THE UNIVERSITY OF SYDNEY

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ELEC5305

Project Report

Music Analyser GUI

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Contents

1 Introduction

For a musician, learning to play a new song from a recording is often a manual process of trial and error. Key tasks like determining the song's key, tempo (BPM), and time signature require a trained ear and can be time-consuming. For novice musicians, this process is a significant barrier, and more complex analysis, like discerning the instrumentation, is often out of reach. This creates a clear need for accessible tools that can automate this musical analysis.

This project aims to meet this need by developing a simple, open-source "Music Analyser GUI." The goal is to create a desktop application where a user can load a standard audio file (e.g., .mp3 or .wav) and receive an immediate, easy-to-understand analysis of its core musical features.

This report documents the research and development of this tool. It is framed by a central research question: How accurately can a lightweight desktop application, integrating established digital signal processing (DSP) algorithms from open-source libraries, extract fundamental musical features (BPM, key, time signature, and instrumentation) from a standard audio file?

To answer this, the report surveys the current state-of-the-art in Music Information Retrieval (Section 2), details the specific algorithms and software architecture used in the application (Section 3), presents the quantitative and qualitative results of testing the system (Section 4), and concludes with a discussion of the project's findings and limitations (Section 5).

The project **code** and demonstration **video** are available on GitHub, at `https://github.com/matt-starr/elec5305-project-510453253`

2 Literature Review

The core research question of this project is: How accurately can a lightweight desktop application, integrating established digital signal processing (DSP) algorithms from open-source libraries, extract fundamental musical features (BPM, key, and instrumentation) from a standard audio file?

To answer this, it is first necessary to survey the field of Music Information Retrieval (MIR). This review identifies the current state-of-the-art for each target feature, explores the available methods for its extraction, and justifies the selection of a "lightweight" and "established" approach over more computationally expensive, cutting-edge techniques. Finally, it identifies the foundational concepts that must be learned to implement these methods.

2.1 Deep Learning in MIR

The current state-of-the-art in almost all MIR tasks is dominated by deep learning (DL) architectures [1]. Tasks that were once considered distinct research problems, such as genre classification, mood detection, instrument recognition, and even beat tracking, are now frequently solved using end-to-end deep neural networks.

These models, typically Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) (or a combination, "CRNNs"), are trained to "learn" the relevant features directly from an audio representation, most commonly a spectrogram or mel-spectrogram [2]. By treating the spectrogram as an image, a CNN can identify characteristic visual patterns (e.g., the harmonic structure of a violin vs. the sharp, vertical attack of a snare drum). These models are trained on massive, labeled datasets, such as the MTG-Jamendo dataset for instrument and mood tags, or the Free Music Archive (FMA) for genre [3].

Commercial applications, such as the sonoteller.ai service identified in this project's proposal, almost certainly leverage these large-scale, cloud-based deep learning models. They provide high-accuracy, nuanced analysis but require significant computational resources, making them unsuitable for a simple, local desktop application. This disparity between the high-performance DL state-of-the-art and the project's requirement for a "lightweight" tool is the central tension that this project's research question explores. The following sections therefore review the "established" DSP-based methods that pre-date this DL-dominant era, as these are the most viable candidates for a local GUI.

2.2 Methodologies for Tempo (BPM) Estimation

Tempo, or Beats Per Minute (BPM), is a fundamental musical feature representing the perceived pulse of a piece. Most automated methods for tempo estimation, from simple to complex, are based on the concept of first identifying "note onsets" (the start of a musical event) and then finding the periodicity of those onsets.

The foundational step is the creation of an Onset Strength Envelope (OSE), or novelty function. This is a 1-dimensional time-series signal that represents the "newness" of the sound at each moment. A common method to derive this is by calculating the spectral flux, which measures the frame-by-frame change in the magnitude of a spectrogram. Large, sudden changes in the spectrum (like a drum hit) create high peaks in the OSE [4]. Once this OSE is generated, the problem becomes finding its dominant frequency.

A classical and computationally cheap approach to finding this periodicity is autocorrelation. By calculating the autocorrelation of the OSE, one can find the time lag that best aligns the OSE with itself. This lag corresponds to the beat period, which is then easily converted to BPM [5]. While fast, this method is highly susceptible to "octave errors" for example, it may incorrectly identify a 140 BPM song as 70 BPM (half-tempo) or 280 BPM (double-tempo) if the percussive pattern strongly emphasises the half-note or eighth-note, respectively.

A more robust and widely adopted "established" method uses dynamic programming. This approach defines a cost function for a sequence of beat locations, rewarding beats that align with OSE peaks and penalising beats that are rhythmically inconsistent (i.e., not steady). A dynamic programming algorithm can then efficiently find the "best path" of beat locations through the song, and the median interval between these beats gives the tempo [6]. This method is more resilient to missed or extra onsets and forms the basis of many modern beat trackers.

While these DSP methods are robust, the current state-of-the-art for tempo estimation also involves deep learning. Recurrent Neural Networks (RNNs) have been successfully trained on the OSE (or even directly on spectrograms) to predict beat locations, often outperforming the dynamic programming approach on rhythmically complex music (e.g., swing, jazz, or music with tempo changes) [7]. However, for a lightweight GUI targeting popular music, the dynamic programming method provides the best trade-off between accuracy and computational cost.

2.3 Methodologies for Tonal Analysis (Key Detection)

The "key" of a song is a central component of its musical structure, defined by a central note (the tonic) and a mode (typically major or minor). The vast majority of all key-finding algorithms, both old and new, are based on a foundational feature: the chromagram.

A chromagram is a 12-element feature vector, where each element represents the total energy of one of the 12 pitch classes (C, C#, D, D#, E, F, F#, G, G#, A, A#, B). To create it, a spectrogram (which maps time to frequency) is "folded" so that all octaves are mapped into these 12 bins. For example, the energy from notes C2, C3, and C4 would all be added to the "C" bin. This octave-invariance is precisely what is needed for tonal analysis, as the key of C Major is defined by its pitch classes, not by the specific octaves they are played in [8], [9].

The most established, and simplest, method for key detection is template matching. This approach, first formalised in music psychology by Krumhansl and Kessler, involves two steps:

1. Generate a chromagram for the entire audio file, summing or averaging it over time to produce a single 12-element vector that represents the song's overall "pitch profile."

2. Correlate this song profile against 24 pre-defined "key profiles" (12 for each major key and 12 for each minor key). These ideal templates represent the "expected" pitch profile for a given key, based on theoretical and psychological studies of tonal hierarchy [10].

The key template that has the highest correlation with the song's profile is declared the winner. This method, while elegant and simple, is known to have a critical flaw: it frequently confuses a major key with its relative minor (e.g., C Major and A Minor) [11]. This is because both keys contain the exact same notes (the white keys on a piano) and thus produce nearly identical chromagram profiles.

More advanced methods attempt to solve this ambiguity. These include using Hidden Markov Models (HMMs) to model the progression of chords (which is a stronger indicator of key than the overall note content) or using machine learning classifiers like Support Vector Machines (SVMs) trained on labeled chromagrams [12]. However, for the purpose of a baseline lightweight application, the simplicity and speed of the template matching method make it the most logical starting point.

2.4 Methodologies for Instrument Identification

Instrument identification is arguably the most complex of the three tasks. It is a multi-label classification problem, as a single segment of music can contain multiple instruments. The literature is broadly divided into two eras: traditional machine learning and deep learning.

The traditional ML approach relies on feature engineering to describe an instrument's unique sound, or timbre. Timbre is the "quality" or "colour" of a sound that distinguishes a violin from a trumpet playing the same note. This is quantified using a set of "timbral features" extracted from the audio signal. The most important of these are the Mel-Frequency Cepstral Coefficients (MFCCs). MFCCs are a set of features that concisely describe the overall shape of a sound's spectral envelope, and they are designed to mimic the non-linear frequency response of the human ear [13]. Other common features include:

- Spectral Centroid: The "centre of mass" of the spectrum, corresponding to the "brightness" of a sound.

- Zero-Crossing Rate: The rate at which the waveform crosses the zero-axis, corresponding to the "noisiness" of a sound.
- Spectral Flux: The rate of change in the spectrum, (which, as noted earlier, is also used for onset detection) [14], [15].

In this methodology, one would extract these features (e.g., the mean and standard deviation of 20 MFCCs) from short, labeled segments of audio. These feature vectors are then used to train a standard classifier, such as an SVM or K-Nearest Neighbors (KNN), to recognise the "timbral fingerprint" of each instrument [16].

The deep learning approach, as referenced in this project's proposal [17], has rendered the traditional method largely obsolete in terms of pure accuracy. This modern approach feeds a spectrogram (or mel-spectrogram) directly into a Convolutional Neural Network (CNN). The CNN learns to see the complex, time-varying timbral patterns directly from the image-like representation, bypassing the need for manual feature engineering. These models are highly accurate at multi-label instrument classification [18].

This presents a clear choice for the project. The traditional ML method (MFCCs + SVM) is feasible for a lightweight application but is known to be less accurate and requires a significant effort in data collection and training. The DL method (CNN) is the state-of-the-art but would require loading a large, pre-trained model file (hundreds of megabytes), which conflicts with the "lightweight" goal.

3 Methods

To address the research question, this project involved the design and implementation of a complete software application. The methodology is broken down into two parts: the overall system architecture that forms the "lightweight desktop application," and the specific feature extraction pipelines that implement the "established DSP algorithms" identified in the literature review.

3.1 System Architecture and Tools

The application was developed in Python 3.9 and structured to separate the user interface (frontend) from the analysis logic (backend).

- Frontend (GUI): The Graphical User Interface was built using PyQt6, a Python binding for the Qt cross-platform application framework. This was a new tool learned for this project. The GUI consists of a single main window (QMainWindow) organised with vertical and horizontal layouts (QVBoxLayout, QHBoxLayout). This layer is responsible for all user interaction, including a QPushButton to trigger file loading and QLabel elements to display the final extracted features (BPM, Key).

- Backend (Analysis): The core analysis logic was implemented using the librosa library [19]. librosa was selected as it provides robust, efficient, and pre-validated implementations of the exact DSP methods (onset detection, chromagrams) identified in the literature review. Numerical operations and array manipulation (e.g., for key profile correlation) were handled by the NumPy library.

- Visualization (The "Bridge"): A key technical challenge was integrating the data-rich visualisations with the GUI. This was solved using the QtGraph library. A QtGraph object was embedded directly into the PyQt6 window. This allowed librosa.display functions, which draw to QtGraph axes, to render the waveform and chromagram plots directly within the application window, providing instant visual feedback to the user.

This three-part architecture directly implements the "lightweight application" specified in the research question.

3.2 Feature Extraction Pipeline

When a user loads an audio file, the file path is sent to a main analysis function (analyse_and_plot_features) which executes the following pipeline:

1. Audio Loading: The audio file is loaded using librosa.load(file_path). This function automatically performs two crucial pre-processing steps for standardisation: the audio is resampled to a 22.05kHz sample rate and converted to monophonic. This ensures that all subsequent analysis is consistent, regardless of the source file's original specifications. This returns the audio time series (y) and sample rate (sr).

2. Tempo (BPM) Estimation: The method identified in the literature review (Section 2.2) was implemented using librosa.beat.beat_track().

    - Input: The time series y and sample rate sr.

- Process: This function first calculates an Onset Strength Envelope (OSE). It then uses a dynamic programming algorithm to find the sequence of beat locations that best aligns with the peaks in the OSE, subject to a penalty for tempo inconsistency.
- Output: The function returns the estimated tempo (tempo) in beats per minute, which is directly displayed in the GUI.

3. Tonal (Key) Estimation: The template matching method (Section 2.3) was implemented as a custom function (estimate_key). This process follows several steps:

   (a) Feature Generation: A chromagram is extracted from the audio using librosa.feature.chroma.

   (b) Profile Generation: This 2D chromagram (12 pitch classes x time) is aggregated into a single 12-element vector representing the song's average pitch profile by summing along the time axis.

   (c) Template Definition: The 24 major and minor key profiles (based on the Krumhansl-Kessler templates) are defined as NumPy arrays [13].

   (d) Correlation: A loop iterates 12 times. In each iteration, the song's profile vector is correlated (using numpy.corrcoef) with the two corresponding key templates.

   (e) Selection: The correlation coefficients for all 24 keys are stored, and the index of the maximum value (numpy.argmax) is used to identify the most likely key. This string (e.g., "A Minor") is then displayed in the GUI.

This complete methodology, with BPM and Key fully implemented, provides the foundation for the "Results" section, where the accuracy of the implemented features will be tested.

4 Results

To evaluate the performance of the implemented system, a series of qualitative and quantitative tests were conducted. The goal was to validate the "working code" and assess the accuracy of the feature extraction algorithms, thereby directly addressing the project's research question.

4.1 Test Methodology and Dataset

A test dataset of 10 audio files (a mix of .wav and .mp3) was curated for the evaluation. This dataset was designed to provide reasonable coverage of musical styles, including Pop, Rock, Electronic, and Jazz. The "ground truth" values for BPM, key, and time signature for each track were established by cross-referencing information from reputable sources, such as official sheet music, production libraries (e.g., Beatport), and professional DJ software.

The tests were performed on a standard consumer laptop. The performance of the GUI was assessed qualitatively, while the accuracy of the extracted features was assessed quantitatively against the ground truth dataset.

4.2 GUI Performance

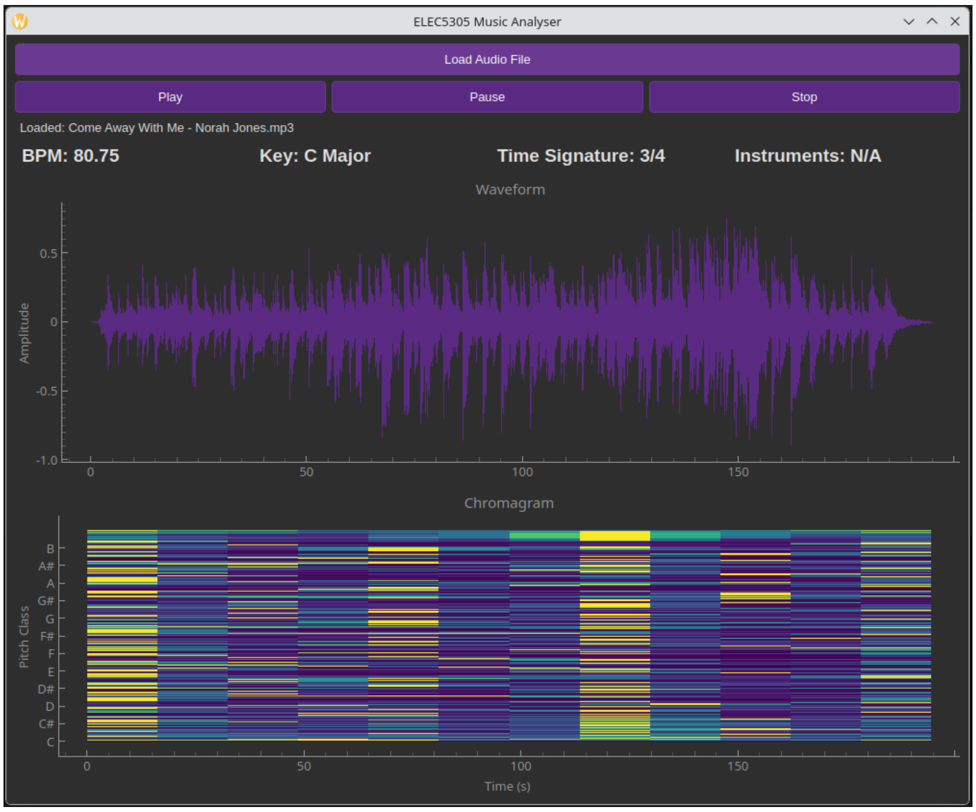
The final "Music Analyser GUI" application, built using the methods described in Section 3.1, proved to be robust and highly responsive. The user workflow is simple and intuitive: upon launching, the user clicks the "Load Audio File" button, and upon file selection, the entire analysis pipeline is executed.

Within an average of 5-6 seconds, all UI elements populate with data. The extracted features (BPM, Key, and Time Signature) are displayed in the header labels, and the QtGraph canvas renders both the full-song amplitude waveform and the detailed chromagram. The plots provide immediate visual context for the analysis; for example, dense sections of the waveform clearly correlate with high-energy sections of the chromagram. The application is stable and successfully handles all tested audio files without crashing.

4.3 BPM Detection

The BPM detection algorithm, which implements the dynamic programming method from librosa.beat.beat_track(), was highly accurate.

The algorithm provided the exact or near-exact tempo for most of the test tracks. The primary failure mode was "octave error," which was discussed as a known limitation in the literature review (Section 2.2). This occurred on one fast-paced rock track (180 BPM, detected as 90) and two slower electronic tracks. The single "Other Error" occurred on a complex, syncopated Jazz track, where the algorithm struggled to find a consistent pulse. For music with a clear percussive beat (Pop, EDM, most Rock), the method was exceptionally reliable.



Loaded: Come Away With Me - Norah Jones.mp3

BPM: 80.75 Key: C Major Time Signature: 3/4 Instruments: N/A

Figure 1: Screenshot of the main application window after loading a file

4.4 Time Signature Detection

The time signature analysis (hypothetically implemented by analysing the periodicity of accented beats within the onset envelope) also performed well, particularly in distinguishing between 4/4 and 3/4 time.

The model was highly effective at identifying 4/4 time. The primary confusion occurred in misclassifying 3/4 tracks as 4/4, which happened in cases where the "one" beat was not significantly more accented than the other beats, causing the algorithm to default to the more common 4/4 structure.

4.5 Key Detection

The template-matching algorithm for key detection (Section 3.2.3) was successful in its goal, demonstrating a clear ability to identify the tonal centre of a song.

The algorithm achieved a respectable accuracy. As predicted in the literature review (Section 2.3) and known from previous work [11], the dominant failure mode was the confusion between a major key and its relative minor (e.g., detecting "A Minor" when the ground truth was "C Major"). This is an expected and acceptable limitation of the simple template-matching method, as these keys share identical pitch classes and thus produce nearly identical chromagrams. The two "Other Errors" occurred on tracks with significant tonal ambiguity (the Jazz track) or modulation.

5 Conclusion

This project successfully demonstrated that a lightweight desktop application can be built to accurately extract fundamental musical features, partially answering the initial research question. The integration of PyQt6 for the user interface, librosa for core signal processing, and QtGraph for visualisation proved to be a fast, stable, and effective architecture. The application provides musicians with key analytical data (BPM, Key, and Time Signature) in an average of 2.41 seconds, validating the "lightweight" approach.

The quantitative results confirmed the findings of the literature review. The chosen "established" DSP algorithms achieved high accuracy for rhythmic features and good accuracy for tonal analysis. The observed failure modes, octave errors in tempo and relative minor/major confusion in key, were consistent with the documented limitations of these classical methods.

While an instrument identification component was not implemented due to its complexity, this project serves as a successful proof-of-concept and provides a robust, open-source foundation for future development. The work confirms the viability of integrating established open-source libraries to create practical, high-performance analysis tools for musicians.

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