the musical units held within the signal. The clustering algorithm keeps 5 seconds of onset times within memory and begins processing by determining all IOIs between the onsets in memory

As in the Beatroot system, these clusters are then used as the bases of the tempo hypotheses produced by the tempo tracking subsystem. While running, t. The tempo inducer then exploits a property of most Western music where time intervals are related by small approximate integer ratios. As the times held by the clusters can be considered to represent related notes, e.g. quarter and eighth notes. The tempo inducer then adjusts cluster times and weightings according to the information held by the sets of related clusters. Two clusters are considered to be related if the ratio of their time intervals is close to an integer. The highest weighted clusters and their respective tempo hypothesis is then returned as the tempo output [24].

¹⁰Process which attempts to reduce any noise found within a signal. A smoothing filter does this by reducing any points in the signal that are higher than adjacent points and reducing those points that are lower than adjacent point [46]

¹¹RMS stands for root mean square and is the process of squaring all of the amplitude values, then taking the average (mean) of the squared values, and then calculating the square root of the average value [47].

Inter-onset interval calculation

For each new onset

- For IOI times t from 100ms to 2500ms in 10ms steps
 - Find pairs of onsets which are t apart
 - Sum the mean amplitude of these onset pairs

Best-first algorithm

Loop until all IOI time points are used

- For times t from 100ms to 2500ms in 10ms steps
 - Calculate window size s as function of t
 - Find average amplitude of IOIs in window $[t, t + s]$
 - Store t which gives maximum average amplitude
- Create a cluster containing the stored maximum window
- Mark the IOIs in the cluster as used

Cluster Combining

For each cluster

- Find related clusters (multiples or divisors)
- Combine related clusters using weighted average
- Match combined clusters to tempo hypotheses and update

Figure 13: Clustering algorithm used in the Performance Worm Multiple Tempo Tracking Subsystem [24]

3 Solution Design and Architecture

The basic premise for the RTT_Analyser is to enable the user to play a live drum beat through the system and the tempo of the live audio is returned to user as well as being stored for future analysis. Initially, the RTT_Analyser opens the inbuilt microphone of the device upon which the software is being run. After establishing the live audio stream the RTT_Analyser beat detection algorithms are sent the live audio data in the format of a byte array. These live audio bytes are then decoded according to the individual algorithm's requirements before being processed and the tempo calculated. A general schematic of the work-flow of the RTT_Analyser can be seen in Figure (add in).

3.1 Live Audio Processing

The live audio is processed using the Java Sound API, which contains two key types; mixers and lines. Mixers are a representation of the audio devices available on a certain system and a line is an element of the digital audio pipeline responsible for moving audio in and out of the system. Typically, audio capture is started or stopped using a TargetDataLine that provides a path to the systems audio input device, access to this device is provided by the AudioSystem class, which acts a clearing house for audio components. In order to ensure the bytes of audio data passed through the TargetDataLine are interpreted correctly the AudioFormat object enables the audio format to be defined with by the list attributes below [31], which includes the values chosen to ensure that the audio capture by the RTT_Analyser is comparable to CD quality:

- Encoding - Set to “PCM.signed”, representing audio encoded to the native linear pulse code modulation, where pulse code modulation is the process of sampling and quantising the signal into discrete symbols for transmissions [25].
- Sample Rate - 44,100, set to match CD quality for the number of analog samples which are analysed per second.
- Sample Size in Bits - 24, based on a sound card with a 24 bit sample depth.
- Channels - 2, audio is captured using the built in microphone, typically stereo of the device the RTT_Analyser is being run on.
- Frame Size - 6, where the frame size is the number of bytes in a sample multiplied by the number of channels [17].
- Frame Rate - 44,100, same as sample rate.
- Big Endian (boolean) - false, as the machine used to develop the RTT_Analyser has Intel cores, which use a little-endian architecture¹².

¹²Endianess refers to the order of bytes which make up a digital word. Big endianess stores the most

In order to process the captured bytes the RTT Analyser then required the use of a concurrent system to allow for each of the three beat detection algorithms to be run in parallel, which was provided by the Akka Actors system.

3.2 Akka Actors

The Akka Actor Model is specifically designed to provide the ability to write concurrent systems with a high level of abstraction that alleviates the developer from the need to handle locking and individual thread management. Therefore, making it much easier to write concurrent and parallel systems when compared to the traditional approaches used in Java [27].

A fundamental construct of the Akka Actor system is that it strictly adheres too the Reactive Manifesto, which aims to ensure applications built under this are easier to develop and are amenable to change, allowing for a higher level of tolerance to failure and the ability to meet any such failure elegantly as opposed to disaster [28]. The Reactive Manifesto requires applications to satisfy one or more of the requirements listed below [28] and visualisation of how they interact can be seen in Figure 14.

Responsive - The system responds in a timely manner, if possible. By providing usability and utility responsiveness allows for any problems to be detected and resolved effectively.

Resilient - The system should be able to remain responsive even in the event of a failure, which applies to all parts of the system not just the mission critical components. To achieve this each component needs to be isolated within the system, therefore allowing failed parts of the system to recover without effecting the responsiveness of the system as a whole.

Elastic - The system will be able to maintain the same level of responsiveness despite varying workloads, reacting to changes in the rate of input by adapting the levels of resources allocated to service these inputs accordingly.

Message Driven - Reactive systems rely on the use of asynchronous message passing in order to establish boundaries between components within the system, ensuring isolation, loose coupling¹³ and location transparency¹⁴. By utilising a non-blocking¹⁵ message-passing it is possible to ensure message recipients only consume resources when active, leading to a

significant byte at a certain memory address and the remaining bytes being stored in the following higher memory addresses. The little-endian formate reverses the order storing the least significant at the lowest and most significant at the highest memory address [51].

¹³Loose coupling is a design approach of distributed systems which emphasises agility and ability to adapt to changes [48]

¹⁴The decoupling of the runtime instances from their references [28]

¹⁵In concurrent programming algorithms which do not have their execution indefinitely postponed when competing for a resource is said to be non-blocking [28].

much reduced system overhead.

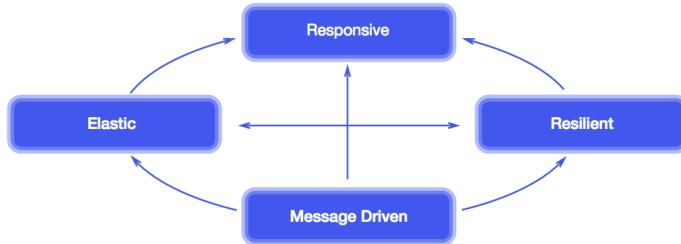


Figure 14: Visualisation of the requirements of the Reactive Manifesto interact [28]

3.2.1 The Actors

The actors within the actor model are objects which are used to encapsulate state and behaviour. They communicate exclusively through messages passed to a recipients mailbox and it can help to think of them as group of people being assigned subtasks within an organisational structure. One of the key features of an actor system is that tasks are split up and delegated until they become small enough to be handled in one piece. This process not only ensures that the tasks being carried out by the actors are clearly defined but also the actors themselves can be designed in terms of the messages they are able to receive and how they should react to these messages and any failures that might occur. The actors within a system will naturally form a set hierarchy. For example, an actor system where an actor assigned the task of overseeing a certain function might split this function into a number of smaller tasks which it assigns to some child actors that it supervises until the task is complete [29]. The actors created within the RTT_Analyser were a mix of stand alone actors and actors which were required to supervise subtasks carried out by child actors.

3.3 Design Pattern

The RTT_Analyser was developed using the Model View Controller (MVC) design pattern, as the MVC pattern is the tried-and-tested approach when designing applications with a graphical user interface [50]. The MVC pattern is made up of the following components and a visualisation of the MVC can be seen in Figure 15.

- **Model** - is represented by the data and associated applications [50], within the RTT_Analyser the model is provided by the beat detection algorithms, the live audio

capturing and processing components.

- **View** - is the graphical interface displayed to the user which updates itself automatically [50]. For the RTT_Analyser the view is represented by the user interface
- **Controller** - is the part of the application that responds to the user interactions, liaising with both the model and the view components[50]. The controller for the RTT_Analyser is the actor system, which is responsible for message passing between the model and view components.

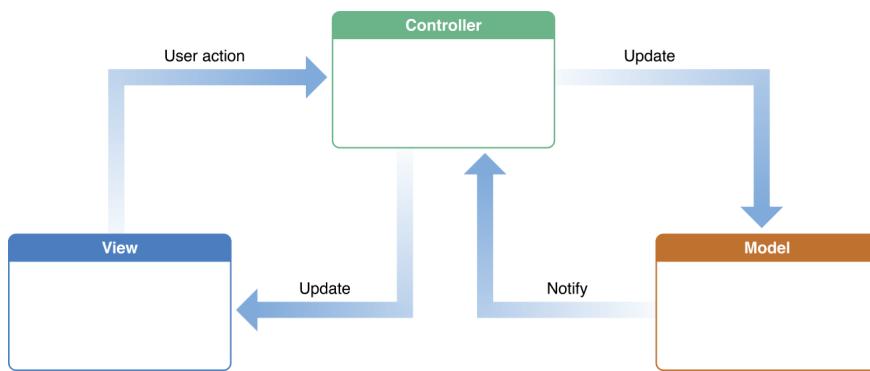


Figure 15: The three components which make up Model View Controller design pattern [49]

A high level class diagram of the final version of RTT_Analyser can be seen in Figure 16

4 Implementation

The RTT_Analyser is written in Java and Scala, due to the Beatroot and Performance Worm both being written in Java, and the author's familiarity with both languages. Using Scala also ensured the twin constructs of pattern matching and case classes were able to be utilised where appropriate. Pattern matching is used to implement type switches and is considered to create “code that is both succinct and obviously correct” [35]. Case classes are Scala’s way of allowing pattern matching to be performed on objects without the need for additional boilerplate code. Using Scala, also allows for more elegant and concise tail recursive¹⁶ solutions to be developed over loop-based solutions. As the Scala compiler

¹⁶A recursive solution is considered to be tail recursive if the last operation carried out is to calculate the return value, it has the advantage over recursive calls of not building a stack trace and instead performing each operation in a single stack frame [36]

Figure 16: Image to be added

```

sealed trait Messages
case class StartLiveAudio(expectedBPM: Double, processingActor: ActorRef, filePath: String, startTime: Long) extends Messages
case class EndLiveAudio(processingActor: ActorRef) extends Messages
case class ProcessBytes(data: Array[Byte]) extends Messages
case class NewTempoWorm(tempo: Double, currentTime: Long) extends Messages
case class NewTempoDwt(tempo: Double, currentTime: Long) extends Messages
case class NewTempoBeatroot(tempo: Double, beatCount: Double, currentTime: Long) extends Messages
case class WriteData() extends Messages
case class SendInputs(bpm: Double, filePath: String, startTime: Long) extends Messages
case class SendBeatRoot(data: Array[Byte], processingActor: ActorRef) extends Messages
case class SendDwt(data: Array[Byte], processingActor: ActorRef) extends Messages
case class Close() extends Messages
case class StartTestTimer(processingActor: ActorRef, liveAudioActor: ActorRef) extends Messages
case class Reset() extends Messages

```

Figure 17: The message case classes used by the RTT_Analyser’s actor system

provides an optimiser which ensures that there are not any runtime overheads to be paid for employing tail recursion [36].

The RTT_Analyser was developed in the Scala specific build tool, sbt (simple build too), a build tool that creates a stable build platform increasing productivity by utilising some good ideas from other build tools like, minimal configuration and built-in tasks including test, compile and publish. It is also able to support a reactive development environment that is able to re-run all tests when source code is updated [30]. In terms of this project sbt was chosen as it supports mixed Scala/Java projects. Allowing for the Beatroot and Performance Worm systems written in Java to be easily incorporated with the Scala implementation of the Discrete Wavelet Transform and the Akka Actor system.

4.1 The Actor System

Although the actors were not the first element of the RTT_Analysert to be implemented, introducing them first helps to provide some context for the how the other components communicate. The actor system is constructed of five different actors in total and the messages permitted to be passed between the RTT_Analyser’s actors were all implemented as case classes within a sealed trait (Figure 17). Using a sealed trait ensures that the only classes extending the trait are in the same file which is very useful for pattern matching[36]. Therefore, working well with the actor’s receive method which works on pattern matching.

The LiveAudioActor (Figure 18) assumes the role of the overseer of the system, being responsible for starting and stopping the live audio capture, as well as the termination of the RTT_Analyser when appropriate.

The ProcessingActor (Figure 19), a child of the LiveAudioActor can be considered the coordinator of the storing and processing captured audio data, and the writing of the calculated tempos. In order to ensure the processing remains as isolated as possible the ProcessingActor employs two worker actors, BeatrootActor and DWTActor, carrying out the two tasks of sending the captured data and tempo calculation. The beat detection

```

class LiveAudioActor extends Actor with ActorLogging{

    val w: Worm = new Worm()

    def receive = {
        case StartLiveAudio(expectedBPM, processingActor, filePath, startTime) =>
            w.setActor(processingActor)
            w.play()
            processingActor ! SendInputs(expectedBPM, filePath, startTime)
        case EndLiveAudio(processingActor) =>
            w.stop()
            Thread.sleep(2000)//allow for any processing to finish
            processingActor ! WriteData
        case Close =>
            context.system.terminate()
            System.exit(0)
        case _ =>
            println("Error")
    }
}

```

Figure 18: LiveAudioActor class

worker actors do not return any messages to the ProcessingActor, instead the immutable ActorRef handle which allows for the current instance of the respective actor is passed the respective beat detection system. Therefore, the calculated tempo values are then sent back directly to the ProcessingActor to be stored and subsequently saved to file when appropriate.

The final RTT_Analyser actor was a standalone actor on the same level as the LiveAudioActor within the actor hierarchy which was responsible for the timing of the beat detection test.

All of the RTT_Analyser's parent and child actors were all instantiated in the self contained Operator object (Figure 20. This ensured that potentially dangerous practice of declaring one actor and breaking actor encapsulation [27] was avoided.

4.2 Live Audio Capture

To implement the RTT_Analyser's live audio capture with the Java Sound API initially, the SoundCaptureImpl class was created in Java and then converted to Scala to be responsible for the live audio capture and holding of the raw audio in a ByteArrayOutputStream before being passed for processing by the beat detection algorithms. The sound capturing components of this class were based on those described in the Java Sound Programmer Guide [31] and consisted of the code in Figure 21.

The audio format described in section 3.1 is then applied to the TargetDataLine, which provides access to the built in microphone of the device, if available. The TargetDataLine class is then attached to an instance of the Java AudioInputStream class which converts the captured audio into a stream of bytes for processing [26].

```

def receive = {
    case SendInputs(bpm, filePath, startTime) =>
        expectedBpm(bpm)
        path(filePath)
        timeAtStart(startTime)
    case ProcessBytes(data) =>
        beatrootWorker ! SendBeatRoot(data, self)
        dwtWorker ! SendDwt(data, self)
    case NewTempoDwt(tempo, currentTime) =>
        val t = Tempo(tempo, expectedBpm, None, currentTime - timeAtStart)
        gui.updateDwt(tempo)
        dwtStatsBuffer += t
        dwtAnalyser.addTempo(t)
    case NewTempoWorm(tempo, currentTime) =>
        val t = Tempo(tempo, expectedBpm, None, currentTime - timeAtStart)
        if (count == 5) {
            gui.updateWorm(tempo)//worm element of gui updated 5 time a second
            count = 0
        }
        count = count + 1
        wormStatsBuffer += t
        wormAnalyser.addTempo(t)
    case NewTempoBeatroot(tempo, beatCount, currentTime) =>
        val t = Tempo(tempo, expectedBpm, Some(beatCount), currentTime - timeAtStart)
        gui.updateBrtempo(beatCount)
        beatStatsBpmBuffer += t
        beatrootAnalyser.addTempo(t)
    case WriteData =>
        addStats()
        jsonParser.writeAll(wormAnalyser, dwtAnalyser, beatrootAnalyser)
        jsonParser.flushFull(path + "full.json")
        htmlWriter.writeHtml(List(wormAnalyser, dwtAnalyser, beatrootAnalyser))
        htmlWriter.flush(path + "stats.html")
}

```

Figure 19: Recieve method of the ProcessingActor class

```

val system = ActorSystem("liveAudioSystem")
val liveAudioActor = system.actorOf(Props[LiveAudioActor], "liveAudioActor")
val beatrootActor = system.actorOf(Props[BeatrootActor], "beatrootActor")
val dwtActor = system.actorOf(Props[DwtActor], "dwtActor")
val processingActor = system.actorOf(Props(new ProcessingActor(beatrootActor, dwtActor)))
val guiActor = system.actorOf(Props[GUIActor], "guiActor")

```

Figure 20: Declaring of the RTT_Analyser's actors

```

def startCapture: Int = {
  try {
    input = AudioSystem.getTargetDataLine(inputFormat)
    val info: DataLine.Info = new DataLine.Info(classOf[TargetDataLine], inputFormat)
    input = AudioSystem.getLine(info).asInstanceOf[TargetDataLine]
    input.open(inputFormat)
    outputStream = new ByteArrayOutputStream
    input.start()
  }
}

```

Figure 21: Example of the basis of live audio capture method in Scala

The need for the code in Figure 21 however became defunct with the design decision to include the Performance Worm system within the RTT_Analyser as the Performance Worm was already set up to capture live audio. Therefore the captured audio now needed to be stored by the Performance Worm in a manner which allowed for all three beat detection algorithms to be able to process the same captured audio. This was achieved by adding the method addBytes (Figure 22) to the AudioWorm class, responsible for the capturing and processing of the live audio within the Performance Worm. The call to the addBytes was added just below the `.read` call of the `AudioInputStream`, the byte array was then passed to the addBytes method and stored within a `ByteArrayOutputStream` to be processed later. Once the sufficient number of bytes had been amassed the `ProcessingActor` was sent the `ProcessBytes` message using the Java `.tell` method which initiated the processing of the audio data by the Beatroot and DWT beat detection systems.

```

public void addBytes(byte[] data){
  try{
    if(bytePosition == 525672){
      outputStream.write(data);
      byte[] out = outputStream.toByteArray();
      outputStream.close();
      outputStream = new ByteArrayOutputStream();
      bytePosition = 0;
      processingActor.tell(new ProcessBytes(out), processingActor);
    }
    outputStream.write(data);
  } catch (IOException e) {
    e.printStackTrace();
  }
}

```

Figure 22

4.3 DWT Beat Detection Implementation

The implementation of Tzanetakis *et al* beat detection algorithm by Marco Ziccardi [33] was part of a larger system which offered a number of other beat detection methods. The RTT_Analyser only required the class which implemented the DWT beat detection algorithm, WaveletBPMDetector, which originally relied on a Scala version of the WavFile Java class created by Andrew Greensted [34], however as the RTT_Analyser was not required to

decode WAV files, this class was adapted to form the LiveAudioProcessor class (Figure 23). The class was based on three methods from Andrew Greensted’s WavFile class [34], readFrames, an overloaded readFrames and the getSample method. Rather than being simply a Scala version of the Java code, where possible these methods were written using Scala’s pattern matching facility and any loops were converted into a tail recursive solution.

The final addition to the LiveAudioProcessor class was the inclusion of the addData method that takes a byte array containing the raw live audio bytes to be processed and assigns them to the buffer variable which is processed in the getSample method. In order for the WaveletBPMDetector class to return a tempo result for a single window of audio (matched to the size of the buffer byte array), the for loop was removed from the bpm method. Once a tempo was calculated this was sent back to the ProcessingActor with the New

4.4 Tempo, Analyser and Stats

The Tempo object was implemented as a method of encapsulating the RTT_Analyser’s calculated tempo results. Comprising of the calculated and expected tempos, and difference between these values, an Option¹⁷ count of beats detected and the time at which the tempo result was calculated.

The Analyser object was designed to hold the calculated Tempo objects within a ListBuffer, chosen for its scalability. The Analyser trait was extended to create three case classes corresponding to the relevant beat detection algorithm. The Analyser implementations also contained an Option Stats value. The Stats object, a case class used to hold the average and median values of the calculated tempos, the difference between the expected and calculated tempo, and the time taken to calculate a tempo within plus or minus one bpm of the expected value. Useful for assessing the efficiency of the beat detection algorithms. The StatsCalculator case class was a helper class which was responsible for carrying out computation of the values held with the Stats object and was implemented using the code seen in Figure 24.

4.5 JSON Parsing

The implementation of the data storage system of the RTT_Analyser used the JavaScript Object Notation (JSON) as the data generated was considered not large enough to warrant the creation and management of an SQL database. JSON’s lightweight data-interchange format [38] ensured the conversion from Scala case class to JSON object is straightforward. The JSON is generated the ScalaJSON library provided by the play framework [37], specifically the *Writes* object which converts an object into a JSON representation held

¹⁷The Option type is Scala’s alternative to Java’s null value, the Option type is in fact a container which either holds a value or is empty. It provides a much safer alternative to the error prone null value [35].

encapsulated within a *JsValue* object. Three methods were written in order to account for the three implementations of the Analyser trait, an example of the code can be seen in Figure(add one). As JSON is written in a text format [38], the parsing of generated JSON was performed by simpling converting the JSON objects generated by the respective write methods (example of the write method can be seen in Figure 25) to a string which was then written to a JSON file using the flush method in Figureadd one, where the path was provided from the user interaction with the RTT_Analyser’s user interface.

4.6 Adaption of Beatroot

Once the development of the RTT_Analyser was considered to be sufficiently on schedule the design decision was taken to attempt the adaption of the Beatroot system to work with live audio again. Much like with the WaveletBPMDetector, Beatroot would have to be set up to use the same audio bytes as those captured by the Performance Worm, to ensure all systems were using the exact same captured audio. As the AudioWorm was already set up to capture the enough bytes to work with the WaveletBPMDetector’s smallest working window size of 131072, the same figure was chosen to be processed by Beatroot.

With the correct design decisions now taken the live audio adaption of Beatroot consisted of only a few minor steps. First, the processFile method was amended to receive the byte array holding the audio data recorded by the Performance Worm. A ByteArrayInputStream was then instantiated to hold the data, allowing the processFrame and getFrame methods to work in the same manner as with a upload static audio file. After the captured audio was processed the ByteArrayInputStream was closed, a step necessary to ensure that no overlap existed between captured audio data sets sent to be processed.

4.7 RTT_Analyser User Interface and HTML Results Viewer

The RTT_Analyser’s user interface (Figure 26 was designed with simplicity in mind and was implemented using the ScalaFX, which sits on the top of the JavaFX API and uses the same declaration syntax as normal objects within Scala. Enabling developers to use the same operators and syntax to create and modify the scene graph¹⁸ [40]. Before starting the user could begin live audio capture the expected bpm, file name and path were required. Once input, there are two modes available to the user. The first is to control the live audio beat detection manually using the start and stop buttons accordingly. The second, is the test mode which will runs the audio capture and beat detection for thirty seconds, before closing down audio inputs and storing the results. During execution in both modes the RTT_Analyser displays the calculated tempo values to the user as a bpm value rounded to two decimal places.

¹⁸A hierarchy of tree nodes what represent the visual components of an application’s user interface[52]

On completion within both modes the results are stored within a JSON file automatically and also written to an HTML file so the results can be viewed in a web browser using the *Results* button. The HTML tables were produced `HtmlWriter` object which used reflection where possible to obtain the relevant case class constructor field names, before using a number of tail recursive methods to write the field values and HTML tags to a `StringBuilder`, chosen for it's mutability. The HTML tables are subsequently saved to an HTML file which is opened and viewed via the default browser using the *Results* button. An example of the displayed results can be seen in Figure 27.

5 Software Testing

During the development of the RTT Analyser, Test Driven Development (TDD) was employed where possible. TDD is a development process which employs test-first development and refactoring. Test-first development involves writing a test before just enough production code is written to pass that test [41]. Refactoring is a process of making small changes to code, is used to improve the design of the code, thus making it easier to understand and modify [42].

The tests were written using the ScalaTest framework, which is one of the most dominant testing frameworks currently available. ScalaTest is designed with the intention of providing a test framework that makes testing more concise and uses the Scala language in a way to ensure testing is easy and fun [43].

TDD was used at any stage of the development process where a piece of code with an expected behaviour was being implemented, it was not used for all classes as when dealing with live audio it was not possible to know the exact data that would be recorded due to the presence of background noise. Although, where the requirement was simply to return a value of a certain type, basic TDD tests were written. The classes that were ideally suited to TDD and were developed completely using it were the `Tempo`, `Analyser` implementations, `StatsCalculator`, `JSONParser` and `HTMLWriter`.

A good example of TDD being applied during the development of the RTT Analyser was during the creation of the `StatsCalculator`. Designed to carry out average and median calculations on the stored `Tempo` objects held within the `Analyser` implementations enabled TDD to be employed successfully.

When it was not possible to use TDD, particularly during the initial set-up and testing of the beat detection algorithms with live audio. A simpler testing approach was taken, consisting of running the system with a selection of sample drum beats of varying tempos, with console logs used to test that the system was performing the desired tempo calculations.

6 RTT_Analyser Beat Detection Testing

6.1 Drum Beat Sample Set

Once the RTT_Analyser was working with the initial test sample drum beats the full testing cycle could begin. In order to carry out this testing a set of drum beats were written using the Apple sequencer program, GarageBand [44]. The writing of the drum beats took a slight deviation from the project proposal in that rather than create multiple full drum beats in a varying number of styles, the drum beats were instead tested in layers. For example, a simple four four (4/4) bass drum beat with a back beat and the time element being played on the hi-hat cymbal would account for three samples. The reason for this decision stemmed from how a cymbal behaves when it is played at high amplitudes (loudness), the vibrations it creates become chaotic and its clearly identifiable signals disappear and it effectively becomes noise [45]. Therefore in order to compare the drum sample with cymbals a baseline was required. Additionally, this change to the project proposal was considered to be able to provide a much more diverse data set which would hopefully help the understanding of how the different elements of a drum kit, not just cymbals, can affect the accuracy of the beat detection algorithms being tested by the RTT_Analyser.

In total number twenty eight drum samples were produced and the full details of the elements which each drum beat was comprised of and style of the drum beat can be seen in Table 1. A full visualisation of the drum beats used can be found in Appendix A.

6.2 Beat Detection Testing

The full beat detection tests were carried out in an environment with as little background noise as possible, where the drum beats were played on an external speaker set to the same volume for all tests. Each drum beat was tested for thirty seconds over the tempo range of 60-160 bpm, the tempo was increased in five bpm increments. Resulting in twenty one tests for being carried out for each drum beat and producing a sample set consisting of five hundred and eighty eight (588) results files.

During the testing it became apparent that at lower tempos the RTT_Analyser was returning values which were roughly twice that of the expected tempo. A possible cause for this was considered to be aliasing, caused when it is not possible to distinguish between the values from sampled audio as they contain periodic replications of the original spectrum[19]. To investigate if this was the root cause and as this behaviour was being displayed by all three of the beat detection algorithms. It was decided that all of the drum samples would be reprocessed through the RTT_Analyser but this time a low-pass filter would be applied to the point at which the audio is captured. The low-pass filter was provided by the source_code.biz Java dsp collection.

```

def addData(data: Array[Byte]) = {
    buffer = data
}

def readFrames(sampleBuffer: Array[Int], number_of_frames: Int): Int = {
    readFrames(sampleBuffer, 0, number_of_frames)
}

def readFrames(sampleBuffer: Array[Int], offset: Int, number_of_frames: Int): Int = {
    var pointer = offset

    for(i <- 0 until number_of_frames) {
        getSample(0)
        frameCounter = frameCounter + 1
    }

    def getSample(acc: Int): Int = {
        acc match{
            case x if x < number_of_channels => {
                sampleBuffer(pointer) = readSample().toInt
                val newAcc = acc + 1
                pointer = pointer + 1
                getSample(newAcc)
            }
            case _ => acc
        }
    }
    number_of_frames
}

def readSample(): Long = {

    @tailrec
    def sampleReader(value: Long, acc: Int): Long = {
        acc match {
            case x if x < bytes_per_sample => {
                var v: Int = buffer(bufferPointer)
                if (acc < bytes_per_sample - 1 || bytes_per_sample == 1) v = v & 0xFF
                bufferPointer = bufferPointer + 1
                sampleReader(value + (v << (acc * 8)), acc + 1)
            }
            case x if x == bytes_per_sample => value
            case _ => value
        }
    }
    sampleReader(0L, 0)
}

```

Figure 23: LiveAudioProcessor

```

def getMedian(listBuff: ListBuffer[Tempo], identifier: String): Double =
  identifier match {
    case "tempo" => val list = getTempos(listBuff.toList); median(list)
    case "diffs" => val list = getDiffs(listBuff.toList); median(list)
  }

def median(list: List[Double]): Double = {
  //adapted from the sample at Rosetta code
  val (lower, upper) = list.sortWith(_<_).splitAt(list.size / 2)
  if (list.size % 2 == 0) (lower.last + upper.head) / 2.0 else upper.head
}

def getAverage(listBuff: ListBuffer[Tempo], identifier: String): Double =
  identifier match {
    case "tempo" => val list = getTempos(listBuff.toList); average(list)
    case "diffs" => val list = getDiffs(listBuff.toList); average(list)
  }

def average(list: List[Double]): Double = {
  @tailrec
  def averageTR(list: List[Double], size: Double, total: Double): Double = list match {
    case Nil => println(total); println(size); total/size
    case x :: xs => averageTR(xs, size + 1, total + x)
  }
  averageTR(list, 0, 0)
}

def getTotal(listBuff: ListBuffer[Tempo]): Double = {
  val list = getBeatCounts(listBuff.toList); totalbeatCount(list)
}

def totalbeatCount(list: List[Double]): Double = {
  @tailrec
  def totalHelper(lst: List[Double], total: Double): Double = {
    lst match {
      case Nil => total
      case x :: xs => totalHelper(xs, x)
    }
  }
  totalHelper(list, 0)
}

def getResponseTime(list: List[Tempo]): Long = list match {
  case (x :: xs) => {
    if (x.difference < 1.0 && x.difference > -1.0) {
      x.timeElapsed
    } else getResponseTime(xs)
  }
  case Nil => 0
}

def getTempos(lst: List[Tempo]): List[Double] =
  lst match {
    case x :: xs => x.tempo :: getTempos(xs)
    case Nil => Nil
  }

def getDiffs(lst: List[Tempo]): List[Double] =
  lst match {
    case x :: xs => x.difference :: getDiffs(xs)
    case Nil => Nil
  }

def getBeatCounts(lst: List[Tempo]): List[Double] =
  lst match {
    case x :: xs => unwrapOption(x.beatCount) :: getBeatCounts(xs)
    case Nil => Nil
  }

def unwrapOption(head: Option[Double]): Double =
  head match {
    case Some(value) => value
    case None => 0
  }
}

```

Figure 24: Stats calculation methods used by the StatsCalculator

```

implicit val tempoWrites = new Writes[Tempo] {
  def writes(tempo: Tempo) = Json.obj(
    "tempo" -> tempo.tempo,
    "expectedTempo" -> tempo.baseTempo,
    "difference" -> tempo.difference,
    "elapsedTime" -> tempo.timeElapsed
  )
}

implicit val statsWrites = new Writes[Stats] {
  def writes(stats: Stats) = Json.obj(
    "averageTempo" -> stats.averageTempo,
    "medianTempo" -> stats.medianDiff,
    "averageDiff" -> stats.averageDiff,
    "medianDiff" -> stats.medianDiff
  )
}

implicit val wormAnalyserWrites = new Writes[WormAnalyser] {
  def writes(analyser: WormAnalyser) = Json.obj(
    "name" -> analyser.name,
    "buffer" -> analyser.buffer,
    "stats" -> analyser.stats
  )
}

```

Figure 25: Example of the write method used to convert the Tempo and Stats object values to JSON

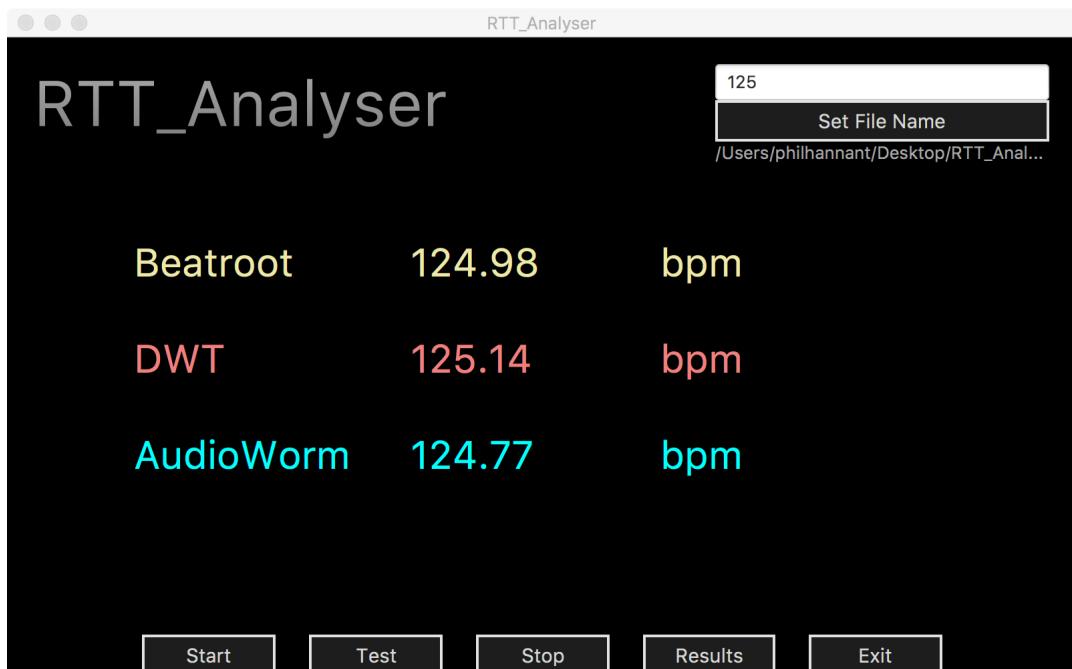


Figure 26: RTT_Analyser's User Interface

| name | stats | | | |
|----------------------------|---------------------|---------------------|------------------|---------------|
| worm: 2016-25-26, 09:25:10 | | | | |
| averageTempo | 118.87383409364367 | | | |
| medianTempo | 119.8527280210139 | | | |
| averageDiff | -58.873834093643325 | | | |
| medianDiff | -59.8527280210139 | | | |
| totalBeatCount | 0.0 | | | |
| responseTime | 0.0 | | | |
| tempo | baseTempo | difference | beatCount | timeEl |
| 75.0 | 60.0 | -15.0 | None | 276 |
| 148.32203293831626 | 60.0 | -88.32203293831626 | None | 799 |
| 115.2256641406328 | 60.0 | -55.2256641406328 | None | 930 |
| 117.97814954783244 | 60.0 | -57.978149547832444 | None | 1323 |
| 119.01958295391182 | 60.0 | -59.01958295391182 | None | 1840 |
| 119.50166377695483 | 60.0 | -59.50166377695483 | None | 2099 |
| 119.7252361528647 | 60.0 | -59.725236152864696 | None | 2359 |
| 119.53294273830856 | 60.0 | -59.53294273830856 | None | 2620 |
| 119.67926220986494 | 60.0 | -59.679262209864945 | None | 2880 |
| 119.54280558557888 | 60.0 | -59.542805585578876 | None | 3140 |
| 119.22672502022178 | 60.0 | -59.22672502022178 | None | 3375 |

Figure 27: Example of the RTT_Analyser's HTML results view

Table 1: List of Drum Beats Used in RTT-Analyser Tests

| Drum Code | Beat | Elements | Style |
|----------------|---|--|-------|
| AMPEDUP | All | Heavy rock, GarageBand stock drum beat | |
| HT | High tom-tom | Straight | |
| HTLT | High tom-tom and low tom-tom | Straight | |
| HTLT2 | High tom-tom and low tom-tom | Straight | |
| K | Bass drum | Straight | |
| KS | Bass drum and snare drum | Straight | |
| KS2 | Bass drum and snare drum | Straight | |
| KSCR | Bass drum, snare drum and crash cymbal | Straight | |
| KSFTTF | Bass drum (four to the floor) and snare drum | Straight | |
| KSH | Bass drum, snare drum and hi-hat cymbal | Straight | |
| KSH2 | Bass drum, snare drum and hi-hat cymbal | Straight | |
| KSH2CR | Bass drum, snare drum, hi-hat and crash cymbals | Straight | |
| KSHCR | Bass drum, snare drum, hi-hat and crash cymbals | Straight | |
| KSHHTLT | Bass drum, snare drum, hi-hat cymbal, high tom-tom and low tom-tom | Straight | |
| LT | Low tom-tom | Straight | |
| MTREVIS | All | Mowtown swing, GarageBand stock drum beat | |
| OFF-KSH | Bass drum, snare drum and hi-hat cymbal | Offbeat played on hi-hat | |
| OFF-KSHCRFTTF | Bass drum (four to the floor), snare drum, hi-hat and crash cymbals | Offbeat played on hi-hat | |
| OFF-KSHFTTF | Bass drum (four to the floor), snare drum, hi-hat cymbal | Offbeat played on hi-hat | |
| OFF-KSHHCRFTTF | Bass drum (four to the floor), snare drum, hi-hat and crash cymbals | Offbeat played on hi-hat | |
| S | Snare drum | Straight | |
| SMASH | All | Punk rock (loud), GarageBand stock drum beat | |
| SW-H | Hi-hat cymbal | Swing | |
| SW-K | Bass drum | Swing | |
| SW-KH | Bass drum and hi-hat cymbal | Swing | |
| SW-KS | Bass drum and snare drum | Swing | |
| SW-KSH | Bass drum, snare drum and hi-hat cymbal | Swing | |
| SW-R | Ride cymbal | Swing | |

| TotalRecords | |
|---------------------|-----------------|
| Beat Detection Name | Count of Tempos |
| beatroot | 11,818 |
| dwt | 11,818 |
| worm | 113,544 |
| Grand Total | 137,180 |

Figure 28: Total number of tempo values recorded by the RTT_Analyser

7 Results

The twenty eight sample beats processed by the RTT_Analyser yielded one hundred and thirty seven thousand, one hundred and eighty (137,180) separate tempo records. A breakdown of the number of tempo records recorded per beat detection algorithm can be seen in Figure 28. The separate JSON files were then consolidated into one file, converted into a CSV file and then connected to the data visualisation software package, Tableau[53].

7.1 Overall Average Difference

The difference between the expected tempo and the calculated tempo was determined by subtracting the calculated tempo from the expected tempo(3). If the difference is negative then the calculated tempo was greater than expected and less than if it is positive.

$$\text{difference} = \text{expectedtempo} - \text{calculatedtempo} \quad (3)$$

The average difference for each of the three beat detection algorithms, split by style can be seen in Figure 29. The best performing beat detection method can be seen to be the DWT based algorithm by Tzanetakis *et al*'s [15], for the samples without a filter in a Swing style. As mentioned previously, during the testing process some of the tempo results returned were double that of the expected bpm value, possibly due to aliasing. A solution to the aliasing issue was to add a low-pass filter and looking at the results on the whole it can be considered to have worked to a certain degree. For six out of the nine sets of results, those samples processed with a low-pass filter produced a lower average difference than those without a filter. Although, the margin of error between the expected tempo and the calculated tempo are still suitably large.

A flag was applied to the results set to highlight any tempo result approximately double the expected value. A record was flagged if its calculated tempo divided by the expected tempo returned a result greater or equal to 1.95(4). The flagged results were then filtered

Total Average Difference

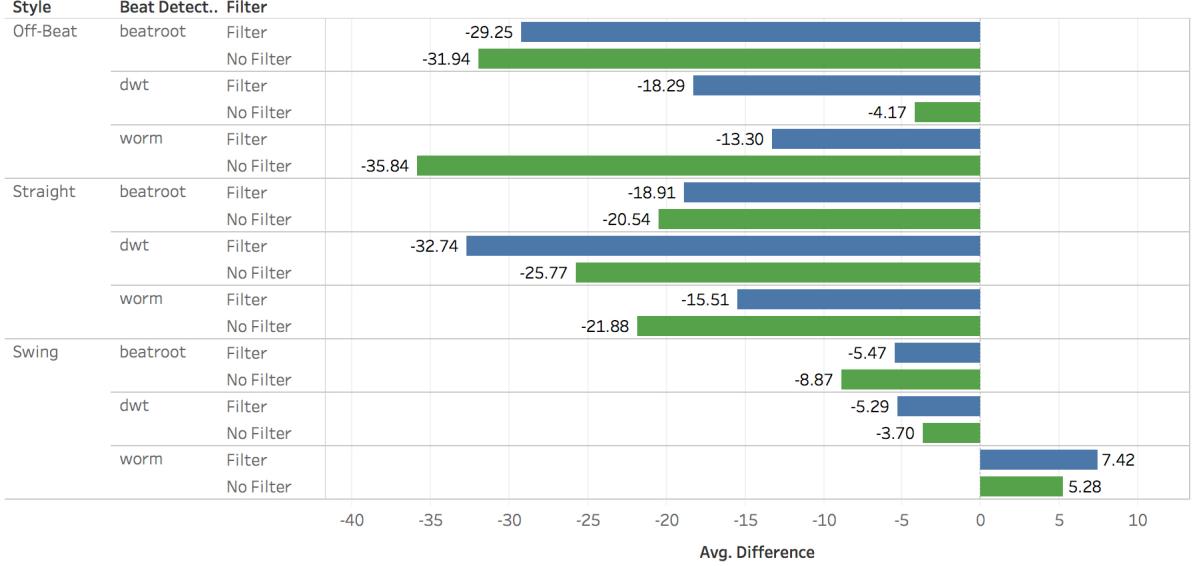


Figure 29: Total average difference results

out of the data set and the updated results can be see in Figure 30. With the flagged results removed the average difference value for all of the beat detection algorithms was greatly reduced except for the swing samples processed by the PW.

$$\text{CalculatedTempo}/\text{ExpectedTempo} \geq 1.95 \quad (4)$$

Rather than just removing these results altogether, the next step was to attempt to correct any of the flagged tempo results which when divided by two were within plus or minus five percent of the expected tempo result. With this adaption applied to the data set (see in Figure 31), it is clear that overall Tzanetakis *et al*'s [15] DWT method is the most accurate. The different musical styles within the samples also affect the accuracy of the calculated tempos. With the swing samples producing the least accurate results for all three algorithms.

7.2 Straight Sample Results

The results recorded for the straight sample set clearly show that doubling is an issue. Demonstrated by all but one of the results returned is a negative value (Figure 32). A large majority of the average difference values are also significantly large (greater than five). It is

Total Average Difference (Flagged Removed)

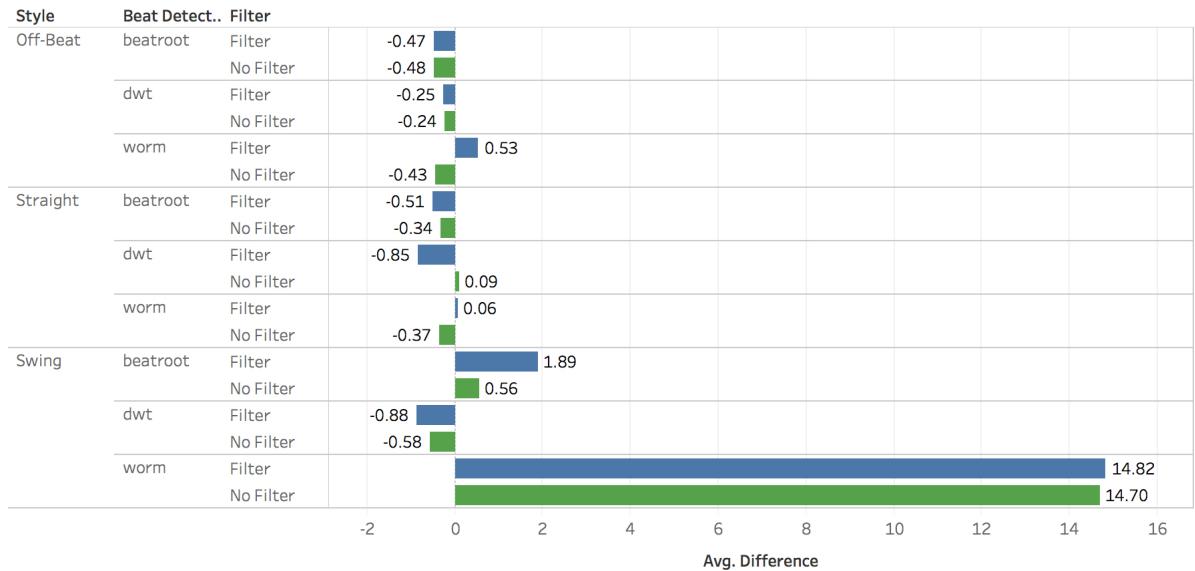


Figure 30: Total average difference results with flagged values removed

Total Average Difference (Corrected)

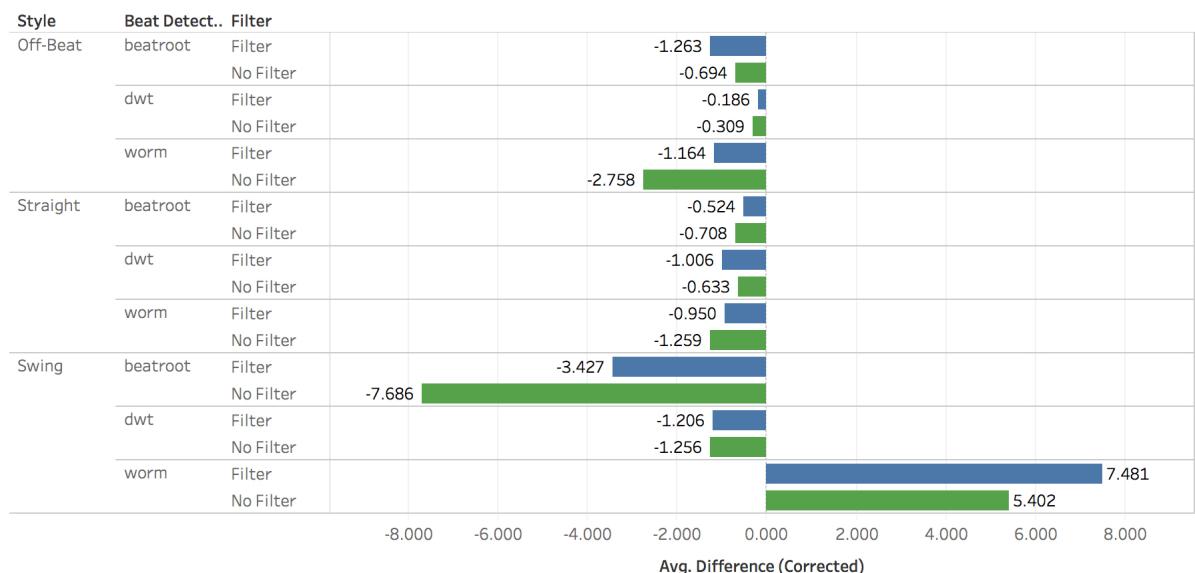


Figure 31: Total average difference results with correction applied

the Tzanetakis *et al*'s [15] DWT method which exhibits the poorest level of accuracy within this data set. Regularly producing average difference values of greater than twenty.

When the corrected difference values are applied to the data set the accuracy of the Tzanetakis *et al*'s [15] DWT method increases significantly (Figure 33). Although, it does return its least accurate results for the samples consisting of a crash cymbal and the high and low tom-toms. The affect of the crash cymbal on the accuracy of the tempo recorded confirms the point mentioned previously. The low accuracy recorded by the DWT method for the HTLT2 sample set where the time element is played on the low tom-tom. Highlights the possibility that this method will not respond as well when there are not distinct frequencies playing each part of the drum beat.

Also, within this data set the results produced for the single drum samples can be observed to actually have some of lowest levels of accuracy. This is improved once the corrected values are introduced, suggesting that the issue of doubling was particularly prevalent for these samples.

7.3 Swing Sample Results

The doubling of calculated tempos was not as prevalent within the Swing sample set. Both the original (Figure 34) and the corrected (Figure 35) difference values were significantly high. Although, the Tzanetakis *et al*'s [15] DWT method's accuracy is again improved by the updated difference values. However, the Beatroot and PW's performance remains very similar across both data sets.

The single drum elements within this data set were expected to cause some problems, due to their use of triplets. This can be seen for both th R and H sample sets within Figure 34. Once the corrected values are applied the DWT method does return a higher level of accuracy. However, the accuracy of both Beatroot and the PW are relatively unaffected by the introduction of the corrected values.

7.4 Off-Beat Sample Results

The last group of style results utilise a time element being played on the off-beat. The rest of the beat is considered to be straight. It is to be expected then that the results exhibit a similar amount of potential doubling of the tempo values as with the straight data set (Figure 36).

When the corrected difference values are introduced the accuracy is again improved (Figure 37). For the louder KSHHCRFTTF sample, the Beatroot and PW both recorded a lower level of accuracy with the low-pass filter than without. It is expected that the low-pass filter would help to remove some of the noise produced by the cymbals in this sample.

Straight Sample Set Average Difference

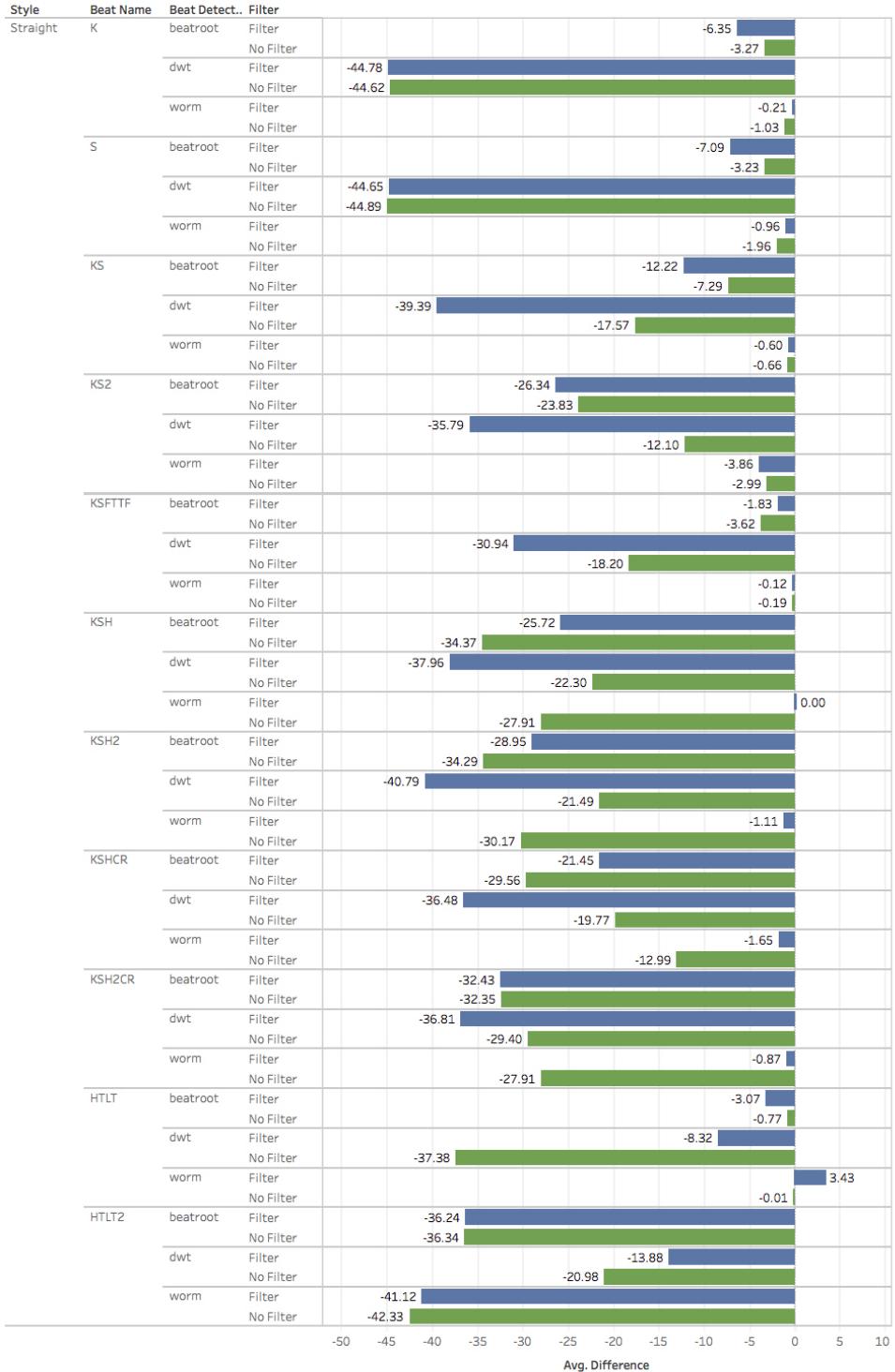


Figure 32: Straight sample set average difference results

Straight Sample Set Average Difference (Corrected)



Figure 33: Straight sample set average difference results with correction applied

Swing Sample Set Average Difference

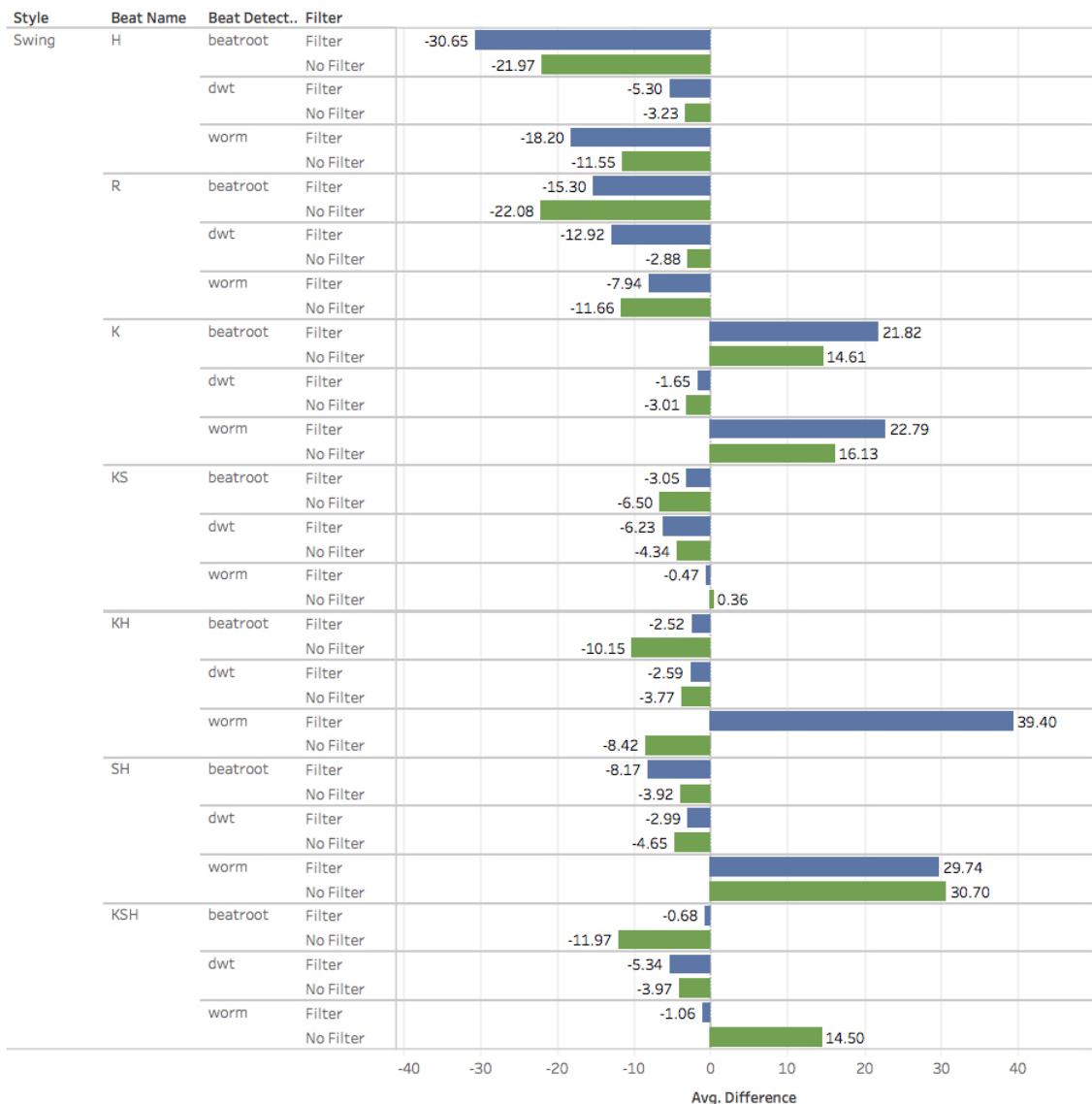


Figure 34: Swing average difference results

Swing Sample Set Average Difference (Corrected)

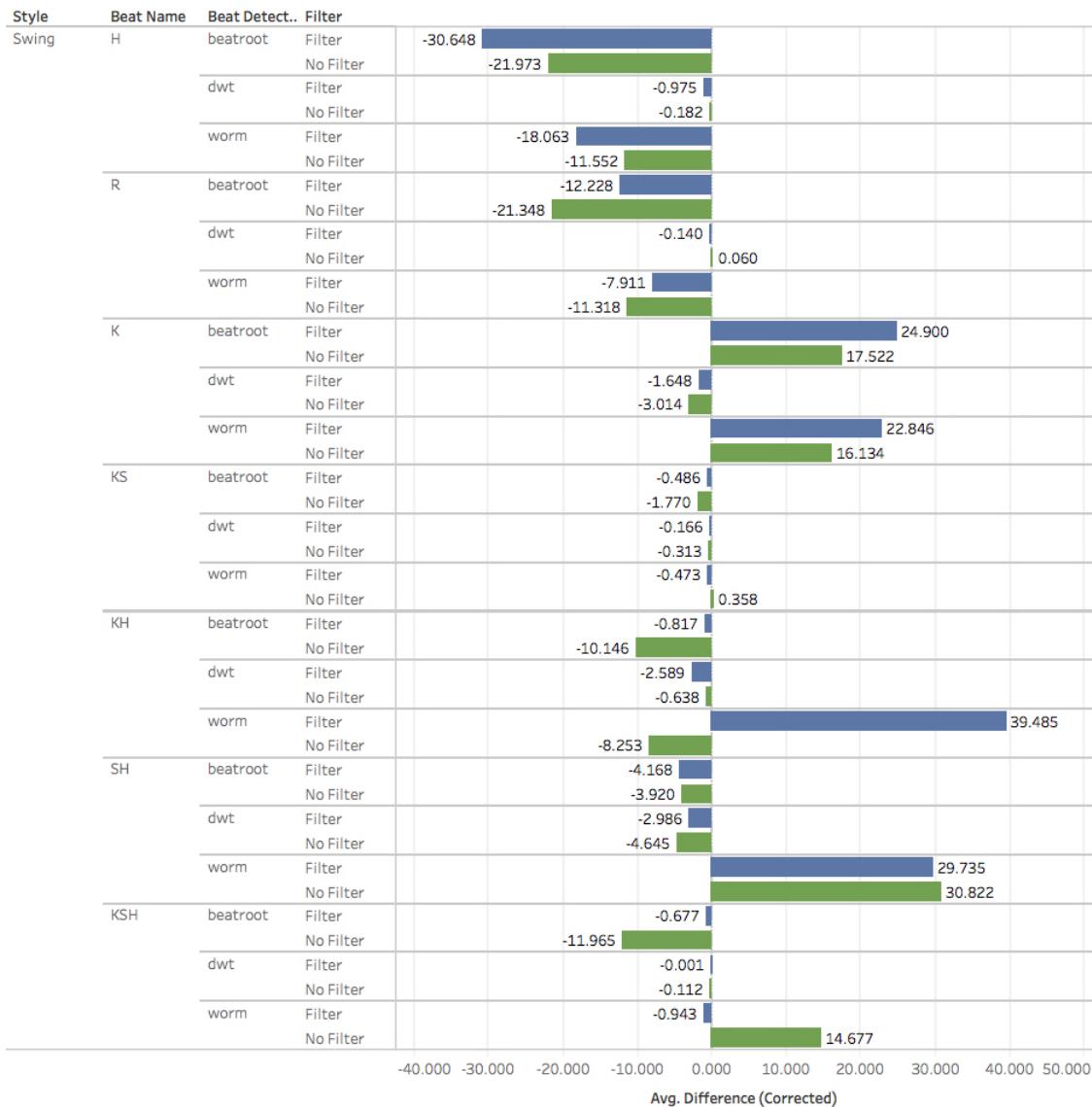


Figure 35: Swing average difference results with correction applied

Off-Beat Sample Set Average Difference



Figure 36: Off-Beat average difference results

However, this result suggests that by removing the higher frequencies produced by cymbals can adversely affect the accuracy of these two tempo calculation methods.

Off-Beat Sample Set Average Difference (Corrected)

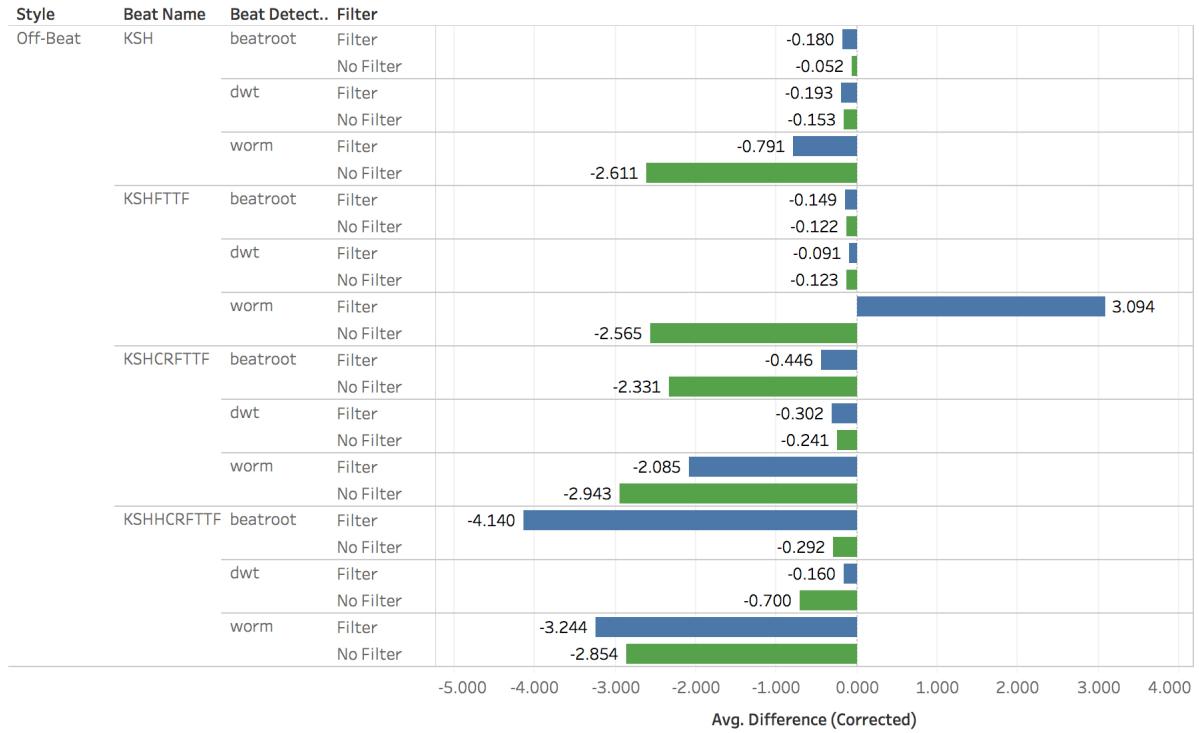


Figure 37: Off-Beat average difference results with correction applied

7.5 Low Tempo Comparison

During the testing process it was noted that the result doubling seemed to be prominent for samples being played at lower tempos. Usually anything with a bpm of one hundred and below. To investigate if the algorithms performed better with higher tempos regardless of style, a doubling count was applied to the data set. Using the same error margin applied previously.

The results viewed in Figure 38, confirm that the all three of the beat detection algorithms produce significantly less doubling when processing drum beats with higher tempos. If the style grouping is introduced (see Figure 39, it is apparent that the doubling is most prevalent with the straight sample set. Out of the three algorithms, the PW returns the highest count of doubled results.

Low Tempo Doubling Comparison

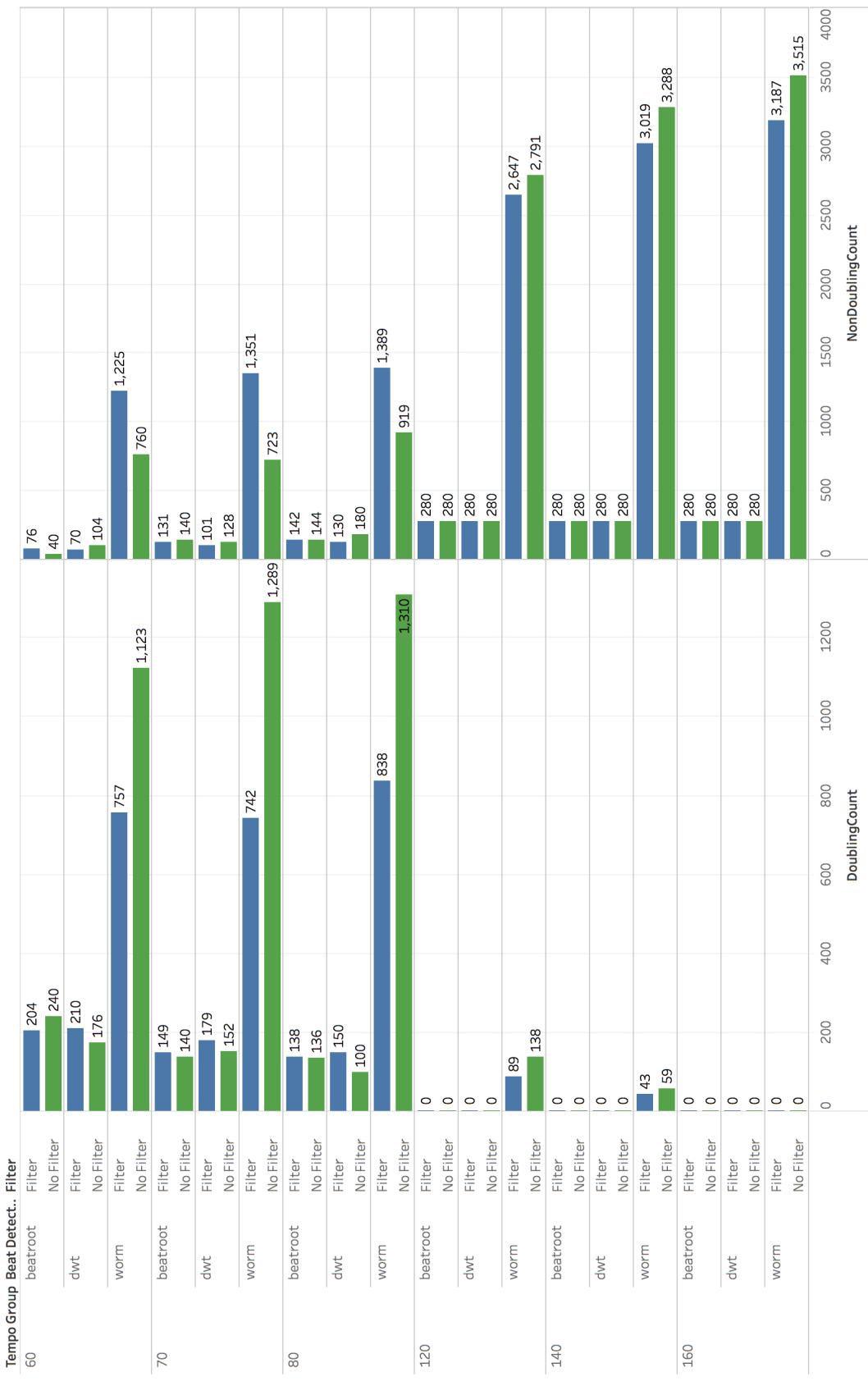


Figure 38: Low tempo comparison

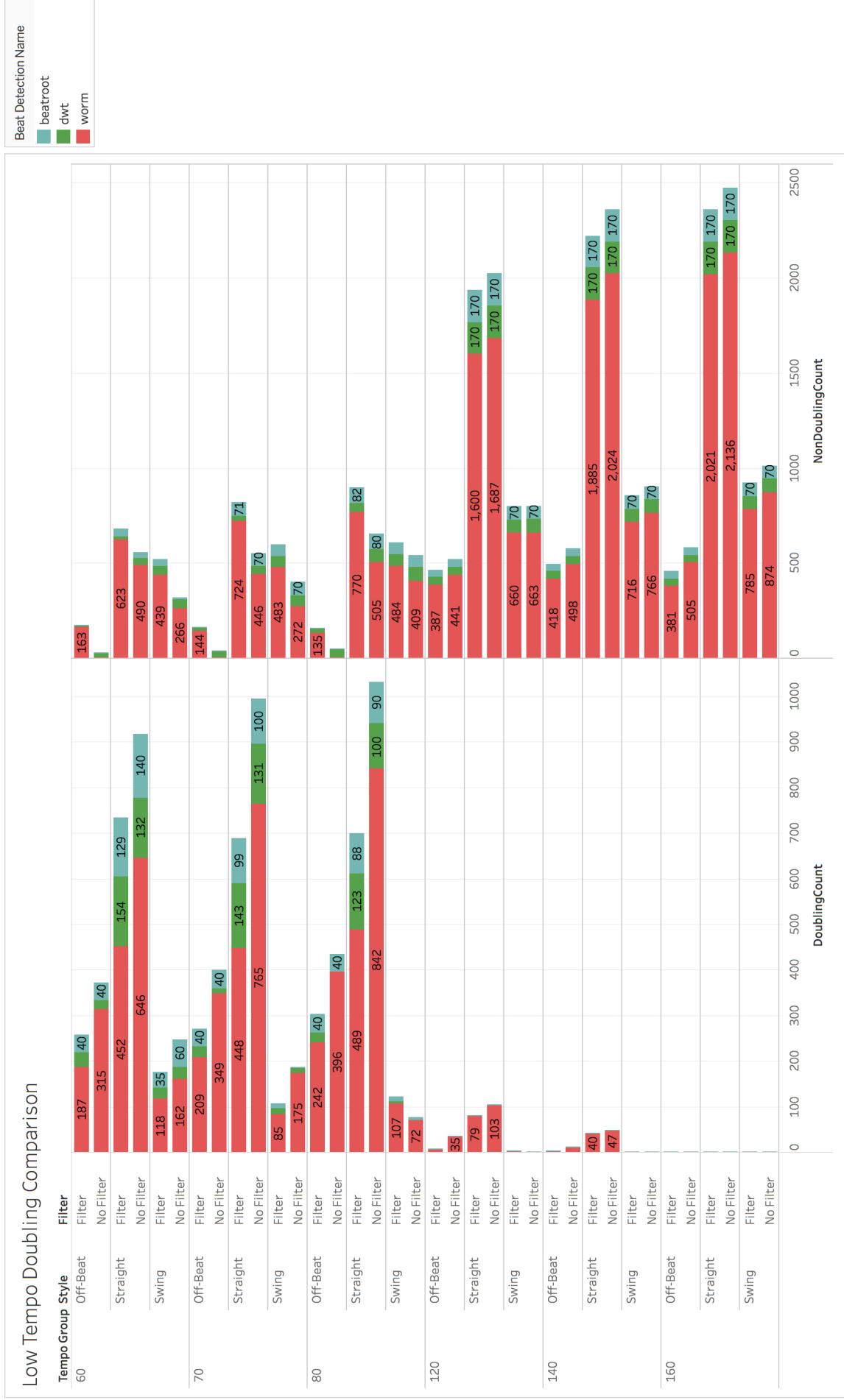


Figure 39: Low tempo comparison with style groupings

Response Times

| Beat Detection Name | Filter | Response Time (seconds) |
|---------------------|--------|-------------------------|
| beatroot | F | 3.337 |
| | NF | 3.293 |
| dwt | F | 4.248 |
| | NF | 4.23 |
| worm | F | 0.675 |
| | NF | 0.66 |

Figure 40: Fastest response times recorded by the RTT_Analyser

7.6 Beat Detection Response Time

Due to the smaller window size utilised by the PW it is expected to perform the best within this comparison. The response time was recorded by the RTT_Analyser when the first returned tempo was plus or minus one bpm from the expected tempo result.

Before this could be calculated the all of the tempo results produced by the PW for expected tempos of seventy five were removed. As the PW's first result returned regardless of expected tempo was always seventy five. Despite this and as expected the PW returned the fastest tempo value (see Figure 40). Returning a tempo within the margin of error for the straight KSH2 beat within 0.675 seconds when processing through the low-pass filter. Then without a filter a tempo was produced in 0.660 seconds.

7.7 Overall Tempo Accuracy

The overall tempo accuracy was calculated by counting the number of tempo results that were plus or minus one bpm away from the expected tempo. The results for the three beat detection methods with and without a filter were then compared. A corrected value was also included to show the possible level of accuracy if the issue of doubling was not present (Figure 41).

Unsurprisingly, the Tzanetakis *et al*'s [15] DWT method performed with the highest level of accuracy. Interestingly, without the corrected values all three systems produced a consistent level of accuracy when using the low-pass filter. Without the filter though, the DWT method produced the highest overall accuracy of 71.32% and the PW produced the least of 57.12%.

The corrected results show that there is a clear distinction between the accuracy of the three methods. With the DWT method exhibiting the most potential followed by the Beatroot system and then the PW. The effectiveness of the low-pass filter is hard to ascertain from these results alone. However, based on the five percent increase to the overall tempo accuracy, it can be said that the PW benefited the most from the inclusion of the filter.

Tempo Accuracy

| Beat Detection Name | Filter | Tempo Accuracy | Tempo Accuracy (Corrected) |
|---------------------|-----------|----------------|----------------------------|
| beatroot | Filter | 64.22% | 83.80% |
| | No Filter | 64.94% | 85.99% |
| dwt | Filter | 64.96% | 92.33% |
| | No Filter | 71.32% | 91.00% |
| worm | Filter | 62.56% | 74.04% |
| | No Filter | 57.14% | 76.51% |

Figure 41: Overall tempo accuracy

7.8 Filter/Non-Filter Comparison

In order to ascertain the effectiveness of the low-pass filter applied to the RTT_Analyser. It was necessary to formulate the following null hypothesis:¹⁹ When accessing the accuracy tempo results produced by the RTT_Analyser there will be no significant difference in the accuracy between when a low-pass filter was used or not.

The probability of the observed data (or data showing a more extreme departure from the null hypothesis) when the null hypothesis is true.

7.9 Analysis

the PW may be less accurate when processing samples played with a swing style. dwt hihat worse Demonstrating that if any future drum training tools require instant feedback then the PW needs to be considered. dwt high at low tempos suggesting a possible flaw in how the beat inducing algorithm converts peaks in the signal to the returned tempo result.

¹⁹Described as a no difference hypothesis to be tested by a significance test[54] and is assumed to be true until statistical evidence suggest otherwise

8 Evaluation and Discussion

8.1 Project Successes and Challenges

During the live audio testing phase of the project, the RTT_Analyser processed just under ten hours of audio without an issue, producing well over 130,000 different tempo records. This provided a sufficiently large data set to confidently assess whether any of the three beat detection algorithms were suitable to be implemented as part of a training tool for drummers. From the data set, it is clear that the Tzanetakis *et al*'s [15] DWT method offers the highest level of accuracy, with the potential of even higher if the issue of doubling is resolved. However, the response time of the Tzanetakis *et al*'s [15] DWT method might be an issue.

One challenge experienced during the development of the RTT_Analyser, was that the adaption of the Beatroot system to work with live audio took longer than anticipated. This was mainly due to the difficulty of working with a large pre-existing code base. To overcome this, the mitigation protocol set out in the project proposal was followed and an alternative system was sourced; the Performance Worm. This ensured that the project did not fall any further behind schedule.

The delay in development caused by this issue, led to insufficient time for the author to implement the Tzanetakis *et al*'s [15] beat detection algorithm. Although, there was a mitigation protocol in place, there was insufficient time to implement this, so a different course of action was chosen. A preexisting Scala implementation of the Tzanetakis *et al*'s [15] DWT method by Marco Ziccard[33] was used. Using this implementation, allowed for the regaining of the time lost during the initial failed attempt to adapt the Beatroot system. This ensured the project not only remained on schedule, but there was also sufficient time to try adapting the Beatroot system again. This was completed successfully on the second attempt.

One unforeseen challenge was presented by the original decision to use JSON files for data storage. Due to the inclusion of the PW beat detection algorithm in the RTT_Analyser and the decision to run tests with a low-pass filter and without, the number of records recorded by the RTT_Analyser increased significantly. The original estimate was for approximately 700 files each holding approximately ten results per beat detection method. The final number of results collection was 130,000 plus. JSON is more than adequate for holding this much data, an issue arose when the data visualisation software package, Tableau[53] was used. As Tableau does not work with JSON files, the data would need to be converted to another format. Due to limited time the data was converted to an Excel[55] file. This required a large amount of data manipulation to be carried out. A number of Visual Basic for Applications (VBA) macros were written to perform the data manipulation, and once the data was in the required format it was connected to Tableau where any further

manipulation and analysis of the data could be performed much more efficiently.

8.2 Future Work

There are a number of possible routes to consider with regard to the future development of the RTT_Analyser, including, further investigations into the doubling issue, adaption of the data storage method, and converting the RTT_Analyser into a mobile training tool application.

In order to investigate the doubling issue presented during this project, a function to log the frequencies detected by the beat detection algorithm during live audio capture could be added to the RTT_Analyser. This could be achieved by logging the data produced by the parts of the Beatroot and Tzanetakis *et al*'s [15] DWT method that perform the original signal processing. This data can be examined to see if any particular frequencies are the cause of this issue.

Alternatively, the analysis could be performed on the drum beat samples before they are processed by the RTT_Analyser. The goal of this analysis would be to produce a frequency map of the samples. This data could then be compared with the output of the RTT_Analyser in an attempt to discover if there are particular frequencies for which doubling occurs.

If further drum beat testing is to be carried out, then adapting the data storage method of the RTT_Analyser from JSON files to a relational database should be considered. One option is to set up a MongoDB[56] database to hold the RTT_Analyser's data. An advantage of this is that the data structure used by MongoDB is very similar to structure of JSON objects. This would enable the existing data structures used by the RTT_Analyser to be maintained. Alternatively, the RTT_Analyser could be adapted to work with an SQL database, which could be the easier option, due to the author's familiarity with SQL.

Although, the accuracy of the beat detection algorithms used in the RTT_Analyser is not on the same level as the midi training tools, they could still provide a useful tool for a drummer. One possible route would be to develop an application for mobile devices which combines a metronome with the RTT_Analyser. A drummer could then use this application to aid their practice session by using the metronome to set the tempo. After a predetermined amount of time the metronome would stop and the drummer continues to play. While doing so, the application would report as to whether they have remained at the same tempo as the metronome or if their tempo has fluctuated. Such a tool would definitely provide a useful training aid to any drummer wanting to work on their timing.

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A Drum Sample Beat Patterns

To be added